Società italiana di economia pubblica

XXI CONFERENZA

AN EMPIRICAL ANALYSIS OF HEALTH CARE UTILIZATIONS: WAITING TIMES IN THE ITALIAN NATIONAL HEALTH SERVICE

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An empirical analysis of health care utilizations: waiting times in the Italian National Health Service

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Abstract

Understanding health care utilization is important to design efficient and effective health systems. Toward this end, we develop a relatively simple and intuitively appealing microeconometric framework (based on the hurdle model for count data) to investigate the determinants that increase the probability and the length of waiting for a health care service. In this framework private health care without waiting time is an option for the patients in the public health queue. In trying to determine how resources are allocated, in this analysis, an effort will be made at taking seriously the idea that there is a margin of choices available within the INHS that can affect the waiting lists.

Key words: health care utilization, count data, Italy

1. Introduction

Long waiting times for health care service and waiting lists remain issues of major concern in several national health services, despite the considerable amount of resources devoted to finance health care supply. Waiting time in countries with dominantly public health care, is often explained by limited public resources. However, it is not clear why a system with a queue should

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cost less than a system without. One obvious explanation is that waiting time allowed for full capacity utilization, despite demand fluctuations. This often results in queues during periods of high demand.

However, if this were the only reason for having waiting time, one would expect the waiting time to fluctuate between something close to zero and a month or two. The waiting times observed for many types of treatments are however considerably larger. More importantly, although they fluctuate, they are always bounded well away from zero. One possible effect is that the queue causes some people to exit from the queue before being treated. Another possible effect has been investigated by (Lindsay and Feigenbaum; 1984). They assume that waiting time induces some people to never join the queue for treatment, due to the existence of costs incurred at the time one joins the queue. When this is the case, it could be better to never receive treatment than to receive treatment after a waiting period. Therefore the queue itself has an effect on how the flow of cases translates into a flow demand for treatment in the public sector. The private alternative may relieve the pressure on the national health service and therefore improves the access and quality of care also for those patients who remain in the public sector or, on the contrary, may drain the resources from the national health service and accordingly lead to a decline in access and quality of care.

For instance, the existence of a queue might reduce the flow demand for health treatment in the public sector. Patients who enter into such a queue for medical treatment sometimes have the option of using a private alternative to the public health care, thus avoiding the queue (Cullis and Jones; 1985). However, by doing this, they often incur larger costs (Iversen; 1997), as they have to pay for the private treatment (directly or through a private supplementary insurance they previously have purchased), while the treatment in the public system would have been free or almost free. The longer the waiting time, the more people choose the private alternative. The waiting time is thus an equilibrating mechanism making the demand for public treatment equal to the supply, which is politically determined.

The literature about the interaction between the private sector and the waiting time in a national health service is rather scanty. In a discussion of competing explanations of waiting lists Cullis and Jones (1985) discuss possible contributions from the private sector. They argue that in order to reduce the public sector waiting time, a subsidy to private treatments is more efficient than an increase in the budgets to the public providers. It seems therefore that, for instance, in Italy, as well as in many OECD

countries where the healthcare sector accounts for a sizable proportion of national expenditures, the issue is not the level of the public funding but the inefficient allocation of resources within the healthcare sector.

The purpose of this paper is to develop a model of the waiting times of selected health care services, focusing on efficient allocation of resources within the Italian National Health Service where most of the health care is publicly provided and where there is waiting time for several types of treatments. In trying to determine how resources are allocated, in this analysis, an effort will be made at taking seriously the idea that there is a margin of choices available within the INHS that can affect the waiting lists.

We investigate the effect of public policies and socio-demographic characteristics on waiting times, focusing on the idea that private health care without waiting time is an option for the patients in the public health queue.

It is noteworthy that in the analysis of waiting times, no common and unified datasets are available, therefore we have to evaluate the strengths and weaknesses of gaps in statistics and situations where measures fail to represent the whole waiting experience. In additions there are significant issues with regard to the definitions used, that makes the interpretation of waiting list and waiting times statistics as a whole problematic.

The paper is organized as follows: section 2 offers a brief outline of the evolution of the Italian health care system. Section 3 deals with the literature review. Section 4 introduce the econometric model used. Section 5 consists of a descriptive analysis of the dataset used and introduce the variables selected. Section 6 provides the results of the econometric analysis. Finally, section 7 contains the main conclusions and some remarks.

2. The Italian National Health Service

Over the last decades, the health care system in Italy, as in most European countries, has experienced deep transformations. The first reform of the health care system, in 1978, was aimed to overcome the prior fragmented and differentiated system of thousands of health funds and institutions, introducing a National Health Service. In 1992-93, a second reform was undertaken aimed to introduce internal markets and to devolve power and financial accountability to regions. A major component of the reforms included changes in hospital financing, moving from a global budgeting approach to Diagnosis Related Groups, DRG-based per case financing of hospitals with the goals of

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controlling the growth of hospital costs and making hospitals more accountable for their productivity. Explicit incentives were included for the increased use of "day hospital" (outpatient) care to reduce a perceived overuse of "ordinary" hospital (acute inpatient) care.

Until then, all public health-care facilities, including hospitals, were directly managed by the local health authorities (Unità Sanitarie Locali USLs) which were in turn administered by local governments. This was intended to promote democratic participation by citizens in the NHS, but led to an excessively bureaucratic and inefficient use of health-care resources and occasionally to corruption and the transformation of some USLs into machines for political patronage (France and Taroni; 2005). In 1999, attention is focused on the suitability of operations seen in a broader perspective (organization and management), with emphasis on the importance of uniform and essential levels of assistance and in 2001 the Essential Levels of Care, LEA, were introduced, with the central government guaranteeing a minimum and uniform level of health-care services for all citizens, in accordance with the regions. In fact, by constitutional amendment, in 2001, the federal system was approved and new laws were enacted that provide for refinements to the financing system. The National Health Care Fund, FSN, was abolished, and the regions were granted independent powers of taxation to finance health care which is mainly funded by general taxation. Nowadays, about 70% of expenditures are publicly financed, with the remaining 30% financed by private expenditures, of which less than 10% is covered by private health insurance and company health plans[1]. Specifically the INHS is financed by the regional surcharges (addizionale) on the national personal income tax (IRPEF) and sharing (compartecipazione) of the national VAT according to the criterion of geographic origin, business regional tax on production activities (IRAP), and surcharges on national gasoline excise taxes. For the ordinary regions, revenues derived from the sharing of the national tax bases are officially recorded as a transfer rather than as its own tax, given that they are totally controlled by the central government, and are therefore somewhat of a gray area.

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[1]Prices are paid for those health care services that are not provided by SSN, such as particular categories of drugs and dental cure; tickets, on the other hand, are partial prices that are paid partly by the patient and partly by the SSN. Premiums are paid to private insurance companies that provide complementary or additional insurance beyond SSN, while taxes are the most common way to fund the public health system.

To guarantee the financing to achieve the LEA in every region[2], a fiscal equalization mechanism (National Solidarity Fund) has been developed to transfer funds to those regions unable to raise sufficient resources to finance all functions[3]. However, since 2001, regions have become accountable for any health care deficit they incur[4] and, according to the magnitude of their deficit and their policy priorities, have made different choices on which of the measures to introduce.

Nowadays, a major problem faced by the INHS is the rational use of resources to reduce inefficiencies, and therefore, waiting times and waiting lists, as well as the percentage of health-care spending met directly by families[5]. Given that waiting lists have been portrayed by the media as signaling imminent NHS breakdown and demonstrating the need for extensive supplementary health insurance, national legislation regulating the LEAs was amended. It now require timeliness of service and an agreement between the state and the regions set guaranteed maximum waiting times for ambulatory care (60 days for five major diagnostic imaging procedures and 30 days for eye and cardiology visits) and for three elective hospital procedures (180 days for cataract surgery and hip replacement and 120 days for PTCA). The

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[2]The LEA should be defined in terms of output, rather than input, so as to encourage the efficient delivery of services; in regions lacking efficiency, more generous services would require increasing taxes, thus improving accountability about government decisions. Here is therefore a need to reform financial arrangements with sub-national governments. In particular, regional equalization transfers should be linked to the "standard cost" of providing essential guaranteed services and to own tax capacity.

[3]An important step in the procedure of the establishment of the health care system finance is constituted by the agreement between State and Regions to decide the aggregate funding and how to allocate it among the regions; this often causes huge political friction. The formula for the allocation of financial resources has changed several times; at the moment it is based on population size, weighed by age-specific utilization rates for hospital care, drugs and residential care, on standardized mortality rate and on an adjustment for interregional patient flows.

[4]To cover deficit regions can raise local taxes only to a limited extent and allow hospitals to dispense drugs to outpatients.

[5]The private health expenditure includes out-of-pocket payments (both cost-sharing and direct payments for the purchase of private health care services) and voluntary health insurance schemes to diagnostic procedures, specialist visits and drugs; patients can benefit of two kinds of exemption, one based on disease categories and special services (e.g. chronic illnesses, organized screening), and the other based on a sort of means test (e.g. income related).

financially straitened NHS, however, received no additional funding for this purpose.

Italian experience suggests that co-payment policy is complex to implement and expensive in political terms: tickets require huge administrative costs and they still are a source of a lively political debate.

3. The analysis of waiting times: a brief literature review

Historically, waiting list were viewed as a rationing device, which plays a pivotal role in equalizing demand and supply in a market that is not subject to price rationing. According to this interpretation, a waiting list tends to grow until the cost, i.e. inconvenience, of waiting reduces the value of treatment for some patients to the point that they either seek alternative forms of treatment, or withdraw altogether. In this way, the waiting lists regulate demand, bringing it into equality with the available supply. Over the years research on waiting-related phenomena has proceeded in two quite distinctive direction. One side of the literature, mainly economists,emphasizes the role of incentives in the generation of waiting; on the other side, waiting is viewed as arising from the dynamic of buffering or smoothing of demand. In a seminal contribution to the economics literature on the waiting list phenomenon, Lindsay and Feigenbaum (1984) developed a theoretical model of rationing through the impact of waiting times on the level of demand in the public health sector. Patients, in systems where demand healthcare is provided free at the point of delivery, have little incentive to restrain their consumption of healthcare. In this demand side approach waiting times are seen as a "time price" as opposed to a "money price". There is an expected wait beyond which the patient is deterred. Propper (1990, 1995) develops a methodology for evaluating the time cost of waiting for surgery when admission dates are uncertain. Johannesson et al. (1998) and Bishai and Lang (2000) develop a willingness to pay (WTP) approach to the estimation of the cost of waiting. In addition according to Xavier (2003) patients choices of hospital depend on a trade-off between waiting time and travel distance. He develops a modified Hotelling duopoly model, to examine the implications of competition between hospitals and GP fundholding for resource allocation and waiting times.

A related stream of economic research stress the role of incentives on the supply side rather than demand side. The public choice perspective in economics raises the question of the economics of processes and the argument

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that all economic actors are maximizing their utility subject to constraints. In this context it means attention has to be directed toward the narrower incentives of producers (hospital physicians, managers, and the like), those in the government (politicians) and central government bureaucracy (civil servants). In Iversen (1993) supply side model observed waiting lists and waiting times for medical treatment are placed in the context of a political bargaining process over resources. He deliberately assumes altruistic agents but recognizes there may well be deviations from this assumption. Iversen (1993, 1997) argued that there are perverse incentives to preserve long waiting times in the public sector if government is willing to sanction higher budgets when waiting times are high, or if public sector surgeons are permitted to work in both the state and private sector. They may have incentive not to exert a maximum level of effort so to allow public sector waiting lists that generate private demand. The growth of private practice is the direct consequence that results in increases in the physicians' income. Cullis and Jones (1986), Goddard et al. (1995), Barros and Olivella (2005) and Olivella (2002) also consider the impact of the public sector waiting times on private sector activity from a theoretical perspective.

Parallel to this incentives approach another rich literature has flourished, with a quite different view of the agents' motivations in the health care sector. This so-called queuing or managerial approach implicitly assumes that healthcare workers are not self-interested. Waiting arises in a system where capacity is fixed in the short run but demand fluctuated. The central idea is that variability in the waiting times arises from variability in the arrival process which is either unpredictable, or predictable but unmanageable (as happens in systems which experience rush-hours). This variability results in the system becoming congested (a so-called busy period), and patients who arrive at this time experience longer waits. For example, Worthington (1987) uses queuing models to simulate the effects on the size of waiting lists, average waiting times and hospital admission rates of various policy or administrative measures. van Ackere and Smith (1999) simulates the effects on waiting times of various possible scenarios for the evolution of patient demand and public and private sector supply at the aggregate level, and Kommer (2002) carries out a similar exercise for a single specialism. Goodyear et al. (1997) discuss applications of queuing theory for the management of NHS hospital resources. They assert that the system cannot be designed so that capacity matches average patient demand, on the grounds that small fluctuations in demand around the average can easily overload the system. In this line

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of research there are other important contribution such as those of Findlay (1998) Thomas et al. (2001) and Gorunescu et al. (2002).

Turning to the empirical evidence, the recent empirical literature has mainly focused on estimating how the demand for and supply of treatment respond to variations in waiting times (Martin and Smith; 1999, 2003; Goddard and Tavakoli; 1998; Blundell and Windmeijer; 2002; Martin et al.; 2007), on the impact of GP Fund-holding on waiting times (Dowling; 1997; Propper et al.; 2002; Dusheiko et al.; 2004), and on the effect of waiting time on the demand of private health insurance. For the UK and Spain respectively, Besley et al. (1999) and Jofre-Bonet (2000) present empirical evidence that the demand for private health insurance is positively related to public health service waiting times.

In most of this theoretical and empirical literature, the availability of the alternative option of paying for treatment in the private sector does not alter the inverse relationship between waiting times and the demand for treatment in the public sector that was originally identified by Lindsay and Feigenbaum (1984)

4. The hurdle model

Our econometric specification is based on the hurdle model for count data as proposed by Mullahy (1986). When defining regression models for the utilization of public utility resources, we need to take into account two essential features. Firstly, the observed outcome (e.g. the number of days waited before the utilization of a health service) can take only non-negative integer values. This calls for the application of count data models (Cameron et al.; 1988); Poisson regression models may represent a natural starting point in such a context.

Let us start supposing we have recorded counts Y_{ij}, $i = 1, \ldots, n$, $j = 1, \ldots, J$. We assume that the observed counts Y_{ij} represent independent Poisson random variables:

$$P(y_{ij} \mid \lambda_{ij}) = \frac{e^{-\lambda_{ij}}}{\lambda^{y_{ij}} y_{ij}!}, \quad i = 1, \ldots, n; j = 1, \ldots, J \tag{1}$$

where

$$E(y_{ij} \mid \lambda_{ij}) = \mathrm{Var}(y_{ij} \mid \lambda_{ij}) = \lambda_{ij} \tag{2}$$

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In a regression context the canonical parameter is modeled as

$$\log(\lambda_{ij}) = \beta_{0j} + \sum_{l=1}^{p} x_{ijl}\beta_{lj}, \quad i = 1, \ldots, n; j = 1, \ldots, J \qquad (3)$$

where $\mathbf{x}_{ij} = (x_{ij1}, \ldots, x_{ijp})$ represents a vector of p covariates and $\beta_j = (\beta_{0j}, \ldots, \beta_{pj})$ is an outcome-specific vector of regression parameters. Clearly, this model is restrictive because it assumes a unit variance-to-mean ratio; further, Poisson models are not suitable for data which are characterized by an excess of zeros.

A possible solution may be represented by choosing the negative binomial (NB) density as the baseline density:

$$P(y_{ij} \mid \lambda_{ij}) = \frac{\Gamma(y_{ij} + \psi_{ij})}{\Gamma(\psi_{ij}) + \Gamma(y_{ij} + 1)} \left(\frac{\psi_{ij}}{\lambda_{ij} + \psi_{ij}}\right)^{\psi_{ij}} \left(\frac{\lambda_{ij}}{\lambda_{ij} + \psi_{ij}}\right)^{y_{ij}} \qquad (4)$$

where $\Gamma(\cdot)$ is the gamma function, $\log(\lambda_{ij})$ is defined as in (3) and $\psi_{ij} = (1 \setminus \alpha)\lambda_{ij}^{k}$. The parameter α measures the degree of overdispersion relative to the Poisson density (which is a special case obtained when $\alpha = 0$). In the empirical application we will consider the family of NB densities since it is the most general and flexible.

The second feature of utilization data is actually a potential two-part decision process: the first process entails the decision to use the service while the second models the decision about the number of visits. In a Poisson model, this two-part feature is ignored, and this may lead to model misspecification and hence to inconsistent parameter estimates. In the hurdle model proposed byMullahy (1986), a *decision* is made about whether to use a given service or not; then a decision on the frequency of times is made (see among others Gerdtham (1997); Gurmu (1997); Santos Silva and Windmeijer (2001)). This model has been widely used in the economic context since it resembles accurately the principal-agent model: homogeneous, observable counted outcomes subject to exogenous selection. The first decision can be represented by a binary choice model, modeled using a probit or logit link; the second can be analyzed through a truncated at zero discrete distribution such as the truncated Poisson, the truncated negative binomial and so on.

The basic hurdle model could be described as follows; let us assume that f_T represents a truncated at zero distribution for non-negative integers; the probability distribution of the hurdle model is given by (Winkelmann; 2004):

$$P(y_{ij}) = \tau_{ij}^{d_{ij}}[(1 - \tau_{ij})f_T(y_{ij} \mid y_{ij} > 0)]^{1-d_{ij}} \tag{5}$$

$$d_{ij} = 1 - \min(1, y_{ij}) \tag{6}$$

$$P(d_{ij} = 1) = P(y_{ij} = 0) = \tau_{ij} \tag{7}$$

where d_{ij} denotes a dummy variable indicating individuals with zero counts; i.e. $d_{ij} = 1 \iff y_{ij} = 0$

The truncated at zero distribution can be written as

$$f_T(y_{ij} \mid y_{ij} > 0) = \frac{f(y_{ij})}{1 - f(0)} \tag{8}$$

where the choice of f may include, among others, Poisson, Negative Binomial as well as overdispersed Poisson distributions. The log-likelihood function for the multivariate hurdle model is therefore given by:

$$\ell(\cdot) = \quad = \sum_i \sum_j [d_{ij} \log \tau_{ij} + (1 - d_{ij}) \log(1 - \tau_{ij})] +$$

$$+ \sum_{d_{ij}=0} \sum_j \{\log f(y_{ij}) - \log[1 - f(0)]\} \tag{9}$$

If model parameters in τ_{ij} and f are distinct and the two parts are independent, the log-likelihood can be factorized as the sum of two terms; where:

$$\ell_1(\cdot) = \sum_i \sum_j [d_{ij} \log \tau_{ij} + (1 - d_{ij}) \log(1 - \tau_{ij})] \tag{10}$$

is the log-likelihood for the binary process and

$$\ell_2(\cdot) = \sum_{d_{ij}=0} \sum_j \{\log f(y_{ij}) - \log[1 - f(0)]\} \tag{11}$$

is the log-likelihood for the positive counts.

Given these assumptions, the parameter vector for the model describing the positive counts can be estimated by maximizing $\ell_2(\cdot)$, while the parameter vector describing d_{ij} behavior can be estimated by maximizing $\ell_1(\cdot)$; as usual, it can be argued that different specifications of the zero truncated models may lead to biased parameters estimates.

Recent literature provides comparisons between the relative performance of the hurdle model with respect to finite mixture approach. The comparison

is even more interesting if one think of the hurdle model as two-component finite mixture with known component labels and known locations (mass at zero). Deb and Trivedi (1997, 2002) and Deb and Holmes (2000) present evidence that finite mixture models often outperform the hurdle model; however, this is not a general evidence, since as stressed by Jiménez-Martín et al. (2004) and Winkelmann (2004), the standard hurdle model can fit data better than the finite mixture model (for a discussion see Bago d'Uva (2006) and Min and Agresti (2005)).

5. Data

In Italy most of the health care is publicly provided, formally universal and free of charge (particularly for the poor). However, early studies indicate that persons with cultural and socio-economic disadvantages may experience difficult access to good quality care (Zocchetti et al.; 2004), while other group of users may be discourage to access public provided care, for several types of treatments, as they perceive waiting time costs (the price of price of the public service), to be higher than the price of private care (the price of health insurance).

In this framework private health care without waiting time is an option for the patients in the public health queue.

To develop a model of resources allocation within the INHS we use waiting time statistics as the primary method of measuring and monitoring access to services with the serious limitation that the variable do not contain the information required to assess whether time waited is appropriate to need. Waiting times are measured as the time elapsed between the date of needs identification and date of service provision. In order to accurately capture the waiting time, data entered onto the waiting list will also be identified, especially when this does not match the date of needs identification.

To investigate the determinants that increase the probability and the length of waiting for a health care service, it seems reasonable to separate the decision-making behavior in two stages. The first stage mainly involves the decision of the patient to use the health care system. Once the initial contact has been made, a person usually has to wait. The length of waiting time changes widely for different treatments as well as across Italian Regions. It appears that the availability of facilities or resources may be an important determinant as well as other factors that will be accounted in the paper.

We illustrate our approach with data from *Health conditions and access to health services* conducted by the Italian National Statistics Institute (Istat) in 1999-2000. The survey contains a perceived health status, symptoms, chronic conditions, disability and health related behavior and health care utilization information (hospitalizations, medical examinations), as well information bout the time needed before a health care service is provided. This information is not available from administrative data sources. The total sample consisted of 60,000 families (approximately 180,000 subjects) which were interviewed during four periods of 3 months (September and December 1999, March and June 2000), 3 weeks each trimester. The survey was conducted by face-to-face interviews with all family members in a sampled family. The families were selected in a representative way for the whole Italian population.

Our choice of control variables is guided by theoretical considerations but constrained by data availability.

Table 1 presents the list of dependent and explanatory variables used in this paper as well as some descriptive statistics. The dependent variables in our analysis reflect the probability to enter the waiting list to receive health services (logit column) and the time elapsed between the date of needs identification and the date of service provision for different types of health services (truncated column). We consider three type of service: (a) Vr - the number of waiting days for a doctor visit (general practitioner or specialist) during the month preceding the survey date; (b) R - the waiting time for hospitalization services during the three months preceding the survey date; (c) A - the number of waiting days for a diagnostic exam during the month preceding the survey date.

It is clearly evident from Table 1 that the data for each health care utilization variable is highly skewed. We use explanatory variables commonly used in the literature to explain health outcomes, such as demographic, socioeconomic and need variables. The list include age, sex (represents the gender by dummy variables female = 1 and male = 0) , autonomy (the dummies variables are = 0 if patient autonomy subsists and 0 otherwise) marital status (characterized by two dummy variables, currently married 1, 0 otherwise, which implies that singles are the reference group).

Among the other variables, rt represents differences in the supply of health care services, in term of the type of hospitalization (with dummy variables equal to 1 if public and 0 otherwise), *choice* reflects if the treatment has been chosen by the patients (dummies equal to 1) or if the decision

has been made by a doctor(then the dummy is equal to 0), and *ins* reflect the availability of supplemental health insurance (dummies variables = 1 or 0 otherwise). Lastly we include 20 dummy variables to capture regional effects.

6. Econometric results

In this section, we discuss the model specification results and provide a brief summary of our empirical findings. As indicated in previous sections, the natural starting point for count data models is to test for overdispersion. The analysis of descriptive statistics clearly reject the imposition of the restriction that the conditional mean is equal to conditional variance; that is, they reject the Poisson regression model as an adequate explanation of the process underlying health utilization behavior in this sample. Overdispersion in the data could arise either from cross-sectional heterogeneity, a distinct data-generating process for 'zero-states', or specification errors. One way to proceed with the hurdle model is to use NB model.

The specification of the hurdle model consists of a logit model for the contact decision and a truncated NB model for the intensity of utilization.

The possession of a private health insurance increases the probability of willingness to wait for private specialist. This may be due to an ex-ante demand for health service that make the frequent health service users to look for supplementary coverage and costs reimbursement. Being double-insured a person is able to access private health care at lower out-of-pocket payments. It is reinforced by moral hazard where incentives by the patient and the physicians for over-treatment align against the insurer.

Chronic conditions, measured considering the need of using health care services, increases the the probability of waiting. These results make a great deal of sense since most of the chronic illnesses require more attention than other diseases. The results are similar in the preferred model specifications for specialist visits and hospitalization. Similar evidence has been found in the literature by Pohlmeier and Ulrich (1995); Deb and Trivedi (1997, 2002); Lahiri and Xing (2004), For hospitalization services, however, the results are weaker.

The education variables are generally insignificant for doctor visits and hospitalization, and they are generally significant and positive for visits to specialists. There are essentially two arguments in the literature regarding the effect of education. Education may be correlated with medical knowledge, so that a person with more education is better informed and tends

to prefer a specialist over a GP. Alternatively, people with higher education may be able to improve their health more efficiently, generating fewer GP contacts. Both these arguments find some empirical evidence in the literature as well as some conflicting evidence. For example, Deb and Trivedi (1997, 2002) find that education increases visits to physicians. Pohlmeier and Ulrich (1995) find that higher education reduces the contact decision for GP visits and increases specialist visits, without affecting frequency in both cases. Santos Silva and Windmeijer (2001) find that the effect of education is negative for the contact decision and positive for specialist visits. Turning to the demographic variables, we find that gender affects the utilization of all non-hospitalization services. Marital status is relevant in the decision to wait for a service. A married person is willing to wait less once he/she is in the waiting list.

The effects of age are consistent across equations. These results are consistent with those found in Deb and Trivedi (1997)in the analysis of health care services utilization, and with health economic literature in general. For instance, Cameron et al. (1988); Pohlmeier and Ulrich (1995) find a significant relationship between age and physician visits.

Regional-specific unobservable factors make the demand for public doctor consultation in central and southern Italy lower than in northern Italy, giving that the waiting time is higher in the southern regions.

7. Conclusion

In this paper, we conduct an econometric analysis of the waiting time within the INHS for different types of health care services. We illustrate our approach with the most recent data available from the ISTAT, using waiting time data for health services.

Econometric investigations of the relationship between waiting lists and resource allocation to the public health care system have provided few definitive results. Early work on the UK NHS suggested an increase in resources had no impact on lists; later work has suggested an increase in supply may decrease lists. Empirical work also indicates connections between the public sectors in which there are waiting lists and the private sector that operates alongside large publicly funded systems on both the demand and the supply side.

Our results suggest offer important insights. First, supplemental health insurance affects the willingness to wait. This moral hazard effect can be

mitigated by designing policies to regulate such consumer behavior. This suggests that an higher willingness to wait by the privately insured reflects an higher ex-ante demand for health service. This is in line with the findings by Deb and Trivedi (1997) that the effect of supplemental health insurance leads to higher utilization of health care.

Future improvements in the data and techniques used can enhance our understanding of the factors underlying the distribution of resources within the health care sector. In terms of the data, future surveys can add important information on waiting time and out-of-pocket spending for each visit to different types of health professionals. The absence of such variables after 2001 limits our ability to identify some of the interesting and crucial parameters related to the demand for health care services.

Policy makers in Italy need to take cognizance of these insights in the design of health care systems, especially in the area of primary care, for efficient and cost-effective health care delivery to the population rather than increasing funding for public sector treatment, waiting for public sector treatment may be reduced by using additional public expenditure to finance a subsidy to those who will leave the waiting list to purchase treatment in the private sectorCullis and Jones (1985) . However equity problems may arise. The scheme should be implemented in order not to be regressive and discourage higher income waiters (more able to purchase private sector treatment) to qualify for this subsidy.

Table 1: Estimates and Descriptive statistics

	R		A		Vr	
	logit	truncated	logit	truncated	logit	truncated
age	0.14*	0.01**	0.01*	-0.00	0.00	0.01*
sex	-0.03	0.03	0.39*	0.10*	0.38*	0.06*
autonomy	0.114	0.04	-0.73*	0.10*	-1.11*	-0.01
married	-0.073	-0.38*	0.35*	-0.17*	0.24*	-0.25*
education	-0.09	0.27	0.05	-0.11	0.01	-0.15*
rt	4.87*	0.38*	-	-	-	-
choice	-	-	2.48	0.22*	2.37	0.60*
ins	0.37*	-0.07	0.30*	-0.24*	0.31*	-0.11*
VDA	-0.04	-0.07	-0.05	0.19	-0.17**	0.19
LOM	-0.07	-0.32	0.16**	-0.13	0.01	-0.14**
BZ	0.01	-0.35	-0.89*	0.10	0.07	0.18**
TN	-0.17	-0.16	-0.28**	-0.13	0.02	0.02
VEN	-0.10	-0.16	0.34*	0.28*	0.13*	0.28*
FVG	-0.32**	-0.06	0.17**	0.21*	0.29*	0.36*
LIG	0.12	-0.13	0.27*	-0.20*	-0.02	-0.52*
EMR	-0.13	-0.09	0.17**	0.01	0.30*	-0.02
TOS	-0.33**	0.20	0.41*	-0.26*	0.24*	-0.10
UMB	-0.24	-0.41	0.08	-0.49*	-0.09	-0.26*
MAR	-0.01	-0.36	0.23**	-0.16	0.14*	-0.19*
LAZ	-0.10	-0.53*	0.51*	-0.19**	0.02	-0.11
ABR	0.28**	-0.45*	0.01	-0.47*	-0.05	-0.36*
MOL	-0.23	-1.06*	-0.13	-0.54*	-0.20*	-0.43*
CAM	0.13	-0.70*	0.29*	-0.75*	-0.46*	-0.60*
PUG	0.18	-0.49**	0.13	-0.52*	-0.31*	-0.21*
BAS	-0.11	-0.85*	-0.13	-0.47*	-0.34*	-0.07
CAL	0.26	-0.53*	0.17 **	-0.56*	-0.15*	-0.19*
SIC	-0.14	-0.52*	0.32*	-0.49*	-0.29*	-0.17**
SAR	0.06	-0.07	0.01	-0.08	-0.09	-0.03
cons	-6.50*	2.77*	-4.06*	2.22*	-1.86*	1.72*

Notes: The symbols * and ** denote 5% and 10% significance respectively.

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