The effect of double insurance coverage on prevention - Draft -

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Abstract

This paper examines the determinants of demand for different health prevention services in Great Britain using data from the British Household Panel Survey (BHPS) from 1997 to 2003. I focus mainly on the impact of private insurance coverage. The empirical analysis uses a probit model and a switching probit model to take into account insurance endogeneity. For most preventive variables the results show that double coverage insurance has a positive effect on preventive care. Private insurance seems to have a big impact on dental care and private dental care and lower impact on pap-smear test and cholesterol check.

The personal characteristics that determine the demand for preventive services are also investigated. Income, education, age and sex, are find as key determinants of demand for preventive services.

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1 Introduction

Health care markets have been studied both in a theoretical and empirical framework. How individual's response to incentives is not a trivial question and its answer has important implications for policy makers. Economic analysis focuses on the determinants of individual decisions, mainly on the effect of income and relative prices.

The analysis of health care markets is different from the study of other markets. The indirect nature of the demand for healthcare, and the existence of asymmetric information are features that researchers need to take into account. This paper will focus on the effects of insurance on prevention. Insurance modifies the out-of pocket price of healthcare, the opportunity cost of time and allows to transfer income between different periods. Insurance introduce new incentives in health care consumption. Moral hazard and adverse selection behaviors have take place in this typical principal agent set up and have been documented in the literature (see Zweifel and Manning, 2000 for a review of this literature). My aim is to test whether complementary private insurance coverage, when universal coverage is available, increases the likelihood of taking different types of preventive care services.

Specifically, I estimate the impact of additional private insurance coverage on the demand for preventive-care using the data from the British Household Panel.

Prevention, as been analyzed in this article, consist of actions that reduce the consequences of illness due to an early detection and treatment (Secondary prevention). I believe demand for dental checks, cholesterol checks, blood checks, mammographies and pap-tests reflect a pure preventive behavior. For example, use of Papanicolaou (Pap Test) has been associated with a reduction of mortality from cervical cancer if screening tests are repeated at appropriate intervals in order to detect disease at an early stage (Morrison AS., 1985).

From a methodological point of view, tests such as the ones I am using here are preferable to using, for example, visits to the specialist since they are more homogeneous and their quality is independent of the insurance status (as argued by Barros, Machado, Sanz-Galdeano, 2006).

The main contribution of this paper to the literature is the usage of an alternative instrument for the insurance coverage (size of the firm) and a panel data set that give me the opportunity to consider unobservable individual heterogeneity.

The article is organized as follows. Section 2 introduces a short literature review. Section 3 describes the UK Health system. Section 4 introduces the data and presents some descriptive analysis of the sample. Section 5 explains the econometric specification of the model. Section 6 presents the results and finally, section 7 presents principal conclusions.

2 Short Review of the Literature

The analysis of the demand for prevention has been developed in the last 40 years. It has been studied both in the context of models of human capital (Becker, 1964; Grossman, 1972; Muurinen, 1982; Ehrlich and Chuma, 1990) and behavior under uncertainty (Ehrlich and Becker, 1972; Phelps, 1978; Nordquist and Wu, 1976, Kenkel´s, 1994). According to Kenkel 2003, the distinction between prevention and cure is not very common in the literature build on Grossman model. Nevertheless, this perspective gives light on the impact that education, intertemporal preferences, the stock of start-up capital and age have on the demand for prevention (Kenkel, 2000).

The strand of the literature that models the demand for prevention using the theory of decisions under uncertainty provides insights into the interactions between insurance and prevention. Theoretically, insurance coverage may have opposite effects on the demand for preventive care. First, since insurance smooths the losses that might happen due to negative health shocks, insured individuals may have incentives to reduce the level of preventive care if this is costly in any sense . This effect is denoted by ex-ante moral hazard. However, this incentive may be neutralized by risk aversion (Zweifel and Manning, 2000). Second, since availability of insurance lowers the marginal cost of preventive care services, the insured individual may increase care above the optimal level under perfect information. This effect is denoted by ex-post moral hazard. Moreover, if adverse selection is present in the market, insured individuals may be the ones with poorer unobservable health and therefore, demand more healthcare. In the case insurance companies are able to discriminate between different levels of health care, denoted by screening, the result is the opposite.

The seminal article of Ehrlich and Becker (1972) analyze the trade-off between insurance and different kinds of prevention (self-insurance and self-protection) in an expected utility framework. Self-insurance corresponds to secondary prevention and, self-protection to those activities that reduce the probability of a certain disease (primary prevention). Using a theoretical model, these authors found that market insurance and self-insurance may be substitutes, in the sense that an increase in the price of market insurance, given a probability of loss, would increase the demand for self-insurance (Ehrlich and Becker,1972).Other theoretical study (Phelps, 1978) distinguish between cure and preventive care. In this article it is shown that an equiproportional change in the price of both types of care (due to insurance coverage, for example) has ambiguous effects on the demand for preventive care.

Empirically, the effect of health insurance on the use of preventive care services is a difficult question to answer because the insurance choice (dummy variable) may be endogenous to health care use, leading to biased estimators. In an experimental setting, such as planned randomized trials, the exogeneity of insurance coverage is guaranteed (Feldsetin, 1973; Newhouse,1982; Manning etal., 1987). In a non experimental setting, however, the decision to buy an extra unit of health insurance depends on individual characteristics, as well as on the expected future consumption of health services (Cameron, 1984; Cameron etal., 1988), and on unobservable variables that affect both the demand of health insurance and the consumption of health care (Holly, 1998; Vera, 1999 and Jimenez-Martín etal. , 2002). As prevention reduces the risk of becoming ill in the future, risk averse consumers are, at the same time, more likely to buy insurance coverage and use preventive care services. Unfortunately, risk aversion is not captured by any specific variable in most surveys (Windmeijer, 1997). Also, people spend more on health services because they are insured but at the same time they have higher insurance coverage because of higher expected expenditures on health care (Cameron etal., 1988; Coulson etal., 1995; Holly etal., 1998; Vera, 1999;Savage and Wright, 2003; Barros etal.,2006). A model estimated without taking into account such a potential endogeneity may over-estimates the effect of insurance coverage on preventive services consumption. Generalized methods of moments for count data models, instrumental variables and matching estimators technics are used to estimate this kind of problems. Moreover, little has been done over prevention variables.

In general, the available studies suggest that the demand for preventive care services may be a declining function of out-of-pocket money price (Zweifel and Manning, 2000). Friedman etal. (2002) found that women enrolled in Preferred Provider Organization (have better office visit coverage) are significantly more likely to obtain a Pap-test and a mammogram than those who are enrolled in the fee for service plan. Deb (2001), uses a random effect probit model, which allows for unobservable heterogeneity, and assumes exogeneity of the insurance status, found that individuals who are insured are substantially more likely to seek each type of preventive care. Barros etal.(2005) using a matching estimator technique also found health insurance status as a relevant variable. Sudano etal. (2003) shows that among individuals who lack health insurance coverage, there is a lower likelihood of seeking recommended follow-up care, care for chronic conditions, and clinically indicated preventive services. There are also other studies that find a significant relation between being insured and prevention care variables. Jepson etal. (2000) shows that from thirty four mammography studies, twelve analyzed the effect of having insurance and seven (58%) found this variable significant. For colorectal cancer screening tests only one investigates the influence of health insurance coverage and also found that individuals who had HMO insurance were more likely to have had a colorectal cancer screen.

3 UK Health System

The United Kingdom's health sector is characterized by a high participation of the public sector. The National Health Service (NHS) was set up in 1948.The system gives universal coverage insurance and is financed by general taxation.

Primary care is the first point of contact most people have with the NHS and it is delivered by GPs, nurses, dentists, pharmacists and opticians. This care focuses on the treatment of routine injuries and illnesses as well as preventive care. Primary Care uses 80 per cent of the total NHS budget. (NHS, 2006)

Indeed NHS is used by most of the population, but private services use has been increasing last years. The length of waiting lists in the NHS system (Dilnot etal., 1998) plus the advantages of the private system such as quicker answer to health problems, access to sophisticated diagnoses tests and better related services are strong incentives for people to take out private medical insurance (PMI). Also, in the face of continual upward pressure on public health spending, government have incentives to encourage growth in private medical insurance (Hall etal., 1998).

Having PMI does not provide cover for every medical eventuality. Which illnesses are covered will depend on the insurance contract. There are two main types of PMI coverage: comprehensive and low cost/budget. The most common plan taken out by individuals or families is the budget option. A comprehensive policy usually covers inpatient treatment, hotel and nursing expenditures, surgeons, physicians and anesthesiologists, X rays, home nursing if it is requested by a doctor after inpatient treatment, outpatient and day-care treatment linked to inpatient treatment (European Observatory of Health, 2006). In the database I used I do not have information to know which kind of PMI people have.

Dental services are covered by the NHS, this service has considerable amount of co-payment with individuals paying 80% of the cost of their treatment up to a maximum charge set at £348 in 1999/2000. Not included in the co-payment regimen are children, those with low incomes, and pregnant or nursing mothers. The numbers of patients that have switched from a public to a private treatment have expanded since 1988 (NHS). One of the reasons is that dental services are provided by independent dental practitioners who have service agreements with their local health authorities but at the same time continue with their private patients. Dentists have incentives to reduce the amount of time devote to the NHS work and increased the amount of time they devote to private patients. This situation leads to access problems for dental care and as a result dental insurance has expanded rapidly in recent years. (European Observatory of Health).

The UK has an active prevention policy for many diseases. Examples are the NHS breast screening program and cervical screening program. The NHS breast screening program provides free mammogram every three years for all women in the UK aged 50 and over, and the NHS cervical screening program provides free cervical screening every three years for women aged between 25 and 49, and every five years for women between 50 and 64 years.

In 2000 a Health system reform was implemented in the UK to increase health care access and to help local health organizations to offer high-quality services. The NHS promised to give greater focus to the prevention of illness, and reduce inequality of access.

4 Data, variable definitions and descriptive statistics

I used data from the British household panel (BHP) over a seven years period (1997-2003). "*The British Household Panel Survey (BHPS) is conducted by the ESRC UK Longitudinal Studies Centre (ULSC), together with the Institute for Social and Economic Research (ISER) at the University of Essex*".

The BHPS sample consists of more than 5,000 randomly selected households, making a total of more than 10,000 individual interviews aged 16 and over per year. The same individuals are re-interviewed in successive waves. The BHPS has included a health related section since the first wave (1992), but only since 1996 has it included questions related to PMI coverage. As I want to evaluate double coverage impact on demand for preventive health I used data from 1997 to 2003.

After eliminating those that do not respond to one of the relevant questions, and those who are aged 65 or more the final sample contains 58,066 observations and 11,688 individuals. I have 10 per cent of attrition. I decided not to include individuals aged 65 years old or more because they report a worse level of health and very low level of PMI. Since, in general, insurance companies do not often give insurance to older individuals.

The unbalanced panel dataset contains information about sociodemographic characteristics, income levels, labor status, health care use, preventive health care use, objective and subjective measures of health status, consumption habits that may affect health (e.g., tobacco and alcohol consumption) and insurance status.

Although nothing ensures that panel attrition is at random with respect to preventive care or insurance, individuals characteristics do not change significantly in different waves.

Having a panel allows me to control for individual heterogeneity, gives more informative data, more variability, less collinearity among the variables, more degrees of freedom and more efficiency (Baltagi, 2005).

Outcome measures: Preventive variables I use different dummy variables to capture the demand for preventive health services during the previous 12 months before the interview: 1) visits to the dentist, 2) blood tests,

3) cholesterol test and; 4) mammography and pap-smear tests for the women sub-sample. All these variables are base on self-reports.

The question asked by the interviewer is the following: "Would you please tell me whether you have had any of the health check-ups and tests listed on this card since September 1st?". As subsequent questions ask about whether they got these services on the NHS or in the private sector I can identify if the visits or tests have been done in the private or public sector.

Table 1 presents outweighed percentages of participants who reported use of each preventive service during the period under analysis. For the whole sample the most uptake check is visits to the dentist. 36.8 per cent of individuals in the sample went to the dentist every year and 51.5 per cent at least one year. Few persons did a cholesterol check or a blood test every year, but these percentages increases significantly when I account for individuals that at least one year did a cholesterol or a blood test (62.3 per cent did a blood test at least one year and 28.5 per cent did at least a cholesterol check).

For the women sub sample (54 per cent) pap-smear test has an uptake of .39.3 per cent, and mammogram 26.2 per cent. These percentages mean that they do a pap-test or a mam-test at least once in the sample period. When I compare the pap-test uptake with the NHS recommendation I found that, for the subsample aged between 25 and 50 years 50 percent of the them follow up NHS recommendation (at least one test in three years) and, in average, do a test once in 2.38 years. For the subsample of women aged more than 50 years old, the recommendation is one over 5 years. The data shows that, in average, they do a pap-smear test (PST) once in 4.5 years and 50 percent of the them once in 6.5 years. Women aged 50 years old and over, in average, follow up NHS recommendation for mam-test. The average periodicity of mam-test is 1 in 3.16 years and the median is 1 in 3.5 years.

The data allows me to identify if individuals use private or public services. For dental check, I find that 17.7 per cent and 39.3 per cent of the individuals that went to the dentist every year and at least one year decide to use private services.[1]

The usage of private services is much lower when I analyze other preventive care services. Because of the lower usage of private services for choles-

[1] Notice that dental services has a copayment of 80 per cent, individuals are facing difficulties in obtaining treatment under the NHS. "In recent years disputes between dentists withdrawing entirely from NHS work, and to others reducing the amount they undertake" (EOH)

terol checks, blood tests, mammography and pap-tests I do not distinguish between public and private demand for these tests.

Table 1: Prevention Variables

Variable	Mean	Std.Dev
Every year goes to the dentist (*)	0.368	0.482
Every year goes to private dentist (*)	0.176	0.381
At least one year goes to the dentist (*)	0.515	0.499
At least one year goes to a private dentist (*)	0.218	0.413
Every year does a cholesterol check (*)	0.016	0.127
At least one year does a cholesterol check (*)	0.285	0.451
Every year does a blood check (*)	0.057	0.233
At least one year does a blood check (*)	0.623	0.485
Every year does a mammography (**)	0.004	0.061
At least once in three years does a mammography (**)	0.181	0.385
Every year does a pap-test (**)	0.011	0.106
At least once in three years does a pap-test (**)	0.393	0.488

(*) Whole sample: n=11,688 individuals (**) Women subsample: n=6,278

Insurance status The level of private sector participation in the provision of care is one of the major points of difference between health care systems. Although UK has relied on a National Health care System, there has always been an active private sector (Besley, Hall and Preston, 1996).

There are two main sources of private medical insurance: individual purchase or employment-provision. Although the second option may has less flexible plans, such insurance may be cheaper because of the pooling of risks it allows and because most employers contribute to its cost.

Individuals in the sample were asked about private medical insurance and whether this coverage is in their own name or through a family member. In 2003 18.35 per cent of adults were covered by private medical insurance, 12.7 per cent were covered into own policies and 5.65 per cent via a family member.

Table 2: Individuals covered by private medical insurance (2003)

Covered by private medical insurance (2003)	Freq	%
Insured in own name	1,080	12.7
Insured via other family member	480	5.65
Not insured	6,942	81.65
Total	8,502	100

Mintel (2002) observed a reduction in the percentage of individually purchased policies and an increase in the percentage of employer paid policies. In 1997 he reports that *"the private medical insurance (PMI) market has divided into two distinct segments since 1996, with individually paid subscriptions declining while the corporate sector has thrived"*. In the BHP data I see that in 1996, 42 per cent of individuals that reported having private medical insurance pay it directly. In 2003, 39 per cent.

Table 3: Segments of private medical insurance

Year	Deducted from wages or paid by employee	Paid directly	# insured individuals
1996	713	519	1232
%	58	42	100
2003	955	605	1560
%	60	39	100

In table 1 appendix 1 I report some basic statistical information regarding the variables used in the empirical analysis. A breakdown of PMI coverage by sex shows that 50 per cent are women but only 36 per cent of them have insurance in own name in comparison to 80 per cent of men. This could be due to the fact that, on average, men tend to have jobs that are more likely to provide medical insurance as a benefit, and this medical insurance may cover family members.

An examination of socioeconomic characteristics of those with private medical insurance indicates that it is heavily skewed towards higher socioeconomic groups. A simple analysis shows that individuals with higher incomes are much more likely to have medical insurance than individuals with lower incomes. This is consistent with the existing literature for insurance demand which shows a positive and significant effect of income on insurance purchase. Being middle-age, married, reporting higher education level, and working as employees seems to be positively correlated with having medical insurance coverage.

Because of adverse selection, I expect that those reporting poor health were more likely to purchase medical insurance because they would have a greater probability to become ill in the future and use medical services. However, I notice that those individuals reporting good health are more likely to have private medical insurance than those reporting bad health (Table 2 in Appendix 1). The more plausible explanation may be that good health is positively correlated with income and education. Another reason could be that poor health individuals face higher premiums that reduce their demand for health insurance (Rothschild, M. and Stiglitz, J.,1976) or that exists sample selection in the employment based insurance coverage. Finally, another one could be that insurance companies are able to discriminate individuals between levels of health (screening).

In a preliminary analysis I find that private medical coverage varies significantly between regions. In London and the South around 23 per cent of the population has PMI, whilst in Scotland, Wales and Northern Ireland, PMI coverage is reduced to 9.4, 8.5 and 5.9 per cent respectively. In Anglia and the North Pi is 12.5 and 13.7 per cent respectively. This findings are in line which the result that shows a positive association between the purchase of private health insurance and the length of local NHS waiting-lists (Besley, Hall and Preston, 1996).

In our sample, in average, 4 percent of individuals obtained insurance per year and 3.88 per cent lost it. 92. percent of individuals maintained the same insurance status of the previous year (See Table 3 in Appendix 1).

Insurance status and demand for prevention As I want to place special emphasis on the role of double insurance coverage as a determinant of preventive demand, I am going to analyze the behavior of these variables jointly. In a preliminary analysis I find that PMI varies significantly between different kinds of prevention. For the whole sample, the percentage of women that went to the dentist or to a private dentist, did a pap-test or a blood-test is greater for the sub sample of insured women than for the sub sample of non-insured. The percentage of men that went to the dentist or to a private dentist, or did cholesterol check is greater for the sub sample of insured men than for the sub sample of non-insured (Table 4).

For mam-test, pap-test and cholesterol check inside women sub-sample and blood test inside men sub-sample I do not observe that individuals with PMI demand more than individuals that do not have it, in average. This behavior changes for the sub-sample of individuals that report not having health problems. In this sub-sample, the percentage of individuals with PMI that do prevention is greater or equal than the percentage without private insurance. Although there are no average differences in pap-smear uptake for the total sample, there are differences for the sample aged more than 50 (for whom the effect of private insurance on the price of the pap-smear test is greater because they have free tests once in five years).

Table 4: Segments of private medical insurance

2003data	Females(N=6278)			Males(N=5410)		
	NoPrivate Insurance	WithPrivate Insurance	Total	NoPrivate Insurance	WithPrivate Insurance	Total
Dentist	0.69	0.80	0.71	0.59	0.69	0.61
PrivateDentist	0.17	0.32	0.19	0.21	0.36	0.25
Cholesterol	0.09	0.09	0.09	0.13	0.15	0.13
Blood-test	0.35	0.35	0.35	0.25	0.26	0.25
Mam-test	0.26	0.26	0.26	-	-	-
Pap-test	0.29	0.30	0.29	-	-	-

5 Econometric specification

Theoretical analysis gives us two main empirical approaches to model health care utilization. Following the traditional consumer theory I can model health care demand as a result of individual preferences and decisions: the patient determines if he goes to the doctor or performed preventive tests or if he does not. The second approach is under the principal agent set-up. The patient is the principal and the physician the agent. The agent is who determines the treatments, tests, and other services the patient (principal) need after visit him. Two different empirical approaches are needed to capture each one of the theoretical approximations. In the first case (classic demand theory), one step econometric models for count data are adequate. In the second case, I need to use two steps count data models, latent class models or the joint generalized methods of moments. See Jiménez Martín etal. (2001) for a detailed analysis and review.

I am going to estimate different models on the decision whether to consult the dentist or not, perform a blood test, a cholesterol test, a mammography or a pap-test. First, I consider the cross-section sample, that includes persons across all the waves. I estimate a probit model assuming exogeneity of insurance status and, a switching probit model when I account for the potential endogeneity of insurance. Tables 1 to 7 in appendix 2 presents the results.

The latent variable specification of the model is the following :

$$y_{it}^{*} = \delta d_{it} + x_{it}' + v_{it}, \qquad \begin{array}{l} i = 1, ...n \\ t = 1, ...T \end{array} \tag{1}$$

Where,

$$v_{it} = \alpha_i + u_{it}, \qquad \begin{array}{l} u_{it} \sim N(0, \sigma_u^2) \\ \alpha_i \sim N(0, \sigma_\alpha^2) \end{array} \tag{2}$$

The sign of the latent variable determines the observed binary outcome variable,

$$y_{it} = \begin{cases} 1 & if \quad y_{it}^{*} > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

Where y_{it}^{*} is a latent continuous variable defining the preventive behavior of individual i at time t. The latent variable is interpreted as the difference between marginal benefit and marginal cost of prevention. Thus an individual does prevention if marginal benefit exceeds marginal cost, and does not otherwise; x is a vector of exogenous variables and d_{it} is a dummy variable that indicates if the individual i is insured at period t. I do not observe y_{it}^{*} , I only observe y_{it}; y_{it} is the index function, which takes value 1 if individuals reports visits to the dentist, blood tests, cholesterol checks, mammographies or pap-smear tests and zero otherwise; x_{it} is the vector of explanatory variables; β represents a vector of parameters to be estimated, δ is the coefficient associated with the dummy regressor, α_i represents the individual specific effect and u_{it} is the random error.

To estimates the models I used Stata 9.

5.1 The endogeneity problem of insurance coverage

The existence of unobservable variables that affect simultaneously the decision of having private insurance and the preventive services utilization may generate an endogeneity problem. To solve it I use instrumental variables in a linear probability model (Heckman and MaCurdy, 1985) and a switching probit model (Terza, 1998; Carrasco, 2001; Miranda, 2004).

Because the endogenous variable is binary, its distribution cannot be normal, and as a consequence, two stage or instrumental variable estimation methods cannot be applied (Carrasco, 2001). If I estimate the insurance decision with a non linear model for example probit, the estimators of the first stage will be consistent but the estimators of the second stage will not.

A simple way to account for endogeneity in this kind of models is to use instrumental variables in a linear probability model (Heckman and MaCurdy, 1985). The problems with this estimation model are well known. First, forecasts are not restricted to the zero-one interval and secondly, given x the effect of insurance coverage is assumed to be constant for all individuals. Nevertheless, it is a first step in order to account for the insurance endogeneity. However, since for my dependent variables I have excess of zeros, using a linear probability model may lead to biased and inconsistent estimators.

Another way to account for insurance endogeneity is using a switching probit model. "the switching regression estimators (SRE) approach allows the coefficients of all covariates in the utilization equation to vary with the insurance decision. The model is developed in Van Ophem (2000).

This approach seems appropriate, when there is reason to believe that the insurance decision affects individuals with different socioeconomic characteristics differently (Martin Schellhorn, 2001).

To estimate the switching probit model I used the model defined in Miranda etal. (2006) for the cross-section sample:

(4) $$y_i^* = x_i'\beta + \delta d_i + v_i,$$

(5) $$y_i = \begin{cases} 1 & if \quad y_i^* > 0 \\ 0 & otherwise \end{cases}$$

where y_i^* is a latent continuous variable, x is a vector of exogenous variables, β represents a vector of parameters to be estimated; δ is the coefficient associated with the dummy regressor d_i and u_i is the residual term. A similar latent model is defined for insurance (d_i):

(6) $$d_i^* = z_i'\gamma + v_i,$$

(7) $$d_i = \begin{cases} 1 & if \quad d_i^* > 0 \\ 0 & otherwise \end{cases}$$

The standard approach to allow correlation between u_i and v_i is to assume that the two random terms are jointly normally distributed (Teza, 1998; Miranda, 2006). Miranda´s model also assume direct dependence between u_i and v_i.

(8) $$v_i^* = \lambda u_i + \zeta_i,$$

with ζ_i distributed as independent normal variates with zero mean. The λ is a "loading" that is estimated along the other parameters of the model (Miranda, 2006). The error terms are assumed to be independent and identically distributed and follow a bivariate distribution with zero mean and covariance matrix defined by equation 9. Given that the variance in a Probit model is only identified up to a constant, Var(ζ_i) is set to one.

(9) $$\Sigma = \begin{bmatrix} \sigma^2 & \lambda\sigma^2 \\ \lambda\sigma^2 & \lambda\sigma^2 + 1 \end{bmatrix}$$

The correlation coefficient ρ is: $\rho = \frac{\lambda\sigma^2}{\sqrt[2]{\sigma^2(\lambda\sigma^2+1)}}$

where ρ is the correlation coefficient between the residuals. If $\rho = 0$ the error terms u_i and v_i are independent and d_i is exogenous. This implies that I can used ρ to performed an endogeneity test for insurance coverage in equation (4).

To estimate the model I used the ssm command in stata 9. The command used gllamm command to fit the maximum likelihood. As in Miranda (2006), to evaluate the likelihood function I used adapted quadrature.

The identification of the switching probit model is guaranteed by the non-linearity and normality assumptions (Manski etal., 1992). However, including variables that are highly correlated with the insurance decision but not with the decision on prevention may improve the identification of the parameters of interest. Thus, variables contained in z´ are not included in x´.

I will use the evidence from the previous literature to propose some candidate instrumental variables to identify the effect of private insurance coverage on the probability of doing prevention. In order to find valid instruments I follow Cameron (1988), Vera (1999), Holly (2001) and Hall etal. (1998), and I look for socioeconomic variables. To be good instruments they need to be highly correlated with the insurance coverage decision and not correlated with the probability of doing prevention.

Employment status has been proved to explained insurance demand Hall etal. (1998)) . "Whether an individual is self-employed and the type of occupation that they are in are likely to have an impact on their insurance demand....Availability of employer-provided private health insurance is also determined by employment" (Besley, Hall and Preston, 1996). In the pool database 21.2 per cent (1,807 individuals) of the sample have been covered at least one year and 11.2 per cent (954 individuals) have been covered all the years. From these 1,807 individuals 1,334 are employed at a firm (73.8 per cent) and 33 per cent work in a firm with more than 200 employees. 5.01 per cent of individuals obtained insurance coverage during the period under analysis and 20.9 per cent lost it. From the employee subset the percentage of individuals that start being covered by insurance increased to 6.47 per cent. Next table shows the transition matrix for insurance coverage.

I argue that the decision of an employee to purchase an insurance contract is conditioned by the firm´s offer. In the case of employment-provision of insurance I believe that the decision of being insured is exogenous and not related with the utilization of preventive services. Even when the decision to offer insurance coverage as additional benefit depends, in some way, on the preferences of the workforce the company wants to attract, the decision to accept or not the job would depend in many other factors. Moreover, as Besley etal. (1996) point out, since individuals may doubt whether they will receive a compensating wage increase if they don´t accept the insurance benefit, they may take the insurance also if they would not purchase it by their own. There is little incentive to unaccepted the insurance coverage, even for those who perceive having lower health risks, once the company offers such a benefit. Therefore, is enough to find an instrument that predicts the likelihood that an employer offers insurance coverage that is not correlated with health status and prevention utilization. Certain characteristics like firm size, industry sector, or if the firm offers pension plans can be used as good proxies of insurance offer. Noting that rates of employer provided insurance differ between industries and size of the firm (Table 5), I propose to use industry dummies and the number of employees as identifying instruments. The validity of these instruments depends on these variables being unrelated with the decision of doing prevention. Therefore, I have to be carefully about the differences in employer-provided insurance coverage. It would be problematic if the firms that offers insurance coverage as an additional benefit also offers regular care prevention to their employees. But also, if industry differences in risk of and size affects individual attitudes to preventive care.

6 Econometric Results

6.1 Definition of variables

My dependent variables for preventive care are dental checks, blood tests and cholesterol checks for the whole sample and pap-test and mammographies for women subsample.

Each preventive variable is defined in two different ways. For dental checks, blood tests, and cholesterol checks, each preventive variable (y) takes value one if individual i demands preventive checks in period t and zero otherwise. For pap-smear tests and mammographies NHS recommends performing these tests at least once in three years. In these cases the dependent variable takes value one if individual i demands at least one of each checks in three years and zero otherwise.

I estimate each demand equation for a pool database, in which I compress the panel into one observation per individual using the median and for the whole panel.

I assume the insurance is exogenous as well I consider its potential endogeneity. the first estimation is used as a benchmark and allows me to perform Haussman´s test to contrast the endogeneity hypothesis of insurance coverage. To take into account the potential endogeneity of PMI and obtain consistent estimators in the first and second stage I used instrumental variables on a linear probability model and a switching probit model.

The set of exogenous variables for each preventive demand equation consists of individual characteristics such as age, gender, marital status, degree of education, employment status, and income level; household characteristics such as house tenure, living region and average number of family members are also controlled for. Health related variables such as the presence of chronic diseases (includes chest, breathing heart blood, diabetes, epilepsy, migraine), and other health problems (stomach problems and anxiety) are taken into account in one specification and not taken into account in another one.

The potential endogenous regressor, PMI, is a binary choice (d) variable what takes value one if individual i reports being insured in period t.

6.2 Results

I find that double coverage has a positive effect over the probability of doing every one of the preventive tests. Indeed the sign for the tests is always positive (except in one case), although the magnitude of the coefficient is different. The nature of the tests and the supply side characteristics may be factors that indirectly affect the magnitude of private insurance coverage on the probability of taking each one of the preventive tests. Table 5 show the estimates for private insurance coverage on different preventive variables using the pooled data. In the table, the first three columns of results gives the estimates of the effect of private insurance on each one of the preventive variables assuming insurance as exogenous and the last one gives the result taking into account potential endogenity. In all cases I report marginal probability effects at mean values of other explanatory variables. All results include regional effects. These could be important if they capture fixed differences in health policy between regions.

I first comment briefly on the estimate of private insurance demand equation. These are consistently across specifications and with previous research. The purchase of insurance is positively related to household income, house tenure (use as a proxy of household wealth) and the highest educational level held by the respondent. As well as capturing a direct effect, the variable education may be capturing a permanent income effect and also attitudinal changes.

I find that individuals in middle age (30-49) are more likely to be insured. As I said before, I truncated the sample at aged 65. I decided not to include individuals aged 65 years old or more because they report a worse level of health and very low level of PMI. Since, in general, insurance companies do not often give insurance to older individuals. However, I observed that individuals between 50 and 65 years old are less likely to be insured even when they probably increase their medical requirements. This may be due to the increase in the insurance premiums faced by this group.

The size of the household reduces the conditional expectation of the respondent being covered by private medical insurance. A similar result is obtained by Hall etal. 1998. They believe that given that income is measure at household level, the result may be interpreted as an equivalent income effect[2].

Except for the South of England, the coefficients for all the other regions are significant at 1 per cent level and negative relative to London. This is consistent with the result that London has the highest percentage of adults cover by PMI.

My instruments seem to be good predictors of having PMI. Individuals who work as employees in bigger firms are more likely to have PMI.

The key effect of interest for the current paper is that of insurance coverage on prevention. An exogenous switch to being privately insured is estimated to increase the likelihood of attaining different types of preventive care. These effects are statistically significant, specially for private dental services. Furthermore allowing for endogeneity of insurance seems to be important for dental preventive care, cholesterol checks and blood tests but not for mam-test and pap-test. Haussman ´s test gives evidence for potential endogeneity of insurance status in the mention variables. Also, estimates of ρ on the non linear model are statistically significant for cholesterol checks, blood tests and dental care but not for mammographies and pap-tests. This may be due to the fact that the size of the firm is not a good instrument for insurance status.

My analysis begins with the estimation results from a linear probability model and a probit model, neglecting unobserved heterogeneity. Regarding the rest of covariates, I obtained similar qualitative effects from nonlinear and linear estimates. I only presents the coefficients of the probit specifications. Column (a) in table 5 presents the results from a probit model that treat insurance as strictly exogenous. Column (b) report switching probit estimates from a model that treats insurance as endogenous. I have used the size of the firm where the individual works as instrument.

[2]Instead of using household size they used number of adults in the household

As it is expected, the insurance coefficient is positive in all the econometric specifications. However it is positive but not significant for mam-tests, pap-tests and blood tests in the probit specification and for mam-tests in the switching probit specifications. This result is in line with the descriptive statistical analysis in which I do not observer differences in the average uptake of these tests.

When I do not take into account individual heterogeneity and considering insurance as exogenous, the probability of visiting the dentist increases 9 per cent assuming insurance as exogenous and 2 per cent when I account for endogeneity.

For private visits to the dentist the coefficient of private insurance is significantly different from zero and greater than for visits to the dentist. In the probit model, having insurance increases the probability to go to the dentist in 15.9 per cent and in the switching probit model in 8.9 per cent. For both, dental and private dental visits to the dentist not taking into account individual insurance endogeneity seems to overestimates the impact of private insurance.

For mammography and pap-tests, private insurance is not significantly different from zero in none of the models estimated. The existence of free mammographies for women in risk groups implies that the out of pocket expenditure for them is zero. If the screening program works well and the non-monetary price (time consuming, quality of service, etc) is not significantly different between women with private insurance and with out it, I expect that having private insurance does not increase the demand for this tests for women inside this group. The results obtained for mammographies and pap-tests are in this line. Moreover, for the rest of the women subsample (not risk group), having private insurance lowers its out-of pocket expenditure and may have a greater positive effect.

For cholesterol checks the effect of double coverage is statistically different from zero and positive in all the models estimated. Assuming exogeneity in the probit model increases the likelihood of doing a cholesterol check in 0.04 per cent.

For blood tests I obtained different results for different models. the results for this test are not conclusive as for the other tests.

Table 8: Private Insurance effect

Pool Sample	Probit Model (a)			Switching Probit Model(b)		
	Ins Coeff	Ins Mg Effect	Std Error	Ins Coeff	Ins Mg Effect	Std Error
DentalCare	0.244**	0.09	(0.044)	0.406**	0.021	(0.104)
PrivatedentalCare	0.421**	0.159	(0.045)	0.654**	0.089	(0.073)
Cholesterol	0.227**	0.004	(0.108)	0.639**	0.003	(0.192)
Bloodtest	0.093	0.09	(0.007)	0.043	0.000	(0.035)
Mam-tests	0.061	0.016	(0.007)	0.158	0.000	(0.140)
Pap-tests	0.033	0.013	(0.064)	0.618**	0.003	(0.111)

For all regressors except insurance, the coefficients are not much changed whether I control for the endogeneity of insurance status or not. Household income is positive in all the specifications and for all the preventive services demand, with a marginal effect bigger for private visits to the dentist. However, for mam-tests and pap-tests the income coefficient is not statistically different from zero. Measurement errors may affect the significance of this variable. But also the existence of the NHS Program may reduce differences in access due to income.

Education shows a statistically significant positive effect on all the prevention variables I used. Grossman´s theoretical model (Grossman, 1972), claims that education implies more investment in health capital. Therefore, may reduce later visits to the dentist. Since going to the dentist leads to more efficient prevention and increase dental health productivity, my result is in line with Grossman´s model. At the same time, education may also reflect the individual level of income and this positive relation strengthens the conclusion that preventive care is a normal good.

In the case of employed and self-employed the coefficient is negative for all the preventive variables and specifications. I think that the high opportunity cost of time is what may reduce the demand for these individuals.

Dummy variables for UK regions were included to account for any regional heterogeneity. However, as I do not have variables that account for the access to health care, these dummies may also reflect differences in the supply between regions. In the regression analysis I obtain that all the regions have a greater probability to go to the dentist than London. But, exists significant differences for private visits to the dentist. Individuals living in the South are more likely to go to a private dentist than persons living in London. All the other regions have a significantly different from zero and negative sign. The differences in the probability of going to a private dentist may be a good management indicator for NHS dental care services and accessibility. For mam-tests and pap-tests I also find differences between regions. Women living in urban areas may be more likely to take a mammography than women living in other regions because of cultural differences or differences in availability of health-care. I find that women living in the north and the south are less likely to take a mammography or a pap-test than women living in London. For most of the prevention variables, men and women living in the south are less likely to do prevention relatively to men and women in London.

7 Conclusion and further research

In this paper I used different models to estimate the effect of insurance coverage on the probability of taking different kind of preventive tests.

My results show that the effect of private insurance coverage, when universal coverage is available, is significantly different from zero and positive for most of the preventive tests under analysis, even when I account for potential endogeneity of private insurance. Except for blood tests, the results obtained from the switching probit model show that individuals that are privately insured have a greater probability to go to the dentist or perform a preventive test. These results do no mean that ex-post moral hazard exists. As I said before, ex-post moral hazard only exists when individuals demand more than an unobservable optimal level, and I do not know how far the observable data is from it.

Indeed the sign is for all tests positive, although the magnitude of the marginal effect is different.

Indeed the sign is for all tests positive, although the magnitude of the marginal effect is different. For tests where the individual pays most of the price of the service, even with public insurance, the marginal effect of private insurance coverage is bigger. For tests where the monetary price is lower because of free programs (mam-tests and pap-tests) or low level of copayment (cholesterol check), the marginal effect of additional private insurance is also lower.

From the first stage estimation (private insurance coverage) I conclude that the size of the firm may be a good instrument for private insurance. Individuals working in large firms are more likely to have private insurance than those working in small firms.

The estimation also help to indicate priority groups which should be targeted to increase prevention. Income, age, gender and education are key determinants of the demand for preventive services. Differences between regions were found for dental services, cholesterol check and blood test but I did not notice that differences for mam-test or pap-test. NHS screenings programs may reduce differences on access between regions. Differences between years are also found. Since 2000, the demand for preventive tests seems to increase. NHS 2000 program may influence this result. However, more years are needed to evaluate its evolution.

Although the panel structure of the data allows me to estimate a count data model, the results from the pooled binary choice model are also conclusive. A maximum likelihood probit model assuming endogeneity of insurance and Chamberline (1984) fixed effects logit estimator and minimum distance random effects probit estimator will be included in further research to estimate the demand for these tests.

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ANNEX 1

Table 1. Sample characteristics - Year = 2003.

Variables	Without insurance			With Insurance			Total		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Age	6942	42.24	12.97	1560	42.34	11.43	8502	42.26	12.70
Female	6942	55.6%	49.7%	1560	48.8%	50.0%	8502	54.4%	49.8%
Married	6941	57.2%	49.5%	1560	68.3%	46.5%	8501	59.2%	49.1%
Divorced	6941	12.5%	33.1%	1560	9.2%	29.0%	8501	11.9%	32.4%
Widowed	6941	2.4%	15.3%	1560	1.4%	11.8%	8501	2.2%	14.7%
Single	6941	27.9%	44.9%	1560	21.0%	40.8%	8501	26.7%	44.2%
High education	6942	44.5%	49.7%	1560	60.3%	49.0%	8502	47.4%	49.9%
Mid education	6942	29.8%	45.8%	1560	28.7%	45.2%	8502	29.6%	45.7%
Low education	6942	25.6%	43.7%	1560	11.1%	31.4%	8502	22.9%	42.1%
Self-emploeyd	6942	8.5%	27.8%	1560	8.4%	27.7%	8502	8.5%	27.8%
Employed	6942	60.6%	48.9%	1560	76.4%	42.5%	8502	63.5%	48.1%
Unemployed	6942	4.4%	20.5%	1560	0.9%	9.4%	8502	3.8%	19.0%
Not in labor force	6942	26.5%	44.1%	1560	14.3%	35.0%	8502	24.3%	42.9%
Employed Small firm	6942	27.0%	44.4%	1560	20.8%	40.6%	8502	25.9%	43.8%
Employed Medium firm	6942	15.9%	36.5%	1560	20.3%	40.3%	8502	16.7%	37.3%
Employed Big firm	5412	45.0%	49.7%	1390	53.8%	49.9%	6802	46.8%	49.9%
Head of Household	6942	50.7%	50.0%	1560	55.0%	49.8%	8502	51.5%	50.0%
Low Income	6942	5.3%	22.3%	1560	0.9%	9.4%	8502	4.5%	20.7%
Medium Income	6942	36.6%	48.2%	1560	15.0%	35.7%	8502	32.6%	46.9%
High Income	6942	58.1%	49.3%	1560	84.1%	36.6%	8502	62.9%	48.3%
Household size	6942	3.00	1.33	1560	3.02	1.23	8502	3.00	1.31
Smoke	6942	30.6%	46.1%	1560	18.8%	39.1%	8502	28.4%	45.1%
Chronic illness	6942	31.4%	46.4%	1560	25.7%	43.7%	8502	30.4%	46.0%
Living in london	5793	6.1%	24.0%	1307	10.4%	30.5%	7100	6.9%	25.4%
Living in the North	6817	18.8%	39.0%	1520	19.1%	39.4%	8337	18.8%	39.1%
Living in the South	6817	17.9%	38.4%	1520	28.9%	45.4%	8337	19.9%	40.0%
Living in Anglia	6817	15.0%	35.7%	1520	14.0%	34.7%	8337	14.8%	35.5%
Living in Scotland	6817	18.4%	38.7%	1520	12.0%	32.5%	8337	17.2%	37.8%
Living in Wales	6817	16.8%	37.3%	1520	12.6%	33.2%	8337	16.0%	36.7%
Living in Northern Ireland	6817	7.9%	27.0%	1520	4.3%	20.4%	8337	7.3%	26.0%

Table2:Insurance Status by Reported level of health-Pool sample-

Reported status of health	**Without Insurance**	**With Insurance**	**Total**
Excellent	10337	3033	13370
%	*77.31*	*22.69*	*100*
Good	21103	5072	26175
%	*80.62*	*19.38*	*100*
Fair	10629	1939	12568
%	*84.57*	*15.43*	*100*
Poor	4105	517	4622
%	*88.81*	*11.19*	*100*
Very Poor	1236	75	1311
%	*94.28*	*5.72*	*100*
Total	47410	10636	58046
%	*81.68*	*18.32*	*100*

Table 3: Transition Insurance status per year

year	**No change insurance status Insurance status**	**Lost Insurance**	**Obtained Insurance**	**Total**
1998	6,480	275	332	7,087
%	*91.44*	*3.88*	*4.68*	*100*
1999	6,204	308	248	6,760
%	*91.78*	*4.56*	*3.67*	*100*
2000	6,733	278	299	7,310
%	*92.11*	*3.8*	*4.09*	*100*
2001	7,403	282	321	8,006
%	*92.47*	*3.52*	*4.01*	*100*
2002	8,041	311	361	8,713
%	*92.29*	*3.57*	*4.14*	*100*
2003	7,820	345	337	8,502
%	*91.98*	*4.06*	*3.96*	*100*

Table 4: Women Pap-Smear test uptake for women aged more than 50 years

	Including women who did not do a PST			Including only those who did at least one P		
	N	Mean	Median	N	Mean	Median
Insured	7579	One in 4.2 years	One in 7 years	4369	One in 2.7 years	One in three years
Uninsured	1356	One in 4.6 years	One in 5 years	861	One in 2.6 years	One in three years
Total	8935	One in 4.5 years	One in 6.6 years	5230	One in 2.6 years	One in three years

NHS recommends one PST in three yhears for women aged more 49 years

I only include women for who I have more than 2 years of information

ANNEX 2

Table 1.First step estimation: Private Insurance equation

Individual Vbles	Coefficient	Marginal Effect	SD
female	-0.044**	-0.004	0.017
logincome	0.471**	0.045	0.024
age	0.032**	0.043	0.004
age2	0.000**	-0.099	0.000
married	0.140**	0.012	0.017
higheduc	0.288**	0.021	0.019
mideduc	0.267**	0.020	0.020
smoke	-0.178**	-0.019	0.016
hoh	-0.098**	-0.010	0.018
cronical_hp	-0.092**	-0.009	0.015
SelfEmployed	0.034**	0.003	0.030
Employed	-0.034**	-0.003	0.022
Unemployed	-0.230**	-0.026	0.051
Num employees (1)			
25_100	-0.026	-0.003	0.073
100_500	0.002	0.000	0.086
More500	0.179**	0.015	0.096
Employed*Numemployees			
25_100	0.162**	0.013	0.076
100_500	0.275**	0.020	0.089
More500	0.058	0.005	0.099
Household Vbles			
ireland	-0.390**	-0.051	0.041
wales	-0.382**	-0.049	0.032
scotland	-0.540**	-0.079	0.030
north	-0.231**	-0.026	0.026
anglia	-0.260**	-0.030	0.027
south	-0.102**	-0.010	0.025
h_size3_5	-0.103**	-0.011	0.016
h_sizemore5	-0.076**	-0.008	0.016
y_1997	0.119**	0.010	0.025
y_1998	0.113**	0.010	0.025
y_1999	0.049	0.004	0.028
y_2000	0.023	0.002	0.025
y_2001	0.015	0.001	0.023
y_2002	0.015	0.001	0.024
_cons	-6.271	-0.955	0.265

Table 2. Second step estimation: Dental care estimation

Variables	Probit		Switching Probit	
	Coeff	SD	Coeff	SD
Insurance	0.244**	(0.044)	0.406**	(0.104)
Income	0.094**	0.02	0.075**	(0.028)
Female	0.279**	(0.025)	0.290**	(0.025)
Age	0.006**	0.001	0.007**	(0.001)
Married	0.166**	(0.033)	0.011**	(0.029)
High education	0.408	(0.034)	0.400**	(0.034)
Mid education	0.368	(0.035)	0.362**	(0.036)
Employed	-0.025	(0.035)	-0.021	(0.035)
Selfemployed	-0.073	(0.046)	-0.066	(0.046)
Chronic illness	-0.121**	(0.025)	-0.115**	(0.005)
Household size 3-5	0.043**	(0.034)	0.046	(0.025)
Household size>5	-0.033	(0.034)	-0.028	(0.034)
Northern ireland	0.520**	(0.061)	0.535**	(0.061)
Wales	0.428**	(0.051)	0.443**	(0.051)
Scotland	0.353**	(0.047)	0.371**	(0.049)
North	0.321**	(0.047)	0.330**	(0.047)
Anglia	0.387**	(0.049)	0.399**	(0.049)
South	0.316**	(0.047)	0.323**	(0.323)
Constant	-1.352**	(0.080)	-1.382**	(-1.382)
ρ			0.095	(0.0089)
Wald	817		1230	
Log likelihood	-7,287.74		-9721	

Table 3. Second step estimation: Private dental care estimation

Variables	Probit		Switching Probit	
	Coeff	SD	Coeff	SD
Insurance	0.412**	(0.044)	0.406**	(0.104)
Income	0.311**	(0.028)	0.075**	(0.028)
Female	0.003	(0.025)	0.290**	(0.025)
Age	0.006**	(0.001)	0.007**	(0.001)
Married	0.043	(0.033)	0.011**	(0.029)
High education	0.313**	(0.034)	0.400**	(0.034)
Mid education	0.174**	(0.035)	0.362**	(0.036)
Employed	0.502**	(0.035)	-0.021	(0.035)
Selfemployed	0.697**	(0.046)	-0.066	(0.046)
Chronic illness	-0.042	(0.025)	-0.115	(0.025)
Household size 3-5	-0.031	(0.034)	0.046	(0.034)
Household size>5	-0.132**	(0.034)	-0.028	(0.034)
Northern ireland	-0.177**	(0.061)	0.535**	(0.061)
Wales	-0.245**	(0.051)	0.443**	(0.051)
Scotland	-0.218**	(0.049)	0.371**	(0.049)
North	-0.221**	(0.047)	0.330**	(0.047)
Anglia	-0.227**	(0.049)	0.399**	(0.049)
South	0.114**	(0.122)	0.323**	(0.047)
Constant	-1.28**		-1.3382**	(0.079)
ρ			0.102**	(0.047)
Wald	817		1230	
Log likelihood	-7287.74		-9721.67	

Table 4. Second step estimation: Cholesterol Check estimation

Variables	Probit		Switching Probit	
	Coeff	**SD**	**Coeff**	**SD**
Insurance	0.227**	(0.108)	0.639**	(0.192)
Income	0.238	(0.000)	-0.033	(0.081)
Female	-0.469*	(0.065)	-0.398**	(0.065)
Age	0.027**	(0.003)	0.029**	(0.003)
Married	0.082	(0.089)	-0.031	(0.047)
High education	-0.066	(0.079)	-0.094	(0.080)
Mid education	-0.12	(0.084)	-0.043	(0.086)
Employed	-0.202	(0.079)	-0.272**	(0.081)
Selfemployed	-0.335	(0.117)	-0.412**	(0.119)
Chronic illness	0.836**	(0.082)	0.837**	(0.082)
Household size 3-5	0.052	(0.087)	0.073	(0.091)
Household size>5	-0.141	(0.098)	-0.144	(0.102)
Northern ireland	0.981	(0.196)	1.008**	(0.198)
Wales	0.792**	(0.186)	0.793**	(0.188)
Scotland	0.703**	(0.189)	0.712**	(0.191)
North	0.426**	(0.188)	0.404**	(0.190)
Anglia	0.273	(0.197)	0.244	(0.200)
South	0.127	(0.199)	0.098	(0.203)
Constant	-4.139	(0.288)	-4.028**	(0.287)
ρ				0.03
Wald	392		949	
Log likelihood	-896.265		-2997.46	
N				

Table 5. Second step estimation: Blood Test estimation.

Variables	Probit		Switching Probit	
	Coeff	**SD**	**Coeff**	**SD**
Insurance	0.093	(0.074)	0.639**	(0.192)
Income	0.045	(0.046)	-0.033	(0.081)
Female	-0.029	(0.040)	-0.398**	(0.065)
Age	0.008**	(0.002)	0.029**	(0.003)
Married	0.013	(0.055)	-0.031	(0.047)
High education	0.015	(0.052)	-0.094	(0.080)
Mid education	0.069	(0.055)	-0.043	(0.086)
Employed	-0.363**	(0.050)	-0.272**	(0.081)
Selfemployed	-0.481	(0.074)	-0.412**	(0.119)
Chronic illness	0.559**	(0.043)	0.837**	(0.082)
Household size 3-5	0.049	(0.055)	0.073	(0.091)
Household size>5	-0.114*	(0.057)	-0.144	(0.102)
Northern ireland	0.469**	(0.091)	1.008**	(0.198)
Wales	0.318**	(0.079)	0.793**	(0.188)
Scotland	0.271**	(0.079)	0.712**	(0.191)
North	-0.094	(0.080)	0.404**	(0.190)
Anglia	0.008	(0.081)	0.244	(0.200)
South	-0.182**	(0.083)	0.098	(0.203)
Constant	-2.345**	(0.129)	-4.028**	(0.287)
ρ			0.132	(0.122)
Wald	392.81		946.69	
Log likelihood	-896.26		-2997.46	
N				

Table 6. Second step estimation: Mam-Test. estimation

Variables	Probit		Switching Probit	
	Coeff	**SD**	**Coeff**	**SD**
Insurance	0.061	(0.071)	0.158	(0.140)
Income	0.018	(0.048)	-0.002	(0.051)
Female				
Age	0.073**	(0.002)	0.074**	(0.002)
Married	0.060	(0.057)	0.071	(0.045)
High education	0.075	(0.053)	0.132**	(0.054)
Mid education	0.149**	(0.056)	0.129**	(0.055)
Employed	0.036	(0.057)	0.035	(0.055)
Selfemployed	0.041	(0.083)	0.056	(0.079)
Chronic illness	0.255**	(0.043)	0.176**	(0.039)
Household size 3-5	-0.007	(0.055)	-0.021	(0.054)
Household size>5	0.077	(0.058)	-0.136**	(0.055)
Northern ireland	-0.043	(0.102)	-0.332**	(0.102)
Wales	-0.194**	(0.086)	-0.285**	(0.087)
Scotland	0.007	(0.086)	-0.298**	(0.087)
North	-0.074	(0.081)	-0.117	(0.078)
Anglia	-+0.069	(0.084)	-0.083	(0.082)
South	-0.070	(0.081)	-0.034	(0.075)
Constant	0.012	(0.165)	-3.739**	(0.149)
ρ	-0.062		-0.065	(0.096)
Wald	-4.013**		1836.97	
Log likelihood			-5397.79	
N				

Table 7. Second step estimation: Pap-Test estimation

Variables	Probit		Switching Probit	
	Coeff	**SD**	**Coeff**	**SD**
Insurance	0.033	(0.064)	0.0243**	(0.115)
Income	0.024	(0.037)	0.039	(0.044)
Female				
Age	-0.012**	(0.002)	0.008	(0.002)
Married	0.234**	(0.044)	0.196**	(0.041)
High education	0.194**	(0.045)	0.266**	(0.048)
Mid education	0.081	(0.459)	0.092*	(0.048)
Employed	0.248**	(0.043)	0.318**	(0.045)
Selfemployed	0.337**	(0.069)	0.434**	(0.074)
Chronic illness	0.007	(0.034)	0.097**	(0.035)
Household size 3-5	0.005	(0.046)	0.074	(0.048)
Household size>5	0.002	(0.047)	0.073	(0.049)
Northern ireland	-0.055	(0.079)	-0.347**	(0.084)
Wales	0.016	(0.066)	-0.184**	(0.072)
Scotland	0.139**	(0.064)	-0.003	(0.072)
North	0.070	(0.061)	0.097	(0.066)
Anglia	0.058	(0.058)	0.089	(0.070)
South	-0.112	(0.064)	-0.099	(0.065)
Constant	0.193*	(0.149)	0.224**	(0.107)
ρ			-0.084	(0.078)
Wald	248		800.19	
Log likelihood	-4051.76		-6314.37	
N				