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Double coverage and demand for health care: Evidence from quantile regression*

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Abstract

An individual experiences double coverage when he benefits from more than one health insurance plan at the same time. This paper examines the impact of such supplementary insurance on the demand for health care services. Its novelty is that within the context of count data modelling and without imposing restrictive parametric assumptions, the analysis is carried out for different points of the conditional distribution, not only for its mean location.

Results indicate that moral hazard is present across the whole outcome distribution for both public and private second layers of health insurance coverage but with greater magnitude in the latter group. By looking at different points we unveil that double coverage effects are smaller for high levels of usage.

We use data for Portugal on the consumption of doctor visits, taking advantage of particular features of the public and private protection schemes on top of the statutory National Health Service.

Keywords: Demand for health services, Moral hazard, Count data, Quantile regression.

JEL codes: I11, I18, C21, C25

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1 Introduction

The aim of this paper is to analyse the impact of health insurance double coverage (i.e. a situation in which an individual is covered by more than one health insurance plan)[1] on the consumption of health care. It is well known that if the demand for health care reacts to budget constraints and preferences changes then, double coverage should also have important effects because it modifies the actual price of services, the income of the insured, and the opportunity cost of time in the case of illnesses. The effect of supplementary health insurance is often associated to an aggravation of moral hazard that creates incentives for people to go to the doctor more frequently and eventually because of less severe illness.[2]

Organizational designs of health systems may generate layers of coverage. The most common situation regards the case where an individual benefit from a compulsory public insurance, and in addition he has purchased a private one. Such supplementary private health insurance usually overlaps the range of health care services provided by the statutory health system. The main purpose of second (and higher) layer of coverage is usually to increase the set of choices about the health care provider (for example, private providers or private facilities in public institutions) as well as to decrease the level of co-payments done by the individual. By increasing the choices of provider, patients may also obtain a faster access to health care. Quantitatively, double coverage is not a negligible phenomenon. It can be found in all European countries, being common in Finland, Greece, Portugal, Spain, Sweden and in the United Kingdom. Furthermore, in the United States, the Obama plan is expected to increase health coverage, inclusively by allowing Americans to maintain their current insurance scheme while accessing new options. In such scenario, double coverage situations are expected to augment significantly in coming years. Research on this phenomenon can help to detect whether possible inefficiencies, causing unnecessary and costly utilization due to moral hazard, should be a concern.

Existing works addressing health insurance double coverage focus on mean effects. In contrast, by looking at other points of the conditional distribution we unveil that stronger effects are found for less frequent users. Our findings are the result of the application of an innovative technique for estimating the quantile regression for counts. The estimates were computed with Portuguese data[3], using as source

[1] The terms "duplicate coverage", "supplementary health insurance" or "additional health insurance" are used alternatively in the literature.

[2] Moral hazard in this context is defined as the "change in health behaviour and health care consumption caused by insurance" (Zweifel and Manning 2000). Some authors criticize the direct association of double coverage with moral hazard, arguing on the existence of other important effects. For instance, Vera-Hernández (1999) refers the impact of insurance on individual' health, which will decrease the future consumption of health care. Also Coulson et al. (1995) points to the importance of supply-inducement by providers.

[3] In particular, the Portuguese Health Survey of 2005/2006, a cross sectional health dataset that provides a wide range of information at an individual level concerning socioeconomic conditions and health status indicators.

of double coverage the existing health insurance schemes beyond the National Health Service (NHS). Approximately a quarter of the Portuguese population has access to a second (or more) layer of health insurance coverage on top of the NHS, through mandatory (occupation-based) health subsystems for workers of some large companies and public employees and voluntary health schemes. We focus our attention on the double coverage resulting from the former type, regarding both health insurance plans provided to public employees and insurance plans of private companies. Results indicate that double coverage impact on the further use of resources is especially high in the private subsystems (2.6 to 2.9 times higher than the one presented by public employees). An interesting finding, which could only be observed through the use of quantile analysis, is that these effects are lower in the upper tail of the outcome distribution. This shows that health insurance double coverage is relatively more relevant for the first levels of usage since for more frequent users consumption behaviour depends less on the health insurance plan.

We measure health care demand through the number of doctor visits during three months. As in most of the research on health care, the dependent variable is a non-negative integer count characterized by a large proportion of zeros, a positive skewness and, as a consequence, a long right hand tail. In what concerns to the econometric tools, until recently, the one-part, Hurdle and finite mixture models have dominated the empirical literature (Deb and Trivedi 2002). Estimators resulting from these frameworks rely on assumptions about the functional form of the regression equation and the distribution of the error term. As a result, standard models determine entirely the distributional behaviour by the functional form once the conditional mean response is known. An attractive alternative is the usage of nonparametric and semiparametric estimators. Introduced for continuous data in Koenker and Bassett (1978), Quantile Regression offers a complete picture of the effect of the covariates on the location, scale and shape of the distribution of the dependent variable. As a semiparametric method it assumes a parametric specification for the quantile of the conditional distribution but leaves the error term unspecified. It was first applied to continuous health data in Manning et al. (1995). As in Winkelmann (2006) and Liu (2007), we apply an approach suggested by Machado and Santos-Silva (2005) in which quantile regression is extended to count data through a "jittering" process that artificially imposes some degree of smoothness. This technique allows an analysis of the effect on the whole consumption distribution, which is an important step forward in the analysis of reforms and is very useful for policy making. In particular, it may help the policy maker to understand why people with similar health conditions differ in their use of medical care, since it enables to determine whether the policy effect is larger among low users or among high users, or may even signal the need for adjustments on the characteristics of the contracts provided by the insurances companies. This kind of information is important to control the expenditures in health care as well as to assess the equity of the system.

Many authors have been investigating the impact of additional health coverage in order to estimate the moral hazard derived from different health insurance plans characterized by different levels of coverage (for example Cameron et al. 1988, Coulson et al. 1995, Vera-Hernández 1999, Lourenço 2007 and Barros et al. 2008). The usage of non-experimental data generally creates an endogeneity problem related to adverse selection since most of the times the decision to buy extra health insurance depends on individual characteristics. In such cases, the insurance parameter does not disentangle moral hazard and adverse selection effects. The solution relies most of the times on finding reasonable instrumental variables. Our empirical application does not have this problem because the membership on public and private health subsystems was mandatory and based on professional category, and as such unrelated to the expected value of future health care consumption. Moreover, contributions are based on income and not on risk characteristics of each individual. Note that we are excluding from the analysis the voluntary health insurance plans.

The paper is structured as follows. Section 2 summarizes the key features of the Portuguese health care system from a provision perspective. Section 3 describes the dataset and the relevant variables, and presents an exploratory analysis of data. In Section 4 we present the quantile regression for counts and discuss the treatment effect specification. In Section 5 we analyse the results and finally, Section 6 presents the final remarks.

2 Overview of the Portuguese health care system

The Portuguese health system is a network of public and private health care providers and different funding schemes.[4] It is possible to identify three overlapping layers: the National Health Service (NHS)[5], employer-provided public and private subsystems and private voluntary health insurance. While the NHS is mainly financed by general taxation, subsystems resources come from employees and employers compulsory contributions (including, in the public schemes, State funds to ensure their balance). According to Barros and Simões (2007), in 2004 public funding represented 71.2 per cent of total health expenditure

[4] This section is mostly based on Barros and Simões (2007) and Lourenço (2007). An interesting comparison between the Portuguese health system and other European systems is available in Bago-d'Uva and Jones (2008).

[5] In the autonomous regions, public health is ensured by regional health services (RHS of Azores and Madeira) following the same principles of the NHS but implemented by regional governments. Here it is not useful to treat them separately.

(of which 57.6 per cent is related with the NHS and 7.0 percent cent with subsidies to public subsystems). Private expenditure is composed by co-payments and direct payments made by patients and, to a lesser extent, by private insurance premiums.

In 1979, with the creation of the NHS, legislation established that all residents have the right to health protection regardless of economic or social status. Until then, the State had full responsibility only for the health care of public employees and some specific health services, as maternity, child and mental care and the control of infectious diseases. One of the features of the period preceding the outset of the NHS that persisted was the existence of public health subsystems that continued to cover a variety of public and private employees.

The individuals covered solely by the NHS (the majority of the population) face some constraints in the access to public providers, in particular because of services excluded from the public network and difficulties of access due to time costs (long waiting lists and queuing) or geographical barriers. Lourenço (2007) among others, argues that the NHS coverage restrictions convert its normative completeness into an incomplete health insurance contract. The NHS is designed in a way that beneficiaries should first seek health care through their general practitioner (family doctor) in health care centers and then, if necessary, get appropriate referrals to a public specialist consultation (generally as out-patient consultations in public hospitals). This gatekeeper procedure is not strictly followed since there are households who do not have access to a family doctor and, when they have, the time lag between the first step to obtain health care and its actual provision is frequently too long. Additionally, the requirements to obtain referrals are generally very demanding. For these reasons, some individuals have their first contact with health care in hospitals' emergency rooms even if their condition would not require it. Given these constraints, the consumption of private services by NHS beneficiaries[6] is very common. The NHS design contemplates a cost-share mechanism that in practice makes the patients pay a mandatory small co-payment to the public provider (variable with the type of service), usually on a fee-for-service basis. There are, however, exemptions for a large share of the population defined on the basis of age and income. When using health services provided by the private sector, NHS beneficiaries, in the absence of private voluntary insurance schemes, support their full cost, having no reimbursement at all.[7] People benefiting from additional health care schemes, either mandatory or voluntary, do not see their taxation affected, and as a consequence they are still eligible to receive health care from the NHS.

[6] In the course of the paper, when it says "NHS beneficiaries", we consider individuals covered solely by NHS. Therefore, this definition excludes the population with double coverage.

[7] The system allows, however, the recovery of some out-of-pocket outlays because both patient co-payments and costs of private services are tax-deductible.

Nowadays, a considerable share of the population (between 20-25 per cent) still benefits from employer-provided health insurance through several subsystems, either private or public. Among the double coverage' schemes, the largest public subsystem is ADSE (*Direcção-Geral de Protecção Social aos Funcionários e Agentes da Administração Pública)*, a Government department acting as a health insurance provider, covering public employees (about 15 per cent of the population). Exceptions enjoying specific schemes also exist, like the military personnel. Private subsystems were created to workers and pensioners (and respective households) of specific companies that have their own insurance schemes, like SAMS (*Serviços de Assistência Médico-Social*) for banking employees. Each subsystem has a distinct array of medical care insurance arrangements to finance and provide health care. As a whole, we can say that they are organized differently from the NHS, in particular because of the lower proportion of services directly provided. They basically provide health care through contracts with public/NHS and private institutions and reimburse patients costs for services supplied by private entities without contract. These features make these schemes more comprehensive health protection plans than NHS, representing both complementary and supplementary types of insurance (Lourenço 2007). The supplementary protection results from the provision/financing of services that are also available in the context of the NHS. This particular feature creates the double coverage problem. The complementarity characteristic is relevant due to the fact that subsystems cover services almost not provided by the NHS, in particular, by reimbursing part of patients costs in private providers (even those without contracts).

3 Data

3.1 Dataset

Data was taken from the fourth Portuguese Health Survey (PHS), a cross sectional health dataset designed to be representative of the Portuguese household population.[8] It provides a wide range of information at an individual level, namely demographic and socioeconomic conditions, type of health insurance, health-care utilization, health status indicators (like chronic diseases and long run and short run disability), lifestyles (like eating habits and sports activity) and some costs with health services. However, some of the questions were only answered by part of the sample. The survey was collected by interviews carried

[8] The PHS are carried out by the Portuguese Ministry of Health in collaboration with the *National Health Institute Ricardo Jorge* and the National Statistical Institute. Until now, four questionnaires have been made (1987, 1995/1996, 1998/1999 and 2005/2006) using representative probabilistic samples of the continental population (1st. 2nd and 3th PHS) and of both continental and autonomous regions of Azores and Madeira population (4th PHS). Here we made use of the last available questionnaire. Note that it is not a panel survey since the sample changes between surveys.

out between February 2005 and January 2006. The PHS sample reflects the geographical structure of the population according to the 2001 census, resulting from a two-stage cluster sampling that followed a complex design involving both stratification and systematic selection of clusters.[9,10] A total of 19,950 households units were selected for the survey and in each household all individuals were face-to-face interviewed.

The sample used in this paper comprises 35,308 observations and was obtained after defining the population of interest and handling the data. Firstly, we restrict our population to individuals without voluntary private health insurance and with less than 80 years old.[11] Secondly, we excluded 40 observations of individuals that did not report the number of visits to a doctor and 8 observations without answer regarding the subsystem they belong to. Finally, we deleted further 1047 observations with missing values for any other relevant variables (according to the set of regressors chosen).

Two points should be made about the latter choices. Firstly, the exclusion of voluntary health insurance individuals can be pointed as a shortcoming. However, the inclusion of such variable could introduce endogeneity problems, which would be difficult to eliminate since there are no suitable instrumental variables (Barros et al. 2008). In this context and given the relatively small number of insured individuals (less than 8 per cent) it seems better to exclude such observations and restrict the analysis to the population exclusively insured through mandatory schemes. Regarding the exclusion of observations of persons with more than 80 years, the decision was related to the measurement of treatments effects, as explained in due course.

Secondly, the simplest way of handling missing data is to delete them and analyze only the sample of "complete observations" (although deleting observations reduces the efficiency of the estimation). This procedure is named as listwise deletion. Its usage is statistically appropriate only if the missing values are missing completely at random (Cameron and Trivedi 2005), which means that the probability of missing does not depend of its own value nor on the values of other variables in the data set (the observed sample is a random subsample of the potential full sample). In our case listwise deletion is clearly acceptable because incomplete observations comprise a small percentage (less than 3 per cent) of total observations.

[9] In "Methodological Note of Portuguese Health Survey 2005-2006".

[10] The database includes weight variables, estimated with the objective of transforming the sample in a representation of the Portuguese population. The problem with the usage of a weighted dataset is that it leads to artificially small standard errors for regression coefficients and therefore incorrect inferences on the significance of the different effects. Following the literature that points that it is possible to ignore the weights without affecting the parameter estimates (Wooldridge 2002, Cameron and Trivedi 2005), we chose to use a unweighted dataset at the cost of including in our regression the variables under the sample design of PHS. Note that this is possible because the sampling weights are solely a function of independent variables, otherwise parameters estimated would be biased.

[11] We also excluded observations of pregnant women whose visits to the doctor were related to their condition.

Moreover, among the relevant questions of our dataset that can create a sample selection problem, the one that generated more missing observations concerns the income level. However, most of the missing (around seventy per cent) does not result from a non answer but from individuals that declare not knowing the household income, which if not deliberately makes unlikely that unobserved factors influenced both the decision to respond and the value of the dependent variable.

3.2 The variables

To capture health care utilization we use the total number of visits to doctors in the three months prior to the interview. The question in the survey was: "How many times did you visit a physician in the last three months?". This measure includes several types of consultations which may be associated to the consumption of different levels of resources. The survey includes a question about the type of doctor (general practitioners or specialist) of the last visit which does not allow to disentangle all the visits taken in the period of three months. Therefore, one limitation of this measure of demand for health care is that it encompasses consultations to general practitioners and specialist doctors, as well as emergency episodes. Another lack of information is related to the nature of the provider of the consultations, in particular because it is not possible to identify if they are public or private (with or without contract).

Table 1 presents the covariates used in our analysis clustered into groups encompassing health insurance status, socioeconomic characteristics, and health status. In addition, two further groups were also included to control for geographic and seasonal effects. We selected the variables among the raw data available in the database[12] in line with their influence on medical care consumption, taking into account the Grossman's health capital model of demand for health (1972) as well as the results of similar empirical studies (Cameron et al. 1988, Pohlmeier and Ulrich 1995, Vera-Hernández 1999, Deb and Trivedi 2002 and Lourenço 2007). According to microeconomic theory, the main factors influencing the estimation of a demand curve should be the budget constraint and individual preferences. Although economists have difficulties in understanding consumer incentives for health care, it is possible to find several channels through which the selected variables affect the number of doctor visits. The problem is that the quantity of visits is only partially a result of consumer incentives because the doctors play an important role in medical choices. Depending on the kind of patient, we can have extreme cases of complete delegation of decision making to the doctor. For this reason moral hazard effects are also relevant on the doctors side (demand inducement).

[12] Some information was excluded from the analysis, particularly the questions reported only by part of the sample according to the week of the interview.

Table 1: Description of the variables

Variables	Description	Type
Health insurance status variables		
pubsub	=1 if the individual is covered by a public subsystem	dummy
privsub	=1 if the individual is covered by a private subsystem	dummy
Health status variables		
sick	=1 if the individual is being sick	dummy
limitdays	number of days with temporary (not long run) incapacity	count
limited	=1 if the individual is limited/handicaped	dummy
rheumatism	=1 if the individual has rheumatism	dummy
osteoporosis	=1 if the individual has osteoporosis	dummy
cancer	=1 if the individual has cancer	dummy
kidneystones	=1 if the individual has kidneystones	dummy
renalfailure	=1 if the individual has renalfailure	dummy
emphysema	=1 if the individual has emphysema	dummy
cerebralhaemorrhage	=1 if the individual had a cerebral haemorrhage	dummy
infarction	=1 if the individual had an infarction	dummy
depressivedisorder	=1 if the individual has a depressive disorder	dummy
otherchronicaldisease	=1 if the individual has another chronical disease	dummy
highbloodpressure	=1 if the individual has high blood pressure	dummy
chronicpain	=1 if the individual has a chronic pain	dummy
diabetes	=1 if the individual has diabetes	dummy
asthma	=1 if the individual has asthma	dummy
stress	=1 if the individual has been taking sleeping pills or anxiety pills in the last two weeks	dummy
smoker	=1 if the individual smokes daily	dummy
meals	=1 if the individual makes at least three meals a day	dummy
Socioeconomic and demographic variables		
householdsize	household size of the individual	count
age	age in years	continuous
female	=1 if the individual is female	dummy
educmax	number of years of schooling completed with success of the most educated person living in the household	count
lincome	logarithm of equivalent monthly income in euros	continuous
single	=1 if the individual is single and not cohabits	dummy
student	=1 if the individual is student or has it fist job or has a not remunerated job	dummy
retired	=1 if the individual is retired	dummy
Geographic variables		
Norte	=1 if the individual lives in the region "Norte" (NUTS II)	dummy
Lisboa	=1 if the individual lives in the region "Lisboa" (NUTS II)	dummy
Alentejo	=1 if the individual lives in the region "Alentejo" (NUTS II)	dummy
Algarve	=1 if the individual lives in the region "Algarve" (NUTS II)	dummy
Açores	=1 if the individual lives in the region "Açores" (NUTS II)	dummy
Madeira	=1 if the individual lives in the region "Madeira" (NUTS II)	dummy
Seasonal variables		
winter	=1 if the interview took place in the winter	dummy
spring	=1 if the interview took place in the spring	dummy
summer	=1 if the interview took place in the summer	dummy

The underlying health status and the socioeconomic characteristics play a major role in the preferences formation. Health status also influences the constraints limiting the pursuit of preferences since illness events usually imply a loss of income (although sometimes partially offset by sickness benefits). In the PHS, health status is only indirectly captured through some questions that reflect details about current medical conditions (e.g. sickness episodes and limited days) and the presence of chronic disease or pain (e.g. rheumatism, cancer and diabetes).[13] Besides including such variables, the consumption of barbiturates as a proxy to the level of exposure to stress, as well as some other regressors related to attitudes with a potential impact on health, like the number of meals and a dummy variable identifying smokers/non-smokers, also play a role. Despite being crude measures, these last regressors may capture some remaining health aspects and some unobserved influences.[14,15]

The variables representing demographic and socioeconomic features of the interviewed can influence simultaneously the decision to seek health care directly and indirectly through their impact on health care status. This is particularly evident when analysing the covariate *age*. According to Grossman (1972), age captures the depreciation of health capital which influences the health status and is an important factor influencing individual preferences. It is expected that the rate of depreciation increases as the individual gets older, at least after some point of the life cycle, making the healthy times decrease. As a consequence, the demand for health care is expected to increase over the life cycle. At the same time, *age* is an extra variable that can be considered as a health status proxy since older individuals are, on average, less healthy and less efficient in producing health. We chose to control for age through a nonlinear relationship and by including variables that allow an assessment of its effect by gender type.

Amongst the socioeconomic covariates, a gender dummy was included because it is believed to influence the rate at which the health stock depreciates and the efficiency in producing healthy times. In particular, it is expected that health depends on biological differences between men and women through innate features, life styles and different attitudes towards health risk. Accordingly, we also control for the marital status with the inclusion of the covariate *single*. Besides the arguments of different life styles and attitudes toward risk, it is our understanding that some decisions when taken by more than one person benefit from advice and more information, which should influence health status and efficiency in producing healthy times.[16]

[13] It can be questionable whether these variables do not introduce a problem of endogeneity. The idea is that individuals usually become aware of their health status through medical consultations. We believe that this is not a problem, especially if one takes into account that the dependent variable is number of visits to doctors in the three months prior to the interview and individuals are likely to be conscious about their diseases for longer time.

[14] Winkelmann (2004) and Winkelmann (2006) also include individual subjective self-assessment of health status. PHS provides that information (with the question "How well do you perceive your own health at the present time?", with responses "very good", "good", "fair", "poor" and "very poor") but we excluded its use. These variables are likely to create an endogeneity problem: the self-understanding of the health status influences the consumption of medical care but it is also influenced by consumption since the assessment is made after visiting the doctor. Moreover, the non-response is extremely high (around 30 per cent). As suggested by Windweijer and Santos-Silva (1997), we partially control for this subjective health evaluation by including long-term determinants of health (smoking and eating habits).

[15] Engagement in sports activities is an alternative proxy for good health but was only available for a small part of the sample, which would imply a substantial decrease in the size of the sample.

[16] Most of the studies include a slightly different variable that assumes one if the person is married instead of single. The design of the survey and some previous results influenced the choice of this particular variable.

To control for the educational level, it was defined a variable with the number of schooling years of the most educated person living in the household. It is expected that more educated people are more productive in the market as well as in the household, therefore even if they seek for more health they need relatively less medical care. Further, different educational levels are associated with different opportunity costs and attitudes towards risk. This particular indicator was chosen, as an alternative to the usual number of schooling years of each individual, because we believe that the decision about the number of visits to a doctor is at least partially a decision of the household and benefiting from a better level of information.

The variables *student* and *retired* capture occupational status which may explain some differences in the depreciation rate. It is expected that a person who does not work, presents lower opportunity costs (in terms both of time and income) of visiting a doctor, than an individual with a regular job. Further, since hours of market and non-market can have different values and the stock of health determines the total amount of time to spend producing earnings and commodities, it is expected that more active individuals invest more in health capital. These particular variables can also capture some income and age effects (traditionally students are the youngest in the database and the retired the oldest).

Another variable included in the model is the monthly equivalent income. In the PHS, income is only compiled for the household as a whole through a categorical ordinal variable with ten thresholds that indicate intervals of net disposable household income in the month prior to the interview (including wages, pensions, and all sorts of social security benefits). A common procedure to control for income effects is including in the model a set of dummy variables, one for each category. Here, such alternative is not very attractive due to the fact that it would be impossible to take into account the composition of households. We chose a more flexible and parsimonious modelling strategy (although not problem-free) with the construction a monthly income variable that, in a first stage assigns an income corresponding to the midpoint of the interval, and in a second stage interpolates grouped data by taking into account differences in the composition of households.[17,18] According to Grossman (1972) there are reasons to believe that medical utilization increase with income: "The higher a person's wage rate, the greater the value to him of an increase in healthy time". The idea is that the cost of being ill is higher. A converse

[17] This procedure has the disadvantage of assuming that the income of the household is the midpoint of its income class and, additionally, for the open-ended category it was necessary to assume an arbitrarily value. We use €2500 but we test the robustness of this value by considering other figures, in particular, the estimate for the median of this last income bracket calculated using a Pareto distribution. To take into account the composition of households we used the square root scale, through dividing the household income by the square root of household size. Note that it is not necessary neither to deflate this variable nor to make it comparable across countries.

[18] The "individual" income is measured with error given the way it is compiled in the survey and the modelling procedure. Concerning the latter, we tested different alternatives and we found only minor differences in the estimates.

argument is that the opportunity cost of going to the doctor is higher for higher wages. In addition to this, income also represents the ability to pay, as a proxy of wealth.

The variables *Norte*, *Lisboa*, *Alentejo*, *Algarve*, *Açores* and *Madeira* (*Centro* being omitted) represent the region of residence and were included to control for possible behavioural differences in the demand and supply of health care services.[19] The regions encompass wide areas but nevertheless, when we compare them in terms of wealth or educational indicators we obtain huge differences, which could justifie different behaviours regarding the use of health care services (not totally captured at the individual level). Apart from this argument, the main reason to include these variables is because they proxy different access to medical care supply, since some regional services are differently organized. Note that in the continent, the five regions correspond to the five regional health administrations, and in the autonomous regions there are two different regional health services.[20]

To control for the period of the year in which the interview took place we included the regressors *spring*, *summer*, and *winter* (*autumn* being omitted). This is important because there may be some seasonal differences in individuals health status.

Finally, we use the health insurance dummy variables to distinguish between control and treatment groups. In this case we have a control group "NHS" composed by individuals with only the default health system, and two different treatments "Public subsystems" and "Private subsystems". We managed to do it by dividing the observations according to the type of health insurance, in particular by considering three mutually exclusive groups that are compared according to their health care coverage: only the NHS, the NHS plus a public subsystem or the NHS plus a private subsystem.[21] These variables are of particular importance since the main goal of this work is to assess how a patient´s use of medical consultations is affected by types of health insurance. From a theoretical point of view, insurance is a price proxy, therefore, these variables together with income set the budget constraint. Note that the differences between health systems as regards costs to beneficiaries (as co-payments and non-reimbursements) work as direct prices and both mechanisms to control for its use and delivery systems are indirect costs of access. When compared to the NHS, the subsystems provide more benefits to their beneficiaries by decreasing the price-per-service faced by patients, which whenever demand is elastic, increases their health care

[19] In accordance with NUT II classification (official territorial nomenclature for statistical analysis), Portugal is divided into seven regions. The survey includes data for all of them. Therefore, we use six dummies.

[20] Lourenço (2007) used a dummy variable for a rural versus urban location that could not be included on the basis of the data from the fourth PHS. The difference, however, is partially controlled for the region variables since they have different proportions of rural and urban areas (e.g. *Lisboa* and *Alentejo*).

[21] Despite having common features, both public and private groups include several subsystems.

demand (Barros et al. 2008).[22] Usually, the estimation of this moral hazard effect is particularly difficult in a context of adverse selection as it leads to endogeneity of the treatment variables and results in an overestimation of its impact. As noted by Barros et al. (2008), taking advantage of the exogeneity of these health protection subsystems, we will not need to use instrumental-variables estimation (for more details see Section 4.3).

3.3 An exploratory analysis of the data

Table 2 presents the empirical distribution of the dependent variable (y) and some statistics. As the table shows, the majority of observations are of the NHS group, followed by the public subsystem. The dependent variable used is a count variable (non-negative integer valued count $y = 0, 1, 2, \ldots$) with a large proportion of zeros (half of the sample) as well as a long right tail of individuals who make heavy use of health care. These features make the estimation particularly difficult since it will be necessary to use flexible models that accommodate them. For the whole sample, the average number of consultations is 1.01 and the average number of visits for those that have at least one visit is 2.04. Moreover, the unconditional variance is more than three times the unconditional mean.

Table 2: Empirical distribution of the dependent variable

	TOTAL	NHS	Public sub.	Private sub.
y		relative frequency		
0	50.31	50.88	48.82	41.91
1	26.94	26.53	28.54	29.83
2	10.78	10.61	11.37	12.61
3	6.77	6.82	6.15	8.72
4	1.99	2.02	1.69	2.84
5	1.12	1.06	1.25	2.10
6	0.98	0.95	1.17	0.95
7	0.20	0.21	0.14	0.21
8	0.22	0.23	0.18	0.42
9	0.08	0.07	0.13	0.11
10	0.19	0.17	0.30	0.11
11-15	0.25	0.28	0.15	0.11
16-20	0.04	0.04	0.06	0.11
21-25	0.06	0.06	0.06	0.00
26-30	0.06	0.07	0.02	0.00
		Observations		
	35,308	28,778	5,578	952
	100%	81.5%	15.8%	2.7%
		Mean		
	1.01	1.01	1.01	1.19
		Standard deviation		
	1.77	1.80	1.64	1.61
		P-value (Ho: $\mu_{Y_{NHS}} = \mu_{Y_{Subsystem}}$)		
	-	-	0.998	0.000

[22]Some additional bias problems are related with the supply-induced demand by health care providers.

Table 3: Descriptive statistics by health insurance system

	NHS		Public subsystem			Private subsystem		
	mean	st.dev	mean	st.dev	p-value	mean	st.dev	p-value
Health status variables								
sick	0.007	0.001	0.005	0.001	0.008	0.005	0.002	0.363
limitdays	0.613	0.015	0.488	0.030	0.000	0.536	0.077	0.327
limited	0.016	0.001	0.004	0.001	0.000	0.006	0.003	0.000
rheumatism	0.168	0.002	0.120	0.004	0.000	0.134	0.011	0.003
osteoporosis	0.069	0.001	0.060	0.003	0.014	0.068	0.008	0.943
cancer	0.019	0.001	0.020	0.002	0.688	0.022	0.005	0.491
kidneystones	0.048	0.001	0.051	0.003	0.473	0.058	0.008	0.224
renalfailure	0.014	0.001	0.011	0.001	0.196	0.014	0.004	0.971
emphysema	0.034	0.001	0.022	0.002	0.000	0.022	0.005	0.015
cerebralhaemorrhage	0.018	0.001	0.013	0.002	0.000	0.020	0.005	0.654
infarction	0.014	0.001	0.011	0.001	0.103	0.014	0.004	0.956
depressivedisorder	0.074	0.002	0.074	0.004	0.934	0.082	0.009	0.395
otherchronicaldisease	0.319	0.003	0.297	0.006	0.001	0.317	0.015	0.928
highbloodpressure	0.221	0.002	0.178	0.005	0.000	0.222	0.013	0.977
chronicpain	0.148	0.002	0.110	0.004	0.000	0.119	0.010	0.006
diabetes	0.077	0.002	0.054	0.003	0.000	0.074	0.008	0.651
asthma	0.051	0.001	0.057	0.003	0.075	0.049	0.007	0.837
stress	0.119	0.002	0.104	0.004	0.001	0.124	0.011	0.631
smoker	0.162	0.002	0.138	0.005	0.000	0.179	0.012	0.200
meals	0.926	0.002	0.949	0.003	0.000	0.933	0.008	0.402
Socioeconomic and demographic variables								
householdsize	3.387	0.009	3.342	0.017	0.020	3.100	0.037	0.000
age	42.044	0.131	38.984	0.285	0.000	42.946	0.685	0.196
female	0.515	0.003	0.537	0.007	0.003	0.419	0.016	0.000
educmax	8.112	0.026	11.949	0.061	0.000	11.625	0.147	0.000
lincome	6.048	0.003	6.624	0.007	0.000	6.669	0.019	0.000
single	0.350	0.003	0.391	0.007	0.000	0.322	0.015	0.076
student	0.164	0.002	0.247	0.006	0.000	0.188	0.013	0.065
retired	0.185	0.002	0.171	0.005	0.012	0.256	0.014	0.000

Note: The p-value indicates the probability of the mean of each variable does not significantly differ across insurance types. The test is performed as a two-sample mean-comparison test (unpaired). For the comparison between the NHS and the public subsystem we considered H0: $\mu_{Y_{NHS}} = \mu_{Y_{Public\ subsystem}}$; and for the comparison between the NHS and the private subsystem we considered H0: $\mu_{Y_{NHS}} = \mu_{Y_{\Pr ivate\ subsystem}}$. Geographic and seasonal statistics (and p-values) not reported. Available from the authors upon request.

When we analyse the average number of visits to a doctor by health insurance systems, it is possible to observe that private subsystems beneficiaries are higher users than NHS and public subsystems groups. Indeed, a mean comparison t-test indicates that the unconditional probability does not differ across NHS and public subsystems but differ when one compares NHS with private subsystems.

Table 3 presents the descriptive statistics of the explanatory variables by health insurance type. The mean comparison t-test indicates that most of the differences between the three types are significant, specially regarding socioeconomic pre-determined variables. The NHS group has relatively less years of education and lower income. On its turn, public subsystems beneficiaries are younger (on average about 4 years less than the other groups), have a greater proportion of students and singles and a smaller share of retired persons. The private subsystems group has less women and a smaller household size. As regards the health status distributions of the three groups, it is possible to conclude that the major differences are found between the public subsystem and the NHS. Public employees seem to be the healthier, in particular when we analyse some variables related to physical limitations (*limited days* and *limited*) and the presence of chronic diseases and pains. Moreover, frequent health problems (e.g. high blood pressure, diabetes and stress) are relatively more common in the NHS and private subsystem groups. This feature can be partially related with age, which is lower among the public subsystems group. Additionally, it is worth highlighting that public employees seem to be less exposed to stress and that the indicators related to attitudes show a smaller proportion of smokers and a higher average number of meals. These sample differences suggest that a more complete account for them is required, so that an appropriate comparison of health care demand across groups can be made.

4 Econometric framework

Econometrics of count data has its own modelling strategies in which discreteness and non-negativity are taken into account. Moreover, in the *count world* it is common that features other than location depend on the covariates, making the estimation of the conditional expectation poorer in the sense that provides very little information about the impact of the regressors on the outcome of interest. In this context it is potentially interesting to study the effect of regressors not only on the mean but also on single outcomes and in the full distribution.

Within the vast literature on count data it is possible to find two general categories of methods that allow a complete description of the conditional distribution of a count outcome. Following the early work of Hausman, Hall, and Griliches (1984), several fully parametric probabilistic models, like Poisson and negative binomial regressions, have been developed in order to describe the effect of the covariates on different points of a count variable. These regressions allow inferences for all possible aspects of the outcome variable (including the computation of the marginal probability effects). However, to do it, they impose restrictive parametric assumptions on the way the independent variables affect the outcome variable. As a consequence, this approach usually face a lack of robustness, even when flexible models like the hurdle or latent class models are applied. Given these limitations, it can be attractive to use non- or semiparametric techniques that freely approximate the conditional distribution. This can be achieved with the estimation of conditional quantile functions, a technique that has been applied in the context of continuous regression for a long time (Koenker and Bassett 1978). Following the contributions of Manski (1975), Manski (1985) and Horowitz (1992) regarding binary models, some effort is being made to extend the method to discrete data. Recently, the seminal work of Machado and Santos-Silva (2005) succeeded in applying the quantile framework to count data models. Since our main aim is to assess the effect of the subsystems on different parts of the outcome distribution without imposing a probabilistic structure, the "Quantile for counts" regression model is a natural choice.[23]

The advantages of applying a quantile regression approach go further than just statistical convenience. Using this technique we are able to study the heterogeneity of moral hazard effects due to double health insurance coverage. Bitler et al. (2006) showed that unlike what is usually done in the majority of welfare reform studies that rely on estimating mean impacts, it is necessary to allow for heterogenous treatment effects, in which the quantile regression methodology can play a very useful role.

4.1 Quantile regression for counts

Let y be a count random variable and their α-quantile defined as:

$$Q_y(\alpha) = \min\left[\eta | P(y \leq \eta) \geq \alpha\right] \qquad \text{where} \qquad 0 < \alpha < 1 \tag{1}$$

The α-quantile has the same discrete support as y and cannot be a continuous function of the covariates (x). Machado and Santos-Silva (2005) suggested a procedure known as "jittering" to artificially impose some degree of smoothness. The basic idea is to build a continuous auxiliary variable (y^*) whose quantiles have a one-to-one known relationship with the quantiles of the count variable of interest. The y^* is obtained by adding to the count variable a uniform random variable, independent of y and x:[24]

$$y^* = y + u \qquad \text{where} \qquad u \sim uniform[0, 1) \tag{2}$$

The continuity problem of the dependant variable is solved but the derivatives are not continuous for

[23] In order to better understand its advantages (and disadvantages), Moreira (2008) compares the implications drawn from the quantile regression approach with those from parametric count data models that have been used quite extensively in the analysis of health care.

[24] Machado and Santos-Silva (2005) showed that there is a little loss of generality in assuming that U is uniform. In fact they argue that it is possible to choose another distribution for U as long as it has a support on $[0, 1)$ and a density function bounded away from 0. The advantages of using a uniform distribution are purely algebraic and computational.

integer values of y^*. Machado and Santos-Silva (2005) proved that given some regularity conditions, valid asymptotic inference is possible. Among those conditions, it is particularly relevant the existence of at least one continuously distributed covariate. The standard quantile regression is applied to a monotonic transformation of y^* that ensures that the estimated quantiles are non-negative and the transformation is linear in the parameters of a vector of regressors.

In order to implement the procedures, the authors suggest the following parametric representation of the α-quantile of y^*:

$$Q_{y^*}(\alpha|x) = \alpha + \exp\left[x'\beta(\alpha)\right], \qquad 0 < \alpha < 1. \tag{3}$$

The reason for adding α to the right side is that y^* is bounded from below at α due to the way it is constructed. The exponential form is traditionally assumed in count data models. We believe that this specification provides a good parsimonious approximation to the unknown conditional quantile functions. The linear transformation is specified as:

$$Q_{T(y^*;\alpha)}(\alpha|\mathbf{x}) = x'\beta(\alpha), \tag{4}$$

where $T(y^*;\alpha) = \{ {}^{\log(y^*-\alpha) \text{ for } y^*>\alpha}_{\log(\varepsilon) \quad \text{ for } y^*\leq\alpha}$, being ε a small positive number $(0 < \varepsilon < \alpha)$.[25]

This is feasible because quantiles are equivariant to monotonic transformations and to censoring from below up to the quantile of interest. The vector of covariates $\beta(\alpha)$ is obtained as a solution to a standard quantile regression of a linear transformed variable by minimizing an asymmetrically weighted sum of absolute errors

$$\min \sum_{i=1}^{n} \rho_\alpha \left[T(y^*;\alpha) - x_i'\beta\right] \qquad \text{where} \qquad \rho_\alpha(v) = v\left[\alpha - I(v<0)\right]. \tag{5}$$

Machado and Santos-Silva (2005) proved that although the quantile regression is not differentiable everywhere, the estimator is consistent and asymptotically normal:

$$\sqrt{n}\left[\widehat{\boldsymbol{\beta}}(\alpha) - \boldsymbol{\beta}(\alpha)\right] \xrightarrow{D} N(0, D^{-1}AD^{-1}) \tag{6}$$

with $A = \alpha(1-\alpha)E(XX')$ and $D = E\left[f_T(X'\beta(\alpha)|X)X'X\right]$, where f_T denotes the conditional density of $T(y^*;\alpha)$ given X.

Because "noise" has been artificially created for technical reasons, Machado and Santos-Silva (2005)

[25] We will use 1.0E-10 as Machado and Santos-Silva (2005) did.

suggest a Monte Carlo procedure - an "average-jittering" - which consists in obtaining an estimator that is the average of m independent "jittering" samples with the same size. The difference between samples is the dependent variable y^* because it is created as the sum of y (constant between samples) with m different draws of the uniform distribution. The main advantage of this procedure is that the resulting estimator is more efficient than the one obtained from a single draw and a misspecification-robust estimator of the covariance matrix is available.

The importance of this procedure derives from the possibility of performing inferences on the variable of interest y. Machado and Santos-Silva (2005) showed that marginal effects of the smoothed variable y^* are easily obtained and interpreted and that there is a correspondence between the two quantile functions:

$Q_y(\alpha|x) = \lceil Q_{y^*}(\alpha|x) - 1 \rceil$, where $\lceil a \rceil$ denotes the ceiling function (returns the smallest integer greater than, or equal to a).

Because of the monotone transformation of y^*($T(y^*; \alpha)$), the relationship between coefficient estimates $\widehat{\beta}(\alpha)$ and $y^*$and y is essentially non-linear, making it hard to interpret $\widehat{\beta}(\alpha)$ in terms of y^* and y. It is possible to test the null hypothesis that a covariate has no effect on $Q_y(\alpha|x)$ because it is equivalent to test whether the variable has no impact on the $Q_{y^*}(\alpha|x)$. The problem is when the variable is significant in $Q_{y^*}(\alpha|x)$. In such case it could be non significant in the conditional quantile of y.[26] This occurs because different quantiles of y^*correspond to the same quantiles of y. In fact, a change in x_j will affect $Q_y(\alpha|x)$ only if it is capable of changing the integer part of $Q_{y^*}(\alpha|x)$. Machado and Santos-Silva (2005) call this "magnifying glass effect" of $Q_{y^*}(\alpha|x)$.

4.2 Empirical specification: treatment effects

Our empirical work presents two main differences relative to general treatment effects approaches. Firstly, the study is about a potential reform, not a real one, as it is usually the case. We can state our interest as to measure the potential impact of the elimination of double coverage (particularly the insurance plans provided to public employees) on the demand of health services, i.e. the potential decrease in the demand for health services amongst the subsystems beneficiaries due to their double coverage. To proxy such impact we study the differences in the consumption of doctor consultations between NHS and public and private subsystems. Generally, the estimation of the impact of a reform occurs after its implementation and uses panel data comparing the outcome before and after the reform (Winkelmann 2006). In that

[26] It is not possible to just look at β_j, as it becomes necessary to evaluate case by case if a given magnitude in x_j induces changes in the α-quantile of y. Inference about the partial effect of a particular variation of the regressor, given that all other variables remain fixed at $\widetilde{\mathbf{x}}$ is made through the following expression:
$\Delta_j Q_y(\alpha|\widetilde{\mathbf{x}}, x_j^0, x_j^1) = Q_y(\alpha|\widetilde{\mathbf{x}}, x_j^1) - Q_y(\alpha|\widetilde{\mathbf{x}}, x_j^0)$

case, the typical empirical strategies include pre-reform/post-reform differences-in-differences where one compares the changes in the utilization between affected and unaffected sub-populations. A drawback in our analysis relative to more general approaches is that we estimate the current impact (the impact in 2005), which may change in case of different time paths between groups. The other distinctive feature of our study is that we allow for heterogeneous treatment effects. By analyzing not only the mean effect but also the impact on the whole outcome distribution, we present a big improvement over past research methodology. Here, as in Bitler et al. (2006), we show that "mean treatment effects miss a lot". With quantile regression we are able to see if the policy impact differs depending of the outcome on the realization of the dependent variable.

As laid out in the previous section, and now presented in a more specific way, the conditional quantiles are defined as[27]

$$Q_{y_i^*}(\alpha|x) = \alpha + \exp\left[\beta_0(\alpha) + \beta_1(\alpha)pubsub_i + \beta_2(\alpha)privsub_i + \boldsymbol{\gamma}(\alpha)\mathbf{z}_i\right], 0 < \alpha < 1 \tag{7}$$

where $pubsub_i$ and $privsub_i$ represent persons "treated" as belonging to the "public insurance health subsystem" and "private insurance health subsystem", respectively. The vector $\mathbf{z}_i$ includes all other characteristics that were controlled for in this regression. In addition to all independent variables referred in Section 3.2, we use a third order polynomial in *age* and a third order polynomial in *age* crossed with the gender variable ($age \times female$). Note that it is absolutely crucial in this analysis to assume ignorability of the treatment conditional on a set of covariates. The alternative to assume ignorability and estimate treatment effect with difference in sample means is obviously bad since, as we tested, there are huge differences between control and treatment groups across their baseline characteristics. Moreover, when selecting the variables we guarantee that treated and untreated groups have a common support by using only observations in the intersection of the domains.[28] This procedure makes us exclude from the population of interest individuals with more than 80 years old and a variable related to unemployment status. Notice that our assumption of ignorability conditional on the set of covariates ($\mathbf{z}_i$) is naturally dependent on the inexistence of unobservable characteristics (omitted variables) with a different distribution among subsystems.

We discard the problem of self-selection into treatment. The exogeneity of the treatments holds because it is very implausible that individuals want to work as public employees or in companies with

[27] The vector of coefficients is now $\beta(\alpha) = [\beta_0(\alpha), \beta_1(\alpha), \beta_2(\alpha), \gamma(\alpha)]$, being $\beta_0(\alpha)$, $\beta_1(\alpha)$, $\beta_2(\alpha)$ scalar and $\gamma(\alpha)$ a vector.

[28] It is necessary to have subpopulations in each state: NHS, *privsub* and *pubsub*. See Wooldridge (2002) for details.

private subsystems just to benefit from this additional health insurance (Barros et al. 2008). Note that they have an alternative since we are studying a country that provides universal coverage through the NHS. Moreover, it is also unlikely that employers choose individuals on the basis of unobservable variables related to their health or even household health. The only requirement is that the potential employee (and not his household) is physically capable and has no infectious disease which could be controlled through our set of pre-determined variables. Nevertheless, even controlling for a large set of health status variables, this kind of procedure can still underestimate $\beta_1(\alpha)$ and $\beta_2(\alpha)$ if the subsystems beneficiaries enjoy more or better treatment than NHS beneficiaries. This is because over life, better health care would translate into a significant accumulation of health advantages not totally captured in $\mathbf{z}_i$. Following the advice of Barros et al. (2008), we will test this possibility restricting the analysis to young beneficiaries who did not yet had time to accumulate such advantages and compare the results with those for a larger sample. Another important comment on the coefficients $\beta_1(\alpha)$ and $\beta_2(\alpha)$ is that they cannot be totally associated with moral hazard behaviour but instead to a joint effect of moral hazard from the beneficiaries and supply-induced demand by the providers. The latter is related to the fact that doctors for patients with health subsystems may require more tests in order to justify more visits. According to Barros et al. (2008), the payments to subsystems providers are relatively low so the magnitude of this effect will be very small. Independently of that, the important here is to capture how much the system design increases the consumption of resources related to consultations, being difficult to make a direct association to demand/supply impacts or moral hazard effects.

5 Results

The results were obtained from the *qcount* package of STATA (Miranda 2006) with some slight adjustments. Regarding the number of jittered samples used to obtain the results, preliminary experiments showed that the coefficients are not very sensitive to a particular sample of uniform random variables used to jitter the data: with 1500 samples almost no changes were detected both in coefficients and in standard deviations.[29] The decision on which quantiles to compute took into account the problem under analysis and the empirical distribution of the relevant outcome. Since the marginal quantiles are zero for all $\alpha \leqslant 0.50$, it becomes more interesting to compute conditional quantiles on the upper tail of the distribution where the effect of covariates changes rapidly. Note that in the lower tail, a variation in the conditional quantiles of the artificial outcome $Q_{y^*}(\alpha|x)$ may be mostly due to the random noise that has

[29] This result was no surprising due to the high number of observations of our database.

been added. Therefore, we expect to find quantiles more flat. Moreover, it is more interesting to look at the behaviour of individuals who make heavy use of health care. In this scenario, and despite the fact that we will still be presenting the first quartile, we will focus on quantiles above the median, computing results for each decile after the median.

Table 4 presents the parameter estimates of the quantiles regressions (the corresponding standard errors are shown in Table A1 of the Appendix). The signs of the regressors do not switch across the different quantiles (except for the dummy *summer*, whose effect, albeit highly insignificant, is positive in the lower tail and becomes negative in the upper quantiles). Regarding the statistical significance, all variables are significant in at least one quantile. In the group of health status regressors, the covariates that control for current medical conditions are highly significant as expected. Among the chronic diseases dummies, only the cerebral haemorrhage effect is not significant in quantiles above the $0.7y^*-$quantile. Concerning indicators related to attitudes with impact on health status, we find that both the number of meals and smoking habits are insignificant in the upper tail of the distribution. In the case of socioeconomic characteristics, the statistical significance is, to a large extent, lower in the tails of the distribution.

We now turn to the analysis of the effects of the regressors beyond their statistical significance. The direct interpretation of Table 4 may suggest some misleading conclusions. Note that $\widehat{\beta(\alpha)}$ is a vector of linear partial effects on $Q_{T(y^*;\,\alpha)}(\alpha|\mathbf{x})$. To fully understand the impacts, the analysis should be made through $Q_{y^*}(\alpha|x)$, which is not so easily computed due to its non-linearity as well as to the fact that it is a function of $\alpha-$quantile. Being non-linear, the parameter provides an incomplete picture of the covariates' effects on the shape of the distribution. And being a function of α implies, for example, that a variable with the same estimated coefficient in all quantiles will have a proportional effect that varies with $\alpha-$quantile. One possible way to take into account the non-linearity is to compute partial effects for specific individuals, say $\widetilde{\mathbf{x}}$. Inference for the marginal effect of a dummy x_j given that all other variables remain fixed at $\widetilde{\mathbf{x}}$ is made through $Q_{y^*}(\alpha|\widetilde{\mathbf{x}}, x_j = 1) - Q^*_y(\alpha|\widetilde{\mathbf{x}}, x_j = 0) = \left[\exp(\gamma_j(\alpha)) - 1\right] \left[Q_{y^*}(\alpha|\widetilde{\mathbf{x}}) - \alpha\right]$ and for a continuous variable x_l is $\gamma_l(\alpha) \left[Q_{y^*}(\alpha|\widetilde{\mathbf{x}}) - \alpha\right]$.[30] To facilitate the comparison of the effects across the different models we also estimate the semi-elasticities of $Q_{y^*}(\alpha|x)$ with respect to the covariates. This is done by simply dividing the partial effect by $Q_{y^*}(\alpha|\widetilde{\mathbf{x}})$. Table 5 shows the results for the *default*

[30] The marginal effects of some covariates are calculated in a different way. This is the case of the income that is computed as $\gamma_{lincome}(\alpha) * \left[1/\overline{income}\right] \left[Q_{y^*}(\alpha|\widetilde{\mathbf{x}}) - \alpha\right]$, the "age when male" that is set as $[\gamma_{age}(\alpha) + 2\gamma_{age^2}(\alpha) * \overline{age} + 3\gamma_{age^3}(\alpha) * \overline{age}^2] * [Q_{y^*}(\alpha|\widetilde{\mathbf{x}}) - \alpha]$, and the "age when female" that is $[\gamma_{age}(\alpha) + \gamma_{agexfemale}(\alpha) + 2(\gamma_{age^2}(\alpha) + \gamma_{(agexfemale)^2}(\alpha)) * \overline{age} + 3(\gamma_{age^3}(\alpha) + \gamma_{(agexfemale)^3}(\alpha)) * \overline{age}^2] * [Q_{y^*}(\alpha|\widetilde{\mathbf{x}}) - \alpha]$.

individual (defined by setting the continuous/count variables at the mean of the sample and the dummy variables equal to zero).[31]

Table 4: Quantile regression results: coefficients

	$\widehat{\beta(0.25)}$	$\widehat{\beta(0.50)}$	$\widehat{\beta(0.60)}$	$\widehat{\beta(0.70)}$	$\widehat{\beta(0.80)}$	$\widehat{\beta(0.90)}$
Health insurance status variables						
pubsub	$0.078^{\dagger}$	0.088	0.095	0.096	0.073	$0.055^{\dagger}$
privsub	0.200	0.229	0.247	0.232	0.185	0.148
Health status variables						
sick	0.680	0.602	0.590	0.601	0.547	0.772
limitdays	0.071	0.073	0.076	0.074	0.071	0.073
limited	$0.136^{\dagger}$	$0.205^{\dagger}$	0.247	0.321	0.335	0.368
rheumatism	0.134	0.140	0.139	0.140	0.148	0.150
osteoporosis	0.282	0.207	0.182	0.152	0.115	0.091
cancer	0.468	0.464	0.430	0.386	0.403	0.525
kidneystones	0.149	0.154	0.175	0.188	0.221	0.211
renalfailure	$0.167^{\ddagger}$	0.220	0.212	0.226	0.260	0.234
emphysema	$0.090^{\ddagger}$	0.210	0.222	0.227	0.232	0.238
cerebralhaemorrhage	$0.133^{\dagger}$	$0.135^{\dagger}$	$0.134^{\dagger}$	0.163	0.191	0.189
infarction	0.228	0.327	0.343	0.341	0.290	0.217
depressivedisorder	0.187	0.231	0.247	0.253	0.246	0.248
otherchronicaldisease	0.435	0.451	0.471	0.458	0.384	0.352
highbloodpressure	0.407	0.382	0.367	0.322	0.260	0.208
chronicpain	0.172	0.197	0.220	0.230	0.221	0.224
diabetes	0.449	0.368	0.340	0.316	0.293	0.292
asthma	0.290	0.325	0.339	0.340	0.275	0.230
stress	0.441	0.360	0.342	0.305	0.293	0.250
smoker	-0.205	-0.176	-0.168	-0.154	-0.095	$-0.034^{\ddagger}$
meals	0.188	0.158	0.129	0.114	$0.081^{\dagger}$	$0.070^{\dagger}$
Socioeconomic and demographic variables						
householdsize	-0.063	-0.060	-0.060	-0.060	-0.039	$-0.017^{\dagger}$
age	-1.072	-1.014	-1.048	-1.071	-0.727	-0.559
age^2	0.234	0.222	0.231	0.241	0.160	0.121
age^3	-0.015	-0.014	-0.014	-0.015	-0.010	-0.007
age∗female	0.558	0.580	0.641	0.750	0.490	0.335
$(age*female)^2$	-0.120	-0.129	-0.146	-0.181	-0.116	-0.078
$(age*female)^3$	$0.007^{\ddagger}$	0.008	0.009	0.012	0.007	$0.005^{\dagger}$
female	$-0.321^{\dagger}$	-0.321	-0.345	-0.357	-0.216	$-0.091^{\ddagger}$
educmax	0.010	0.014	0.015	0.015	0.010	$0.005^{\dagger}$
lincome	0.069	0.058	0.060	0.060	0.053	$0.030^{\ddagger}$
single	-0.218	-0.198	-0.202	-0.218	-0.164	-0.116
student	-0.252	-0.246	-0.272	-0.253	-0.179	-0.172
retired	0.168	0.149	0.134	0.115	0.120	0.143

Notes: Coefficients marked with ‡ and †are not significant at a 5 and 1 per cent level, respectively. Standard errors can be found in the Table A1 of the Appendix. Geographic and seasonal controls not reported. Available from the authors upon request.

[31] The *default* individual is a healthy man with an average household size, educational level and income, not single or retired, living in the Centre region of Portugal and interviewed in autumn. Also note that, the vector $\widetilde{\mathbf{x}}$ is set with the dummies *pubsub* and *privsub* equal zero, so the *default* individual has the NHS insurance plan (is from the control group).

Table 5: Quantile regression results: semi-elasticities

	SE(0.25)	SE(0.50)	SE(0.60)	SE(0.70)	SE(0.80)	SE(0.90)
Health insurance status variables						
pubsub	0.026	0.029	0.032	0.036	0.034	0.031
privsub	0.070	0.080	0.091	0.093	0.092	0.087
Health status variables						
sick	0.310	0.258	0.260	0.295	0.329	0.630
limitdays	0.023	0.024	0.025	0.027	0.033	0.041
limited	0.046	0.071	0.091	0.136	0.180	0.241
rheumatism	0.046	0.047	0.048	0.054	0.072	0.087
osteoporosis	0.104	0.072	0.065	0.059	0.055	0.052
cancer	0.190	0.185	0.174	0.169	0.224	0.374
kidneystones	0.051	0.052	0.062	0.074	0.111	0.127
renalfailure	0.058	0.077	0.077	0.091	0.134	0.143
emphysema	0.030	0.073	0.081	0.091	0.118	0.146
cerebralhemorrhage	0.045	0.045	0.047	0.064	0.095	0.113
infarction	0.110	0.121	0.132	0.145	0.152	0.131
depressivedisorder	0.066	0.081	0.091	0.103	0.125	0.152
otherchronicaldisease	0.173	0.178	0.195	0.208	0.211	0.228
highbloodpressure	0.160	0.145	0.144	0.136	0.134	0.125
chronicpain	0.060	0.068	0.080	0.093	0.111	0.136
diabetes	0.180	0.139	0.131	0.133	0.153	0.183
asthma	0.107	0.120	0.131	0.145	0.143	0.140
stress	0.176	0.135	0.132	0.128	0.153	0.153
smoker	-0.059	-0.051	-0.050	-0.051	-0.041	-0.018
meals	0.066	0.053	0.044	0.043	0.038	0.039
Socioeconomic characteristics variables						
householdsize	-0.020	-0.019	-0.019	-0.021	-0.018	-0.009
age when male	0.004	0.004	0.004	0.005	0.004	0.003
age when female	0.001	0.000	0.000	-0.001	-0.001	-0.001
female	0.155	0.151	0.169	0.209	0.179	0.179
educmax	0.003	0.004	0.005	0.005	0.004	0.003
lincome	0.003	0.003	0.003	0.003	0.004	0.003
single	-0.062	-0.056	-0.059	-0.070	-0.068	-0.059
student	-0.071	-0.068	-0.077	-0.080	-0.074	-0.085
retired	0.058	0.050	0.046	0.044	0.058	0.083

Notes: Semi-elasticities are calculated for a vector $\widetilde{\mathbf{x}}$ containing the mean value of the continuous (and count) variables and zeros for the dummy variables. The type of the covariates is presented in Table 2 and the mean values can be obtained from Table 3. Geographic and seasonal controls not reported. Available from the authors upon request.

Using the quantile regression framework it may happen that a significant coefficient of a variable on $y^*_\alpha-$ quantile may not affect a particular conditional $y_\alpha-$ quantile. But when it is found that the $y^*_\alpha-$ quantile depends on the covariate for several quantiles, then it should be possible to detect a subpopulation for which the semi-elasticity on $y_\alpha-$ quantile is different from zero (Miranda 2008). For example, if we consider the median and compute the $Q_{y^*}(0.50|x = \widetilde{\mathbf{x}})$ we obtain 0.79 as a consequence $Q_y(0.50|x = \widetilde{\mathbf{x}})$

is equal to zero consultations. When the *typical* individual ($\widetilde{\mathbf{x}}$) changes to the public health plan, it is expected that an increase in Q_{y^*} to 0.82, but leaving Q_y unchanged. Hence the marginal effect of the public subsystem on the $y_\alpha-$ quantile is zero, even though it has a significant positive effect on $y^*_\alpha-$ quantile. Conversely, if we utilize the sixth decile the $Q_{y^*}(0.60|x = \widetilde{\mathbf{x}})$ is equal to 0.97 and as a consequence $Q_y(0.60|x = \widetilde{\mathbf{x}})$ is also equal to zero consultations. But now, a change from NHS to a public subsystem will increase Q_{y^*} to 1.01 making Q_y equal to one consultation.

Starting with the analysis of insurance treatment effects, it is visible that they do not change a lot across the estimated quantiles, but it is possible to find a pattern: both public and private subsystems have an increasing positive effect on the number of doctor visits until the $0.60y^* - 0.70y^*$ quantiles and a decreasing positive effect thereafter (Table 5). The similarities between the patterns of both subsystems are clear when we compute the ratio between them across quantiles, since it remains almost unchanged. In fact, the effect of private subsystem insurance plans is between 2.6 and 2.9 times higher than the impact of those of public employees. Therefore, health insurance double coverage does lead to further demand of health care (visits). The origin of double coverage is also quite important, as private subsystems double coverage induces much more demand than public subsystems double coverage.

To better understand the effect of health subsystems on the demand for health care we used the point estimates to predict the $y_\alpha-$ quantile (note that here we use the relevant outcome) for each observation in a simulation exercise in which all variables are set equal to their actual values, except the health insurance status. About this one three possibilities are considered: no treatment, public subsystem or private subsystem. The results measured by relative frequencies are presented in Table 6. Given that half of the sample has zero visits, it is not surprising that the first conditional quartile is zero for almost all observations. When we compare the estimates from different quantiles, we have the perception that the distribution changes differently across the health insurance plans. For example, the proportion of individuals with a predicted quantile of zero or one consultation is always lower with the treatment (either public or private) than with NHS, but these relative effects change with the $\alpha-$quantile. More particularly, the proportion of NHS individuals is 91.0, 70.7 and 23.4 per cent for the $0.50y-$, $0.75y-$, $0.90y-$quantile, respectively, while with the "public subsystem" the proportion is 89.6, 66.4 and 19.5 per cent for the $0.50y-$, $0.75y-$, $0.90y-$quantile, respectively. This means that holding double coverage causes a decreasing path in the difference of proportion of individuals with a certain (increasing) number of visits that is steeper from the $0.50y-$quantile to the $0.75y-$quantile than from the $0.75y-$quantile to the $0.90y-$quantile.

Table 6: Frequencies of estimated quantiles for the number of visits to a doctor

	0	1	2	3	4	5	6	7	8	9	$\geqslant 10$
					NHS						
$Q_y\widehat{(25}\vert x)$	89.4	8.3	1.4	0.4	0.2	0.1	0.1	0.0	0.0	0.0	0.0
$Q_y\widehat{(50}\vert x)$	58.2	32.8	5.5	1.7	0.7	0.4	0.2	0.1	0.1	0.1	0.2
$Q_y\widehat{(75}\vert x)$	1.3	69.3	17.9	5.6	2.5	1.1	0.7	0.5	0.2	0.2	0.7
$Q_y\widehat{(90}\vert x)$	0.0	23.4	46.3	15.1	6.2	3.1	1.8	1.1	0.7	0.5	1.8
					Public subsystem						
$Q_y\widehat{(25}\vert x)$	87.9	9.4	1.6	0.5	0.3	0.1	0.1	0.0	0.0	0.0	0.0
$Q_y\widehat{(50}\vert x)$	54.0	35.7	6.3	2.0	0.9	0.5	0.2	0.2	0.1	0.1	0.2
$Q_y\widehat{(75}\vert x)$	0.7	65.7	20.1	6.5	2.9	1.4	0.8	0.5	0.3	0.2	0.8
$Q_y\widehat{(90}\vert x)$	0.0	19.5	47.2	16.6	6.7	3.5	1.9	1.2	0.8	0.6	2.0
					Private subsystem						
$Q_y\widehat{(25}\vert x)$	83.6	12.3	2.4	0.8	0.3	0.2	0.1	0.1	0.1	0.1	0.1
$Q_y\widehat{(50}\vert x)$	46.8	40.3	7.5	2.6	1.2	0.6	0.3	0.2	0.1	0.1	0.3
$Q_y\widehat{(75}\vert x)$	0.2	60.0	23.4	7.6	3.6	1.8	0.9	0.7	0.5	0.3	1.0
$Q_y\widehat{(90}\vert x)$	0.0	13.2	47.7	19.5	7.7	4.0	2.3	1.5	1.0	0.7	2.4

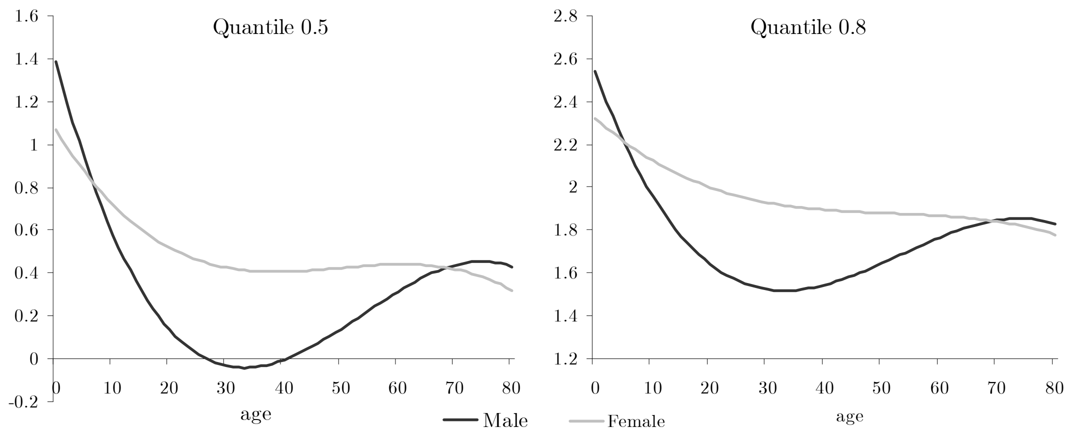
Notes: Estimates are based on a simulation exercise that start by predicting the $y^*_\alpha-$ quantile for all 35,308 individuals setting all control variables in their actual values except the health insurance status, which is set in the three possible cases. After that, the $y_\alpha-$ quantiles are computed applying $Q_y(\alpha|x) = \lceil Q_{y^*}(\alpha|x) - 1\rceil$ and tabulated according to their frequencies.

Regarding the effects of health status variables as a whole, it is visible that most of the regressors have a positive effect that increases with α. Being sick seems to be especially important to determine whether or not the individual visits a doctor but, taking into consideration the results of the last decile, it is much more important in explaining the subsequent visits. The same kind of behaviour is observed for the effect of long term incapacity, since for the first quantiles it is not significant whereas for higher levels of consumption it becomes a very important explanatory variable. In the case of the sickness effect this does not happen, which can be explained by the fact that only in the $0.90y-$quantile the impact is substantial whereas the variable *limited* becomes gradually more relevant. Amongst the chronic diseases we found evidence of a positive increasing effect along the estimated quantiles, except for the dummy *osteoporosis* that has a decreasing impact, while *infarction*, *otherchronicaldisease*, *highbloodpressure*, *diabetes* and *asthma* have a constant effect in the different parts of the distribution. The proxy for the level of exposure to stress has an effect that does not vary much across quantiles, and the other regressors related to attitudes towards health care have decreasing effects. The negative and decreasing impact of being a smoker contrasts with the results of Lourenço (2007), which although using a slightly different variable found positive effects on the consumption of doctor visits. Another interesting result is that having the habit of eating more times a day has also a positive impact. These results show that individuals that take better care of their health by not smoking and having a higher number of meals also complement their care by being more pro-active in the visits to doctors. These attitudes towards health care seem more than offset the impact of the improved health (and correspondingly lower demand for doctor visits) stemming from non-smoking and having a higher number of meals. Note that in the lower tail of the outcome distribution it is more clear the first situation and in the upper tail, the second situation may play a more important role.

The impact of variables related to the socioeconomic characteristics seem to be similar across quantiles. Concerning the household size effect, the results indicate that an individual consumes on average less consultations if the number of members of his/her household is larger. These results are in accordance with the previous parametric models and are similar to the ones found by Winkelmann (2006). A possible economic explanation for this effect is the presence of "economies of experience" within the family due to the fact that decisions taken by more than one person benefit from more in-depth information, which on its turn influence health status and efficiency in producing healthy times. It is also plausible that scale economies play a role if it is true that when visiting a doctor patients often also ask for symptoms of diseases of their relatives in order to prevent further visits.

Regarding the effect of age, from Figure 1 we see that the consumption is very high in the first years of life and decreases until $30-40$ years old, more for men than for women, and thereafter it increases for men while remaining fairly constant for women. These results seem intuitive and are consistent with the literature: the initial decreasing path may be related to the fact that children often require more health care (having therefore periodic doctor appointments); and after some point in the life cycle it is expected an increasing recourse to health services both if we consider that age is a health status proxy or a indicator of the depreciation rate (Grossman 1972). Most of the applications studying health care demand consider that the age has a quadratic relationship with health care utilization (Pohlmeier and Ulrich 1995, Winkelmann 2006 and Lourenço 2007). We first tried to do so but both coefficients did not appear significant and we found that a third order polynomial allows a much better fit to the data. Additionally, we modelled the ageing and gender effects together. Note that in our specification, it makes little sense to interpret the dummy *female* alone. The advantages of assessing the ageing effect by gender type are clear from Figure 1: men tend to consume less while women's behaviour towards health demand is smoother over the life cycle. By comparing the effects on the median with the $0.80y-$ quantile, we observe that the shape of the effects is similar but as a whole the impact of age is less pronounced in explaining high levels of visits to a doctor. This is very much in line with the results of Winkelmann (2006) that shows that age in the upper tail of the distribution of the number of visits has an insignificant effect.

Figure 1: Effect of age in the 0.5y*-quantile and 0.8y*-quantile



The level of income has a positive but negligible effect on health care demand, constant across the different quantiles. Conceptually, it is possible to find at least two channels of income influences. The fist derives from the Grossman's model (1972), in which the income determines the budget constraint and, therefore, the ability to pay for health care. The second channel is related to be fact that different levels of income can explain differences in the opportunity cost of being ill and in the cost of visiting the doctor, especially if we closely relate income with the wage rate. In Portugal, the first channel may not actually exists as a consequence of the design of health care systems. This is broadly applicable to both private and public subsystems and to NHS beneficiaries, although the latter in a minor extent. Direct costs of beneficiaries are relatively small as most of the cost of a consultation is borne by the health care system, which is financed predominantly by general taxation or employers and employees compulsory contributions.[32] In this context, the second channel can be more relevant and it is consistent with the estimated small effect of income over all the outcome distribution. Also the educational level has a small positive impact on health care demand that does not change significantly across the estimated quantiles. This appears to indicate that individuals with high educational levels face a higher opportunity cost of being ill and this more than offset the opportunity cost of visiting the doctor. Also, there is no evidence

[32] In this scenario, it makes no sense to do simulations of how much should the wages of public employees be increased in order to compensate them for the elimination of their health insurance plan.

regarding the idea that more educated people are able to improve health more efficiently generating fewer doctors' consultations. The previous empirical evidence of Pohlmeier and Ulrich (1995), Winkelmann (2006) and Lourenço (2007) also found small positive effects for both income and education variables.

Concerning the marital status influence, the results point out that single people visit doctors less often. These findings may indicate that they are less risk-averse regarding their health. As to the occupational status, the estimated semi-elasticities are positive for retired individuals and negative for students, meaning that the demand for health care increases over the life cycle, being lower when we study, higher when we work and much higher when we retire.[33]

5.1 Cumulative health effects of double coverage´s age

As mentioned in Section 4.2, some individuals may have enjoyed health insurance double coverage for a long period of time which may generate health benefits from a hypothetical better treatment accumulated over time. If this occurs, the difference in the number of consultations between the two groups should decrease with age. The idea is that the recent beneficiaries of a health subsystem (more likely the younger generations) did not have time to accumulate such health benefits, whereas the older beneficiaries (more likely the older generations) had time to do so, and that will make them relatively healthier when compared with untreated individuals. If this behaviour is not fully controlled by the health status variables, $\beta_1(\alpha)$ and $\beta_2(\alpha)$ previously estimated can be positively bias. Following Barros et al. (2008), we estimate our specification in different age groups, within the quantile regression framework. Table A2 of the Appendix present the estimated coefficients obtained from a subsample of individuals with more than eighteen years old (28,736 observations) and Table A3 of the Appendix show results for a subsample of individuals with age between eighteen and forty five (12,637 observations). When compared with the full sample results[34], we observe differences in all groups of variables and as expected the coefficients of the third order polynomial in *age* and the third order polynomial in *age* crossed with the gender dummy are now not significant.

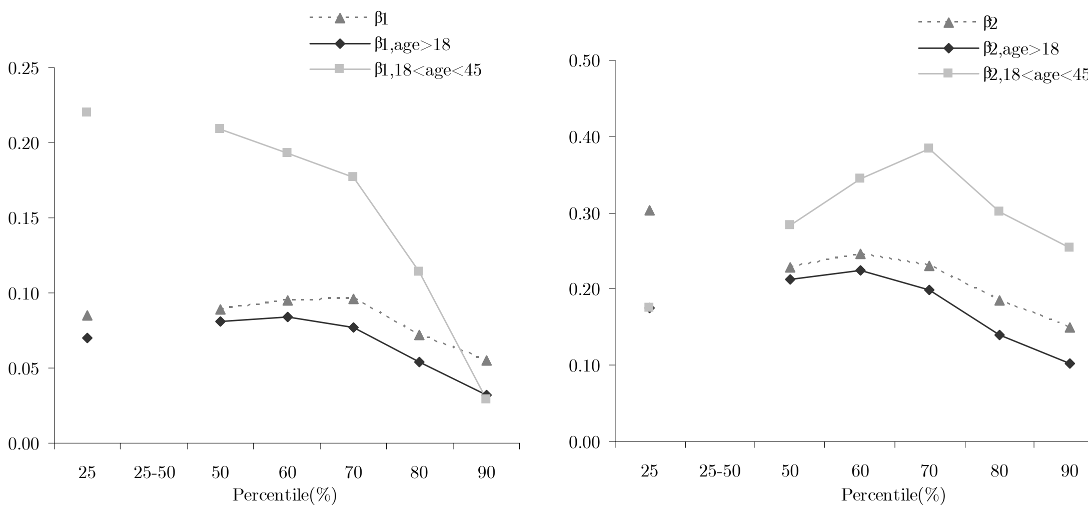
Figure 2 provides a graphical comparison of the estimated coefficients $\beta_1(\alpha)$ and $\beta_2(\alpha)$ focusing on the upper tail results. The most important fact is that the effects of both public and private subsystems are higher for the younger generations and this occurs in the whole distribution. When we restrict the analysis to observations with more than eighteen years old, thus rising the average age, both $\beta_1(\alpha)$ and

[33] In the interpretation of the results we should be aware that these particular variables may capture to some extent Grossman's income and age effects.

[34] Note that the sample used in the previous section includes individuals from zero to eighty years old.

$\beta_2(\alpha)$ decrease (slightly more in the upper tail of the distribution), whereas the younger cohort (the one with individuals with more than eighteen and less than forty five) has the largest estimated treatment effects. The differences are very expressive, especially for the public employees. This is consistent with Barros et al. (2008) findings.

Figure 2: Effects of the public and private subsystems in different age groups



For different levels of visits to the doctor, beneficiaries from private subsystems and public subsystems behave now in a quite different way. Regarding the public subsystems, quantile regression results show that the treatment effect of the younger cohort decreases considerably across the distribution, which indicate that the moral hazard is relatively lower among young high users. Also note that this was not the case for the full sample and that the coefficients of the different age groups are similar in the $0.90y^*$-quantile. For the private subsystem, the estimated impact of the younger group increases until the $0.70y^*$-quantile and decreases thereafter. This a similar path to the one obtained with the full sample. The results seem to confirm the suspicion that the estimated effects for the elder groups are lower, possibly reflecting accumulated health benefits from the existence of the subsystems. In this context the best indicator of moral hazard would be one obtained from the sample of individuals that possibly did not have time to incorporate such benefits. The caveat is the reduction of the sample, in particular of the treated individuals.

6 Conclusions

This paper examines the impact of additional coverage on the demand of visits to the doctors at different levels of the outcome distribution, contributing to the empirical literature on moral hazard in the health sector. Using a recent quantile regression method for count data, we overcome the limitation of traditional parametric count data models by investigating the effect of covariates on the shape of the whole distribution. We discarded the selection bias problem by using only individuals that enjoy an exogenous health insurance double coverage and by analysing its impact in different age cohorts.

The results show that the additional coverage is very important in explaining the demand for doctor consultations, especially in the lower tail and at the middle of the distribution. That is, double coverage leads to a relatively higher increase in demand (visits to a doctor) for regular (but not heavy) users of the health system. When the effects of the public and of the private health insurance plans (providing double coverage) are compared it is clear that the moral hazard derived from private health insurance double coverage is much higher than the one derived from the health insurance plan of public employees. Another important finding is that the relative effect of both sources of double coverage is almost constant across quantiles, which means that they display a similar path along the distribution. The analysis for the youngest cohort shows that the estimated effects of both public and private health insurance on top of the NHS are higher than the ones for the full sample, possibly reflecting accumulated health benefits.

The estimation of a positive effect of the double coverage derived from the subsystems corroborates the findings from traditional parametric models (Moreira 2008). Nevertheless, quantile regression provides us with a more detailed description of the effect of the treatments on the distribution of doctor visits, thus becoming a valuable tool to complement parametric models.

To explain the differences in the demand for doctor consultations between the different health insurance status we control for several demographic, socioeconomic and health status variables, besides the geographic and seasonal effects. Results indicate that the existence of chronic diseases or pain is extremely relevant in explaining doctor visits, especially for high users. Among the demographic and socioeconomic characteristics, age (also as proxy of health status) assumes a unique role, especially when combined with gender. In the first years of living the consumption of health care is very high and it decreases until 30-40 years old, more for men than for women, and thereafter it increases for men and remains fairly constant for women. Education and income present significant positive effects (constant over the whole distribution) although less important than those of other regressors. Results from quantile regression are similar to those from previous literature in terms of the significance of key covariates, but the combination of age and gender is novel in the literature.

In short, health insurance double coverage generates additional demand for health care. This additional demand effect is slightly higher for medium-intensity users than for heavy users. Also interesting is the large difference in impact according to the source of health insurance double coverage. The second layer of health insurance coverage adds more to demand when provided by private organizations than when obtained from Government-sponsored entities.

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A Appendix

Table A1: Quantile regression results: standard errors

	$\widehat{\beta(0.25)}$	$\widehat{\beta(0.50)}$	$\widehat{\beta(0.60)}$	$\widehat{\beta(0.70)}$	$\widehat{\beta(0.80)}$	$\widehat{\beta(0.90)}$
Health insurance status variables						
pubsub	0.032	0.029	0.028	0.028	0.024	0.025
privsub	0.070	0.055	0.053	0.051	0.046	0.053
Health status variables						
sick	0.097	0.095	0.081	0.106	0.120	0.097
limitdays	0.004	0.003	0.003	0.003	0.003	0.004
limited	0.094	0.081	0.080	0.078	0.077	0.073
rheumatism	0.032	0.025	0.024	0.023	0.023	0.024
osteoporosis	0.039	0.031	0.030	0.029	0.028	0.032
cancer	0.065	0.050	0.042	0.047	0.056	0.068
kidneystones	0.045	0.039	0.038	0.038	0.035	0.038
renalfailure	0.075	0.069	0.064	0.065	0.059	0.067
emphysema	0.060	0.049	0.043	0.043	0.046	0.050
cerebralhaemorrhage	0.076	0.055	0.054	0.061	0.051	0.062
infarction	0.079	0.063	0.063	0.053	0.050	0.065
depressivedisorder	0.042	0.035	0.032	0.030	0.030	0.034
otherchronicaldisease	0.025	0.021	0.020	0.019	0.017	0.019
highbloodpressure	0.030	0.024	0.022	0.021	0.020	0.022
chronicpain	0.031	0.026	0.025	0.023	0.022	0.024
diabetes	0.037	0.028	0.027	0.028	0.028	0.030
asthma	0.047	0.038	0.036	0.035	0.035	0.037
stress	0.035	0.027	0.024	0.024	0.025	0.025
smoker	0.035	0.031	0.033	0.034	0.028	0.028
meals	0.044	0.041	0.040	0.039	0.036	0.036
Socioeconomic and demographic variables						
householdsize	0.010	0.009	0.008	0.009	0.008	0.007
age	0.080	0.067	0.066	0.071	0.063	0.059
age^2	0.022	0.019	0.019	0.020	0.018	0.017
age^3	0.002	0.002	0.002	0.002	0.001	0.001
age*female	0.112	0.095	0.093	0.092	0.082	0.085
(age*female)^2	0.031	0.026	0.026	0.026	0.023	0.023
(age*female)^3	0.002	0.002	0.002	0.002	0.002	0.002
female	0.109	0.092	0.089	0.083	0.074	0.085
educmax	0.003	0.003	0.003	0.003	0.002	0.002
lincome	0.021	0.018	0.019	0.018	0.016	0.017
single	0.041	0.037	0.038	0.040	0.034	0.034
student	0.042	0.039	0.039	0.042	0.034	0.034
retired	0.037	0.029	0.027	0.026	0.028	0.027

Note: Geographic and seasonal controls not reported. Available from the authors upon request.

Table A2: Quantile regression results: estimated coefficients when age>=18

	$\widehat{\beta(0.25)}$	$\widehat{\beta(0.50)}$	$\widehat{\beta(0.60)}$	$\widehat{\beta(0.70)}$	$\widehat{\beta(0.80)}$	$\widehat{\beta(0.90)}$
Health insurance status variables						
pubsub	$0.070^{\dagger}$	0.081	0.084	0.077	$0.054^{\dagger}$	$0.032^{\ddagger}$
privsub	$0.174^{\dagger}$	0.213	0.224	0.198	0.140	$0.103^{\ddagger}$
Health status variables						
sick	0.746	0.664	0.648	0.625	0.582	0.805
limitdays	0.065	0.067	0.068	0.067	0.064	0.066
limited	$0.165^{\ddagger}$	0.234	0.271	0.334	0.352	0.379
rheumatism	0.141	0.150	0.149	0.145	0.149	0.148
osteoporosis	0.294	0.222	0.198	0.166	0.128	0.104
cancer	0.461	0.454	0.424	0.375	0.382	0.494
kidneystones	0.159	0.168	0.187	0.201	0.228	0.214
renalfailure	$0.151^{\dagger}$	0.193	0.197	0.198	0.238	0.215
emphysema	$0.052^{\ddagger}$	0.152	0.169	0.165	0.184	0.213
cerebralhaemorrhage	$0.135^{\ddagger}$	0.136	$0.128^{\dagger}$	$0.143^{\dagger}$	0.191	0.195
infarction	0.303	0.347	0.347	0.342	0.297	0.209
depressivedisorder	0.201	0.241	0.256	0.253	0.249	0.234
otherchronicaldisease	0.379	0.393	0.407	0.391	0.340	0.320
highbloodpressure	0.417	0.390	0.372	0.321	0.259	0.209
chronicpain	0.175	0.198	0.221	0.223	0.211	0.212
diabetes	0.449	0.364	0.336	0.307	0.289	0.293
asthma	0.232	0.268	0.283	0.278	0.241	0.193
stress	0.454	0.368	0.345	0.310	0.286	0.245
smoker	-0.209	-0.182	-0.175	-0.157	-0.095	$-0.036^{\ddagger}$
meals	0.189	0.160	0.130	0.107	0.092	$0.089^{\dagger}$
Socioeconomic and demographic variables						
householdsize	-0.049	-0.048	-0.049	-0.048	-0.031	$-0.012^{\ddagger}$
age	$-0.365^{\ddagger}$	$-0.319^{\ddagger}$	$-0.359^{\ddagger}$	$-0.139^{\ddagger}$	$0.177^{\ddagger}$	$-0.061^{\ddagger}$
age^2	$0.094^{\ddagger}$	$0.084^{\ddagger}$	$0.096^{\ddagger}$	$0.062^{\ddagger}$	$-0.021^{\ddagger}$	$0.022^{\ddagger}$
age^3	$-0.006^{\ddagger}$	$-0.005^{\ddagger}$	$-0.006^{\ddagger}$	$-0.004^{\ddagger}$	$0.001^{\ddagger}$	$-0.001^{\ddagger}$
age*female	$-0.078^{\ddagger}$	$0.032^{\ddagger}$	$0.226^{\ddagger}$	$0.133^{\ddagger}$	$-0.108^{\ddagger}$	$0.285^{\ddagger}$
$(age*female)^2$	$0.007^{\ddagger}$	$-0.022^{\ddagger}$	$-0.068^{\ddagger}$	$-0.066^{\ddagger}$	$0.004^{\ddagger}$	$-0.070^{\ddagger}$
$(age*female)^3$	$-0.001^{\ddagger}$	$0.001^{\ddagger}$	$0.004^{\ddagger}$	$0.005^{\ddagger}$	$0.000^{\ddagger}$	$0.004^{\ddagger}$
female	$0.660^{\ddagger}$	$0.548^{\ddagger}$	$0.357^{\ddagger}$	$0.683^{\ddagger}$	$0.701^{\ddagger}$	$0.011^{\ddagger}$
educmax	$0.004^{\ddagger}$	0.010	0.011	0.010	$0.006^{\dagger}$	$0.002^{\ddagger}$
lincome	0.068	0.057	0.058	0.054	0.046	$0.020^{\ddagger}$
single	-0.215	-0.189	-0.192	-0.202	-0.147	-0.100
student	$0.039^{\ddagger}$	$0.016^{\ddagger}$	$0.014^{\ddagger}$	$0.052^{\ddagger}$	$0.064^{\ddagger}$	$0.033^{\ddagger}$
retired	0.190	0.166	0.152	0.135	0.137	0.163

Note: The subsample has 28,736 observations. Results were obtained with 1500 jittered samples. Coefficients marked with ‡ and †are not significant at a 5 and 1 per cent level, respectively. Geographic and seasonal controls not reported. Available from the authors upon request.

Table A3: Quantile regression results: estimated coefficients when 18<=age<=45

	$\widehat{\beta(0.25)}$	$\widehat{\beta(0.50)}$	$\widehat{\beta(0.60)}$	$\widehat{\beta(0.70)}$	$\widehat{\beta(0.80)}$	$\widehat{\beta(0.90)}$
Health insurance status variables						
pubsub	0.220	0.209	0.193	0.177	0.114†	0.029‡
privsub	0.176‡	0.284†	0.345	0.384	0.300	0.255†
Health status variables						
sick	0.254‡	0.515†	0.686†	0.732	0.634	0.651†
limitdays	0.142	0.134	0.132	0.130	0.120	0.105
limited	-0.044‡	0.092‡	0.117‡	0.218‡	0.347‡	0.492
rheumatism	0.239	0.203†	0.229	0.263	0.267	0.276
osteoporosis	0.497‡	0.524	0.501	0.469†	0.380	0.301‡
cancer	0.556	0.438†	0.422	0.312†	0.276‡	0.482‡
kidneystones	0.136‡	0.163‡	0.270‡	0.406	0.444	0.458
renalfailure	0.046‡	0.071‡	0.009‡	0.309‡	0.366‡	0.420‡
emphysema	0.040‡	0.105‡	0.218‡	0.389†	0.400	0.344†
cerebralhaemorrhage	0.170‡	0.014‡	0.371‡	0.702‡	0.722‡	0.657†
infarction	0.971‡	0.882‡	0.814‡	0.872‡	0.857‡	0.494‡
depressivedisorder	0.370	0.421	0.425	0.438	0.393	0.365
otherchronicaldisease	0.507	0.552	0.613	0.631	0.521	0.437
highbloodpressure	0.435	0.535	0.560	0.524	0.425	0.294
chronicpain	0.218	0.270	0.341	0.376	0.368	0.360
diabetes	0.465	0.368	0.392	0.415	0.372	0.380
asthma	0.217†	0.250	0.257	0.311	0.273	0.278
stress	0.808	0.730	0.724	0.664	0.560	0.427
smoker	-0.136	-0.140‡	-0.124	-0.105†	-0.072‡	-0.012‡
meals	0.178†	0.142	0.130‡	0.135‡	0.118‡	0.057‡
Socioeconomic and demographic variables						
householdsize	-0.036†	-0.041	-0.046	-0.053	-0.045	-0.024‡
age	-1.326‡	-1.285‡	-1.263‡	-2.047‡	-2.445‡	-1.387‡
age^2	0.372‡	0.350‡	0.343‡	0.597‡	0.765‡	0.441‡
age^3	-0.033‡	-0.030‡	-0.030‡	-0.056‡	-0.077‡	-0.046‡
age*female	1.639‡	2.061‡	1.851‡	2.295‡	2.049‡	1.084‡
(age*female)^2	-0.552‡	-0.671‡	-0.605‡	-0.744‡	-0.690‡	-0.373‡
(age*female)^3	0.054‡	0.065‡	0.059‡	0.072‡	0.070‡	0.039‡
female	-0.989‡	-1.471‡	-1.242‡	-1.610‡	-1.391‡	-0.648‡
educmax	0.022	0.023	0.024	0.024	0.017	0.008‡
lincome	0.120	0.116	0.113	0.100†	0.068	0.034‡
single	-0.185	-0.177	-0.194	-0.237	-0.234	-0.166
student	-0.063‡	-0.068‡	-0.065‡	-0.040‡	0.003‡	0.018‡
retired	0.216‡	0.260‡	0.287‡	0.433‡	0.345‡	0.221‡

Notes: The subsample has 12,637 observations. Results were obtained with 1500 jittered samples. Coefficients marked with ‡ and †are not significant at a 5 and 1 per cent level, respectively. Geographic and seasonal controls not reported. Available from the authors upon request.