Understanding the Determinants of Health Care Demand in the United Kingdom: A Microeconometric Analysis

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Abstract

The main objective of this thesis is to empirically identify the influence of personal characteristics, health and health related variables, socioeconomic and health care supply factors on health care utilisation in the United Kingdom using microeconometric analysis. In addition to looking at utilisation of General Practitioner (GP) services, which have been widely researched, this study also focuses on the utilisation of outpatient, inpatient and district nurse services. For the latter, econometric analysis is still very limited, where it exists, within the UK health system. The empirical work is divided into three main parts. Data from the General Household Survey 2004/2005 for Great Britain are used for cross-sectional analysis in the first and second empirical chapters while data from the British Household Panel Survey (BHPS) are used in the third. The first empirical chapter specifically deals with the endogeneity problem of self-assessed health (SAH) in the demand models. Based on the Full Information Maximum Likelihood (FIML) model, there is evidence that SAH is endogenous in the model for GP but not for outpatient and inpatient use. The second empirical part aims to deal with excess-zero problems in the data by using several extended approaches - zero-inflated, two-part and latent class models. Based on model selection criteria, it is established that the extended models are preferred to the standard count models. Some effects vary quite markedly between the different models, underlining the importance of identifying best-fitting models. The third empirical chapter aims to model health care demand by the elderly by using individual-effects and sample selection models. In all empirical chapters, health status and health related variables are found to have a strong influence in determining demand for all health care services. Age, gender, education and other socioeconomic variables, although significant in some models, have limited effects. There is no evidence that income plays an important role in health care demand in this study. Findings from this study may provide some information for policy analysts in designing health and health care policy. Some policy implications have also been discussed which specifically concentrate on health-promoting programs in order to control health care use in the future.

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CHAPTER ONE

1 INTRODUCTION

1.1 BACKGROUND

Health care expenditure as a percentage of Gross Domestic Product (GDP) is rising every year in almost every country. Therefore, inevitably, most countries are very concerned with cost containment in their health policy. The increase in expenditure might be due to changes in demographic and socioeconomic patterns, type of morbidity, technology, as well as policy. As in other sectors, the health care sector faces the economic problem of scarce resources. Thus understanding the determinants of health care demand by the population and continuous study on this subject matter are essential for every government in distributing these scarce resources, and therefore achieving the objectives of its health policy. These determinants might also have different impacts depending on which health care system is in place in the country under consideration. Health systems vary between publicly financed national health services (e.g. UK, Spain), national health insurance systems (e.g. Denmark, Norway and Canada), and private insurance systems (e.g. US). Therefore, the determinants of health care utilisation might also vary between countries which mean they require country-specific analysis to determine them. In this study, data from the UK are used to model the demand, specifically the utilisation for selected health care services by using several econometric techniques. An overview of health care and health facts in the UK is presented in the next section.

1.2 HEALTH CARE AND HEALTH FACTS IN THE UNITED KINGDOM: A SNAPSHOT

The health care system in the United Kingdom is mainly based on the publicly-funded National Health Service (NHS). The NHS was established in 1948 and was funded by general taxation and National Insurance. In England, the Secretary of State for Health, who is the head of the Department of Health, is responsible for health care provision under the NHS. The Department of Health is responsible for monitoring the functioning of Strategic Health Authorities (SHAs). The SHAs are responsible for health care provision at the regional level, which include *primary* and *secondary* care.

A simple view is that primary care is provided by the Primary Care Trusts which include community health services, general practitioners (GPs), pharmacists, dentists and opticians. Secondary care is supplied by hospitals, ambulance services, mental health services or other units that provide medical care. Scotland, Wales and Northern Ireland have a similar system with some different features. Table 1.1 outlines the structure of the NHS in the UK. As the first point of reference person by most of the patients and acting as a 'gatekeeper' to secondary care, GPs play a major role in primary health care. In other words, in most circumstances, GPs decide on behalf of the patient the need of further referral to secondary services. Public health care is available to everyone based on needs, not ability to pay. It is free at the point of service. However, there are some charges for prescription, dental and optical services, with some exemptions for children, elderly, pregnant women, unemployed or low-income people.[1] Private health care exists as a complement to the NHS. In spite of this, private expenditure only accounts for around 1.2% of Gross Domestic Product (GDP) in the years 2002 to 2006 (Hawe, 2007, pp.70-71).

The expenditure of the NHS as a proportion of GDP has risen steadily from 4.9% in 1987 to 8.2% in 2006 as shown in Figure 1.1. Figure 1.2 exhibits health care expenditure per capita, at constant 1973 prices, for the twenty years from 1987 to 2006. It indicates that real expenditure per capita has increased steadily over the years from £162 in 1987 to £442 in 2006. In 2004/5, Scotland spent 14% more than England (per head) while Wales spent 5% more than England (Hawe, 2007, pp.70-71).

This increase in real expenditure has seen clear pay-offs in terms of improvements in key health indicators of the population. For example, infant mortality has declined almost every year; from 11.2 per 1,000 live births in 1981 to 5.1 in 2004. The same can be said for perinatal mortality where there was a 31.67% decline from 12 still births and death of infants under one week of age per 1,000 live and still births in 1981 to 8.2 in 2004 (*Regional Trends 39*, 2006). Life expectancy at birth for males and females also rose over time and are expected to reach 77.3 for males and 81.8 for females during the years 2010 to 2015 compared to 71.2 for males and 77.2 for females between 1980 to 1985. Table 1.2 shows

[1] NHS prescription charge was abolished for people in Wales with effect from April 1st 2007.

the life expectancy in years at birth for males (M) and females (F) for selected countries.

Table 1.1 The structure of the NHS in the UK

Organisation	England	Wales	Scotland	Northern Ireland
Government Department	The Department of Health	NHS Wales Department	The Scottish Executive Health Department	The Department of Health, Social Services and Public Safety
Strategic Direction	Strategic Health Authorities	Regional Offices	NHS Unified Board	Health and Social Services Boards
Primary Care Management	Primary Care Trusts	Local Health Boards	Primary Care Operating Division	Local Health and Social Care Groups
Hospital Management	NHS Trusts	NHS Trusts	Secondary Care Operating Division	Health and Social Service Trusts
Community Care Management	Primary Care Trusts & NHS Trusts	NHS Trusts	Operating Division	Health and Social Service Trusts
Social Services Management	Local Authorities	Local Authorities & Local Health	The Scottish Executive Health Department &	Health and Social Service Trusts

Source: The RCGP Information Sheet No.8, November 2004[2]

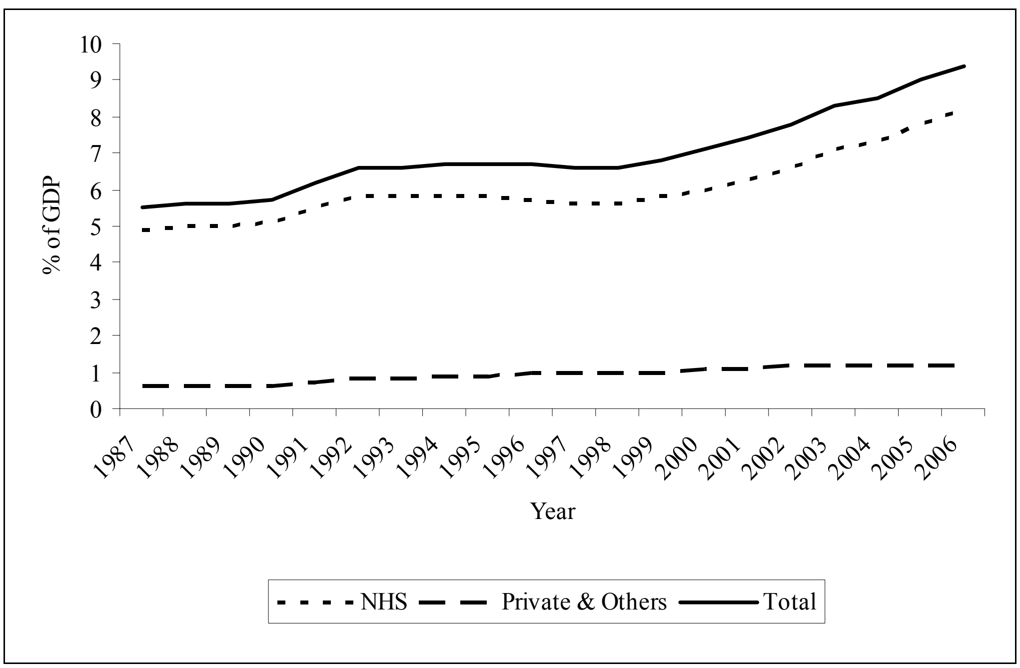
[2] Retrieved from http://www.rcgp.org.uk/pdf/ISS_INFO_08_NOV04.pdf on 16 June 2009.

Table 1.2 Life expectancy, 1980-2025

	1980-85		1990-95		1995-2000		2000-05		2010-15[1]		2020-25[2]	
	M	F	M	F	M	F	M	F	M	F	M	F
OECD	70.0	76.6	72.2	78.7	73.5	79.7	74.8	80.7	76.5	82.2	77.9	83.5
EU	71.1	77.6	73.2	79.6	74.5	80.5	75.6	81.5	77.1	82.8	78.4	83.9
Australia	71.9	78.7	74.7	80.6	75.9	81.5	77.6	82.8	79.2	84	80.4	85.1
Belgium	70.4	77.2	73.3	80.0	74.7	81.1	75.7	81.9	77.3	83.2	78.6	84.2
France	70.8	78.9	73.3	81.5	74.6	82.3	75.8	83.0	77.3	84.1	78.5	85.3
Italy	71.5	78.0	74.0	80.5	75.7	81.8	76.8	83	78.1	84.2	79.4	85.4
Japan	74.2	79.7	76.2	82.4	77.1	83.8	78.3	85.3	79.9	87.4	81.3	89.2
Netherlands	72.8	79.4	74.3	80.2	75.1	80.5	75.6	81.0	76.9	82.2	78.0	83.3
Spain	72.8	78.9	73.8	81.0	74.9	82.0	75.8	83.1	77.2	84.4	78.5	85.6
Sweden	73.5	79.5	75.5	80.9	76.8	81.8	77.8	82.3	79.4	83.6	80.6	84.8
UK	71.2	77.2	73.6	79.0	74.7	79.7	75.9	80.6	77.3	81.8	78.6	82.9
US	70.7	77.9	72.2	78.9	73.6	79.3	74.6	80.0	75.8	81.2	76.9	82.3

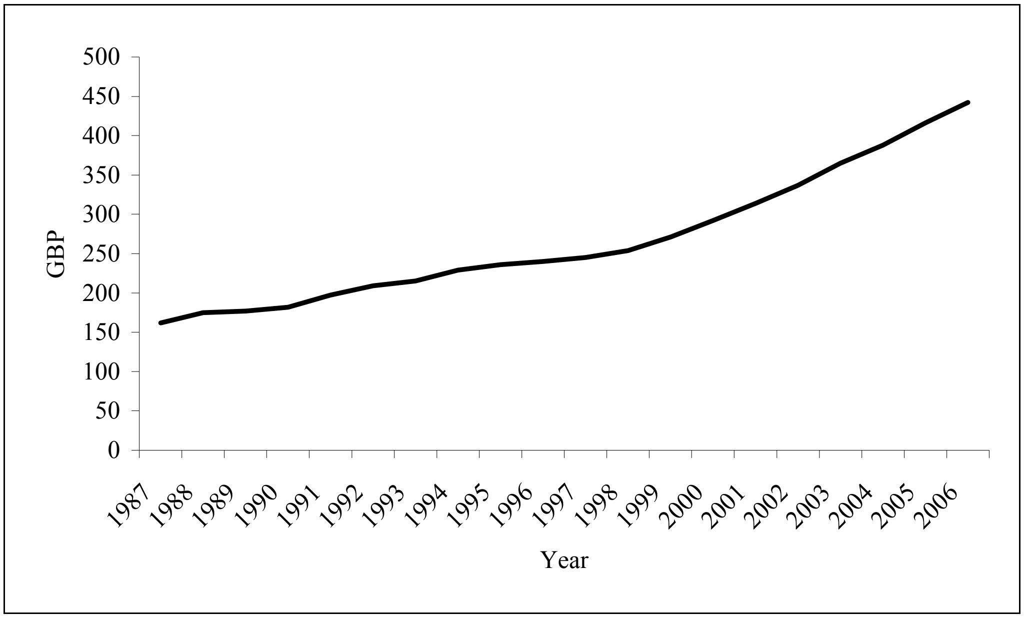
Notes:
[1] Given figures are UN estimates
[2] Given figures are UN projections
Source: Compendium of Health Statistics (Hawe, 2007)

Figure 1.1 Health care expenditure as percentage of GDP



Source: Compendium of Health Statistics (Hawe, 2007)

Figure 1.2 Real health care expenditure per capita (1973 prices)



Source: Compendium of Health Statistics (Hawe, 2007)

1.3 THE PURPOSE OF THE STUDY

The main purpose of this study is to model the demand for health care services in the UK in order to identify the role of personal characteristics, health and health related, and socioeconomic factors in determining demand. Throughout the analyses, the utilisation of health care services is used to represent its demand. The thesis is divided into three empirical analyses in which every empirical analysis has its specific objectives, which also deal with specific econometric problems. The systematic review in Chapter 3 provides a foundation for all empirical analyses in the thesis.

1.4 CONTRIBUTION OF THE STUDY

This study is a continuation of past studies on modelling health care demand. It systematically reviews across literature within the subject area and embarks on three original empirical studies with the aim to provide new evidence on factors that affect health care utilisation in the UK. In addition to looking at utilisation of General Practitioner (GP) services, which have been widely researched, this study also focuses on the utilisation of outpatient, inpatient, and district nurse services. For the latter, econometric analysis is still very limited, where it exists, within the UK health system. This study also models the demand for health care by the older age groups of which empirical analysis using econometric approach, specifically using count data model are needed using data from the UK.

1.5 THE STRUCTURE OF THE THESIS

This thesis consists of seven chapters. Chapter 1 provides the background information of the study. An overview of the UK health care provision is presented in order for one to get a broad understanding of the system prior to further empirical work. The purpose of the study is discussed with some justifications of the contribution of the study.

In Chapter 2, the concept and theoretical framework for health and health care demand are discussed. The concept and theoretical framework for health is discussed because of the fact that health care is a derived demand for good health. Thus, it is believed that one needs to first understand why people demand health and later, health care, and understand the relation between them.

A systematic review of health care demand is carried out in Chapter 3. The review aims to synthesise evidence across published empirical studies on health care demand or utilisation and use them in answering research questions outlined in the chapter. The review is also used as a foundation for empirical analyses in Chapter 4, 5 and 6.

Chapter 4 concentrates on modelling utilisation for GP consultations, outpatient visits and inpatient episodes by using count data models. While developing the models, one of the regressors, self-assessed health (SAH), is suspected to be endogenous within the model. Therefore, the analysis is divided into two parts; one with the assumption that SAH is exogenous and the other one is when SAH is assumed to be endogenous. Data from General Household Survey 2004 is used for the analysis in this chapter.

Chapter 5 is an extended analysis of Chapter 4 which deal with excess zeros problems in health care demand model. Several econometric models are used and compared which includes zero-inflated negative binomial, two-part model and latent class models.

Chapter 6 focuses on health care demand by older age groups. In this chapter, panel data from British Household Panel Survey, wave 12 to 16 are used. The problem of attrition bias is also discussed in this chapter. Individual-effects and sample selection models are used for analysis.

Chapter 7 presents the conclusion with a discussion of policy implications, limitations in the study and directions for future research.

CHAPTER TWO

2 THE CONCEPT OF HEALTH AND HEALTH CARE

2.1 INTRODUCTION

Health and health care are two related terms that serve as a basis of a broad health care system. According to the World Health Organization (WHO), health is *'a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity*' (as cited in Bergner & Rothman, 1987). In spite of ongoing debates pertaining to the definition or measurement of health, the broad and well accepted definition by the WHO above is a good starting point of any discussion within the field (Bergner & Rothman, 1987; Chen & Bryant, 1975; Salomon et al., 2003).

By referring to the definition of health above, health care can be classified as any goods and services that are intended to promote physical, mental and social wellbeing of every individual. It includes a wide range of medical services by health related professions like medical consultations, examinations, diagnoses, treatment and evaluation. Health care is therefore consumed in order to increase an individual's level of health. Since the use of health care depends on the demand for good health, this chapter begins by discussing some theoretical framework of health production and demand for health in order to understand the roles of health care, age, education, income and other environment factors in determining the stock of health. This is discussed in Section 2.2 and later followed by a review on studies of health demand in Section 2.3. The concepts of health care are discussed in Section 2.4.

2.2 THE PRODUCTION AND DEMAND FOR HEALTH

The level of health depends on various dimensions and individuals demand certain levels of health subject to diverse factors. Unlike other commodities, individuals also become the producer of their health which also signifies that the level of demand and the production of health is unique due to various reasons. One factor is that the production of health does not depend on the expectation of the future demand which suggests that the production's process has a lack of control as well, as it cannot be traded in the market like other commodities (Goodman, Stano, & Tilford, 1999).

Individuals produce their own health and mainly determine the amount of inputs to use which, among others, include the consumption of health care, healthy food and living a healthy lifestyle. In the utility function, by incorporating intrinsic health state, one is building up one's own health span in order not only to consume the immediate benefits of having good health but also to enjoy them in future life or it can be viewed as an investment to increase health stocks (Grossman, 1972; Muurinen, 1982; Wagstaff, 1986). Many studies on health demand have referred to the work of Grossman (Grossman, 1972) as a foundation to their development of theoretical or empirical investigations (e.g.

Acton, 1975; Cropper, 1977; Muurinen, 1982; Wagstaff, 1986). In Grossman's framework, health is discussed in the light of human capital theory where health capital is subject to depreciation overtime. The stock of health, however, can be improved via investment activities such as consuming medical care and healthy food, engaging in healthy lifestyle and avoiding health-damaging activities such as drinking (alcohol) and smoking that can decrease the capital. Health stock is controlled over time by the individual and the marginal utility of possessing one incremental unit of health stock can be divided into two components: namely consumption benefits, which may increase utilities and investment benefits which may also increase potential earnings.

Within the household production framework, Grossman (1972) treats the individual as a sole decision-maker in determining the amount of health care used. Following the model and structure of discussion in Grossman (1972), one derives utility based on the intertemporal utility function which depends on the total consumption of healthy time service and total consumption of other goods:

$$U = U(\phi_0 H_0, \phi_t H_t ....., \phi_T H_T, Z_0, Z_t ....., Z_T) \tag{2.1}$$

where H_0 is the inherited health status, H_t is a stock of health at time *t* and Z_t is a consumption of other goods at time *t*.

Total consumption of healthy days of each *t*th time period, h_t, is endogenous and determined by the service flow per unit stock, ϕ_t, over the stock of health, H_t ($h_t = \phi_t H_t$). Death occurs when $H_t \le H_{\min}$ and net investment in health capital depends on gross investment which is subject to depreciation:

$$H_{t+1} - H_t = I_t - \delta_t H_t \tag{2.2}$$

where I_t is gross investment at time *t*, δ_t, is the rate of depreciation which depends on age at time *t*. To increase utility, consumers are assumed to produce two goods, which consist of investment in health, I_t and other commodities, Z_t. The production functions are

$$\begin{aligned} I_t &= I_t(M_t, TH_t; E) \\ Z_t &= Z_t(X_t, T_t; E) \end{aligned} \tag{2.3}$$

where M_t is a vector of inputs (medical care) that determines the amount of gross investment in health, I_t, while X_t determines the production of other goods, Z_t. Both TH_t and T_t are time inputs and E is the individual stock of knowledge which is assumed to be exogenous and does not vary over time. The present value of individual expenditure on medical care and other goods is equal to the present value of labour income plus the discounted initial assets:

$$\sum_{t=0}^{n} \frac{P_t M_t + Q_t X_t}{(1+r)^t} = \sum_{t=0}^{n} \frac{W_t TW_t}{(1+r)^t} + A_0 \tag{2.4}$$

The total time available, Ω, must be totally utilised which consist of time use in labour market (TW), production of health (TH) and other goods (T) and unexploited time due to sick time (TL). Thus, time constraint is

$$TW_t + TH_t + T_t + TL_t = \Omega \tag{2.5}$$

From (2.4) and (2.5) one can derive a single full wealth constraint

$$\sum_{t=0}^{n} \frac{P_t M_t + Q_t X_t + W_t (TL_t + TH_t + T_t)}{(1+r)^t} = \sum_{t=0}^{n} \frac{W_t \Omega}{(1+r)^t} + A_0 = B \tag{2.6}$$

where P_t is a vector of prices for medical care, M_t; Q_t is a vector of prices for inputs of other goods, X_t; and A_0 is the initial assets.

Equation (2.6) shows that the discounted values of total wealth of which some fraction is spent on health inputs and market goods and some fraction is lost due to illness is equal to the discounted value of the possible earning that one would have gained if he uses the total amount of time available in the labour market plus the initial assets. Therefore, the equilibrium of amount of health capital H_t and other goods Z_t, can be obtained by maximising the utility function in Equation (2.1) subject to constraints in Equations (2.2), (2.3) and (2.6) which shown by the Lagrangian function

$$L = U(\phi_0 H_0, \phi_t H_t, ...\phi_T H_T, Z_0, Z_t ...., Z_T) + \lambda \left[B - \sum \frac{C_t + C_{1t} + W_t TL_t}{(1+r)^t} \right] \tag{2.7}$$

where $C_t = P_t M_t + W_t TH_t$ and $C_{1t} = Q_t X_t + W_t T_t$

Since inherited health status and depreciation rate are exogenous, health capital, H_t is determined by the optimal quantities of gross investment in health. In this case H_t depends on the investment in period *t*-1, known as I_{t-1}. By differentiating (2.7) with respect to I_{t-1} and setting the partial derivatives equal to zero, one gets the optimality conditions for I_{t-1}. With some algebraic manipulation, the optimal amount of gross investment in period *t-1* is given by

$$\frac{\pi_{t-1}}{(1+r)^{t-1}} = \frac{W_t G_t}{(1+r)^t} + \frac{(1-\delta_t)W_{t+1}G_{t+1}}{(1+r)^{t+1}} + \dots \frac{(1-\delta_t)\dots(1-\delta_{T-1})W_T G_T}{(1+r)^t} + \frac{Uh_t}{\lambda}G_t + \dots + (1-\delta_t)\dots(1-\delta_{T-1})\frac{Uh_T}{\lambda}G_T \tag{2.8}$$

with the following information:

The marginal cost of gross investment in health in period t-1= π_{t-1}; the marginal utility of healthy days = $Uh_t = \partial U / \partial h_t$; the marginal utility of wealth = λ; the marginal product of the stock of health, $G_t = \partial h_i / \partial H_t = -(\partial TL_t / \partial H_t)$. It is important to note that an increase in gross investment in period t-1 affects the quantity of health capital in all future periods. Equation (2.8) shows that the optimal amount of gross investment in health is achieved when the marginal costs of investment on the left hand side is equal to the marginal benefits on the right hand side- both are measured in current value. From (2.8) one can determine the present value of the marginal benefits at point t as

$$G_t\left[\frac{W_t}{(1+r)^t} + \frac{Uh_t}{\lambda}\right] \tag{2.9}$$

Equation (2.9) states that the marginal product of health capital, G_t, can be translated in terms of monetary value by dividing it into two components- discounted wage rate and monetary equivalent of the marginal utility of healthy days. In order to understand the underlying process between the determination of investment and health, the current marginal costs of the investment, π_t, can be obtained by converting (2.8). With a positive gross investment in period t, the optimal level health capital in that period (t) is determined by

$$\frac{\pi_t}{(1+r)^t}t = \frac{W_{t+1}G_{t+1}}{(1+r)^{t+1}} + \frac{(1-\delta_{t+1})W_{t+2}G_{t+2}}{(1+r)^{t+2}} + ... \frac{(1-\delta_{t+1})....(1-\delta_{T-1})W_T G_T}{(1+r)^T}$$
$$+ \frac{Uh_{t+1}}{\lambda}G_{t+1} + ... + (1-\delta_{t+1})....(1-\delta_{T-1})\frac{Uh_T}{\lambda}G_T \tag{2.10}$$

From (2.8) and (2.10), one gets

$$\frac{\pi_{t-1}}{(1+r)^{t-1}} = \frac{W_t G_t}{(1+r)^t} + \frac{Uh_t G_t}{\lambda} + \frac{(1-\delta_t)\pi_t}{(1+r)^t} \tag{2.11}$$

By performing some algebraic manipulation on (2.11), the optimality condition can be written as

$$\pi_{t-1}(r - \tilde{\pi}_{t-1} + \delta_t) = G_t\left[W_t + (\frac{Uh_t}{\lambda})(1+r)^t\right] \tag{2.12}$$

which represents the optimality condition for health capital, in period *t*, that requires the marginal cost of health capital, $\pi_{t-1}(r - \tilde{\pi}_{t-1} + \delta_t)$ to be equal to the undiscounted value of the marginal product of health capital. The term $\tilde{\pi}_{t-1}$ represents the percentage rate of change in marginal cost between period *t*-1 and *t*. In this framework, health benefits can be discussed based on two different models: pure investment model and pure consumption model. For example, health can be treated as a pure investment good if healthy time does not exactly influence the utility in which $Uh_t = 0$. In this case the optimality condition in (2.12) becomes:

$$\pi_{t-1}(r - \tilde{\pi}_{t-1} + \delta_t) = G_t W_t \tag{2.13}$$

where the marginal cost of health capital is equal to the marginal monetary returns of health investment only. The gross investment in health capital, as shown in (2.3) depends on medical care, M_t; time input; TH_t and education, *E*. This study specifically focuses on demand for medical or health care as the important inputs in determining the stock of health. Within the consumers' utility function, the determinants for health care demand will be investigated later in the thesis (Chapters 4 to 6).

2.3 PAST STUDIES ON HEALTH DEMAND

Though Grossman argues that the distinction between health investment and consumption models is for theoretical simplicity, Muurinen (1982) believes that considering the benefits as two separate specifications is intuitively wrong. This is because health is demanded to increase both utility and other physical activities simultaneously.

Thus in Muurinen (1982), though health benefits were still being viewed as two different types as in Grossman (1972), they are not treated as alternative to one another. Furthermore, according to Muurinen, the inclusion of the education variable as a productivity factor in the Grossmann model needs more justification. By using the same foundation as Grossman, Muurinen presents a more extensive framework which includes health, education and wealth as durable capital goods for service production. Better education may reflect a better lifestyle, being well informed on medical conditions and needs, consuming a good diet and exercise, etc. Since then, many empirical studies have been carried out which were largely based on the above frameworks.

Based on a 1976 Danish Welfare Survey, Wagstaff (1986) estimates the demand for health in the light of both the pure investment and pure consumption models. While the stock of health capital is considered as a latent variable, some other health variables have been used as a signal of health conditions. After utilising the Principal Component Analysis (PCA) on the health indicators from the survey, he has come up with four main components in determining health status namely ‘mobility’, ‘mental’, ‘respiratory’ and ‘pain’. Other variables used in his health equations are education, use-related depreciation variables, work environment variables, wage, life wage, initial assets and age. In the pure investment model, Wagstaff (1986) found that wage rates, years of formal schooling completed and age are significant and the effects are consistent with Grossman’s model in relation to health.

Grossman (2000) runs some empirical testing on his pure investment model by utilising a survey by the National Opinion Research Center and Center for Health Administration Studies of the University of Chicago. Stock of capital is measured by self-evaluation of health status by individuals; healthy time by the complement of restricted activities due to illness or injury; and medical care is measured by personal expenditure on doctors, hospital care, drugs, and so forth. The explanatory variables consist of the number of years in formal education, weekly wage rate and family income is used as the proxy of wealth. It was found that education and wage have significant positive effects on health, while health stock decreases when age increases.

By using the data sets from two national surveys, Leigh (1983) focuses on the direct and indirect effects of education on health. The direct effect of schooling is determined by estimating it alongside healthy habits and choice of work on health. The indirect effect of schooling, on the other hand, is estimated from the reduced form by substituting ‘healthy habits and work choice function’ into the schooling function. Indirect effects of education are thus reflected by the practise of healthy habits which in turn, affect the level of health. The level of health in this study is self determined by the individuals ranging from 1 (totally and permanent disabled) to 7 (perfect health). Leigh (1983) found that the indirect effects of education (which in that study includes smoking, exercise and engagement in hazardous occupations) dominated the direct effect in determining health. Positive significant effects of education are also found in Erbsland, Ried, and Ulrich (1995) and Wagstaff (1993).

The effects of health habits or lifestyle is also studied by Contoyannis and Jones (2004). They examine the relationship between lifestyles and self-assessed health (SAH) by estimating a recursive system with structural health equations and reduced forms for lifestyles. Lifestyle variables are assumed to be endogenous in the SAH model. Indicators of lifestyles include sleeping, breakfast, smoking, alcohol consumption, exercise and obesity. There is evidence that some lifestyles have an impact on SAH. Other important variables in many empirical studies of health demand include income and age. Income is used as a proxy of unobserved wealth state while age determines the rate of depreciation of health stock.

Lee (1982) estimates the impact of wage by using simultaneous equations of multiple discrete indicators consisting of sample of middle-aged males (45-59). Health is again indicated by SAH and health limitation. Wage rate is found to have a positive relationship with demand, while age has an opposite impact where similar findings are also found in Ersbland et al. (1995). Ettner (1996) estimates the structural impact of income on a variety of health proxies consisting of SAH, work and functional limitation and number of inpatient days. Besides ordinary regression which treats income as exogenous, it has been instrumented by other variables which are believed not to affect health status directly other than via income (i.e. employment rate, work experience, parents' education, and spouse characteristics). Both specifications though have different marginal effects, suggest a similar qualitative interpretation that income has a negative relationship with indicators of poor health which effects are also consistent with other studies (Cropper, 1977; Erbsland et al.1995; Gerdtham & Johannesson, 1999).

From the brief discussion above, one can conclude that health might be determined by several variables including level of education, wealth, which is sometimes proxied by income, and age. In empirical analyses, unobserved health capital is frequently proxied by several indicators, for example, self-assessed health status, physical or mental limitation and presence of reported diseases.

The effects of health care consumption on health are rarely tested in these empirical works as most studies are based on cross-sectional data, where effects of health care consumption in a previous period are not available. The effects of health care consumption on health status can be appropriately tested if panel data is available. The consumption of health care, on the other hand, also depends on the stock of health as people consume health care in order to maintain a certain level of the stock or capital in order to maximise utility.

Within Grossman's framework, Wagstaff (1986) estimates the demand function for health care by considering health status, which represents the stock of health, as a latent variable. Besides health status, demand for health care depends on several other factors, including wage rate, price of medical care, age, environmental variables and education. In his approach, individuals act as the main decision maker in determining the amount of health care used.

2.4 THE CONCEPT OF HEALTH CARE

Whilst based on the same objective, that is to enhance the health of every individual in the population, a health care system at various levels might diverge because of differences in inputs and processes involved. Inputs can be classified as resources used for health care which consist of human resources, building, land, technology, drugs and patients while processes include activities and interactions between inputs within the system (Black & Gruen, 2005, p. 9).

Although the process of demand and supply for health care might differ from those of other goods and services, the conventional market framework with essential economic theories may be useful as a benchmark for discussion and comparison. Price plays very important role in demand and supply in a regular market. With the objective to maximise the utility function, consumers demanded goods and services subject to price, income constraint, price of other goods and tastes.

However, within the same framework, the role of price in determining health care demand and supply is not straightforward, there is even evidence that prices influence health care demand through insurance choice (Deb, Li, Trivedi, & Zimmer, 2006; Deb, Munkin, & Trivedi, 2006; Gurmu & Elder, 2000). One plausible explanation is that the amount of health care demanded largely depends on one's health condition, and is thus based on need more than other factors like income, tastes or price of other goods. Need is also one of the most important factors for health care supply by health care providers, although in some cases, the need is not met by formal health care. Like other goods and services, demand and supply of health care are also exposed to market failures such as externalities and asymmetric information. Externalities occur when any action by an economic agent influences other parties in a good or bad manner. Transmitted diseases and vaccination are some examples of externalities in health, which may affect the system of health care (Phelps, 2003, p. 468).

In a physician-patient framework, asymmetric information exists when physicians or health professionals have more information on patient's health conditions, and can therefore determine what and how much treatment should be given. A physician acts on behalf of a patient based on the patient's health needs but sometimes he or she can supply more health care than needed and therefore, induce unnecessary demand. This framework, known as the *agency approach*, is different from Grossman's model where health care use is primarily determined by a patient in order to maximise his or her utility function.

These two approaches (either agency or Grossman approaches) have become a basis of many empirical works in health care literatures since then (Cameron, Trivedi, Frank, & Pigott, 1988; Geil, Million, Rotte, & Zimmermann, 1997; Gurmu, 1997; Mocan, Tekin, & Zax, 2004; Pohlmeier & Ulrich, 1995). This study is also based on these two frameworks which will be discussed in the next empirical chapters.

CHAPTER THREE

3 SYSTEMATIC REVIEW

3.1 INTRODUCTION

This chapter utilises a more structural approach in reviewing evidence from the past literatures on health care utilisation. It systematically reviews the empirical studies on health care demand in order to answer the three key questions as stated in Section 3.2.1. In spite of a broad possible definition of health care, this review focuses on one specific context of demand, which is the utilisation of formal health care services. Throughout the discussion in this section, utilisation of health care services is treated as a proxy for health care demand and in some places 'utilisation' is used in place of 'demand'.

Systematic review is a tool to gather evidence from all valid sources and efficiently and critically review them in order to answer the research questions for a specific purpose. Systematic review is intended to be more objective, structured and transparent than traditional approaches, using all means possible to minimise biased interpretation. It is essential to provide a strong direction or guidance in carrying out the empirical investigations in Chapter 4, 5 and 6.

3.2 REVIEW PROCESS

According to Higgins and Green (2006) there are seven main steps involved in systematic review. Those steps are (1) Formulating the problem, (2) Locating and selecting studies, (3) Quality assessment of studies, (4) Collecting data (5) Analysing and presenting results, (6) Interpreting results and (7) Improving and updating reviews. Since these guidelines are for reviews of effective health care interventions, there are some adaptations needed in carrying out the review in this chapter, though the structure is maintained as close as possible.

3.2.1 Formulating the problem

The world is changing in many respects including demographic and socioeconomic patterns and technology. Thus understanding health care utilisation, which reflects demand for health care, is a continuous process for any government in distributing the resources efficiently and thus achieving health goals. There is also a substantial development in econometric methods in this subject area which requires further assessment for better understanding. In this chapter three key questions have been outlined which will serve as guidelines to empirical work in the coming chapters. The questions are:

1. Which of the searched econometric models are employed in estimating health care demand and how to deal, if discussed, with the endogeneity bias of the regressor in the model?
2. What are the variables used in health care utilisation models?
3. What are the effects of health status, income and education on the utilisation of a General Practitioner?

3.2.2 Locating and selecting studies

3.2.2.1 Searching for studies

This procedure helps to identify as many relevant studies as possible on health care utilisation. Searching can be done in various ways, including searching from electronic databases, hand searching, checking the reference lists of known papers or other reviews and finally seeking unpublished studies. Despite the existence of many electronic and non-electronic databases, this search was limited (due to time and money constraints) to those electronic databases which have a higher potential to cover the health economics or social science literature area and are easily accessible. These include Social Science Citation Index (SSCI) and EconLit.

3.2.2.2 Developing a search strategy

By exploring known relevant studies, I have first listed some potential 'keywords' to be used in retrieving relevant articles for the review. In all databases, the important keywords are 'health care demand' or 'health care utilisation'. I started to retrieve relevant studies with these two terms and then refined it by using other keywords with a Boolean operator. As the review focuses on empirical works, I used 'empirical' or 'econometric' as the key to limit the search to empirical works. In addition to that, I have also used other empirical terms in order to retrieve as many empirical studies as possible, as documented in the next section. While the area of health care demand is very broad, I have limited my review by excluding some studies that focus on specific conditions for example studies on prenatal care, pregnancy, newborn or mental health. Besides being precise, the exclusion contributes to more meaningful results. At this stage, due to time and money constraints, only published English language articles are included; language that is understood by the reviewer. The basic structure of the search process (for all databases) follows the steps below:

1. Retrieve studies on health care demand OR health care utilisation.
2. Retrieve empirical studies or other studies that explicitly stated econometric OR empirical analysis.
3. Join together (1) AND (2)
4. Retrieve studies on prenatal, pregnancy, newborn or mental health
5. Exclude (4) from (3)

3.2.2.3 Documenting a search strategy

(I) Database : The Social Science Citation Index
Name of Host : ISI Web of Knowledge
Date Search : 16 August 2007 & 10 May 2008

A. Search Results on 10 May 2008 from SSCI

No	Key words	Records
1	TS=health* OR healthcare	>100,000
2	TS=Demand OR utilization OR utilisation	>46,674
3	#1 AND #2	11,600
4	TS=(latent class OR latent-class OR two part OR two-part OR hurdle OR count data OR poisson OR negative binomial OR econometric OR empirical OR MIMIC OR LISREL)	>82,782
5	#3 AND #4	831
6	TS=mental health	39,923
7	TS=(prenat* OR perinat* OR pregnan* OR newborn OR new born OR birth)	>36,462
8	#5 NOT (#6 OR #7)	672

Note: TS=Topic

Of 672 records retrieved, I further refined the search to citations under 'economics category' option only, which in my opinion, seems to be more relevant to answer my research questions. There are 220 records on economics categories which have potential to be included in the review.

(II) Database : EconLit
Name of Host : EBSCO
Date Search : 10 May 2008

B. Search Results on 10 May 2008 from EconLit,

((health care OR healthcare) and (demand OR utilisation OR utilization) and (latent class OR latent-class OR two part OR two-part OR hurdle OR count data OR poisson OR negative binomial OR econometric OR empirical OR MIMIC OR LISREL)) not (mental health or prenatal or new born) .

The above search was later refined to studies which fall under 'Analysis of Health Care Markets' option which option is believed to be the most suitable category compared to other options given. There are 82 records retrieved from this database. In both databases, the years covered are from 1972 to 2008. The year 1972 is chosen as a base year because many empirical works on health care demand emerged after the study of health demand by Grossman (1972).

3.2.2.4 Selecting studies

Based on the initial inclusion/exclusion criteria, the selection process involves a single author decision. Of all 302 records from both datasets, 20 duplicate items were removed which left us with 282 articles to be considered for review. The titles and abstracts from these 282 articles have been scanned in order to identify the relevancy of studies within the scope of analysis. The selection of articles was based on the initial predetermined inclusion/exclusion criteria. Studies on utilisation/demand for health care services which consist of physician, nurse, outpatient or inpatient services were included while other studies on other types of health care services, cigarette demand or consumption, demand for health insurance and those without any empirical analysis were excluded.

From the abstracts, 49 studies are potentially relevant to answer the questions raised in Section 3.1.2 (see *Appendix 3-1*, pp. 185-187 for the list of the studies). The full texts of these articles were retrieved online through the University of East Anglia (UEA) e-journals database. Full texts that were not available through the e-journals were requested from the interlibrary loan via the UEA library. At this stage all retrieved full-texts were examined carefully. During this process, further exclusion criteria were developed to exclude studies, though relevant, that were not appropriate for further synthesis.

Based on the objective of the review, 11 articles were excluded at this stage. Second-stage exclusion criteria consist of the exclusion of studies that have greater emphasis on other specific problems which was reflected in the theoretical approach and discussion of the results by the researcher(s). Those studies were Carlsen and Grytten (1998), Carrin and Vandael (1984), Chiappori, Durand and Geoffard (1998), Jiminez-Martin, Labeago and Martinez-Granado (2002), Kenkel (1994), Schneider and Mathios (2006), and Windmeijer, Gravelle and Hoonhout (2005). Studies that did not specify types of health care services were also excluded (e.g. they included all formal services). They were Lindelow (2005), Liu, Wu, Peng and Fu (2003), Mocan, Tekin and Zax (2004), and Mwabu, Ainsworth and Nyamete (1993). After the exclusion, only 38 studies were subject to methodological quality assessment.

3.2.2.5 An overview of included studies

Studies in this section are referred to using the study number in the first column of Table 3.1. Of all 38 studies included, 13 studies are based on United States datasets, 7 from Germany, 3 from Switzerland and 3 from the UK, 2 from Spain, Sweden and Ireland, and 1 each from Italy, Australia, Portugal, Egypt, Taiwan and Canada. Year of studies varies from 1995 to 2006.

All studies, except for Lopez-Nicolas (1998), use individual level data in the analysis where each study focuses on a specific age group. One study included all age groups [24]; 4 studies on elderly only group [6,18,29,31]; 16 studies on a specific age interval [4,5,8,9,10,11,12,13,17,23,26,30,32,35,37,38]; 12 studies (excluding 3 studies on 'elderly only') specify the minimum age of the sample [1,2,15,16,20,21,22,25,27,28,33]; 2 studies indicate the maximum age only [3,7,] and 4 studies do not state the age group in the study explicitly [14,19,34,36].

The selection of age groups is based on availability of the data and objectives of the studies. All data in the studies under investigation are from secondary sources. A total of 27 of the studies utilise cross-sectional data or information while the remaining 11 exploit the availability of panel data for dynamic analysis. The size of the sample used in each study also depends on the objectives of the study as well as the nature of data and types of utilisation. A study on the elderly [e.g. 6,31], for example, has fewer observations when compared to a study on doctor visits of the whole population [e.g. 24].

Numbers of observations of all studies are between 884 and 53,821. All selected studies empirically analyse the utilisation of health care that includes services provided by general practitioner (GP), physician/doctor, emergency, outpatient and inpatient department and non-physician. Studies on GPs' utilisation are investigated in countries where the GP acts as a 'gate-keeper' to further services, as in the UK, Italy, Ireland and Portugal while other countries uses 'doctors' or 'physicians', which include a wide range of medical practitioners; which in some studies also include specialists services.

3.2.3 Quality assessment

I have assessed the methodological quality of the 38 included studies in order to determine the validity of these studies in providing evidence for the review. The evaluation was based on the quality assessment rubric and scoring criteria developed by the econometrician for a study by the Canadian Council on Learning (2006, pp. 49-50)[3]. In order to suit the types of study being analysed, minor modifications or simplifications have been made to the rubric (e.g. in Type of Analysis-Score 3 criteria), otherwise all criteria are maintained as in the original format (see *Appendix 3-II*, pp. 188-189 for the Scoring Criteria).

The quality of methodology was assessed based on three main categories which consist of quality of data, quality of model and quality of results. In each main category, there are sub-categories where each criterion contributes to a score of 1 (poor), 2 (fair) and 3 (good). When a score for a criterion is between two levels, the lower score is used. The assessment is summarised in Table 3.2. Criteria that have been examined are:

[3] In "Measuring Quality in Post-Secondary Education (2006). Ottawa: Canadian Council on Learning.

Quality of data

1. Data sources
2. Data completeness
3. Representative sample
4. Data description

Quality of model

1. Type of analysis
2. Model assumptions
3. Model specification
4. Choice of variable

Quality of results

1. Statistical significance
2. Estimation bias
3. Objectivity of discussion

There are eleven criteria altogether which allow each study to have an overall score of between 11 and 33. Studies that have scored more than or equal 28 are considered as of good quality, between 22 and 27 are fair while below 27 are of poor quality. The findings from studies of a good rated quality are assumed to provide reliable evidence for the analysis while evidence from fair quality studies, despite some weaknesses in some features, will also be used in the analysis. Since all studies at this stage were selected subject to the inclusion criteria that require these studies to undertake empirical analysis, most of the studies have scored reasonably well in every element which is inevitably vital in empirical study. Of 38 studies under investigation, 33 fall under 'good' quality, while the remaining 5 are considered of very good 'fair' quality. All studies have clearly stated the objectives or research questions. These can either focus on specific issues of health care utilisation or methodological issues, support by health care demand data.

3.2.3.1 Analysis

1. **Quality of data**

The quality of data is measured by four criteria comprising the sources, and completeness of the data, the representation of the selected sample and the description of the variables used in the analysis. All studies score the maximum '3' for sources of data which suggests that the sources are clearly documented. The documentation of the sources is quite straight forward as all studies are based on secondary sources.

In terms of data completeness, since the problem of missing data is unavoidable in most studies especially for studies that are based on survey data, the maximum '2' seems realistic. Though in some studies, missing data is not explicitly discussed, it is believed that the results are not seriously affected by that problem (among others are Deb, Munkin & Trivedi, 2006; Bago d'Uva, 2006; Erbsland et al. 1995).

Except for Lopez-Nicolas (1998), all studies have described the variables they used in the analysis. The description can be either in a table format, which is sometimes combined with the descriptive statistics of the variables or in the paragraph. Of 37 studies that have described the data employed, 30 have provided clear description, while the description in the remaining 7 is considered unclear, mostly because these studies fail to provide a clear definition of every variable.

2. Quality of model

Similar to the quality of data, quality of model also consists of four criteria. Type of analysis, model assumption, model specification and choice of variables are the elements that decide the quality of the model. No study has attained more than '2' in the 'type of analysis' criterion as they rely on one type of analysis, for example, solely relies on econometric methods without enhancing the analysis with other approaches like qualitative or experimental analysis. Nevertheless some of the studies have provided descriptive analysis in addition to the econometric approach (among others are Hunt-McCool, Kiker, & Ng, 1995; Lee & Kobayashi, 2001; Lourenco & Ferreira, 2005).

In many cases, references are made to support the approach and assumptions used in the analysis. For example, studies that utilise hurdle (two-part) model assume that the utilisation of medical services is determined by two separate processes by referring to other relevant studies (for example, Pohlmeier & Ulrich, 1995; Deb & Trivedi, 2002). This assumption provides a strong basis for using two-part framework instead of other alternatives.

The same goes for studies which utilise a finite mixture approach which assumes that the population is divided into several latent classes (Bago d'Uva, 2005, 2006; Deb & Trivedi, 2002; Gerdtham & Trivedi, 2001; Lourenco & Ferreira, 2005. A score '2' is given to studies that do not explicitly or clearly explain the assumptions used in the analysis but is believed that this problem does not critically affect or invalidate the results as long as the specifications used are relevant to the type of data and issues under investigation.

If the validity of the functional form specification is tested by the researchers or at least justified by referring to other reliable sources, the score of '3' will be given; otherwise score '2' is given if the specification is consistent with the type of data and commonly used in other similar studies. Of all studies, only six studies failed to score 3 points. This is because, though reference(s) is made in introducing the employed model, the justification and support references are not judged to be sufficient for a maximum score to be given.

For instance, Hunt-McCool et al. (1995) have used the Almost-Ideal Demand (AID) model in their analysis. Except for a brief justification and introduction on why the study selected the model, it neither provided reliable sources to support the approach throughout the discussion nor tested the validity of the functional form of the specification.

Though the specification is consistent with the nature of data, Mangalore (2006) also failed to test the validity of the functional form, or at least discuss the model and econometric specification by referring to reliable sources. Similar problems occur in both of the studies by Winkelmann (2004a, 2004b).

As most of the studies have included important factors in the model, only the inclusion of supply variables differentiate between a fair and good score in the 'choice of variables' criterion. Studies that include supply variables, for example the density of health care per number of population, have attained the highest score (Gurmu, 1997; Lourenco & Ferreira, 2005; Mangalore, 2006; Pohlmeir, 1995; and Santos-Silva & Windmeijer, 2001). Nevertheless, although they fail to score the maximum '3', some studies have used location as a proxy of health care supply. People in urban areas for example, are believed to have good access to health care as opposed to people in the rural areas (e.g. Holly, Domenighetti & Bisig, 1998; Sarma & Simpson, 2006; Vera-Hernandez, 1999).

3. **Quality of results**

Quality of results largely depends on the quality of the two main categories as discussed above especially, for the potential bias of the estimation. Besides estimation bias, statistical significance and overall objectivity are essential factors determining the quality of the results. Again, most of the studies (36 studies) have scored '3' for discussing the statistical significance of their analysis. The other 2 are either emphasis at the difference of results between models (Deb & Trivedi, 2002) or does not provide sufficient discussion in terms of statistical significance (Holly et al., 1998). Despite this, the approach taken in discussing the results in these two studies is considered appropriate based on their research objectives.

A study may produce a biased estimation for several reasons. In this assessment, most of the studies score a 'fair' quality for this criterion mainly because of two reasons: the sample is or may not be representative because of missing data or these studies ignore the endogeneity of self selection variables like insurance status or self-perceived health status without justification. Thus most studies that have scored '2' for 'representative sample' criterion have also scored '2' for 'estimation bias'.

Since this assessment is downward biased, studies that do not mention the representativeness of the sample is given 2 points rather than the maximum '3'. On the other hand, the results in all studies are 'discussed in an objective manner', which means that implications and inferences made are within the estimation results. As a result, all studies have been given 3 points for this criterion.

3.2.4 Collecting data

After the methodological quality assessment, important information from all selected studies is extracted using data collection forms and transferred into a worksheet for further process. The information extracted consists of

A. Basic Information- Author, Title, Year, Theoretical Framework
B. Study characteristics- country, health system, sources of data, type (cross-sectional/time series/panel), year, and sample size and age-group.
C. Empirical Specification

   Variables

   Model type (Linear, Non-linear, Logistic, Count data)

   Framework (Single equation, Simultaneous equation, Two-part (hurdle), Finite Mixture)

   Estimation Method (Ordinary Least Square, Maximum Likelihood, Generalised Method of Moments, Instrumental Variables, others)
D. Findings

The extracted information is transferred into Tables 3.1, 3.3 and 3.4.

Figure 3.1 The flow of selection process

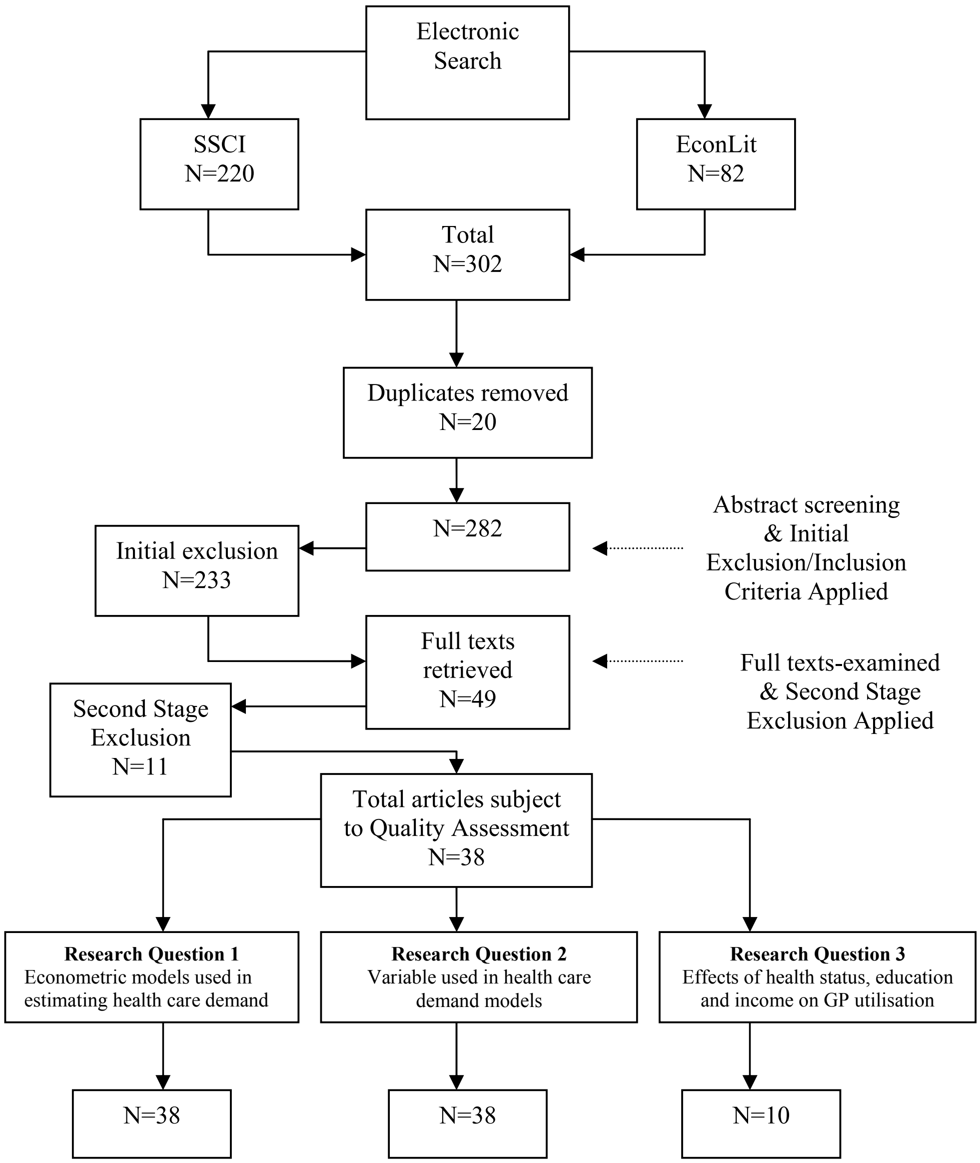


Table 3.1 Summary of the extracted information from selected studies

Study No.	Author (year)	Country	Financing system[1]	Type of data (Wave No.)	Age group	Number of observation	Types of utilisation	Health status	Health related	Age	Gender	Income	Education	Marital status	Employment	Insurance	Supply	Other[2]
1	Atella et al. (2004)	Italy	1	Cross-sectional	>=18	53,821	GP, specialist	✓	✓	✓	✓	✓	✓					✓
2	Bago d'Uva (2005)	United Kingdom	1	Panel (11)	>=16	10,890	GP	✓	✓	✓	/[3]	✓	✓	✓	✓		✓	✓
3	Bago d'Uva (2006)	United States	3	Panel (5)	<65	20,186/yr	Outpatient	✓	✓	✓	✓	✓	✓			✓		✓
4	Deb, Li et al. (2006)	United States	3	Cross-sectional	18-64 (2 datasets)	8,129/26, 514	Doctor, non-doctor, ER	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
5	Deb, Munkin et al. (2006)	United States	3	Cross-sectional	25-64	30,124	Doctor	✓	✓	✓	✓	✓	✓	✓		✓		✓
6	Deb & Trivedi (1997)	United States	3	Cross-sectional	>=66	4,406	Physician, non- Physician, ER, hospital stays	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
7	Deb & Trivedi (2002)	United States	3	Cross-sectional	<65	20186/yr	Doctor, outpatient, all providers	✓	✓	✓	✓	✓	✓			✓		✓
8	Deb & Trivedi (2006)	United States	3	Cross-sectional	18-64	8,129	Doctor, non-doctor, outpatient, hospital, ER	✓	✓	✓	✓	✓	✓	✓		✓		✓
9	Ersbland et al. (1995)	Germany	2	Cross-sectional	working age	3,317	GP, specialist, hospital days	✓	✓	✓	✓	✓	✓			✓	✓	✓
10	Geil et al. (1997)	Germany	2	Panel (8)	25-64	30,590	Inpatient	✓		✓	✓	✓	✓	✓	✓	✓		✓
11	Gerdtham (1997)	Sweden	1	Cross-sectional	18-76	5,011	Physician, inpatient	✓	✓	✓	✓	✓	✓	✓	✓			✓
12	Gerdtham & Trivedi (2001)	Sweden	1	Cross-sectional	1g8-76	5,011	Physician, inpatient	✓	✓	✓	✓	✓	✓	✓	✓			✓
13	Gurmu (1997)	United States	3	Cross-sectional	15-65	485/511	Physician	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
14	Gurmu & Elder (2000)	Australia	1	Cross-sectional	Not stated	5,190	Doctor, health professional	✓	✓	✓	✓	✓				/[3]		

Table 3.1 Summary of the extracted information from selected studies

Study No.	Author (year)	Country	Financing system[1]	Type of data (Wave No.)	Age group	Number of observation	Types of utilisation	Health status	Health related	Age	Gender	Income	Education	Marital status	Employment	Insurance	Supply	Other[2]
15	Holly et al. (1998)	Switzerland	2	Cross-sectional	>=15	15,288	Insured, inpatient	✓		✓	✓	✓	✓		✓	✓		✓
16	Hunt-McCool et al. (1995)	United States	3	Cross-sectional	>=18	14,000	Physician, inpatient, ER	✓	✓	✓	/	✓	✓	✓	✓	✓		✓
17	Koc (2005)	United States	3	Cross-sectional	18-64	11,518	Physician, inpatient (no. of nights)	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
18	Lee & Kobayashi (2001)	United States	3	Panel (2)	born in 1931-1941	8,484/w	Doctor, hospital days	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
19	Lopez-Nicolas (1998)	Spain	1	Panel (8)	Not stated	6100 h/h /Q	Private medical care			✓		✓	✓		✓	✓		✓
20	Lourenco & Ferreira (2005)	Portugal	1	Cross-sectional	>=18	6,791	GP	✓	✓	✓	✓		✓		✓		✓	✓
21	Maden et al. (2005)	Ireland	1	Panel	>=16	20,466	GP	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
22	Mangalore (2006)	United Kingdom	1	Panel (3)	>=16	7702/y	GP	✓		✓	✓	✓	✓	✓	✓		✓	✓
23	Munkin & Trivedi (2003)	United States	3	Cross-sectional	16-65	2,893	Physician	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
24	Nandakumar et al (2000)	Egypt	3	Cross-sectional	all age	50,824	Outpatient	/[3]		✓	✓	✓	✓	✓	✓	✓		✓
25	Nolan (2007)	Ireland	1	Panel(7)	>=16	49,237	GP	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
26	Pohlmeier & Ulrich (1995)	Germany	2	Cross-sectional	working age	5,096	GP, specialist	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
27	Sarma & Simpson (2006)	Canada	1	Cross-sectional	>=12	13, 189	GP, inpatient specialist, eye specialist,	✓	✓	✓	✓	✓	✓	✓		✓		✓
28	Schellhorn (2001)	Switzerland	2	Cross-sectional	>=15	9,003	Physician-primary, specialist	✓		✓	✓	✓	✓		✓	✓		✓

Table 3.1 Summary of the extracted information from selected studies

Study No.	Author (year)	Country	Financing system[1]	Type of data (Wave No.)	Age group	Number of observation	Types of utilisation	Health status	Health related	Age	Gender	Income	Education	Marital status	Employment	Insurance	Supply	Other[2]
29	Schellhorn et al. (2000)	Switzerland	2	Panel (3)	>=75	746/yr	Physician-primary, specialist	✓	✓	✓	✓	✓	✓			✓		✓
30	Santos-Silva & Windmeijer (2001)	Germany	2	Cross-sectional	working age	5,096	Specialist	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
31	Van Houten & Norton (2004)	United States	3	Cross-sectional	>=70	4,752	Nursing home, hospital care, physician	✓	✓	✓	✓	✓	✓		✓	✓		✓
32	Vera-Hernandez (1999)	Spain	1	Cross-sectional	18-59	7,281	Specialist	✓	✓	✓	✓	✓	✓		✓			✓
33	Windmeijer & Santos-Silva (1997)	United Kingdom	1	Cross-sectional	>=25	4,814	GP	✓	✓	✓	✓	✓	✓	✓	✓			✓
34	Winkelmann (2004a)	Germany	2	Panel (5)	Not stated	37,319	Doctor	✓		✓	✓	✓	✓	✓	✓	✓		✓
35	Winkelmann (2004b)	Germany	2	Panel (5)	20-60	32,837	Doctor	✓		✓	✓	✓	✓	✓	✓	/[3]		✓
36	Winkelmann (2006)	Germany	2	Panel (2)	Not stated	18,683	Doctor	✓		✓	✓	✓	✓	✓	/[3]	/[3]		✓
37	Yen et al. (2001)	Taiwan	2	Cross-sectional	15-64	13,616	Chinese medicine physician	✓		✓	✓	✓	✓	✓		✓		✓
38	Zimmer & Trivedi (2006)	United States	1	Cross-sectional	18-64	6636 couples	Physician, non -physician, ER	✓		✓	✓	✓	✓		✓	/[3]		✓

Notes:
[1]Health care financing systems: (1) Mainly tax-financed, (2) Mainly financed by social security contributions and (3) Mixed system, mainly private financing
[2]Other variables include region, size of workplace, race, household size, exercise, smoking, appointment delay, quality of care, children, distance to health care facilities, degree of disability, alcohol consumption, language, quality of life and social class.
[3]Symbol '/' represents variable in which sample has been divided by it, thus is not included in the model as a regressor
ER = number of emergency room visits; yr=year; w=wave; h/h=households

Table 3.2 Summary of methodological quality

Study No.	Author (Year)	Data Sources	Data Complet-ness	Represen-tative Sample	Data Descript-ion	Type of Analysis	Model Assump-tions	Model Specifi-cation	Choice of Variables	Statistical Signifi-cance	Estimation Bias	Overall Objectivity	Total Score	Quality
1	Atella et al. (2004)	3	2	3	2	2	3	3	2	3	2	3	28	Good
2	Deb, Li et al. (2006)	3	2	3	3	2	3	3	2	3	2	3	29	Good
3	Deb, Munkin et al. (2006)	3	2	2	3	2	3	3	2	3	2	3	28	Good
4	Deb & Trivedi (1997)	3	2	2	3	2	3	3	2	3	2	3	28	Good
5	Deb & Trivedi (2002)	3	2	3	3	2	3	3	2	2	3	3	29	Good
6	Deb & Trivedi (2006)	3	2	3	3	2	3	3	2	3	3	3	30	Good
7	Bago d'Uva (2005)	3	2	3	3	2	3	3	3	3	3	3	31	Good
8	Bago d'Uva (2006)	3	2	3	2	2	3	3	2	3	3	3	29	Good
9	Erbsland , Ried & Ulrich (1995)	3	2	2	3	2	3	3	2	3	2	3	28	Good
10	Geil et al.(1997)	3	2	3	3	2	3	3	2	3	3	3	30	Good

Table 3.2 Summary of methodological quality

Study No.	Author (Year)	Data Sources	Data Complet-ness	Represen-tative Sample	Data Descript-ion	Type of Analysis	Model Assump-tions	Model Specifi-cation	Choice of Variables	Statistical Signifi-cance	Estimation Bias	Overall Objectivity	Total Score	Quality
11	Gerdtham (1997)	3	2	3	3	2	3	3	2	3	3	3	30	Good
12	Gerdtham & Trivedi (2001)	3	2	2	3	2	3	3	2	3	2	3	30	Good
13	Gurmu (1997)	3	2	2	3	2	3	3	3	3	2	3	27	Fair
14	Gurmu & Elder (2000)	3	2	2	3	2	3	3	2	3	2	3	28	Good
15	Holly et al. (1998)	3	2	3	3	2	3	2	2	2	2	3	27	Fair
16	Hunt-McCool et al. (1995)	3	2	2	3	2	3	2	2	3	2	3	27	Fair
17	Koc (2005)	3	2	2	3	2	3	3	2	3	2	3	28	Good
18	Lee & Kobayasyi (2001)	3	2	2	2	2	3	3	2	3	2	3	27	Good
19	Lopez-Nicolas (1998)	3	2	3	1	2	3	3	2	3	3	3	28	Good

Table 3.2 Summary of methodological quality

Study No.	Author (Year)	Data Sources	Data Complet-ness	Represen-tative Sample	Data Descript-ion	Type of Analysis	Model Assump-tions	Model Specifi-cation	Choice of Variables	Statistical Signifi-cance	Estimation Bias	Overall Objectivity	Total Score	Quality
20	Lourenco & Ferreira (2005)	3	2	3	3	2	3	3	3	3	2	3	30	Good
21	Madden et al. (2005)	3	2	2	3	2	3	3	2	3	2	3	28	Good
22	Mangalore (2006)	3	2	3	3	2	2	2	3	3	3	3	29	Good
23	Munkin & Trivedi (2003)	3	2	3	3	3	3	3	2	3	3	3	31	Good
24	Nandakumar et al. (2000)	3	2	3	3	2	2	2	2	3	2	3	27	Fair
25	Nolan (2007)	3	2	3	3	2	3	3	2	3	3	3	30	Good
26	Pohlmeier & Ulrich (1995)	3	2	2	3	2	3	3	3	3	2	3	29	Good
27	Sarma & Simpson (2006)	3	2	3	3	2	3	3	2	3	2	3	29	Good
28	Schellhorn (2001)	3	2	2	3	2	3	3	2	3	2	3	28	Good
29	Schellhorn et al. (2000)	3	2	2	2	2	3	3	2	3	2	3	27	Fair

Table 3.2 Summary of methodological quality

Study No.	Author (Year)	Data Sources	Data Complet-ness	Represen-tative Sample	Data Descript-ion	Type of Analysis	Model Assump-tions	Model Specifi-cation	Choice of Variables	Statistical Signifi-cance	Estimation Bias	Overall Objectivity	Total Score	Quality
30	Santos-Silva & Windmeijer (2001)	3	2	2	3	2	3	3	3	3	2	3	29	Good
31	Van Houten & Norton (2004)	3	2	3	3	2	3	3	2	3	3	3	30	Good
32	Vera-Hernandez (1999)	3	2	2	3	2	3	3	2	3	2	3	28	Good
33	Windmeijer & Santos-Silva (1997)	3	2	2	3	2	3	3	2	3	2	3	28	Good
34	Winkelmann (2004a)	3	2	3	2	2	3	2	2	3	3	3	28	Good
35	Winkelmann (2004b)	3	2	3	2	2	3	2	2	3	3	3	28	Good
36	Winkelmannn (2006)	3	2	3	2	2	3	3	2	3	2	3	28	Good
37	Yen (2001)	3	2	3	3	2	3	3	2	3	2	3	29	Good
38	Zimmer & Trivedi (2006)	3	2	3	3	2	3	3	2	3	3	3	30	Good

3.2.5 Analysing and presenting results

3.2.5.1 Modelling techniques

The aim of this section is to explore the modelling techniques employed in the selected studies. The summary of the techniques used is presented in Table 3.3. While all the relevant information in explaining the method used have been extracted as much as possible from each article, some information may have been missed as they are not discussed explicitly in the paper. On the other hand, some studies have employed several models before selecting the superior model [12,13, 27,30,33,35,37,38]. This section serves as a background for further discussion of econometric methods for health care demand in the next three empirical chapters. Therefore the discussion here mainly refers to the information from the summary in Table 3.3.

From Table 3.3 one can see that most studies (at least 26 studies) work within count data framework that utilise Poisson or negative binomial specification, which is appropriate for non-negative dependent variable. This is consistent with the type of data used in most of the included studies in which demand is measured by the number of visits to health services. Poisson model is always used as the starting point in a count data model. In the evidence of overdispersion (which may be generated by unobserved heterogeneity) the specification is extended to the negative binomial where the error term is assumed to be *gamma* distributed. Unlike Poisson, which assumes the equidispersion property between conditional mean and variance, the negative binomial model specifies the variance to be a proportional or quadratic to the mean. They are known as negative binomial type-1 (negbin1 or NB1) and negative binomial type-2 (negbin2 or NB2) respectively.

Though in some studies the estimation method is not mentioned, the standard count estimation for the count data model is maximum likelihood estimation (MLE). An alternative estimation to MLE when the assumption that the model is correctly specified is neglected is Pseudo maximum likelihood (PML). Among studies that utilise Pseudo maximum likelihood estimation are Deb & Trivedi (2002), Windmeijer & Santos-Silva (1997) and Winkelmann (2004a). In health care utilisation data in the general population, zero events often occur. This is a natural situation as the reference period in the survey for certain type of utilisation is limited, for example, for the period of two weeks prior to interview. Unobserved heterogeneity, which is one of the possible causes of overdispersion, provides some explanation for excess zeros and can be modelled with the negative binomial.

However, when utilisation of health care is controlled by the doctor, modelling techniques that permit two distinct processes to be modelled separately, are essential in treating excess zeros. The contact decision by the patient and frequency of use determined by the doctors are assumed to be generated by different process. Within this framework, excess zeros can be modelled by zero inflated or hurdle model. From the table, only Gerdtham (1997), and Sarma and Simpson (2006) employed zero inflated models in the analysis. Sarma and Simpson (2006) have employed Vuong tests and compared the likelihood ratio statistics between zero-inflated negative binomial (ZINB), zero-inflated Poisson (ZIP) and negative binomial (NB) to identify the superior specification. Both tests favoured ZINB over the said alternatives.

Gerdtham (1997), on the other hand, found that the ZINB model failed to converge. Hurdle models or two-part models are used in 13 included studies [4,5,8,11,12,13,19,26,27,30,31,35,37]. These studies employed a binary regression (logit or probit) for the first part to distinguish users from non-users and least square or truncated at zero count data model (truncated Poisson or negative binomial) to model expenditure or frequency of utilisation among users. Most studies prefer negative binomial specification for the second part of the regression [4,5,8,11,12,26,27,35]

Recently, an alternative of hurdle approach has developed, which is finite mixture or latent-class approach. In this approach, sample is divided into two or more categories based on characteristics that are not observable to the researcher, e.g. long term health status, attitude toward health, etc. Eight from 38 studies use this approach [1,4,5,7,8,12,20,27]; where five of them have compared the finite mixture method with hurdle specification [4,5,8,12,27]. Studies that have compared these two specifications seem to favour finite mixture over hurdle, except for specialist visits and number of nights stay in Sarma and Simpson (2006) which prefer ZINB instead. All preferred models are selected on the basis of log likelihood, Akaike information criterion (AIC) or Bayesian information criterion (BIC).

Other frameworks that are not commonly used by selected studies under review include the Bayesian model [3], the Almost-Ideal demand (AID) [16], quantile regression [36] and the non-linear model based on Copula estimates [38]. One of the challenges in estimating demand for health care is to take into account the self selection bias or endogeneity problem in the model. One of the variables that are exposed to self-selection problem is insurance choice as this might be influenced by some unobserved characteristics which in turn affect the utilisation of health care.

As shown in Table 3.3, of 26 studies that include insurance variables in their model(s), 10 have dealt with endogeneity problems of insurance. Three studies treat health status as endogenous [9,29,33]. Among methods used in modelling utilisation models with endogeneity problems are simultaneous equations which are estimated by Maximum Simulated Likelihood, Generalised Method of Moment (GMM) or Full Information Maximum Likelihood (FIML).

3.2.5.2 The explanatory variables in health care demand model

1. **Health status and health related variable**

The most important variable that determines health care utilisation is health status. All studies, except for Lopez-Nicolas (1998) and Nandakumar et al. (2000), include health status variables in their analysis. Since health status is not directly observed by the researcher, self-rated health status is commonly used to represent it. Of 36 studies that include health status variables, 24 studies have used the self-assessed health status (SAH) to represent the state of health.

Self-assessed health, also known as self-perceived or self-rated health status is a categorical variable which represents the level of health perceived by the respondent within a certain period of time. This variable can be binary or ordinal with more than two categories. In most of the cross-sectional studies, except for Schellhorn et al. (2000) and Windmeijer and Santos-Silva (1997), the possibility that SAH is endogenous is not tested. As for studies that utilise panel data, SAH is treated as exogenous as it was determined at the beginning of the wave (Bago d'Uva, 2005; Deb & Trivedi, 2006; Schellhorn, 2000). Besides self-rated health status, other common measures of health state are a binary status or number of chronic or acute conditions, number of illnesses (e.g. Geil et al., 1997; Gerdtham, 1997; Gurmu, 1997; Gurmu & Elder, 2000), whether diagnosed with specific disease (Lee & Kobasyi, 2001; Madden et al., 2005), health score using Goldberg's Method (Gurmu & Elder, 2000) or constructed health groups (Koc, 2005). Other variables that are related to one health status are also frequently used in the model. One of the most common health related variables used are physical limitation due to health conditions (e.g. Deb, Munkin & Trivedi, 2006; Munkin & Trivedi, 2003).

Two studies also include Body Mass Index (Holly et al., 1998; Schellhorn, 2001) in their analysis. Sarma and Simpson (2006) even include a health status index score to support their analysis. This score combines the effects of both quantitative and qualitative aspects of health which cover eight attributes such as vision, hearing, speech, mobility, dexterity, cognition, emotion, and pain and discomfort. A higher score signifies better health.

2. Personal characteristics – Age and gender

Grossman (1972) suggests that people demand health care in order to increase or minimise decline in their health capital. Health capital depreciates over time and the depreciation rate rises with age (Grossman, 1972). Therefore, as one of the most important factors in a health care demand model, all studies under review have included age in their model so as to determine the influence of health capital on the utilisation of health care. However the effect of the age variable should be interpreted carefully and cannot easily be compared between studies as different studies concentrate on different age-groups. Without discussing much detail on the result of each study, on balance, it is found that age and health care utilisation has a positive or nonlinear (convex or concave) relationship, though in some cases the effect is not statistically significant. For example, although the sample used in the analysis does not cover the population in the early age[4] (children under 5 for instance) a non-linear "U-shaped" relationship of age and utilisation is found in Pohlmeier and Ulrich (1995); and Windmeijer and Santos-Silva (1997).

The inclusion of gender has important policy implications. As for gender, only 3 studies do not include gender in their model (Bago d'Uva, 2005; Hunt-McCool et al., 1995; Lopez-Nicolas, 1998). Bago d'Uva (2005) and Hunt-McCool et al. (1995) do not include a gender variable because they have divided the sample according to the gender and examined them separately. The information on the influence of gender on health care demand can help policy makers to design an efficient policy as diseases or health seeking behaviour might be influenced by gender. .In all studies that reported the significant effect of gender, it is found that being a female increases the demand or that a woman is more likely to use health services. However, these studies do not mention whether or not the maternity care is excluded from the utilisation data as maternity care may contribute to a higher utilisation rate among females.

3. Socioeconomic variables

Apart from age and gender above, other socioeconomic variables that are frequently used in the selected studies include income, education, marital status and working status. All of these are correlated factors and it is important to

[4] Children under 5 is believed to utilise more health care as they are more prone to health problems or have schedule visits for health check-ups or vaccinations.

consider the net effects of each on health care use. Income is taken as a proxy for wealth that represents the ability to demand health care when needed. It is also important in understanding the equity issues in health care utilisation. It is said that when there is evidence of significant impact of income on health care utilisation, there might be evidence of inequity as utilisation should be based on the needs rather than other factors. Examples of studies that discussed equity issues are Bago d'Uva (2005), Gerdtham (1997) and Mangalore (2006).

Almost all studies include income as one of the variables in their model except Lourenco et al. (2005), who use purchasing power at county level as a proxy of wealth. There are a few types of income used in the models that include family income, personal income, equivalised income and household income. Education, on the other hand (in the Grossman model) is assumed to represent the productivity of producing health capital. People with more education are said to be more productive in generating the stock of health, and as a result, will demand less health care.

In testing this hypothesis, all studies except for Gurmu et al. (2000) have included education in their analysis. Education levels are represented by the number of years in education or dummy variables for education levels of the individual or head of the family/household. Marital status is no less important in the health care demand model. Twenty-five studies have tested this factor in their model. Though living arrangements may not be explained by looking at the marital status *per se*, it may give some insight to the discussion; specifically on the role of the partners in health care utilisation patterns. In a way, it might shed some light on the importance of the marriage institution on health and health care demand. From the review, being married may increase or decrease the demand for doctors. For example, Deb, Munkin and Trivedi (2006) and Nandakumar (2000) found that being married increases the probability of doctor visits/seeking care while Gerdtham (1997) found the opposite results on the frequency of visits. Some studies also found insignificant results (e.g. Gurmu, 1997; Gerdtham and Trivedi, 2001; Nolan, 2007). However, no interaction between gender and marital status is tested.

Employment or working status is used as a proxy of opportunity costs for seeking health care. Twenty-seven studies have included this variable that indicates that employment status might have some role in determining the decision to seek health care. Other variables that may affect the utilisation and have been included in some studies include region, size of workplace, race, household size, exercise, smoking, appointments delay, quality of care, survey year, children, distance to health care facilities, degree of disability, alcohol consumption, language, quality of life and social class.

4. Insurance status

The insurance variable is one of the enabling variables that determines the level of access (Sarma & Simpson, 2006). From Table 3.1, it is clearly seen that the insurance variable is often included in studies that are based on mixed system health care financing, as in the United States. Eleven of 13 studies that are based on US datasets include an insurance variable in their analysis, while the remaining two studies have already selected or divided their samples according to their insurance status (Gurmu & Elder, 2000; Zimmer & Trivedi., 2006). Gurmu and Elder (2000) have utilised samples among Medicaid beneficiaries while Zimmer and Trivedi (2006) limit the sample to people with private insurance only. In other studies, in which the datasets are based on tax-financed system, such as Italy, UK, Sweden, Portugal and Spain, the role of insurance status in health demand is not prominent. Therefore 8 from 13 studies that are based on tax-financed system do not include an insurance variable in their analysis.

5. **Supply side variables**

Of all included studies, only 5 studies include the supply variables which contain the information on the density of doctors per certain number of population (Erbsland 1995; Lourenco et al., 2005; Mangalore, 2006; Pohlmeier et al., 1995 and Santos-Silva et al., 2001). Gurmu (1997), on the other hand, uses the availability level of health services by rating them between 0 (zero) for low access to 100 (hundred) points for high access. Due to lack of information in the dataset used, many studies used location, region or area as a proxy for the availability of health care services. The inclusion of the supply side variables is important as to determine whether supply variables have significant effect in inducing more demand, thus supporting the hypothesis of supply-induced demand (McLaughin, Normalle, Wolfe, McMahon Jr., & Griffifth, 1989; Wennberg et al., 2004; Wilson & Tedeschi, 1984).

3.2.5.3 The roles of health status, income and education on the utilisation of GP services

In this section, the effects between health status, income and education on the utilisation of GP services are explored. Understanding the relationship of these three variables on the utilisation of primary health care, especially the GP, is important for health and social policy. Developing and improving primary care that includes GP and primary care infrastructure may improve health outcomes and control costs (Glasby, 2007). The discussions in this section are referred to Table 3.4 and each study is referred according to the study number from the table. Of all 38 papers, there are 10 studies which specifically examine the utilisation of GP services. Three studies are based on the UK data [2,6,33], two studies on Germany [9,26] and Ireland [5,7] while the remaining are based on Italy, Portugal and Canada [1,20,27 respectively].

Except for Germany, the GP plays a gate-keeper role in the public health system in all the studies considered. The impacts of all of these factors, if represented by dummies might be reported differently based on the reference variable in each paper. These impacts, however, have been adjusted and consistently reported across studies to allow comparison. For example, for all variables, poor or very poor status is used as the reference variable.

Four studies have utilised a finite mixture or also known as latent class approach, for analysis [1,2,20,27]. Thus, results are discussed based on latent classes which in these four papers; samples are divided into two classes [1,20,27] or three classes [2] based on predicted means of the samples. A latent class model may distinguish the samples according to the unobserved characteristics, for example, the health status that reflects the frequency of use.

As discussed in Section 3.1.6.2 health status is inevitably an important determinant of health care utilisation. From Table 3.4, we can see that people with a good level of health status, regardless of the type of variables that represent the status, utilise less GP services than people with a poor level health status. Except for the effect on frequent user class in the study by Lourenco and Ferreira

(2005) and low user males in Bago d'Uva (2005), other studies clearly suggest that utilisation of GP services significantly depends on health status, which represent the need for health care. As for income, and controlling for other variables, there is no clear pattern of the relationship with utilisation. Of eleven significant effects (from nine studies) for income, six are negative effects which suggest people with high income utilise less GP services than people with low income [1,9,20,22,26,27], four are positive [2,21] while Windmeijer and Santos-Silva (1997) suggest a non-linear relationship.

Atella et al. (2004) suggests that high income people are less likely to visit GP as this group prefer private specialist than GP in Italy. Both studies based in Germany, where GP has no gate-keeper role also suggest the similar effect that high income people prefer services by specialist than GP. On the other hand, all three studies based in the UK, obtain disagreeing results. All significant results in Bago d'Uva (2005) are positive effects while Mangalore (2006) and Windmeijer and Santos-Silva (1997) obtain a negative and a non-linear relationship respectively.

These effects, although the directions are different, suggest that income has some influence on GP utilisation in the UK even though it is free at the point of service. It also supports the presence of income-related inequity among some groups in the system (Bago d'Uva, 2005). The effects of income in the remaining eight equations from six studies [1,2,20,25,26,27] are not significant. Unlike income, the significant effects for education exhibits a clearer direction where most of them suggest a negative relationship between education level and utilisation of GP services. Of all 19 effects, seven are significant from which six are negative. The negative relationship supports the theoretical prediction of Grossman model which suggest that more educated people have higher productivity in producing health capital, and thus demand less health care. Of all three variables of interest, health status shows the strongest influence towards GP utilisation with consistent negative effects. While education and income have revealed some effects, the influence of these variables on GP utilisation requires more investigation as results are not consistent across studies. Within this sample of ten studies, there are also no common factors (eg. by country, year, model type or nature of analysis) that can explain the influence or magnitude of income and education effects on GP utilisation.

Table 3.3 The modelling techniques of selected studies

Study No.	Study (Year)	Framework/Type of Model/Estimation Method	Endogenous regressor
1	Atella et al. (2004)	Latent class (joint choice) Seemingly unrelated probit Constrained quasi-Newton optimization algorithm	-
2	Bago d'Uva (2005)	Latent class panel Logit MLE	-
3	Bago d'Uva (2006)	Hurdle, finite mixture, finite mixture hurdle-NB1 MLE/ Broyden-Fletcher-Goldfarb-Shanno quasi Newton algorithm	-
4	Deb,Li et al. (2006)	Joint models- insurance choice and utilisation Insurance choice-multinomial logit Utilisation-NB2 Simulation likelihood function	Insurance choice
5	Deb, Munkin et al. (2006)	Roy model Bayesian approach Markov Chain Monte Carlo Algorithm (MCMC)	Insurance choice
6	Deb & Trivedi (1997)	Hurdle and finite mixture NB (preferred model) MLE	-
7	Deb & Trivedi (2002)	Two-part and latent class NB Psuedo MLE (PMLE)	Insurance choice
8	Deb & Trivedi (2006)	Latent factor structure-NB Simulated likelihood method-quasi-Newton algorithm	Insurance status
9	Erbsland et al. (1995)	Linear covariance structured model Full Information Maximum Likelihood	Health Capital
10	Geil et al. (1997)	Poisson/NB2/random-effects NB	-
11	Gerdtham (1997)	Zero inflated Poisson/NB, hurdle- Logit and NB1 MLE	-
12	Gerdtham & Trivedi (2001)	Two-part and finite mixture Logit and NB2 Pseudo MLE (PMLE)	-
13	Gurmu (1997)	Parametric and semi-parametric hurdle Binary choice and count data MLE	-

Table 3.3 The modelling techniques of selected studies

Study No.	Study (Year)	Framework/Type of Model/Estimation Method	Endogenous regressor
14	Gurmu & Elder (2000)	Generalised bivariate NB	-
15	Holly et al. (1998)	Simultaneous equation MLE	Insurance status
16	Hunt-McCool et al. (1995)	Modified Almost-Ideal Demand (AID) Two-stage model	-
17	Koc (2005)	Endogenous switching Probit and non-linear least square	Insurance choice
18	Lee & Kobayasyi (2001)	NB2 MLE, Method of moment estimator, quasi conditional MLE	-
19	Lopez-Nicolas (1998)	Two-part MLE	-
20	Lourenco & Ferreira (2005)	Finite mixture NB2 Broyden-Fetcher-Goldfarb-Shanno algorithm	-
21	Madden et al. (2005)	Generalised NB	-
22	Mangalore (2006)	Binomial probit	-
23	Munkin & Trivedi (2003)	Non-linear simultaneous model-Poisson and exponential Markov Chain Monte Carlo Algorithm	Insurance choice
24	Nandakumar et al. (2000)	Probit	
25	Nolan (2007)	Dynamic random-effect Poisson	
26	Pohlmeier & Ulrich (1995)	Hurdle-Binary and NB1 MLE with robust standard error	
27	Sarma & Simpson (2006)	Hurdle, zero-inflated and finite mixture Binary, Poisson and NB MLE	-
28	Schellhorn (2001)	Simultaneous equation Multiplicative Poisson Generalised method of moment	Deductible choice
29	Schellhorn et al. (2000)	Random-effect NB MLE	Self-Assessed Health Status
30	Santos-Silva & Windmeijer (2001)	Heterogeneous NB MLE	-

Table 3.3 The modelling techniques of selected studies

Study No.	Study (Year)	Framework/Type of Model/Estimation Method	Endogenous regressor
31	Van Houten & Norton (2004)	Two-part-probit and least square	-
32	Vera-Hernandez (1999)	NB2 Exponential function MLE and GMM-IV	Duplicate coverage
33	Windmeijer & Santos-Silva (1997)	Simultaneous equation Binary/latent and exponential conditional model GMM, Poisson Pseudo-Likelihood and Poisson Pseudo two-stage	Self-assessed health status
34	Winkelmann (2004a)	Poisson and NB Pseudo MLE	-
35	Winkelmann (2004b)	Structural and two-part Poisson, NB, probit-Poisson-log normal MLE	-
36	Winkelmannn (2006)	Poisson, NB, quantile regression	-
37	Yen (2001)	Single and double hurdle Probit and truncated Poisson MLE	-
38	Zimmer & Trivedi (2006)	Non-linear simultaneous model Copula and maximum simulated likelihood	-

Notes:
MLE - Maximum Likelihood Estimation
NB1 - negative binomial type-1
NB2 - negative binomial type-2

Table 3.4 The relationship between health status, income, and education and the utilisation of GP services.

Study No.	Studies (Type of data)	Country	GP as a gate-keeper[1]	Number of Equations	Health Status	Income	Education
1	Atella et al. (2004) (Cross-sectional)	Italy	Yes	Two	-ve	-ve in latent class 2; Not significant in latent class 1	-ve
2	Bago d'Uva (Panel)	UK	Yes	Six 3 Females 3 Males	-ve for high, medium and low users (females); high and medium users (males)	+ve for medium and low user (females); low users (males)	No clear effects
9	Erbsland et al. (1995) (Cross-sectional)	Germany	No	One	-ve	-ve	-ve
20	Lourenco & Ferreire (2005) (Cross-sectional)	Portugal	Yes	Two	-ve for low user; Not significant for frequent users	-ve for frequent user; Not significant for low users	-ve
21	Madden et al. (2005) (Panel)	Ireland	Yes	One	-ve	+ve	-ve
22	Mangalore (2006) (Panel)	UK	Yes	One	-ve	-ve	+ve
25	Nolan (2007) (Panel)	Ireland	Yes	One	-ve	Not Significant	Not significant
26	Pohlmeier & Ulrich (1995) (Cross-sectional)	Germany	No	Two	-ve	-ve for contact; Not significant for frequency	-ve for contact ; Not significant for frequency

Table 3.4 The relationship between health status, income, and education and the utilisation of GP services.

Study No.	Studies (Type of data)	Country	GP as a gate-keeper[1]	Number of Equations	Health Status	Income	Education
27	Sarma & Simpson (2006) (Cross-sectional)	Canada	Yes	Two	-ve	-ve for high user; Not significant for low users	Not significant
33	Windmeijer & Santos-Silva (1997) (Cross-sectional)	UK	Yes	One	-ve	Non-linear-highest & lowest utilise more	-ve

Notes:
[1] Source (except Sarma & Simpson, 2006) : Jiménez-Martín et al. (2002)
1. -ve -negative effects; +ve -positive effects
2. For studies that utilise finite mixture or hurdle approach [1,2,4,8, 9], results are for all classes or parts unless otherwise is stated.

3.2.6 Summary of results

In this section, results are summarised based on the questions highlighted in Section 3.2.1. The summary is based on the results from the 38 selected studies, unless otherwise mentioned.

1. *Which of the searched econometric models studied are employed in estimating health care demand and how to deal, if discussed, with the endogeneity bias of the regressor in the model?*

- The majority of studies use count data that permit the utilisation of count data models. The negative binomial model is preferred to the Poisson when data is overdispersed.
- When contact decisions and frequency of use are assumed to be generated by different processes, hurdle or zero-inflated models are used. However, the zero-inflated model is not common in the studies under review.

- An alternative approach in treating excess zeros is 'finite mixture'. Studies that compared hurdle with finite mixture approach mostly prefer the latter approach.
- Of 38 studies under investigation, twelve studies have dealt with endogeneity problems of the regressors (i.e. insurance status or SAH).
- Simultaneous, endogenous switching or joint models are used when insurance choice or SAH is expected to be endogenous in the utilisation models. Studies that examine the self selection (endogeneity) bias of insurance suggest that self selection bias exists while the endogeneity of SAH has mixed results depending on specification used.

2. *What are the explanatory variables used in the health care utilisation model?*

- The explanatory variables used in the selected studies under review are more concentrated on individual determinants rather than other types of determinants, such as health care characteristics or technology (see utilisation framework proposed by Andersen and Newman (1973) and later discussed by Aday and Andersen (1974)).
- Table 3.1 summarises the variables frequently used in the empirical studies for health care services. Variables that may represents the need for health care (i.e. health status), either self-assessed, observed or evaluated seem to be the most important variables, especially if researchers are interested in testing the equity issues of health care utilisation.
- Age, gender, education and income, apart from health status, are the most frequently used variables tested in the health care utilisation models.

- The role of marital status and work status is also tested in some studies, but not as frequently as other variables mentioned above.
- The inclusion of health insurance on the other depends on how important that variable is in the study, which is clearly important in a country like the United States.
- Despite the important roles of supply variables in determining demand, only a few studies include the density of doctors or other facilities in estimating the models. Nevertheless, the impact of availability of health care supply is often proxied by variables such as region or the level of urbanisation.
- The effects of life style variables like smoking, alcohol intake, diet and exercise, though included in some studies, are not very common in the health care demand model. Though the effects might have no direct effects on health care, it can be explained through the impact on health status. However, the appropriateness of these variables as instruments of health status needs more investigation.

3. *What are the effects of health status, income and education on the utilisation of a General Practitioner (GP)?*

- Effects of variables of interest on utilisation reported in all studies are the main effects without interactions between variables.
- Health status is related to GP utilisation regardless of whether the GP acts as the gate-keeper or not. The effects are consistent across studies which suggest that healthy people utilise less GP services than those with poor health status.

- Effects of income are not clear. Of 19 equations, incomes are significant in 11 equations, of which six are negative, four are positive and one has a non-linear effect. Studies that investigate the utilisation of private services suggest that high income earners prefer private specialists [1,3,8]. It is difficult to be certain of the effects of income due to different characteristics of different studies, thus for policy purposes, more specific research is essential in every country.
- The effects of education are clearer than income, although only seven out of 19 effects are significant. Despite that, six of seven significant effects suggest a negative relationship between education and utilisation level. There is evidence that individuals with a higher level of education use their GP less often. These findings therefore show some possible connection between education and health care policy. In the long term, an education policy promoting higher education may decrease the utilisation of GP services.
- The findings that have been discussed above, however, may be affected by measurement effects as income and education variables used in the analyses are not consistent across all studies.

3.2.7 Improving and updating reviews

As highlighted in Section 3.2.2.1, the bibliographic databases considered for this review are very limited due to time constraints. Therefore, in order to improve the review, more databases should be included. Besides databases, the language constraint should also be relaxed, though Eggner, Jüni, Bartlett, Holenstein, & Sterne (2003) suggest that in health care systematic reviews, language restrictions have been shown not to be a major source of bias. In order to get recent evidence, this review can be updated over time by replicating the same research procedure.

3.3 CONCLUSION

This chapter systematically reviews the literature on health care demand, specifically the utilisation of health services. The findings from this review will be used to support the empirical analysis in Chapters 4, 5 and 6. In the review I have tried to determine how to model health care utilisation by exploring the empirical methods and variables used in selected studies. Variables used in health care demand models can be categorised into several categories: health status, socioeconomic factors, insurance status and supply side variables (e.g. density of doctors and beds per certain number of population). Consistent with the nature of the data used in many studies, count data model is frequently employed in the analysis. The influence of health status, income and education on GP utilisation has also been examined. Of these three variables of interest, only health status shows significantly consistent results, which suggests healthy people demand less health care than those of poorer health. Income and education show mixed findings.

CHAPTER FOUR

4 MODELLING HEALTH CARE DEMAND WITH A BINARY ENDOGENOUS REGRESSOR

4.1 INTRODUCTION

This chapter focuses on modelling the utilisation of three types of health care services in the United Kingdom (UK). The analysis is based on the framework that people utilise health care in order to increase their utility resulting from the increase in health capital. From the review of selected studies in Chapter 3, it reveals that apart from utilisation of GP services, other health services receive less attention in empirical studies based on the data from the UK, particularly in studies within count data framework.

It is undeniable that as a 'gatekeeper' GP plays important roles in deciding further health care use which is based on health conditions, but individuals may still play a major part in determining the use. Besides health status, the utilisation of further services, such as outpatient and inpatient services, may be influenced by other factors as well, thus requiring further investigations. Therefore in this chapter, in addition to GP utilisation, I have also modelled the utilisation for outpatient and inpatient. However, care needs to be exercised whilst developing the models, since self-reported health status has a strong possibility of being simultaneously determined by other variables appearing within the model, and therefore endogenous. Hence, using the binary health status, the model has been estimated using the Full Information Maximum Likelihood (FIML) in order to take into account the endogeneity of the health status. After the introduction in this section, the objective of the study is explained next in Section 4.2 and followed by the methods in Section 4.3. Results are presented in Section 4.4, Section 4.5 discusses the results and Section 4.6 concludes the analysis.

4.2 OBJECTIVE OF THE STUDY

The objective of this chapter is to identify the influence of personal characteristics, health and health related, socioeconomic and supply side factors of the population on three types of healthcare utilisations which are potentially exposed to endogeneity bias. The study begins with the standard count data models, followed by models that are based on an endogeneous binary treatment approach. The three health care utilisations that have been modelled are: GP consultations, outpatient visits; and number of inpatient episodes.

4.3 METHODS

4.3.1 Data

4.3.1.1 Background

For this empirical analysis, data from the General Household Survey (GHS) 2004/2005 for Great Britain are used. The GHS is used because it contains rich information on the frequency of utilisation of various types of medical care, as well as other important variables that might influence the utilisation level. This information allows the use of count data models in estimating the uses of medical care. The GHS[5] is a national survey on various issues concerning private households which have been carried out annually. It has two types of questionnaires namely (1) household questionnaire which is completed by the Household Reference Person (HRP) and (2) individual questionnaire which is completed by a household member aged 16 and over.

In 2004/2005 survey, it covers 8,700 households which consist of 20,421 individuals of all ages. All adults aged 16 or over were interviewed while proxies were used to answer on behalf of the children. Sampling process involves a two-stage sampling technique. The first stage, known as Primary Sampling Units (PSU), were based on postcode sectors, while the second stage, or Secondary Sampling Units (SSU), were addresses within those sectors. All individuals or proxies within selected households are interviewed.

4.3.1.2 Sample selection and missing values

Due to missing data, only 14,706 observations are left for data analysis which represents 72% (known as *reduced sample* henceforth) of the original sample size, consisting of 20,421 observations. All observations that have at least one missing value in variables used are deleted. The summary statistics of the original sample and reduced sample are compared (see *Appendix 4-I*, p. 190). It shows that the maximum age for the reduced sample is only 69 compared to 99 in the original

[5] The General Household Survey 2004-2005 was produced by the Office for National Statistics-Social and Vital Statistics Division, sponsored by the Office for National Statistics, Department of Health, Office of the Deputy Prime Minister, Department for Culture, Media and Sport, Department for Work and Pensions, Inland Revenue, Department for Education and Skills, Scottish Executive Government Actuary's Department and supplied by the UK Data Archive. The data are Crown copyright.

sample. This variable is checked and it is confirmed that all observations aged 69 and above are dropped from the estimation sample due to missing values for education level. In this case, all analyses and discussions are confined to members of the population aged 0 to 69 only.

4.3.2 Selection of variables

4.3.2.1 Dependent variables

There are three types of health care demand modelled in this study, as shown in Table 4.1. The values of these three types of health care have been recoded from their original values in order to suit the econometric models that include zero counts, which are assumed to represent the non-users.[6]

Table 4.1 Dependent variables for health care demand equations

Variables	Definitions
GP	Number of doctor consultations for the past 2 weeks excluding the consultations made on behalf other person in the household
OUTPATIENT	Number of outpatient visits (casualty or outpatient department) in the last 3 months
INPATIENT	Number of separate stays as inpatient in the past 12 months excluding maternity stays

4.3.2.2 Explanatory variables

Explanatory variables have been selected based on the previous literature as discussed in Chapter 2. This selection has been narrowed down from a large set of variables to the set reported in Table 4.2. Detailed definitions of variables as given in the GHS 2004/2005 documentation, and also the transformation process, are explained in *Appendix 4-II*, pp. 191-194.

[6] For example, frequency of usage of *GP*, *OUTPATIENTt* and *INPATIENT*, were previously coded as missing values for non-users. Such missing values have been recoded to zeros.

Table 4.2 Explanatory variables for health care equations

Variables	Definitions
I. Personal characteristics	
AGE	Age in years
AGESQ	Square of age in years/100
MALE	1 if gender is male, 0 if female
Marital status[7]	
SINGLE	1 if single, widowed, divorce, separated, 0 otherwise
COHAB	1 if cohabitate, 0 otherwise
MARRIED	1 if married, 0 otherwise
II. Health status and health related variables	
GOODHLTH	1 if assessed health state is good, 0 poor
LIMITACT	Number of days with activities prevented because of illness
LONG ILL	Number of longstanding illnesses
III. Socioeconomic status	
Education level	
HIGH EDU	1 if has higher qualification, 0 otherwise
OTHER EDU	1 if has other qualification, 0 otherwise
NO EDU	1 if has no qualification, 0 otherwise
Income	
INCOME	Log of equivalised household income
Country	*Country*
ENGLAND	1 if live in England, 0 otherwise
WALES	1 if live in Wales, 0 otherwise
SCOTLAND	1 if live in Scotland, 0 otherwise
Density of GP	
GPPOP	Number of GP per thousand populations

Note: Variables in *italics* are the reference variables

4.3.3 Descriptive statistics

Prior to any complex statistical analysis, it is important to convey an overall picture of the distributions of the key variables, and to provide summary statistics of all the data used. Descriptive statistics is a basic form of statistical analysis that is used to exemplify the basic properties of the data in a clear and sensible way. The most commonly used of these methods come under the heading of univariate analysis, which involves the determination of: the distribution which is normally captured by the frequency distribution of each variable; measures of central

[7] Marital status of children have been recoded according to HRP marital status.

tendency which consist of mean and median; and the dispersion of the data that have been represented by variance and standard deviation.

The descriptive analysis begins by presenting the summary statistics of the dependent variables. This is followed by a discussion on the frequency distribution and pattern of use by age-category, gender and health status. Then, the summary statistics of independent variables are presented. The distributions of other independent variables according to the level of self-assessed health status (SAH) are also discussed in order to get a broad understanding of the relationship between them.

4.3.4 The empirical specifications

In this section, two categories of specification are discussed by assuming (1) exogeneity of self-assessed health (SAH) and (2) endogeneity of SAH. Figure 4.1 exhibits the organisation of the steps taken in the analysis.

4.3.4.1 Exogenous health state

The initial empirical model for health care demand, Y, is specified as below:

$$\mathrm{E}\left(Y = y_{ij} \middle| x_i\right) = \exp\left(x_i^{'}\beta_j\right), \qquad i = 1...N, \quad j = 1...J \tag{4.1}$$

where y_{ij} is the realised demand for health care type *j* for individual *i* and x_i is a vector of characteristics of individual *i*, assumed to be exogenous, that determine y_{ij} (subscript *j* will be dropped in the following discussion for notational convenience).

Since the dependent variables are all restricted to non-negative integer values, count data models are required. The most popular of these models are the Poisson and Negative Binomial (NB) models. As no assumption has been made to distinguish different decision processes between the contact decision and the utilisation decision, hurdle specifications are not called-for at this stage. Besides, it is difficult to identify from the survey whether the demand for a particular health care is from the same episode of illness, which makes it difficult to differentiate the types of process.

Suppose the number of occurrences for y_i, given x_i, is Poisson distributed with density:

$$f(y_i|x_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, \qquad y_i = 0,1,2... \tag{4.2}$$

with the consequence that

$$\mathrm{E}(y_i|x_i) = \lambda_i = \exp(x_i^{'}\beta\ ) = \mathrm{V}(y_i|x_i) \tag{4.3}$$

Equation (4.3) shows the equality of the conditional mean and conditional variance (equidispersion). Count data may turn out to be overdispersed because of unobserved heterogeneity; a different reason for occurrences of the same consequent events; or the number of the events are dependent on the number of events occurs in the previous units. In these cases, the restrictive assumption of the Poisson model that its mean equals variance is violated. In the case of overdispersion, the NB model could be used as an alternative to the Poisson model. Suppose, for every individual *i*, we introduce the random term that may cause by specification error or unobserved heterogeneity, ε_i, into the conditional mean function of the Poisson model as the following

$$\mathrm{E}[y_i|x_i,\varepsilon_i] = \exp(x_i^{'}\beta + \varepsilon_i), \qquad y_i > 0,1,2.....$$

$$= \lambda_i \upsilon_i, \qquad \lambda_i = \exp(x_i^{'}\beta) \text{ and } \upsilon_i = \exp(\varepsilon_i) \tag{4.4}$$

Conditional on x_i, and with some algebraic manipulations, Y has a negative binomial (NB) distribution with the density function given by

$$\Pr\left(y_i \middle| x_i\right) = \frac{\Gamma(y_i + \psi_i)}{\Gamma(y_i + 1)\Gamma(\psi_i)} \left(\frac{\psi_i}{\lambda_i + \psi_i}\right)^{\psi_i} \left(\frac{\lambda_i}{\lambda_i + \psi_i}\right)^{y_i}, \qquad y_i = 0,1,2,.... \tag{4.5}$$

where $\Gamma(.)$ is a *gamma* function; the index $\psi_i = (1/\alpha)\lambda_i^k$; $\alpha > 0$ is an overdispersion parameter and *k* is a constant. The mean and variance functions are specified as

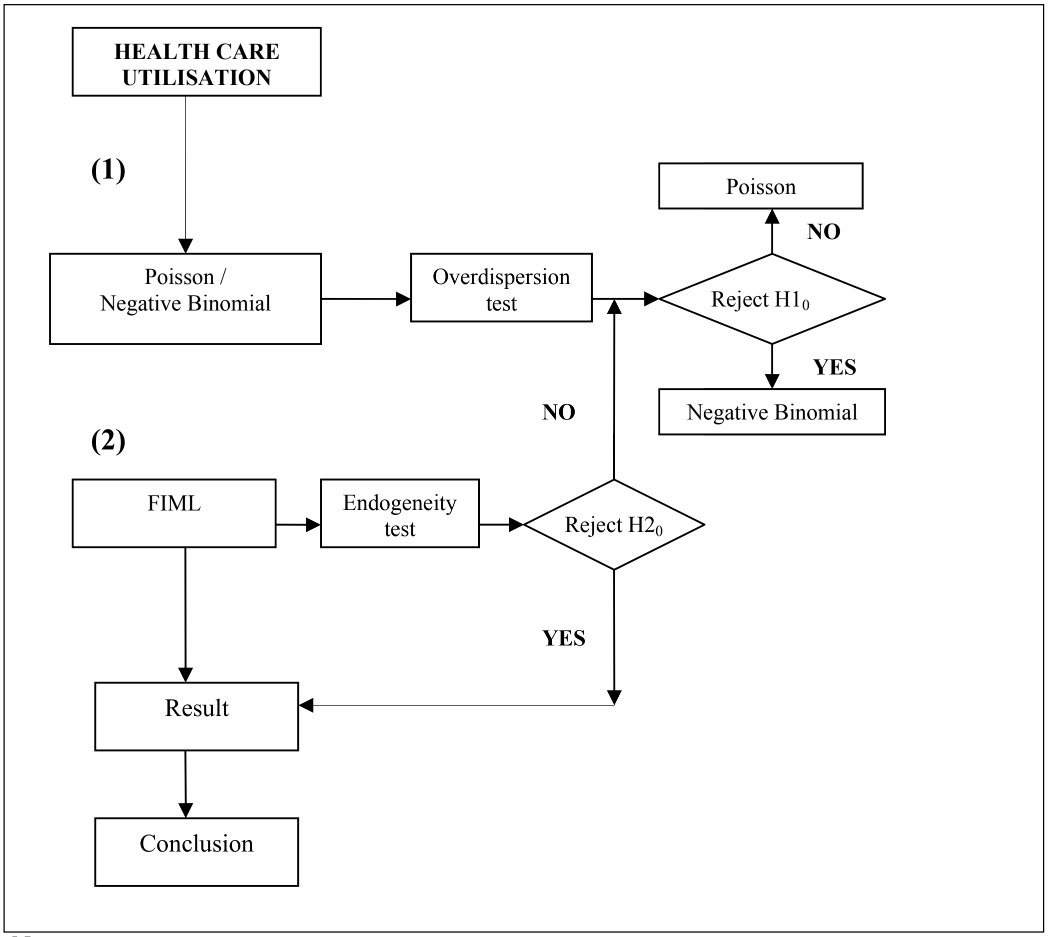
$\mathrm{E}\left(y_i \middle| x_i\right) = \lambda_i$ and $\mathrm{V}\left(y_i \middle| x_i\right) = \lambda_i + \alpha\lambda_i^{2-k}$

There are two variance functions depending on *k*. If we set *k*=1, the variance becomes proportional to the mean (known as the NB1 model) while by setting *k*=0, the variance becomes a quadratic function of the mean (known as the NB2) model (see Cameron & Trivedi, 1986). The model will simplifie to the Poisson if $\alpha = 0$. The LR and Wald tests are used to test for overdispersion of all equations by considering the quadratic variance function of the negative binomial model:

$$\mathrm{V}\left(y_i \mid \lambda_i, \alpha\right) = \lambda_i + \alpha\lambda_i^2$$

The null hypothesis for the overdispersion test is when α equals 0. The LR test and Wald test are tested at 1% critical value. Since errors may be correlated within household, cluster-robust standard errors are used in all models.

Figure 4.1 The organisation of the empirical analysis



Notes:

$H1_0 = \alpha = 0$

$H2_0 = \rho = 0$

4.3.4.2 Endogenous health state

In health care demand models, true health capital is unobserved, therefore the self-assessed of general health (SAH) is chosen in this paper to represent the level of health. The ordinal values are assigned for this health state where each respondent chose to rate his or hers as 'not good', 'fairly good' or 'good'. As the estimation procedure adopted here allows only for a binary endogenous switching variable, the 'not good', and 'fairly good' are combined into one category known as ‘poor’. Table 4.3 shows the frequency distribution of SAH. It shows that around two thirds of those observed, perceived their health status as good.

While developing the demand model, one of the regressors, GOODHLTH, is suspected to be dependent on the recent utilisation of health care. For example, any idiosyncratic shock in health might influence demand for health care, which then influences the individual’s perception of their own-long term general health (Windmeijer & Santos-Silva, 1997).

Besides, the SAH is a self-selection variable which is possibly determined by other factors. In this case, models that assume health state as an exogenous variable would be inconsistently estimated. Accordingly, GOODHLTH is instrumented by a set of covariates z_i. Although some instruments are not significant when they are directly being included in the health care demand models, they might help in explaining the self-assessed health state by the respondents. The chosen instrumental variables that have been excluded from the main equations are described in Table 4.4 which includes ethnicity, socioeconomic activities and housing tenure. In many studies (e.g. Bago d'Uva, 2005; Geil et al., 1997; Yen et al., 2001), socioeconomic activities are included in health care demand model as a proxy of opportunity costs for seeking health care.

Given that the data in this study also consist of individuals aged less than sixteen, the use of socioeconomic activities of the Household Reference Person (HRP) is believed to be more appropriate. This is because, for children, the decision to seek health care might depends on the decision of the HRP. However, there is no evidence in this study that socioeconomic activities of the HRP have a significant direct effect on health care demand. Therefore it was excluded from the main equations and used as an instrument for health status. Housing tenure is used as an instrument because as found in some studies, housing tenure might influence health status (Dunn, 2002; Macintyre, Hiscock, Kearns, & Ellaway, 2001; Pollack, Knesebeck, & Siegrist, 2004).

Table 4.3 Frequency distribution of self-assessed health state

		Frequency	Percent
Not Good	1,416		
Fairly Good	3,270		
Poor		4,686	31.9
Good		10,020	68.1
Total		14,706	100.00

Table 4.4 Instruments for health care demand models

Variables	Definition	Mean	Std. Dev.	Min	Max
WORK	1, if working, 0 otherwise	0.766	0.423	0	1
UNEMPLOYE	1, if unemployed, 0 otherwise	0.017	0.129	0	1
INACTIVE	1, if economic inactive, 0 otherwise	0.217	0.412	0	1
NONWHITE	1 if non-whites, 0 if whites	0.087	0.282	0	1
OWNERS	1 if house owners, 0 otherwise	0.714	0.452	0	1
SOCIAL	1 if social renters, 0 otherwise	0.180	0.384	0	1
PRIVATE	1 if private renters, 0 otherwise	0.106	0.307	0	1

Note: Variables in *italics* are the reference variables

In dealing with the endogeneity problem, the *Full Information Maximum Likelihood (FIML)* estimation as discussed in Terza (1998) is used. The code for fitting the FIML model is based on Miranda (2006).

1. The Full Information Maximum Likelihood (FIML)

Suppose that the model has the exponential form as below:

$$y_i = \exp\left(\delta \mathrm{GOODHLTH}_i + x_i^{'}\beta + u_i\right) + \varepsilon_i, \quad i = 1 \ldots N \tag{4.6}$$

$$y_i^* = \varphi y_i + z_i^{'}\gamma + w_i \tag{4.7}$$

where y_i represents health care use, y_i^* is an unobserved health capital, x_i is a vector of explanatory variables for y_i, GOODHLTH_i is a binary endogenous switching variable and z_i is a vector of explanatory variable that determine y_i^*; consisting all x_s and three excluded variables from the main equation - that are ethnicity (NONWHITE) dummy variables for the economic status of the household reference person (*WORKING*, UNEMPLOYED, AND OTHER UNEMPLOYED) and housing tenure (*OWNER*, SOCIAL, PRIVATE). Variables in *italics* are the reference groups. We observed

$$\text{GOODHLTH}_i = 1 \text{ if } y_i^* > 0$$
$$\text{GOODHLTH}_i = 0 \text{ otherwise}$$

As pointed out by Windmeijer and Santos-Silva (1997), the model is only *coherent* when the system is triangular. By referring to Equation (4.6) and (4.7), the coherency is achieved when δ =0 or φ =0, such that

$$\Pr\left[\text{GOODHLTH}_i = 1\right] + \Pr\left[\text{GOODHLTH}_i = 0\right]$$
$$= F\left[\varphi \exp\left(\delta + x_i'\beta\right) + z_i'\gamma\right] + \left[1 - F\left(\varphi \exp\left(x_i'\beta\right) + z_i'\gamma\right)\right] = 1$$

only if either δ or φ is equal to 0 (see Blundell & Smith, 1994; Gourieroux, Laffont, & Monfort, 1980). In this case, I assume φ =0, which means that current health care consumption, y_i, does not directly affect y_i^* that represents long term health capital. Thus Equation (4.7) becomes:

$$y_i^* = z_i'\gamma + w_i$$

The error term u_i and w_i are supposed, conditional on the exogenous variables, to be jointly normal with mean zero and covariance matrix

$$Cov[u_i, w_i] = \begin{pmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}$$

Based on Terza (1998), the log likelihood function is

$$LogL = \sum_{i=1}^{n} \ln\left\{ f\left(y_i, \text{GOODHLTH}_i \left| x_i, z_i \right.\right)\right\}$$

The mean of the model is μ_i which is equal to

$$\mathrm{E}\left[y_i \left| \text{GOODHLTH}_i, x_i, z_i \right.\right] = \exp\left(x_i^{'}\beta + 0.5\sigma^2 \right).$$
$$\left[\text{GOODHLTH}_i \left\{ \frac{\Phi\left(z_i^{'}\gamma + \sigma\rho \right)}{\Phi\left(z_i^{'}\gamma \right)} \right\} + \left(1 - \text{GOODHLTH}_i \right) \left\{ \frac{1 - \Phi\left(z_i^{'}\gamma + \sigma\rho \right)}{1 - \Phi\left(z_i^{'}\gamma \right)} \right\} \right]$$

with variance

$$\mathrm{V}\left[y_i \left| \text{GOODHLTH}_i, x_i, z_i \right.\right] = \mu_i + k\mu_i^2; \qquad k = \exp\left(2\sigma^2 \right) - \exp\left(\sigma^2 \right)$$

GOODHLTH_i is an exogenous switching variable if ρ =0, in which case u_i and w_i are independent. Hence exogeneity can be tested using Wald test of H_0: ρ =0.

4.4 RESULTS

This section begins by reporting the descriptive statistics and is later followed by the results based on both specifications that are, assuming the exogeneity and endogeneity of SAH.

4.4.1 Descriptive statistics for health care demand

4.4.1.1 Summary statistics of dependent variables

Each type of utilisation has a different reference interval which reflects the amount of visits reported. For instance, as shown in Table 4.5, in a two-weeks reference interval, the maximum number for GP consultations is 7 and for a three months reference period, the number of outpatient visits reached a maximum of 36 visits. The number of separate stays as inpatient or inpatient episodes is measured by using a one year reference period and has a maximum of 6 separate inpatient stays. By looking at the mean values, all types of demand have values less than 1, which reflects that most respondents have zero demand within the reference periods.

Table 4.5 Summary statistics of dependent variables

Variables	Mean	Std. Dev.	Min	Max
GP	0.184	0.515	0	7
OUTPATIENT	0.272	1.182	0	36
INPATIENT	0.079	0.367	0	6

4.4.1.2 Frequency distribution of dependent variables

Figures 4.2 to 4.4, show the histograms of the utilisation percentage of each health care type within the specific time period. From the histograms, it clearly suggests that all types of demand have an excess zero occurrence with long right tails. Zero count in the data represents that respondents have not utilised specific health care within the specific period at all. For instance, around 85% of the observations have never visited a GP or outpatient department within the reference period, while 93% have never been an inpatient in the last year.

4.4.1.3 Frequency of use by gender and age category

In all cases, men have a higher percentage of zero utilisation than women. For example, for GP consultations, 88% of men have never consulted a GP, compared to 83% of women. As for outpatient and inpatient use, although women have higher utilisation, the differences are marginal, especially for outpatient visits with only 0.5% difference. Individuals aged between 0-4 and 64-69 have more GP consultations compared to other age categories while 91.5% of those who are between 5-15, are non-users within the reference period. Individuals within this category (age 5-15) also have the lowest utilisation rate for outpatient and inpatient. People in age category 64 and over have the highest utilisation rate for both outpatient and inpatient.

Figure 4.2 Frequency distribution of GP consultations

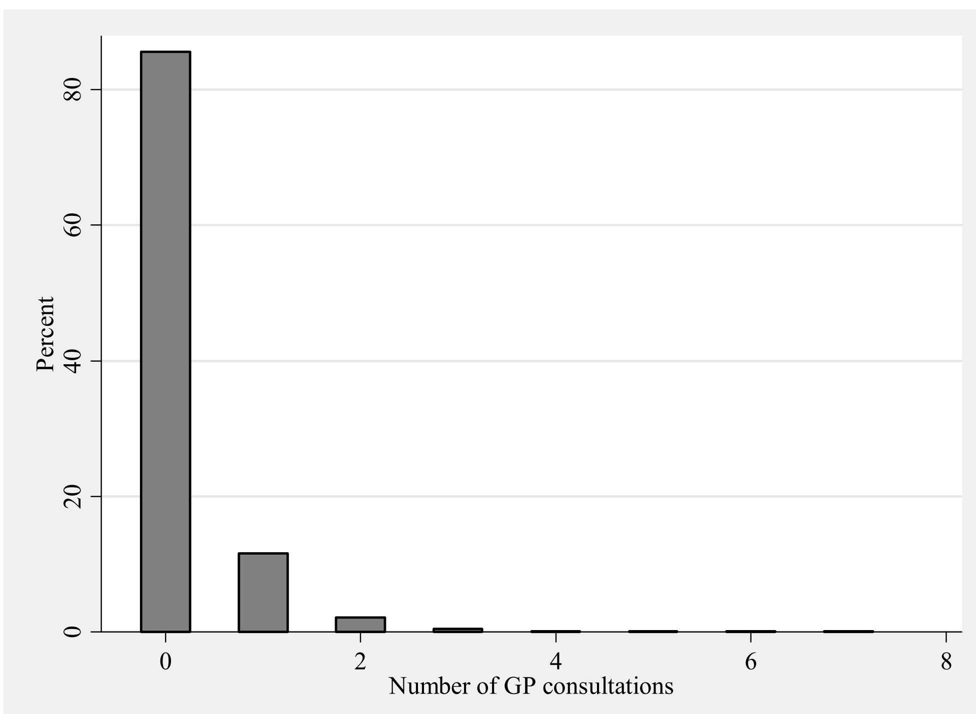


Figure 4.3 Frequency distribution of outpatient visits

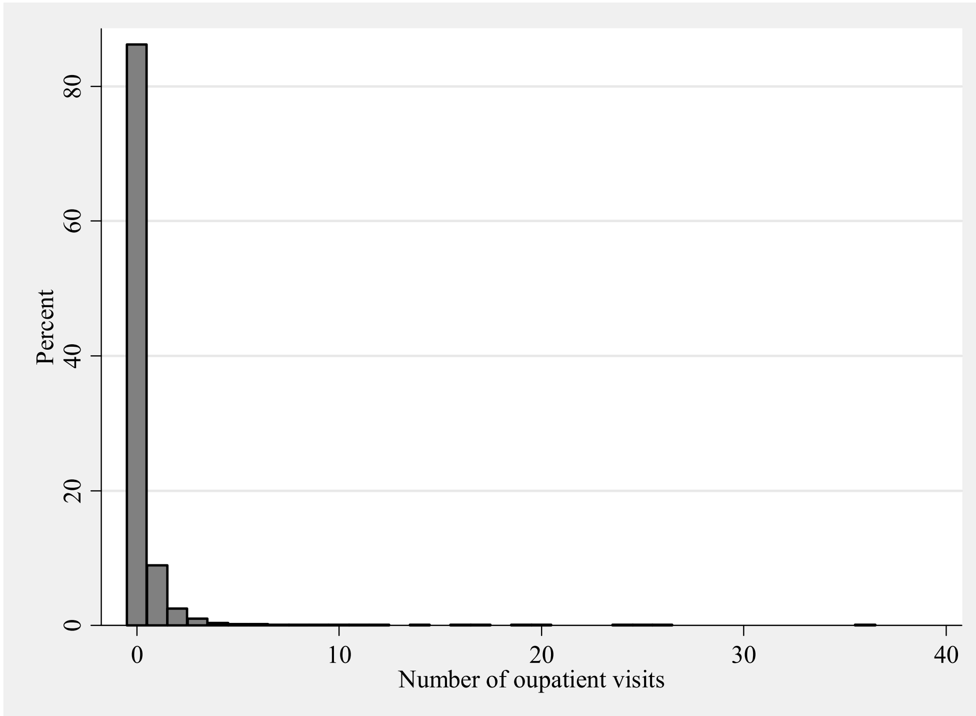
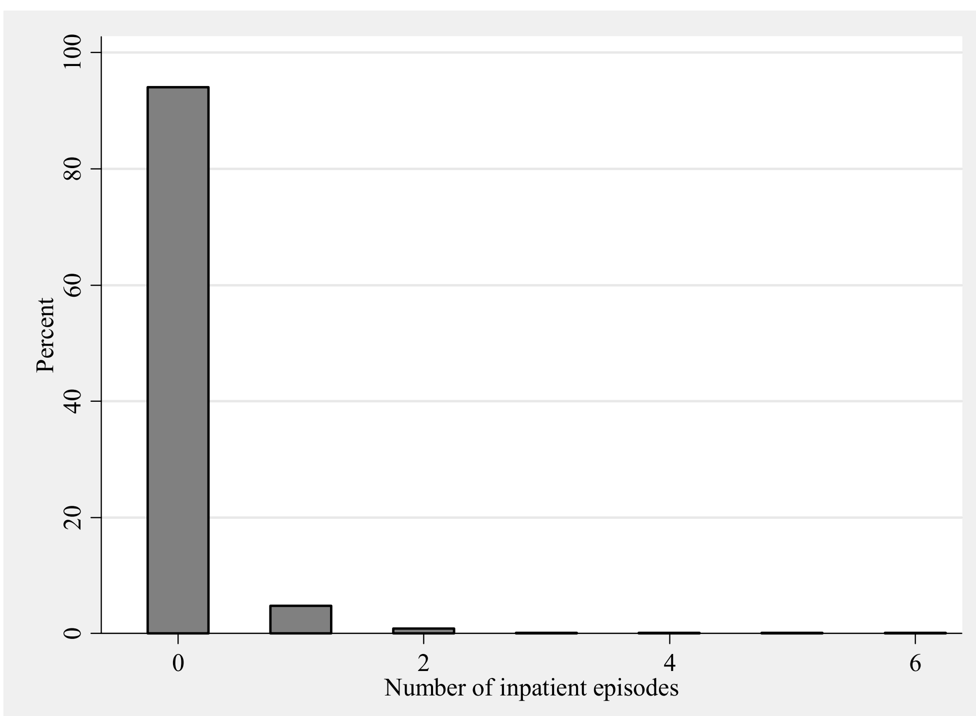


Figure 4.4 Frequency distribution of inpatient episodes



4.4.1.4 Summary statistics of explanatory variables

Table 4.6 presents the summary statistics of explanatory variables from 14,706 observations. The summary includes the mean, standard deviation of the mean values, and the minimum and maximum observation of each variable. Although the maximum days with activities prevented due to illness (LIMITACT) in the past two weeks before the interview is 14, its mean is just 0.94. This is because 87.58% of the observations have no limitation in performing daily activities due to health reasons. The mean of the number of longstanding illness (LONG_ILL) is also less than 1 while its maximum occurrence is 6 illnesses. Average age is 34 while 48% of the samples are males.

More than half (57.5%) of the observations are married while 50% have qualifications other than higher qualifications. Most of the respondents are from England. The GP:population ratio (GPPOP) suggests that, on average, there are about six GPs per ten thousand of the population. From health care demand literatures, health status is confirmed to be one of the most important variables that determine utilisation. The self-assessed health status (SAH) is frequently used as a proxy of health status. However, in this study SAH is believed to be endogenous within the model. Before more formal treatments for the endogeneity problem of SAH, some exploratory statistics of the distribution of SAH by other explanatory variables are presented in the next three tables.

Table 4.7 shows how SAH is distributed by gender. The majority of both males and females have perceived their health as 'good' rather than 'poor'. The distribution of SAH by age-category as shown in Table 4.8, shows that more than 70% of the observations within age-category 0-4, 5-15, 16-44 have regarded themselves as having good health. This percentage decreases to only 54.95% for age-category 45-64. On the other hand, only 47.8% who are aged 64 and over assessed their health as poor.

The association between number of reported longstanding illnesses and SAH is also reported here (see Table 4.9). The types of illness reported are based on the International Classification of Diseases (ICD). Although the majority of individuals (81%) with no longstanding illness have rated themselves as having a good SAH, there are some remaining that perceived their health as poor. However, on average, the proportions of individual reported poor health are greater than good, when longstanding illnesses are reported.

Table 4.6 Summary statistics of explanatory variables in health care demand equation

Variables	Mean	Std.Dev.	Min	Max
GOODHLTH	0.681	0.466	0	1
LIMITACT	0.940	3.100	0	14
LONG_ILL	0.413	0.808	0	6
AGE	34.317	19.664	0	69
AGESQ (AGE*AGE/100)	15.643	13.720	0	47.6
MALE	0.480	0.500	0	1
SINGLE	0.311	0.463	0	1
COHAB	0.113	0.317	0	1
MARRIED	0.575	0.494	0	1
INCOME	5.054	1.089	0	9.6
HIGH_EDU	0.296	0.457	0	1
OTHER_EDU	0.502	0.500	0	1
NO_EDU	0.201	0.401	0	1
ENGLAND	0.860	0.348	0	1
WALES	0.040	0.197	0	1
SCOTLAND	0.100	0.300	0	1
GPPOP	0.640	0.048	0.58	0.74

Table 4.7 SAH by gender

SAH	Gender				
	Male	%	Female	%	Total
Good	4,952	69	5,095	66.63	10,020
Poor	2,134	30.23	2,552	33.37	4,686
Total	7,059	100.00	7,647	100.00	14,706

Table 4.8 SAH by age-category

SAH	Age category										
	0-4	%	5-15	%	16-44	%	45-64	%	≥65	%	Total
Good	837	79.0	2,023	83.6	4,456	71.9	2,318	55.0	386	47.8	10,020
Poor	223	21.0	397	16.4	1,744	28.1	1,900	45.0	422	52.2	4,686
Total	1,060	100	2,420	100	6,200	100	4,218	100	808	100	14,706

Table 4.9 SAH by number of longstanding illnesses

SAH	Number of illnesses												
	0	%	1	%	2	%	3	%	4	%	>5	%	Total
Good	8,638	81.7	1,172	40.5	174	21.7	29	10.7	6	5.8	1	1.5	10,020
Poor	1,932	18.3	1,723	59.5	627	78.3	242	59.3	97	94.2	65	98.5	4,686
Total	10,570	100	2,895	100	801	100	271	100	103	100	66	100	14,706

4.4.2 Exogenous health state

Following the sequence described in Figure 4.1, the next section reports the results from several regression models starting with the Poisson and the negative binomial (NB) as shown in Table 4.10. This is followed by the overdispersion tests which consist of the LR and Wald tests (see Table 4.11).

4.4.2.1 GP consultations

While the effects of all variables in the Poisson and the NB models have the same direction, the significant level might be different. For instance, although the direction of the effect of OTHER_EDU is the same in these two models, it is only significant in the NB model. All health related variables in both the Poisson and NB models - GOODHLTH, LIMITACT and LONG_ILL are significant at 1%

significant level. Males have less frequency of visits than females and the effects are very significant in both models. Age, marital status, income, country and GP:population ratio have no significant effects in determining GP visits.

4.4.2.2 Outpatient visits

Except for health related variables, the significant determinants for outpatient visits are quite different from those of the GP. For outpatient visits, age is not significant in both models with different directions. Age has a 'U' shaped effect in the NB model while in the Poisson, it has the opposite effect. Education, country and GP density also play some roles in both models for outpatient visits. The effects of income and being married are only significant in the NB model.

4.4.2.3 Inpatient episodes

As for inpatient episodes, the direction of effects in these two models is comparable for all variables except for COHAB. However, the effect of COHAB is not significant in both models. Health status and other health related variables, age and gender have significantly determined inpatient episodes in both models while marital status, income, education level and country do not show any significant influence. The effect of GP density is only significant in the Poisson model.

4.4.2.4 Summary

All health related variables which are GOODHLTH, LIMITACT and LONG_ILL are very important variables in determining all types of health care use. The effects are consistent between models and type of use. Respondents with a good self-assessed health state demand less health care then those who rated themselves as having poor health. Although the effect is not significant in outpatient visits, males utilise less health care than the females in all types of services considered in this analysis. The same can be said for respondents with no education. They demand less health care when compared to those with other or higher education, though this is not significant for inpatient visits.

Dummy variables for country which are used to pick up the differences in health system between England, Wales and Scotland show that people in Scotland demand less health care compared to those in England. However, the impacts are significant for outpatient visits only. The only variable that represents supply side factor for the health care in this study is the ratio of a GP per thousands of population, GPPOP. It shows that GPPOP has a positive effect in all equations and suggests that the more GPs in the area there are, the more frequent the demand for health care. However, GPPOP is significant for outpatient visits and inpatient episodes (Poisson model) only. Except for health related variables, the effects of other variables depend on the care types and specification required. Since some significant levels are different between both models, the LR test and Wald test are required in selecting the superior model in explaining the data.

Table 4.10 Poisson and Negative Binomial estimates for GP, outpatient and inpatient utilisations

N=14706

	GP				OUTPATIENT				INPATIENT			
	Poisson		NB		Poisson		NB		Poisson		NB	
	Coef	s.e	coef	s.e	coef	s.e	coef	s.e	coef	s.e	coef	s.e
AGE	-0.006	0.005	-0.008	0.005	0.004	0.007	-0.008	0.007	-0.022***	0.008	-0.022***	0.008
AGESQ	0.002	0.007	0.006	0.007	-0.001	0.010	0.018*	0.010	0.026**	0.011	0.027**	0.011
MALE	-0.299***	0.045	-0.305***	0.045	-0.037	0.071	-0.018	0.063	-0.176**	0.074	-0.141*	0.075
COHAB	0.048	0.083	0.053	0.084	0.082	0.138	-0.064	0.106	0.0003	0.145	-0.049	0.138
MARRIED	0.026	0.052	0.020	0.052	-0.091	0.081	-0.149**	0.070	-0.059	0.086	-0.031	0.088
GOODHLTH	-0.872***	0.054	-0.859***	0.053	-1.078***	0.082	-1.034***	0.071	-1.425***	0.092	-1.397***	0.091
LIMITACT	0.092***	0.005	0.097***	0.005	0.074***	0.009	0.090***	0.008	0.069***	0.008	0.073***	0.007
LONG_ILL	0.114***	0.022	0.131***	0.024	0.237***	0.033	0.341***	0.033	0.235***	0.032	0.258***	0.035
INCOME	-0.013	0.023	-0.015	0.023	-0.008	0.043	0.061*	0.032	-0.014	0.034	-0.009	0.034
OTHER_EDU	-0.089	0.055	-0.111**	0.056	-0.196**	0.082	-0.159	0.072	-0.069	0.093	-0.093	0.092
NO_EDU	-0.125*	0.066	-0.146**	0.068	-0.262**	0.112	-0.227**	0.097	-0.063	0.114	-0.046	0.114
WALES	-0.047	0.125	-0.065	0.126	-0.287**	0.140	-0.326**	0.145	0.056	0.177	0.106	0.192
SCOTLAND	-0.065	0.111	-0.064	0.112	-0.378*	0.201	-0.340**	0.156	-0.234	0.175	-0.176	0.166
GPPOP	0.896	0.691	0.822	0.704	2.330*	1.241	1.142**	1.042	2.007**	1.014	1.127	0.981
CONSTANT	-1.610***	0.454	-1.551***	0.465	-2.415***	0.784	-1.994***	0.684	-2.883***	0.708	-2.421***	0.675
α			0.857	0.100			4.321	0.246			3.022	0.340
LogL	-6950.388		-6842.7379		-10179.302		-7893.9289		-3753.613		-3558.7541	

The symbols ***, ** and * denote 1, 5 and 10% level of significance, respectively

4.4.2.5 Overdispersion tests

1. **The Likelihood Ratio (LR) tests**

Table 4.11 The Likelihood ratio Tests

	GP	OUTPATIENT	INPATIENT
LR statistics	2(6950.388-6842.738) =215.3	2(10179.302-7893.929) =4570.75	2(3753.613-3558.754) =389.72
Reject/Accept H_0 * Reject H_0 if test statistics > $\chi^2(01)$ * At 1% critical value, $\chi^2(01)$=6.63	Reject H_0	Reject H_0	Reject H_0

The LR tests on all equations suggest that the negative binomial models are more favoured than the Poisson models in explaining the data.

2. **The Wald tests**

From the negative binomial models, the Wald test[8] for GP, outpatient and inpatient equations are 8.57, 17.56 and 8.89 respectively. At 1% critical value, we reject H_0 for all the types of demand since all the test statistics are greater then 2.33 which is the value of. $z_{0.99}(01)$. From both LR and Wald tests, it suggests a strong rejection of the Poisson models.

4.4.3 Endogenous health state

In this section, results from the Full Information Maximum Likelihood (FIML) model are reported and compared to those from the negative binomial model (NB). Table 4.12 presents the results of GP consultations, outpatient visits and inpatient episodes from FIML model.

[8] Wald Test test statistics = α/s.e

4.4.3.1 GP consultations

From Table 4.12 it shows that except for INCOME, all variables in FIML model report the same sign as in the NB model but with a different significant level. MALE still plays a very significant role in determining the number of GP consultations with a negative relationship. The p-value for σ indicates that the data are overdispersed and the p-value for ρ suggest the exogeneity of GOODHLTH is rejected at 1% significant level.

4.4.3.2 Outpatient visits

All health related variables, age, marital status, income and education are very significant in the FIML model but MALE is not significant. The hypothesis of σ equals zero is rejected at 1% significant level which suggests overdispersion but the exogeneity of GOODHLTH in the outpatient equation cannot be rejected at 1% level.

4.4.3.3 Inpatient episodes

As a decision to stay as an inpatient depends on a doctor's decision, many demographic factors (except for age and gender) become less important in determining inpatient episodes. Health related variables are very significant with expected directions in both FIML and NB models. The hypothesis that ρ equal to zero cannot be rejected at 1% significant level which implies that the model, statistically, is not exposed to endogeneity bias, thus health status can be treated as exogenous in the model.

Table 4.12 FIML estimates for GP, OUTPATIENT and INPATIENT

N=14706

GP	GP		OUTPATIENT		INPATIENT	
	coef	s.e	coef	s.e	coef	s.e
AGE	-0.013***	0.005	-0.022***	0.005	-0.021**	0.008
AGESQ	0.009	0.007	0.037***	0.007	0.026**	0.010
MALE	-0.298***	0.045	-0.042	0.046	-0.137*	0.074
COHAB	0.043	0.078	-0.306***	0.082	-0.041	0.127
MARRIED	0.033	0.051	-0.217***	0.051	-0.041	0.082
GOODHLTH	-1.624***	0.239	-0.834***	0.088	-1.578***	0.228
LIMITACT	0.081***	0.007	0.091***	0.004	0.074***	0.009
LONG_ILL	0.002	0.051	0.405***	0.027	0.241***	0.050
INCOME	0.010	0.024	0.102***	0.020	0.001	0.036
OTHER_EDU	-0.140***	0.053	-0.158***	0.057	-0.079	0.091
NO_EDU	-0.206***	0.069	-0.359***	0.070	-0.056	0.110
WALES	-0.072	0.114	-0.083	0.119	0.128	0.181
SCOTLAND	-0.074	0.107	-0.048	0.097	-0.219	0.178
GPPOP	0.874	0.673	-0.160	0.664	1.556	1.106
CONSTANT	-1.354***	0.479	-2.352***	0.468	-3.547***	0.770
GOODHLTH						
AGE	-0.023***	0.003	-0.023***	-0.023	-0.023***	0.003
AGESQ	0.017***	0.004	0.017***	0.017	0.017***	0.004
MALE	0.071***	0.024	0.017***	0.004	0.070***	0.024
COHAB	-0.094**	0.042	-0.009	0.029	-0.095**	0.042
MARRIED	-0.010	0.029	0.070	0.024	-0.010	0.029
LIMITACT	-0.078***	0.005	-0.076***	0.005	-0.076***	0.005
LONG_ILL	-0.745***	0.020	-0.744***	0.020	-0.745***	0.020
INCOME	0.090***	0.013	0.091***	0.013	0.092***	0.013
OTHER_EDU	-0.138***	0.029	-0.137***	0.029	-0.136***	0.029
NO_EDU	-0.236***	0.038	-0.237***	0.038	-0.238***	0.038
WALES	0.021	0.062	0.019	0.062	0.020	0.062
SCOTLAND	0.017	0.059	0.015	0.059	0.014	0.059
GPPOP	-0.196	0.369	-0.172	0.370	-0.165	0.370
UNEMPLOYED	0.083	0.094	0.087	0.095	0.091	0.095
INACTIVE	-0.091***	0.034	-0.090***	0.035	-0.090***	0.035
NONWHITE	-0.109**	0.043	-0.110**	0.043	-0.109**	0.043
SOCIAL	-0.245***	0.036	-0.238***	0.036	-0.239***	0.036
PRIVATE	-0.110***	0.041	-0.103**	0.041	-0.102**	0.041
CONSTANT	1.250***	0.247	1.229***	0.247	1.224***	0.247
σ	0.906***	0.045	1.436***	0.020	1.349***	0.051
ρ	0.494***	0.127	-0.056	0.039	0.089	0.097
LogL	-13971.34		-15003.43		-10697.26	
AIC	28014.67		30078.86		21466.51	
BIC	28288.13		30406.94		21739.97	

The symbols ***, ** and * denote 1, 5 and 10% level of significance, respectively

4.5 DISCUSSION

In the presence of endogeneity bias, result from FIML model is used for final discussion for GP consultations. As for outpatient and inpatient episodes, results are based on the negative binomial model which treats a self-assessed health state as an exogenous regressor. The self-assessed health (SAH) and number of days with activities prevented has a major influence on all equations with consistent directions. People with a good SAH utilise less health care than people with poor SAH while an increase in the number of activities prevented contribute to more utilisation. The number of longstanding illnesses also determines the frequency for outpatient visits and inpatient spells with a positive sign.

While age has a concave relationship with a maximum turning point in Gurmu (1997) and Windmeijer and Santos-Silva (1997), my analysis suggests the opposite findings which are consistent with Pohlmeier and Ulrich (1995) and Cameron et al. (1988). Age is significant in the number of GP consultations and inpatient episodes with a minimum point at 72 and 41 respectively. Nonetheless, these results cannot be directly compared as contradiction occurs and might be due to variation in type of demand investigated or utilisation of different dataset which focus on different age groups.

Consistent with other studies, (Atella, Brindisi, Deb, & Rosati, 2004; Gerdtham, 1997; Hunt-McCool et al., 1995) males utilise health care less frequently However, this effect is not significant for outpatient visits. The effects of marital status depend on the type of health care. It does not have a significant role in both GP consultations and inpatient episodes though being married or cohabiting is expected to decrease the demand for health care, especially for primary health care, as partners, sometimes, could provide alternative care at home. Being married and cohabiting is found to reduce the outpatient visits compared to being single. Income does not influence most types of utilisation except for outpatient visits with a positive effect. Even with insignificant effects, the demand for primary care, that is for GP consultations show a positive relationship with income while inpatient stays have a negative impact. Education has similar effects in all equations, which suggests that people without qualifications or who obtain other types of qualifications, demand less health care then those with higher qualification, though the effects are not significant for being an inpatient.

These findings, do not support the theoretical role of education in the Grossman theory of health demand (Grossman, 1972) which suggests that the efficiency of producing health stock depends on other forms of human capital, which include education. People with education are believed to have higher productivity in producing better health, and thus require less health care. These findings could be explained in a reverse direction. People with education might be more aware of their health condition and demand more health care to achieve a better health. However, there is no significant impact for inpatient spells. This is no surprise as some previous studies, which were based on a similar health system, also found a limited impact of education on health care demand (Bago d'Uva, 2006; Gerdtham, 1997).

The effect of country, which represent some different features in health care system within the UK suggest a significant difference in outpatient use only. Nevertheless, it shows that people in Scotland have demanded less health care compared to those in England. Finally, the GP:population ratio has shown a consistently positive effect in all equations. Except for having insignificant effects for GP consultations and inpatient episodes, these outcomes are consistent with Sarma & Simpson (2006) and Pohlmeier & Ulrich (1995).

4.6 CONCLUSION

In this chapter, the determinants of three types of health care are determined by using count data models. Health status and health related variables are not the only factors that affect utilisation for secondary care. Other factors may have some influence as well. While developing the utilisation models, one of the regressors, GOODHLTH, is believed to be endogenous within the models. As such, a model assuming endogeneity of this self-perceived health state variable have been considered, i.e. FIML model. The endogeneity test on all FIML specifications suggest that self-assessed health status is endogenous in GP consultations but not in outpatient visits and inpatient episodes. Thus, neglecting the endogeneity of the self-perceived health status in the GP equation would cause the model to be inconsistently estimated. The discussions for outpatient and inpatient use are based on the negative binomial model. The health care utilisations in this chapter have been modelled and based on the assumption of single data generating (DGP) process whereby the DGP between users and non-users are assumed to be the same. The two separate processes are discussed in the next chapter.

CHAPTER FIVE

5 MODELLING HEALTH CARE DEMAND WITH EXCESS ZEROES

5.1 INTRODUCTION

In survey data where the reference periods are short, zero occurrences of count events are inevitable. Respondents, for instance, may report zero utilisation when asking to report the number of doctor visits in the last two weeks or three months before the interview. Zeros would be of two types here which are reported by users who have not utilised the services within the reference period, known as *frequency zeros*, and zeros reported by the non-users; the latter type of zeros may be considered analogous to *abstention* in the consumption context.

Therefore, there is a large number of zeros in the datasets due to the short reference periods. However, short reference periods are preferred to those of the longer periods in order to minimise recalled bias among the respondents. Events that might be easier to be recalled (though it is not true in all cases) like hospitalisation episodes, may have longer reference periods, for example, between six or twelve months interval. Like unobserved heterogeneity, excess zeros could also cause overdispersion. In addition to the standard count data models, health care utilisation can be modelled by several extended count approaches in order to deal with excess zeros problems. These models include zero-inflated models which could distinguish between frequency zeros and abstention, two-part and latent class model (see Atella et al., 2004; Bago d'Uva, 2005; Deb & Trivedi, 1997; Gerdtham, 1997; Mangalore, 2006).

By referring to Chapter 4, we could see that at least 85% of the observations are the non-users within the reference periods. Therefore, this chapter aims to extend the model developed in Chapter 4 by using these extended count approaches. After this introduction, the specific objective of this chapter is presented in Section 5.2. Research methods which cover the source of data and empirical specifications are presented in Section 5.3. Results are presented and discussed in Section 5.4 while sections 5.5 and 5.6 end the analysis with a discussion and conclusion.

5.2 OBJECTIVES OF THE STUDY

This study attempts to model health care utilisation (as in Chapter 4) by using several extended count data approaches by exploiting the information of the frequencies of health care used from General Household Survey 2004/2005 for Great Britain. Results from the best model are compared with those from the standard count data models by using several model selection criteria. At the end of the section, the importance of four types of determinants which are personal characteristics, health and health related; socioeconomic and supply side variables are discussed with some possible policy implications.

5.3 METHODS

5.3.1 Data

Data and variables used throughout this chapter are the same as in Chapter 4 (see Sections 4.3.1 and 4.3.2 for data and variables descriptions)

5.3.2 The empirical specifications

There are a numbers of approaches taken in modelling demand for health care by considering the nature of the data used. This section outlines several models that are regularly used in the literatures in modelling health care with count dependent variable. The specifications of the models are based on Cameron and Trivedi (2006), Deb & Trivedi (1997; 2002) and Winkelmann and Zimmermann (1995). Throughout the discussions, y_i is used to represent the observed value of random variable Y (number of utilisation) for every individual i.

5.3.2.1 Negative binomial

Count data may turn out to be overdispersed because of unobserved heterogeneity, a different reason for occurrence of the same consequent events, or the number of the events are dependent on the number of events that occur in the previous units. In these cases, the restrictive assumption of the Poisson model that its mean equals variance is violated. Suppose, for every individual *i*, we introduce the random term that may cause by specification error or unobserved heterogeneity, ε_i, into the conditional mean function of the Poisson model as the followings

$$
\begin{aligned}
\mathrm{E}[y_i | x_i, \varepsilon_i] &= \exp\left(x_i^{'}\beta + \varepsilon_i\right); && y_i = 0,1,2.....\\
&= \lambda_i \upsilon_i; && \lambda_i = \exp(x_i^{'}\beta) \text{ and } \upsilon_i = \exp\left(\varepsilon_i\right) \qquad (5.1)
\end{aligned}
$$

Conditional on x_i, and with some algebraic manipulation, Y has a negative binomial (NB) distribution with the density function given by

$$\Pr\left(y_i \middle| x_i\right) = \frac{\Gamma(y_i + \psi_i)}{\Gamma(y_i + 1)\Gamma(\psi_i)} \left(\frac{\psi_i}{\lambda_i + \psi_i}\right)^{\psi_i} \left(\frac{\lambda_i}{\lambda_i + \psi_i}\right)^{y_i}, \quad y_i = 0,1,2,.... \qquad (5.2)$$

where $\Gamma(.)$, is a *gamma* function, the index $\psi_i = \left(1/\alpha\right)\lambda_i^k$, $\alpha > 0$ is an overdispersion parameter and *k* is a constant. The mean and variance function is specified as

$$\mathrm{E}\left(y_i \middle| x_i\right) = \lambda_i \quad \text{and} \quad \mathrm{V}\left(y_i \middle| x_i\right) = \lambda_i + \alpha\lambda_i^{2-k}$$

There are two variance functions depending on *k*. If we set *k*=1, the variance becomes proportional to the mean (known as the NB1 model) while by setting *k*=0, the variance becomes a quadratic function of the mean (known as the NB2) model (Cameron and Trivedi, 1986). The model will simplifies to the Poisson if α=0.

5.3.2.2 Zero-inflated model

The zero inflated Poisson (ZIP) and zero inflated negative binomial (ZINB) models take into account the distribution with excess zeros and tries to resolve it by adding extra weight to the probability of zero observation (Jones, 2000). In this model, individuals are split into two categories: non users and potential users or according to Deb & Trivedi (1997), *not at risk* and *at risk* population. Two possible processes are involved here where the first process observes zero values while the second process involve either Poisson or negative binomial, which allows for non-zero values and some zero values to be observed. The observed zeros in the second process might be among users that have potential to become health care users but have zero utilisation between the reference periods. Suppose we observe

$$y_i \sim \begin{cases} 0 & \textit{with probability}\, \varphi_i \\ g(y_i|x_i) & \textit{with probability}\, 1-\varphi_i \end{cases}$$

The conditional probability of observing y_i is given by

$$\Pr(y_i|x_i, z_i) = \begin{cases} \varphi_i(z_i'\gamma) + \{1-\varphi_i(z_i'\gamma)g(0|x_i)\} & \textit{if}\;\; y_i = 0 \\ \{1-\varphi_i(z_i'\gamma)g(y_i|x_i)\} & \textit{if}\;\; y_i > 0 \end{cases} \tag{5.3}$$

The vector of zero-inflated covariates is z_i' and γ is the vector of zero inflated coefficients to be estimated. The term $\varphi_i(z_i'\gamma)$ can be modelled as logit or probit functions while $g(y_i|x_i)$ has Poisson or negative binomial distributions. The pobit function is used to model $\varphi_i(z_i'\gamma)$ in the analysis of this chapter.

5.3.2.3 Two-part model

To understand health care demand in the light of two-part model (TPM) or also known as hurdle model, we may divide the decision process into two processes. First process is when the individual decides to demand health care in a certain period of time and the second process is when the health care provider, after the first contact, determines the next visit(s). This model is always being associated with the *principal-agent* framework, where the doctor acts as an agent for the patient (principal) and demands health care on behalf of the patient, based on the belief that the doctor knows more than the patient about the types of health care needed. This model, however, assumes that the demands are determined by a single spell of illness. In a simple way (see Deb & Trivedi (2002) or Sarma & Simpson (2006) for more constructions), we can show that the probability of these two distinct processes are given by

$$\Pr(y_i = 0) = f_1(0)$$

and

$$\Pr(y_i | y_i > 0) = \frac{1 - f_1(0)}{1 - f_2(0)} f_2(y_i), \qquad y_i > 0 \tag{5.4}$$

It collapses to standard model if $f_1(.) = f_2(.)$

Model is estimated separately in which the first part involves binary model; i.e. the probit or logit and the second part involves truncated count data model; i.e the truncated Poisson or truncated negative binomial. In some countries where a GP acts as a gatekeeper, the utilisation of health care services like outpatient and inpatient are jointly determined by the patients and the GPs in the first stage..

Thus, the decision to hospitalise or consult a doctor in the hospital cannot be interpreted as similar to GP consultations (Gerdtham, 1997). In this case, however, the first stage could be interpreted as the contact decision by the patient via the GP, followed by the frequency of visit/events once the first contact has taken place. Studies that have utilised the TPM include Pohlmeier and Ulrich (1995), Jiménez-Martín et al. (2002), Mocan et al. (2004) and Sarma and Simpson (2006). Pohlmier and Ulrich (1995) employ a negative binomial distributed hurdle model to explain the demand for health care. They suggest that a two-part model is essential because of different decision processes whereby the initial visit to the physician is determined by the individual while the frequency is decided by the physician. Jiménez-Martín et al. (2002) compare the two-part models with the latent class models in order to estimate demand for physician services of twelve countries in European Union. By using two model selection criteria which are known as the *Akaike Information Criterion (AIC)* and the *Bayesian Information Criterion (BIC)*, it was found that the two part models are more favoured for specialist demand framework while latent class models are better in explaining demand for GPs.

5.3.2.4 Latent class model

The latent class model is another mixture model that could accommodate the problem of excess zeros. It allows for individual heterogeneity by dividing population into several latent classes based on unobserved criteria, for example, an individual's long term health status (Deb & Trivedi, 1997, 2002). Unlike the TPM, which is also a mixture model, the LCM is believed to be more flexible as it does not differentiate the density between zero and positive values. Suppose population is divided into C-latent classes in proportion $\pi_1, \pi_2, ... \pi_c$.

The density of C-component latent (*j*) classes can be specified as

$$f(y_i|\Theta) = \sum_{j=1}^{c-1} \pi_j f_j(y_i|\theta_j) + \pi_c f_c(y_i|\theta_c), \qquad i = 1,2........n, \quad j = 1....,C \tag{5.5}$$

where $\pi_1 \geq \pi_2 ..... \geq \pi_c = \left(1 - \sum_{j=1}^{c-1} \pi_j\right)$ are the mixing probabilities estimated along with other parameters from all components, $\theta_{1,} \theta_2 ... \theta_c = \Theta$.

The component density for the finite-mixture Poisson and negative binomial is similar to the standard density function of those models but varying across components. The mean and variance functions for the finite-mixture Poisson are given by

$$\mathrm{E}\left(y_i \middle| x_i\right)=\mathrm{V}\left(y_i \middle| x_i\right)=\sum_{j=1}^{c}\pi_j\lambda_{ji}=\overline{\lambda}$$

while as for the finite-mixture negative binomial

$$\mathrm{E}\left(y_i \middle| x_i\right)=\sum_{j=1}^{c}\pi_j\lambda_{ji}=\overline{\lambda} \text{ and } \mathrm{V}\left(y_i \middle| x_i\right)=\sum_{j=1}^{c}\pi_j\lambda_{ji}^2\left[1+\alpha_j\lambda_{ji}^{-k}\right]+\overline{\lambda}_i-\overline{\lambda}_i^2$$

By using the data from Canadian National Population and Health Survey, Sarma and Simpson (2006) have compared several demand models with LCM. They found that both the AIC and BIC suggest that LCM are more preferred to the hurdle models for doctors and GPs' visits. By utilising the data from RAND Health Insurance Experiment, the AIC and BIC in Deb and Trivedi (2002), also favour the LCM over TPM. However, the LCM seems to be depending on statistical convenience rather than theoretical reasoning of the two-part process involved in the health care utilisation decision.[9]

5.4 RESULTS

From the histograms in Figures 4.2 to 4.4 in Chapter 4, it clearly suggests that all types of demand have excess zeros with a long right tail. Therefore, the standard count models may not be sufficient in this situation as it assumes that the data generating process between zero and positive counts is identical. For comparison, nine specifications have been fitted for three types of utilisation. They are standard the Poisson and negative binomial, zero inflated Poisson (ZIP), zero inflated negative binomial (ZINB), two-part logit-truncated Poisson (TPP), two-part probit-truncated negative binomial (TPNB), latent class Poisson-two components (LCP-2), latent class negative binomial- two components (LCNB-2)

[9] The latent class models in this study have been fitted using Stata's user-written command in Stata 10 by Partha Deb, Hunter College and The Graduate Center, City University of New York.

and latent class negative binomial-three components (LCNB-3). In the negative binomial regressions, all variances are specified to have a quadratic function of the mean (NB2) as some models using NB1 specification fail to converge. The LCNB-3 models for all services also do not converge. The standard errors reported here are based on clustered sandwich estimators that allow for the correlation between individuals in the same household. The results have been first presented according to the type of the services before a final discussion take place that comparing results from the selected model across different utilisation types. The selection processes of the best model are described diagrammatically in Figure 5.1.

5.4.1 GP consultations

As suggested in Chapter 4, there is evidence that self-assessed health status (SAH) is endogenous within the model of GP use. However, in this chapter, SAH is treated as exogenous. This is because it is difficult to deal with both endogeneity and excess zeroes problems simultaneously. Furthermore, in this chapter I am more interested in comparing the performance of standard count model with extended models and to discuss how results vary between models. The comparison of standard and extended models is discussed in Section 5.5.

Before any lengthy discussion, selections between nested models are made. The selections are between the Poisson and negative binomial; the ZIP and ZINB; the TPP and TPNB; and the LCP-2 and LCNB-2. Selections are made using the likelihood ratio (LR) test with null hypothesis that an overdispersion parameter α equals 0. The LR tests indicate that models based on the NB assumption are superior to the corresponding Poisson models. Therefore, for further discussion, only results from models that are based on negative binomial assumption are reported and compared which consist of ZINB, TPNB and LCNB-2. Results are presented in Table 5.1[10]. To select the best model, three model selection criteria have been used which consist of log likelihood values, the AIC and BIC.[11] For each criterion, values are compared across models. The AIC and BIC prefer models with a smaller value while log likelihood favour models with a greater value. The comparison in Table 5.2 shows a unanimous selection between criteria which prefer the ZINB model over others. Beside the comparison using the model selection criteria above, Vuong test (Vuong, 1989) also statistically suggest that ZINB is more favoured than the negative binomial specification.[12].

In the ZINB, the split between the potential users and the non-users is determined by all covariates within the model. Variables like MALE, GOODHLTH and LIMITACT are significantly determining the use among the potential users with the directions similar to those from other competing models. The number of longstanding illnesses (LONG_ILL), however, shows no significant effect among the potential users in which without a separate classification as in the NB model, these variables have a large effect.

As for the non-users, MALE, GOODHLTH and LONG_ILL are among variables that have significant effects where the directions of these variables are the opposite from those of potential users. Individuals with good health status, male, or who have had no education are more likely to be among the non-users.

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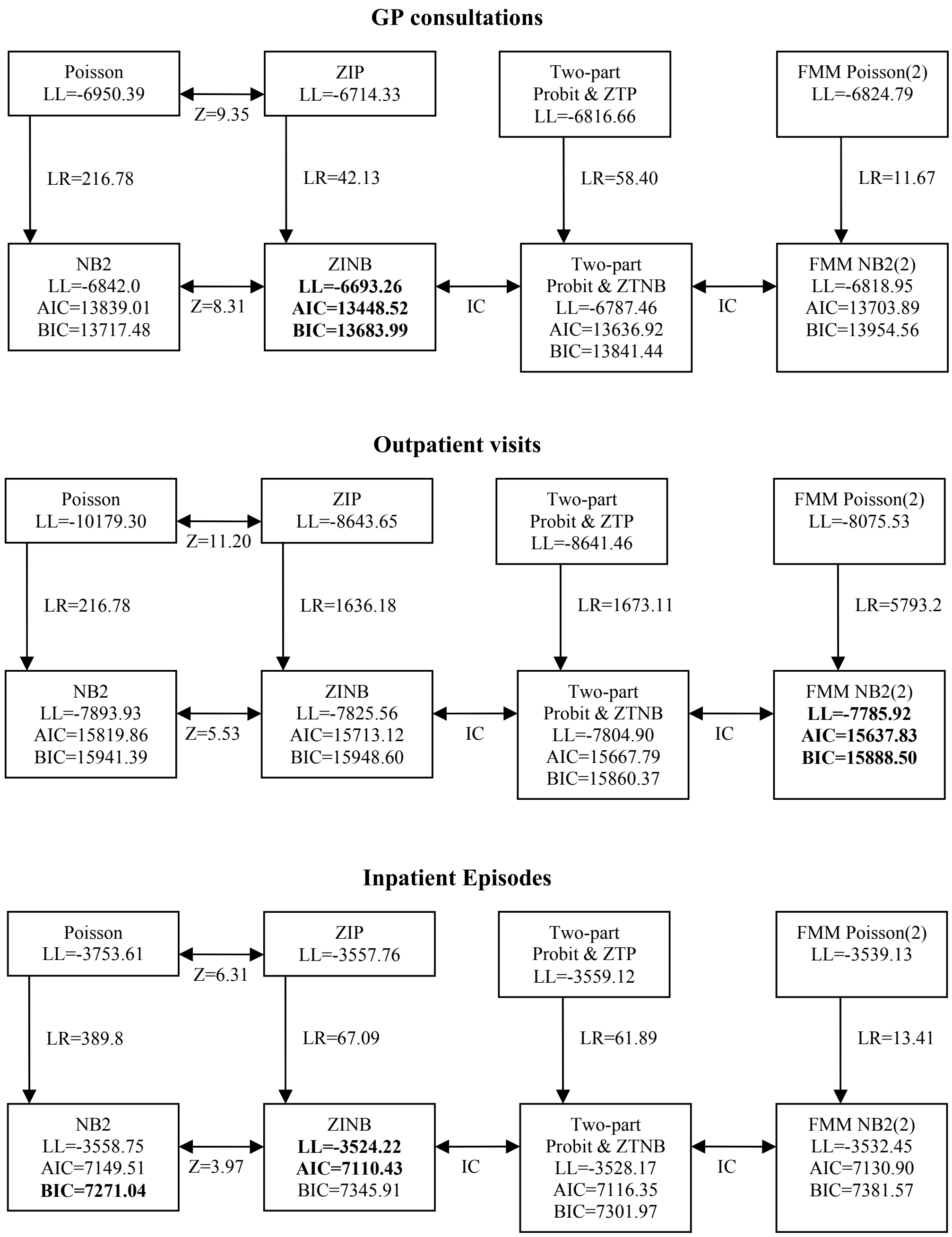
[10] Table 4.10 in Chapter 4 presents the estimates of NB model for GP, outpatient and inpatient visits.

[11] AIC formula=-2log(L)+2K and BIC=-2log(L)+Klog(N); where K is the number of parameters and N is the number of observations. Log(L) is the values of maximum log likelihood.

[12] The Vuong test is used because, according to Greene (1994), the models are non-nested.

Figure 5.1 The selection process between nested and non-nested models



Notes:
1. Single-pointed arrows represent the nested tests while double-pointed arrows indicate the non nested tests.
2. The Likelihood ratio test statistics (LR) are used to select between the nested models while Z statistics are from Vuong tests, the AIC and BIC are used for the non-nested models.
3. All LR tests prefer the NB2 specifications over the Poisson while Vuong tests prefer the inflated models (ZIP and ZINB).
4. Values in **bold** indicate the best value according to LL, AIC or BIC.

Table 5.1 Zero-Inflated, Two-Part and Latent Class estimates for GP consultations

N=14706

	Zero Inflated Negative Binomial (ZINB)				Two-Part Negative Binomial (TPNB)				Latent Class NB-2			
			Inflate		Zero truncated NB		Probit		Component 1		Component 2	
	Coef	s.e	coef	s.e	Coef	s.e	coef	s.e	coef	s.e	coef	s.e
AGE	-0.005	0.006	0.007	0.008	0.021*	0.012	-0.008**	0.003	-0.019**	0.016	0.005	0.022
AGESQ	-0.007	0.008	-0.027**	0.012	-0.043**	0.018	0.009**	0.004	0.019*	0.023	-0.010	0.032
MALE	-0.185***	0.064	0.233***	0.089	-0.050	0.112	-0.199***	0.027	-0.465***	0.133	-0.115	0.128
COHAB	0.117	0.105	0.100	0.140	0.198	0.181	0.011	0.051	-0.114	0.197	0.261	0.225
MARRIED	0.061	0.068	0.083	0.097	0.056	0.122	0.008	0.032	-0.016	0.137	0.070	0.188
GOODHLTH	-0.514***	0.087	0.319***	0.115	-0.614***	0.136	-0.478***	0.032	-1.130***	0.242	-0.558***	0.200
LIMITACT	0.059***	0.007	-5.304***	0.821	0.073***	0.009	0.070***	0.004	0.089***	0.016	0.106***	0.017
LONG_ILL	0.019	0.029	-0.560***	0.116	0.058	0.052	0.106***	0.018	0.131***	0.044	0.131*	0.071
INCOME	0.005	0.033	0.052	0.058	-0.004	0.055	-0.011	0.014	-0.025	0.049	-0.005	0.070
OTHER_EDU	-0.050	0.076	0.064	0.100	-0.041	0.145	-0.069**	0.033	-0.040	0.115	-0.195	0.158
NO_EDU	0.017	0.088	0.228*	0.131	0.088	0.168	-0.104**	0.042	-0.133	0.166	-0.147	0.222
WALES	0.062	0.152	0.217	0.178	0.044	0.287	-0.060	0.071	-0.025	0.342	-0.122	0.467
SCOTLAND	-0.102	0.147	-0.099	0.223	-0.095	0.254	-0.032	0.071	-0.221	0.239	0.142	0.316
GPPOP	0.842	0.959	-0.308	1.446	1.439	1.666	0.442	0.438	2.010	1.571	-0.798	2.130
CONSTANT	-1.131*	0.626	-0.038	0.955	-2.977***	1.131	-0.885***	0.291	-2.026**	0.903	-0.847	1.258
α			0.297	0.247	2.668	2.139			0.000	0.000	2.086	1.110
π									0.643	0.110	0.357	0.110
LogL	-6693.26				-1330.269		-5457.188		-6818.95			
Vuong	8.31											

The symbols ***,**,and * denote 1, 5 and 10% level of significance, respectively

Table 5.2 Model Comparison using Log Likelihood, AIC and BIC for GP consultations

	NB	ZINB	TPM (Logit & Truncated NB)	LCNB-2
LogL	-6842.0	-6693.26 [a]	-6787.46	-6818.95
AIC	13839.01	13448.52 [b]	13636.92	13703.89
BIC	13717.48	13683.99 [c]	13841.44	13954.56

Notes:
[a] Model with the highest log likelihood value
[b] Model preferred by the AIC
[c] Model preferred by the BIC

5.4.2 Outpatient visits

Following the steps of analysis as in doctor consultations, the LR tests are employed in selecting between the Poisson and negative binomial densities models. Similar to the doctor consultations, the negative binomial densities are more favoured than the Poisson for outpatient visits data. Results are presented in Table 5.3 and the performance is compared in Table 5.4. All model selection criteria seem to prefer the latent class model which is LCNB-2.

The result suggests that individuals can be divided into two latent classes based on some unobservable characteristics. The fitted values of each component are computed and compared. For LCNB-2, the mean and the maximum values[13] of use are larger for class 2. Therefore we could refer component 1 is mainly for 'infrequent users' (or type 1) and component 2 as the class mainly for the 'frequent users' (or type 2).

Figure 5.2 shows the distribution of the posterior probability of being of 'type 1' users. By examining the distribution of the data which consist of many zero values, this classification seems reasonable as the vast majority of the samples

[13] For class 2, the mean and the maximum values are 0.65 and 24 respectively while for class 1, the mean is 0.17 with a maximum value of 5.6 visits.

have a high probability (around 0.74) of being of "type 1" or infrequent users. Wald's test is used to compare the equality of all regressors across two components. In this test, the equality of all coefficients between two latent classes is rejected at 5% significant level which supports the division of populations into different classes. All health related variables are significant in the model. Age and education level are significant in component 1 but not 2 which may suggest that for frequent users, these variables are have less effect in determining outpatient visits. Income and country, on the other hand, plays an important role in component 2. In component 2, people in Wales and Scotland have fewer visits when compared to those in England.

Figure 5.2 Outpatient visits: Posterior probability of component 1

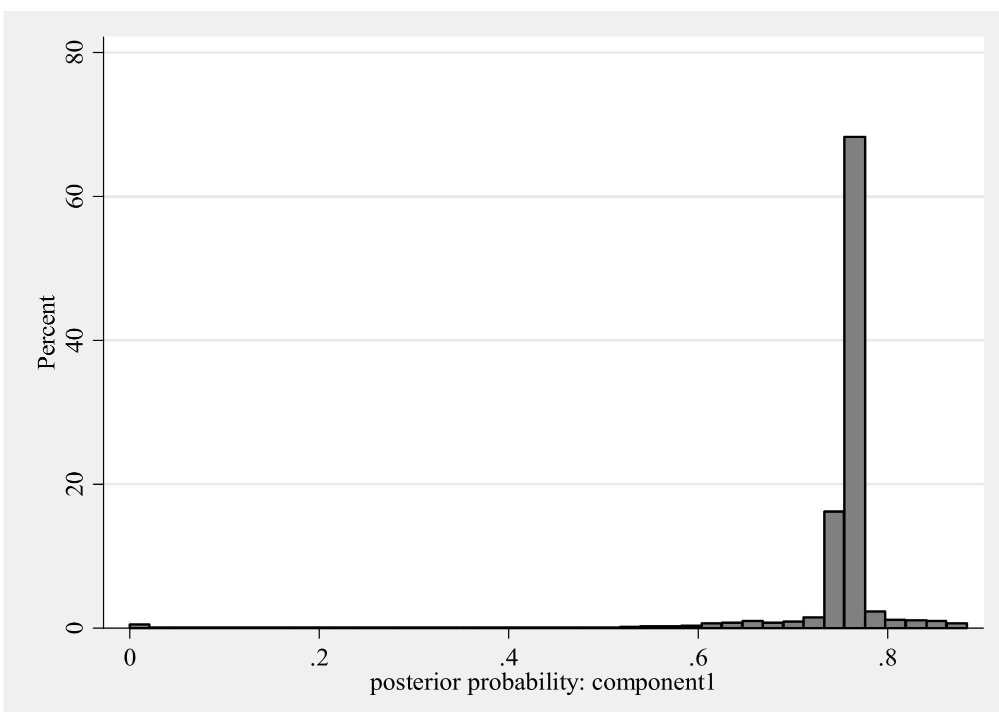


Table 5.3 Zero-Inflated, Two-Part and Latent Class estimates for outpatient Visits

N=14706

	Zero Inflated Negative Binomial (ZINB)				Two-Part Negative Binomial (TPNB)				Latent Class NB-2			
			Inflate (Probit)		Zero truncated NB		Probit		Component 1		Component 2	
	coef.	s.e	coef.	s.e	coef.	s.e	coef.	s.e	coef.	s.e	coef.	s.e
AGE	0.005	0.012	0.033**	0.016	0.032**	0.013	-0.012***	0.003	-0.027***	0.010	0.004	0.013
AGESQ	-0.004	0.017	-0.055**	0.022	-0.037**	0.019	0.018***	0.004	0.041***	0.014	0.004	0.019
MALE	-0.034	0.091	-0.008	0.129	-0.068	0.123	0.004	0.027	0.048	0.080	-0.074	0.113
COHAB	-0.045	0.157	-0.042	0.214	0.020	0.206	-0.034	0.049	0.009	0.145	-0.176	0.189
MARRIED	-0.129	0.094	0.017	0.138	-0.101	0.131	-0.073**	0.032	-0.150	0.096	-0.203	0.124
GOODHLTH	-0.777***	0.112	0.380**	0.157	-0.744***	0.141	-0.488***	0.032	-1.150***	0.107	-0.987***	0.125
LIMITACT	0.066***	0.010	-0.159***	0.033	0.064***	0.011	0.041***	0.004	0.065***	0.009	0.106***	0.012
LONG_ILL	0.184***	0.038	-1.055**	0.531	0.168***	0.048	0.190***	0.018	0.393***	0.041	0.277***	0.063
INCOME	-0.038	0.042	-0.201***	0.055	-0.031	0.052	0.044***	0.015	0.071	0.051	0.089*	0.052
OTHER_EDU	-0.262**	0.104	-0.201	0.148	-0.244*	0.140	-0.051	0.033	-0.161	0.101	-0.134	0.130
NO_EDU	-0.308**	0.132	-0.169	0.229	-0.175	0.182	-0.125***	0.043	-0.436***	0.137	-0.063	0.164
WALES	-0.326**	0.162	-0.004	0.320	-0.619***	0.223	-0.083	0.079	-0.030	0.228	-0.699**	0.302
SCOTLAND	-0.447*	0.253	-0.203	0.341	-0.592	0.299	-0.071	0.069	0.096	0.222	-0.579**	0.262
GPPOP	2.664	1.689	2.907	2.060	3.635*	2.009	-0.134	0.430	-2.027	1.296	2.507	1.731
CONSTANT	-2.095*	1.118	-1.305	1.464	-20.194***	1.376	-0.886***	0.287	-0.225	0.877	-2.418**	1.202
α	3.154	0.262							1.423	0.384	5.386	1.790
π									0.743	0.097	0.257	0.097
LogL	-7825.561				-5340.02		-2464.88		-7785.917			
Vuong	5.53											

The symbols ***,**,and * denote 1, 5 and 10% level of significance, respectively

Table 5.4 Model Comparison using Log Likelihood, AIC and BIC for outpatient visit

	NB	ZINB	TPM (Probit & Truncated NB)	LCNB-2
LogL	-8003.106	-7825.56	-7804.90	-7785.92[a]
AIC	16038.21	15713.12	15667.79	15637.83[b]
BIC	16159.75	15948.60	15860.37	15888.50[c]

Notes:
[a] Model with the highest log likelihood value
[b] Model preferred by the AIC
[c] Model preferred by the BIC

5.4.3 Inpatient episodes

Based on the negative binomial assumption which proves to be superior to the Poisson through the LR tests, the regression results are reported in Table 5.5. The statistics results from the selection criteria are reported in Table 5.6. Based on the log likelihood and AIC, the ZINB seems to be superior again while based on the BIC, the one stage negative binomial is preferred. This is not surprising as the BIC always tends to discriminate models with larger degree of freedom. Since log likelihood and AIC prefer the negative binomial model the least, our discussions are based on the ZINB model. Results can be divided into two parts.

The first part shows the estimates for the potential users while the second part, are estimates for the non-users. Unlike in the standard negative binomial model, country and GP densities also play some roles in inpatient episodes in the ZINB. The influence of health related variables, gender and age are similar to those in the standard negative binomial model. The maximum value observed is six episodes per year which is not very different from the maximum number of doctor consultations which is six times over the reference period and also has similar predicted patterns.

Table 5.5 Zero-Inflated, Two-Part and Latent Class estimates for inpatient episodes

N=14706

	Zero Inflated Negative Binomial (ZINB)				Two-Part Negative Binomial (TPNB)				Latent Class NB-2			
			Inflate (Probit)		Zero truncated NB		Probit		Component 1		Component 2	
	coef.	s.e	coef.	s.e	coef.	s.e	coef.	s.e	coef.	s.e	coef.	s.e
AGE	-0.021*	0.012	0.005	0.013	-0.019	0.017	-0.009**	0.004	-0.025	0.024	-0.021	0.015
AGESQ	0.019	0.016	-0.016	0.020	0.007	0.022	0.013**	0.005	0.038	0.032	0.021	0.022
MALE	-0.272**	0.132	-0.183	0.163	-0.222	0.180	-0.055	0.035	-0.358	0.239	-0.043	0.139
COHAB	0.057	0.251	0.078	0.254	-0.156	0.321	-0.002	0.064	0.400	0.361	-0.305	0.293
MARRIED	-0.209	0.152	-0.249	0.168	-0.375	0.203	0.017	0.042	0.132	0.192	-0.152	0.160
GOODHLTH	-0.761***	0.196	0.655***	0.230	-0.944***	0.248	-0.610***	0.040	-1.960***	0.513	-1.136***	0.198
LIMITACT	0.034***	0.012	-0.116***	0.021	0.022	0.014	0.043***	0.004	0.114***	0.032	0.030	0.027
LONG_ILL	0.164***	0.048	-0.246***	0.089	0.216***	0.071	0.130***	0.020	0.200**	0.079	0.303***	0.066
INCOME	-0.032	0.039	-0.033	0.049	0.064	0.074	-0.012	0.018	-0.089	0.072	0.047	0.074
OTHER_EDU	-0.116	0.153	-0.061	0.164	-0.166	0.230	-0.026	0.043	0.035	0.236	-0.175	0.181
NO_EDU	-0.120	0.174	-0.142	0.231	0.179	0.253	-0.037	0.055	-0.445	0.332	0.188	0.208
WALES	0.296	0.244	0.320	0.311	0.453	0.333	-0.004	0.094	-0.628*	0.370	0.376	0.243
SCOTLAND	-0.515*	0.282	-0.375	0.304	-0.410	0.363	-0.081	0.085	0.058	0.466	-0.451	0.401
GPPOP	5.341***	1.711	5.176***	1.973	3.868*	2.319	0.320	0.517	2.705	2.805	0.412	1.711
CONSTANT	-4.026***	1.113	-2.758	1.308	-18.584	2.422	-1.367***	0.345	-3.439*	1.967	-1.915	1.297
α	1.566	0.252			1.09e+07	2.3e+07			0.302	0.653	5.124	2.092
π									0.526	0.265	0.474	0.265
LogL	-3524.217[a]				-597.207		3528.173		-3532.45			
Vuong	3.97											

The symbols ***,**,and * denote 1, 5 and 10% level of significance, respectively.

Table 5.6 Model Comparison using Log Likelihood, AIC and BIC for inpatient episodes

	NB	ZINB	TPM (Logit & Truncated NB)	LCNB-2
LogL	-3558.75	-3524.22[a]	-3528.17	-3532.45
AIC	7149.51	7110.43[b]	7116.35	7130.90
BIC	7271.04[c]	7345.91	7301.97	7381.57

Notes:
[a] Model with the highest log likelihood value
[b] Model preferred by the AIC
[c] Model preferred by the BIC

5.5 DISCUSSION

In order to discuss the consequence of modelling excess zeroes in this chapter, it would be meaningful if we could directly compare the results from extended models with those from standard models in Chapter 4. Tables 5.7 and 5.8 present the results in terms of marginal effects. The marginal effects here are calculated at the means of the independent variables and for extended models, there is no separation between processes or classes.

The sign of effects in GP equation are slightly different between standard and extended models. The effect of education dummies is only significant in the standard negative binomial model and the associated standard errors (cluster-robust standard error) in this model are smaller than those in the zero inflated model.

In zero-inflated model, more weight is given to the probability of zero observation and effects are initially divided into two different classes. Therefore, by calculating marginal effects at the mean value of independent variables and without the separation between the non users and potential users, we would see no significant effect of education, specifically NO_EDU in this model.

Table 5.7 Standard models: Marginal effects for GP, outpatient and inpatient utilisations

GP	GP		OUTPATIENT		INPATIENT	
	dy/dx	s.e	dy/dx	s.e	dy/dx	s.e
AGE	-0.0012	0.0007	-0.0015*	0.0012	-0.0011***	0.0004
AGESQ	0.0087	0.0010	0.0032	0.0018	0.0013**	0.0005
MALE	-0.0434***	0.0064	-0.0033	0.0114	-0.0069*	0.0037
COHAB	0.0078	0.0124	-0.0113	0.0183	-0.0024	0.0065
MARRIED	0.0029	0.0074	-0.0273**	0.0132	-0.0016	0.0044
GOODHLTH	-0.1477***	0.0107	-0.236***	0.0204	-0.0959***	0.0079
LIMITACT	0.0138***	0.0008	0.0163***	0.0016	0.0036***	0.0004
LONG_ILL	0.0187***	0.0034	0.0618***	0.0061	0.0127***	0.0018
INCOME	-0.0022	0.0033	0.1106*	0.0059	-0.0005	0.0017
OTHER_EDU	-0.0158**	0.0079	-0.0289**	0.0132	-0.0046	0.0046
NO_EDU	-0.0200**	0.0089	-0.0386**	0.0154	-0.0022	0.0054
WALES	-0.0090	0.0169	-0.0512***	0.0196	0.0055	0.0104
SCOTLAND	-0.0089	0.0152	-0.0541**	0.0217	-0.0081	0.0071
GPPOP	0.1174	0.1005	0.2072	0.1889	0.0554	0.0482

The symbols ***,**,and * denote 1, 5 and 10% level of significance, respectively.

Table 5.8 Extended models: Marginal effects for GP, outpatient and inpatient utilisations

GP	GP		OUTPATIENT		INPATIENT	
	ZINB		LCNB-2		ZINB	
	dy/dx	s.e	dy/dx	s.e	dy/dx	s.e
AGE	-0.0015	0.0018	-0.0017	0.0013	-0.0015***	0.0005
AGESQ	-0.0020	0.0026	0.0036**	0.0018	0.0019*	0.0008
MALE	-0.0561***	0.0201	-0.0034	0.0110	-0.0056	0.0047
COHAB	0.0371	0.0352	-0.0155	0.0168	-0.0010	0.0081
MARRIED	0.0184	0.0207	-0.0325**	0.0129	0.0017	0.0056
GOODHLTH	-0.173***	0.0271	-0.241***	0.0196	-0.0999***	0.0083
LIMITACT	0.0178***	0.0015	0.0157***	0.0014	0.0081***	0.0012
LONG_ILL	0.0059	0.0086	0.0586***	0.0065	0.0224***	0.0040
INCOME	0.0016	0.0100	0.0144**	0.0055	-0.00006	0.0023
OTHER_EDU	-0.0153	0.0228	-0.0260**	0.0126	-0.0033	0.0054
NO_EDU	0.0053	0.0269	-0.0369**	0.0154	0.0006	0.0074
WALES	0.0194	0.0488	-0.0533***	0.0187	-0.0023	0.0142
SCOTLAND	-0.0297	0.0414	-0.0379*	0.0212	-0.0103	0.0082
GPPOP	0.2554	0.2932	0.0854	0.1750	0.0250	0.0626

The symbols ***,**,and * denote 1, 5 and 10% level of significance, respectively.

The direction of the marginal effects in outpatient and inpatient visits is identical between the extended and standard models. The standard errors in extended model of inpatient visits are greater than those in standard negative binomial model. While the direction of the significant effects is similar, the value is different and in outpatient model, the different could reach up to 86%.

Although the direction of significant effects in outpatient and inpatient model is comparable between standard and extended models, model selection criteria suggest that extended count models are preferred for modelling health care utilisation data with excess zeros. Furthermore, the decision to utilise health care could be generated by more than one process and it is important to select the best-fitting model for better interpretation. The ZINB model is preferred in GP consultations and inpatient episodes while LCNB-2 is preferred in outpatient visits.

The frequency of GP consultation and inpatient episodes are quite low while for outpatient visits, the maximum frequency can reach up to 36 visits per reference period. There is more variation in the frequency of outpatient visits than in GP visits or inpatient episodes that might explain why the division of population into two latent groups is preferred. Sarma and Simpson (2006) has also found that ZINB model is superior for services with less utilisation frequencies while latent class model is more favoured for services that have less zero incidence and a higher rate of utilisation.

As for outpatient visits, although the joint equality test of all coefficients of covariates between components is rejected, there is no strong evidence that coefficient of health related variables are significantly different across components except for the number of days with activities prevented. Therefore, the distinction is made based on the mean values of each component which suggest that population may be divided into two groups of 'infrequent' and 'frequent' users but not 'ill' and 'healthy'. According to posterior probability, the mean of the posterior probability for being of "type 1" or infrequent users is 0.74.

The performance of two-part specification, which is believed to support the principal-agent approach, on average, is the second best model for all types of services. Nevertheless, in a health system such as in the UK, it is important to note that outpatient visits and inpatient episodes are highly dependent on the GP referral, which means that the two-stage system is conceptually applicable in different ways.

There is statistical evidence that health related variables which consist of self-assessed health status, the number of days of prevented activities and the number of long standing illnesses play important roles in determining utilisation with expected direction, specifically for outpatient and inpatient services. Country and GP densities show more influence for outpatient visits rather than for doctor consultations and inpatient episodes. These effects, however, differ across different components.

Being male, on the other hand, has some roles for doctor consultations and inpatient episodes, but not outpatient. These significant effects suggest that males utilise less health care than females in all cases. The influence of the covariates on health care utilisation is important in formulating health policy in order to achieve its objectives. Among factors that stir great interest are health status, income, education and supply-side factors. As mentioned earlier, health related variables have a stronger influence than other variables which may suggest that the needs for health care are superior to other variables such as income and education, though income has some roles in determining outpatient visits among frequent users. Education has consistent directions in all models for outpatient visits. Although it is only significant in LCNB-2 component 1, it suggests that people with other qualification or no qualification utilise outpatient services less than those with higher qualification. These results might be affected by the fact that the outpatient attendances in this analysis include visits to private hospitals and consultative outpatient services which may be preferred more among higher educated individuals.

Furthermore, individuals with higher qualifications are said to be better informed, more health conscious and have higher access to information compared to other groups. In this case, controlling for health conditions, we may predict that the more educated the population is, the more likely they are to utilise some types of health care services. The density of GPs also does not show any significant effect (except for LCNB-2) in outpatient visit. However it is worth noting that in most cases, especially for GP consultation, the association to use is positive.

5.6 CONCLUSION

Chapter 5 extends the analysis in Chapter 4 by considering, in addition to standard Poisson and negative binomial models, zero-inflated, two-part, and latent class models. Model selection criteria suggest that standard count models, as discussed in Chapter 4, are not sufficient for modelling health care utilisation data with excess zeros. The ZINB model is preferred for GP consultations and inpatient episodes while LCNB-2 is preferred for outpatient visits. As anticipated, most all health related variables show significant effects in determining health care use. Socioeconomic variables have less influence in determining health care use in these extended models. Some effects vary quite markedly between the different models, underlining the importance of finding the best-fitting model.

CHAPTER SIX

6 HEALTH CARE UTILISATION BY THE ELDERLY

6.1 INTRODUCTION

This chapter focuses on the demand for health care by the population in older age groups in the UK whose demand has not been investigated[14] in the previous two empirical chapters. Studies on health care demand by the elderly are important for the health system to be more responsive in providing health care to those needed. The number and proportion of people in older populations in many countries has increased over time as a result of an increase in the life expectancy and decrease in mortality rate of the population. This phenomenon is known as *ageing population* which could be defined as the change in the age distribution of the population. In the UK, for instance, life expectancy for both females and males has increased over time since the 50s and projected to be increased in the future (see Table 1.2 in Chapter 1). According to Office of National Statistics[15], the remaining life expectancy for men and women at 65 has increased over the

[14] Due to missing value in education variable, all respondents aged 69 and over are dropped from the sample in the previous analyses.
[15] Information retrieved from http://www.statistics.gov.uk/pdfdir/leb1008.pdfhub/population/deaths/life-expectancies/index.html on 16 June 2009 on 16 June 2009

years. This may contribute to the increase in the percentage of population aged 65 and over. For females and males who were at age 65 in 2005-2007, the remaining life expectancy is 19.9 and 17.2 years respectively, which shows an increase of 3.0 years for males and 2.0 year for women in 1991 to 1993 (see Table 6.1). The increase in life expectancy has also contributed to the increase in the old age dependency ratio which represents the number of people of state pension age (SPA) and over as a percentage of the working age population. With a prior assumption of constant state pension age, the ratio is predicted to be increased 49 per cent by year 2051.[16]

Are the ageing populations a burden to the governments, especially in providing health services? This depends on whether the increase in the life expectancy is associated with more ill-health, disabilities or mobility problems that have been translated into an increase in utilisation of health services or not. The elderly are more prone to health problems such as osteoporosis, heart disease and dementia. Mobility problems are also prominent among the elderly, which includes the ability to walk, climbing the stairs, bathing and dressing or carrying groceries. If these health problems increase the need for health care, one may expect the shortage of health care supply if the health system fails to respond to the rapid changing in demand.

The role of primary care is crucial in meeting the increasing demand for health care. The teamwork between GPs, practice nurses, district nurses and health visitors[17] contribute to an effective primary system. Like a GP and practice nurse, the role of health visitors and district nurses in the community is equally

[16] Information retrieved from http://www.statistics.gov.uk/pensiontrends/ on 16 June 2009.

[17] Health visitors' services are more prominent for children and young families.

important. District nurses are responsible in assessing, facilitating health needs of the population under their responsibility, mostly home-based, and provide referral when necessary. Their engagement in health promotion which include health education, protection and prevention are considered essential in improving well-being. One instance is by supporting active and healthy lifestyle among older people.

The role of health promotion, specifically health education, is also to ensure the accessibility of health care services and how to use them reasonably (Draper, Griffiths, Dennis, & Popay, 1980). Direct engagement between primary care givers and the elderly are important as health needs are sometimes hidden, which can either be hidden from the patient or from the doctors. People with excellent health might consume more health services than those with health problems- which is known as the *inverse care law* (Hart, 1971).

An awareness of factors affecting health care utilisation is therefore essential in understanding this phenomenon. For example, people with poor health status are expected to utilise health care more than those with excellent health, otherwise we might expect that there might be hidden needs in the system. The system has also failed to be effective if the healthier but educated or wealthier people could exploit the system for their own benefits.

All these issues lead to an empirical analysis in this chapter with the objective to increase understanding of underlying factors that affect the use of selected health services among the older age groups in the UK and of the system and the population it serves. Selected studies that have been reviewed in Chapter 3 (see Table 3.1 for the list of reviewed studies) which focus on health care demand by the elderly include Deb & Trivedi (1997), Lee & Kobasyi (2001), Schellhorn et al. (2000) and Van Houten & Norton (2004).

This chapter has been divided into 5 main sections. Objectives of the study are outlined in section 6.2 after the introduction. Section 6.3 focuses on the methods for analysis followed by presentation of the results in section 6.4. The analysis ends with a discussion in Section 6.5 and conclusion in section 6.6.

Table 6.1 Period of life expectancy at age 65

	1991-1993		2005-2007	
	Males	Females	Males	Females
UK	**14.2**	**17.9**	**17.2**	**19.9**
England	14.3	18.0	17.3	20.0
Wales	14.1	17.8	16.9	19.6
Scotland	13.3	16.8	16.0	18.7
Northern Ireland	14.0	17.9	16.8	19.7

6.2 OBJECTIVES OF THE STUDY

The review in Chapter 2 reveals that the role of district nurses or health visitors as a key player in the community within the broad health care system has not received great attention in studies under review. As one of the key players in elderly health, understanding the determinants of utilisation of district nurses and health visitor is believed to be important to both governments and society as a whole. This chapter has been extended by including the utilisation of district nurses and health visitor services, apart from GP and outpatient services, as one of the variables of interest within the context of the United Kingdom. Two main objectives of this chapter are

1) To identify the roles of personal characteristics; health status, health related and health care variables; and socio-economic factors in

determining the utilisation of district nurse, GP and outpatient services among the elderly.

2) To identify the effect of district nurse visits in determining GP and outpatient visits.

6.3 METHODS

6.3.1 Data

6.3.1.1 Background

The data used in this chapter is from British Household Panel Survey (BHPS)[18]. The BHPS is an annual survey started in 1991 which includes nationally representative sample of adults aged 16 and over from sampled households. In 1991, there were 5,505 sampled households from 250 postcode sectors, which consists of approximately 10,000 individuals interviewed every year. If in any case, an individual moves into a new household, he (she) is interviewed together with his (her) new eligible household members. Any new members in the household or children who reached 16 are also interviewed.

In wave 9 (1999), the number of samples from Scotland and Wales have been extended in order to allow independent analysis within countries as well as to allow comparisons between countries. Another development in sampling is when a sample of 2,900 households from Northern Ireland was included into BHPS in wave 11 (2001), allowing independent analysis of Northern Ireland and comparative studies between country in the UK. The definition and transformation of variables used in this study are explained in *Appendix 6-I*.

[18] University of Essex. Institute for Social and Economic Research, *British Household Panel Survey: Waves 1-17, 1991-2008* [computer file]. 6th Edition. Colchester, Essex: UK Data Archive [distributor], March 2009. SN:5151

6.3.1.2 Sample selection

Data from wave 12 (2002) to wave 16[19] (2006) are used in this chapter. A subset of respondents aged 61 and over in wave 12 were selected and followed for five years. The use of only 5 waves is believed to minimise the non-response among the elderly due to health conditions, being institutionalised or death. Besides that, it allows more samples from Scotland, Wales and Northern Ireland. In order to identify the cohort effects of respondents aged 61 and over in year 2002, samples are chosen according to predetermined age conditions shown in Table 6.2. The new household members or newcomers that satisfied the conditions were included in the analysis.

Table 6.2 The selection process

Wave (Year)	Selected age	No. of observations
Wave 12 (2002)	Aged 61 and over	3,240
Wave 13 (2003)	Aged 62 and over	3,082
Wave 14 (2004)	Aged 63 and over	2,805
Wave 15 (2005)	Aged 64 and over	2,638
Wave 16 (2006)	Aged 65 and over	2,465
Total		14,230

6.3.1.3 Missing values

Before deleting observations with missing values in at least one variable of interest, the sample consist of 16,614 observations from 3,978 unique individuals (known as *selected sample* henceforth). Of the 16,614 observations, 14,991 have completed the individual[20] and self-completion questionnaire; 776 have completed the individual questionnaire only; 485 have been interviewed through the

[19] BHPS wave 16 is the latest wave (fully published) during the time of analysis.
[20] Individual questionnaire is conducted by the interviewer.

telephone and 362 have had a questionnaire answered by proxy respondents. Proxy respondents are used because of several reasons such as being in an institution (20 cases), being unwell for long term (92 cases) or being a carer (107 cases). The use of proxy respondents has contributed to many missing values in many variables of interest such as number of health care utilisations and health and health related variables

After dealing with missing values which was deleting observations with at least one missing value of interest variables, sample has reduced to 14,230 observations from 3,566 unique individuals (known as the *reduced sample* henceforth). Summary statistics from the selected sample and reduced sample are compared (see *Appendix 6-II*, pp. 200-201 for comparison) which later reveals that the statistics of variable of interest are comparable between these two sample types. The frequency and patterns of respondents' distribution that have been used in the analysis, throughout wave 12 to wave 16 (w12-w16) are shown in Table 6.3.

6.3.1.4 Nonresponse and attrition problems

Table 6.3 has shown that the minimum number of waves for a respondent to be observed is one while more than half (56.65%) of the respondents have been observed every year for five years and these contribute to 10,100 observations in the balanced sample. Around 70% were observed in the first three years. Respondents can also be missing in between waves, for example; there are 71 respondents who are not observed in wave 14 but return in wave 15 and 16.

In some cases, respondents were absent completely from the panel after one or several waves of participation, which is known as *attrition*. For example, there are 257 respondents who participated in wave 12 only and are missing in the future waves. Wave non-response or attrition may lead to estimation bias in the study. This is because attrition may be associated with poor health status or because the 'end of life' is likely to happen, which requires greater end of life related services that may not be picked up in the analysis.

In order to identify the presence of selectivity bias in this study, I use two steps suggested by Verbeek and Nijman (1992) and later being use by Nijman and Verbeek (1992). First step is a Hausman-type test. It is used to compare the estimates between balanced and unbalanced random-effects models. Both estimates are consistent under the null hypothesis and inconsistent under the alternative.

Estimators from both models are consistent if there is no significant difference between them of which estimators from unbalanced panel is efficient. Another test proposed by Verbeek and Nijman (1992) is by including some additional variables into the unbalanced random-effects models. These new regressors exhibit participation patterns of the respondents. There are three additional variables that have been tested which are whether individuals are present in all waves (allwave), whether presence in the previous wave (prevwave), and number of waves presence (numwave).

Table 6.4 shows the results from the selectivity bias tests. The significant influence of participation patterns suggests that there is evidence of wave non-response and attrition bias. All additional regressors have negative coefficients which suggest that respondents who are present in previous wave(s), participated in all waves, or participated in longer periods have utilised less health care. This may reflect that those who are in a balanced sample or those who remained observed for five consecutive years, may have different health care utilisation or health status distributions from those who dropped out from the survey after participating in one or more of the waves. Therefore, the use of unbalanced sample in the analysis is believed to reduce bias in the analysis.

Table 6.3 The distribution of respondents

Permutations[1]					Frequency	Percent	Cumulative
W12	W13	W14	W15	W16			
1	1	1	1	1	2020	56.65	56.65
1	0	0	0	0	257	7.21	63.85
1	1	1	1	0	236	6.62	70.47
1	1	0	0	0	233	6.53	77.01
1	1	1	0	0	204	5.72	82.73
0	1	1	1	1	101	2.83	85.56
1	1	0	1	1	71	1.99	87.55
1	1	1	0	1	56	1.57	89.12
1	0	1	1	1	47	1.32	90.44
other patterns					341	9.56	100.00
					3566	100.00	

Note:
[1]Equal to '1' if participated, 0 otherwise.

Table 6.4 Tests of selectivity bias

	Prob>chi2		
	NURSE	OUTPATIENT	GP
Hausman	0.9993	0.0000	0.0038
p-value of "allwave"	0.0000	0.0000	0.0000
p-value of "prevwave"	0.9161	0.0021	0.0017
p-value of "numwave"	0.000	0.0000	0.0001
Remarks	Non-response and attrition bias may exist		

6.3.2 Selection of variables

6.3.2.1 Dependent variables

The services which utilisation has been focused on in this study include two services that have been modelled in the preceding chapters - GP and outpatient visits, and utilisation of services by district nurses or health visitors.[21] The reference period for reporting all services is one year. Data for nurse visits take the value of either zero for non-users or one for users which allowing the use of the binary model, i.e. logit model. Data for GP[22] and outpatient visits are categorical where each category represents a specific number or interval of frequency of visits.

The appropriate econometric technique to model utilisation in interval form is by using group poisson regression model (Moffatt, 1995; Moffatt & Peters, 2000). However, due to some problems while executing the group poisson model, the standard count data model is utilised at this stage. In order to utilise standard count data techniques, data on GP and outpatient visits have been recoded from grouped to single count data. Respondents who visited between one and two times have been recoded as two; three to five as four; six to ten as eight and more than ten as twelve.

Results may be sensitive to the recoding process. Therefore, for comparison, an alternative model has been fitted for GP and outpatient use using different recoding values, of which value of more than ten visits have been recoded as 15 instead of 12. For simplicity and comparison purposes, these models have been

[21] From the survey, the utilisation of district nurses and health visitors' services has been combined into one variable. Therefore, for simplicity these services were addressed as 'nurse' throughout the analysis.
[22] For convenience, consultations or visits to a GP or family doctors are referred to GP visits, use or utilisations throughout the chapter,

estimated using random-effects approach without any adjustment in standard errors. It reveals that though there are slightly different in the coefficients; the direction of effects is similar. *Appendix 6-III*, pp. 202-203, presents the comparison of results for GP visits model.

6.3.2.2 Independent variables

The selection of independent variables is based on the studies reviewed in Chapter 2. These variables can be divided into three main categories - personal characteristics; health status, health related and health care; and socioeconomic variables. One of the issues discussed in Chapter 3 is endogeneity of self-assessed or self-reported health status. In dealing with this problem, the lagged values of self reported health variables are used in the model. The use of predetermined values of health status could avoid the simultaneity problems between health status and health care use (Bago d'Uva, 2005; Schellhorn et al., 2000). Again, to avoid simultaneity problems, lagged values for GP visits (nurse visits) are used in modelling utilisation for nurse (GP) use. The division of independent variables can be summarised as below where variables in *italic* are the reference variables:

1. **Personal characteristics**

Age (AGE), square of age (AGESQ), gender (MALE), marital status (*SINGLE*, COUPLED, MARRIED, SEPARATED, DIVORCED, WIDOW).

2. **Health, health related and health care (Lagged values)**

Five categories of self-perceived health status (*EXCELLENT_L*, GOOD_L, FAIR_L, POOR_L, V_POOR_L), limitation of daily activities because of health reasons (LIMIT_L), and 15 groups of reported health problems consisting

ARMS_L, SIGHT_L, HEAR_L, SKIN_L, CHEST_L, HEART_L, STOMACH_L, DIABETES_L, ANXIETY_L, ALCOHOL_L, EPILEPSY_L, MIGRAINE_L, OTHER_L, CANCER_L, STROKE_L. The effects of nurse utilisation (NURSE_L) on GP and outpatient visits are also tested. Similarly, in the nurse utilisation model, lagged values of GP (GP_L) visits are use as explanatory variables.

3. **Socioeconomic**

Education (*HIGH_EDU*, OTHER_EDU, NO_EDU)[23], log of adjusted and equivalised income (INCOME), housing tenure that represent wealth (*OWNED*, MORTGAGE, LOCAL_RENTED, OTHER_RENTED), current economic activity (*SELF_EMP*, EMPLOYED, UNEMPLOYED, RETIRED, CARE, SICK, OTHERS), country (*ENGLAND*, WALES, SCOTLAND, N.IRELAND)

6.3.3 Descriptive analysis

The aim of the descriptive analysis is to provide an overview and summary statistics of the data used in this chapter. It begins by presenting the summary statistics of dependent variables and frequency distribution of utilisation of GP, nurse and outpatient and their transition of use. This is followed by the mean of visits to GPs and outpatients by age categories and gender. The summary statistics for independent variables are presented after that. This is followed by discussing the frequency distribution of self-assessed health status and its year-to-year transitions. The numbers of self-reported health problems by gender and age

[23] Higher education includes higher degree, first degree, teaching and nursing qualifications, and other higher qualifications; other education includes GCE A level, GCE O level or equivalent, commercial qualification, CSE grade 2-5, Scot grade 4-5, apprenticeship and other qualifications.

categories are also discussed in order to get some impression of how the numbers of health problems differ by age and gender.

6.3.4 Empirical specification

In this section, it is first assumed that there is no sample selection bias in the dataset. Throughout the discussion, y_{it}, represents dependent variable for individual i at time t and x_{it}, represents the vector of covariates for individual i at time t and α_i is multiplicative individual effect. The models for health care use in this chapter are estimated using fixed-effect (FE) and random-effects (RE) approach depending on the assumption made on the individual effect α_i. In the FE model, α_i are possibly correlated with the regressors x_{it} but in the RE, it is treated as an unobserved random variable that are not correlated with x_{it}.

In the FE models, we can estimate the model, specifically for logit and count models, by eliminating the unknown parameter α_i, for example, by conditioning on $\sum_{t=1}^{T} y_{it}$ (see Hausman, Hall, & Griliches, 1984). In the RE models, α_i is treated as an unobserved random variables of which estimation could be made by assuming its distribution. To correct for over time dependency of certain individuals, cluster-robust standard errors are used in the RE models (Zeger, Liang, & Albert, 1988).

6.3.4.1 Fixed and Random effects logit

The logit individual-effects model is used to model utilisation for nurse visits, y_{it}.

Suppose y_{it}^* is an unobserved variable with the index function model given by

$y_{it}^{*} = x_{it}^{'}\beta + \upsilon_{it} + \alpha_i$

We can only observe dependent variable y_{it} that linking to y_{it}^{*} by

$$y_{it} = \begin{cases} 1\, if\ y_{ti}^{*} > 0 \\ 0\, if\ y_{ti}^{*} \leq 0 \end{cases}$$

Depending on the assumption made on the relationship between α_i and x_{it}, we could differentiate between fixed-effects (FE) and random-effects (RE) model. In the FE model, α_i and x_{it} are allowed to be correlated while in the RE model the individual-effects α_i is assumed to be independent on x_{it}. In the FE model, it is possible to eliminate α_i by obtaining the joint distribution of $y_{i1}\ldots, y_{iT_i}$ conditional on their sum (see Cameron & Trivedi, 2009; Greene, 2008). This method can be easily applied using two time periods where later could be generalised into a longer period.

Suppose we have a situation of two time periods of which $y_{i1} = 1$ and $y_{i2} = 0$ - condition on $y_{i1} + y_{i2} = 1$

$$\Pr\left(y_{i1=}1, y_{i2} = 0 \middle| y_{i1} + y_{i2} = 1\right) = \frac{\Pr\left(y_{i1=}1, y_{i2} = 0\right)}{\Pr\left(y_{i1=}1, y_{i2} = 0\right) + \Pr\left(y_{i1=}0, y_{i2} = 1\right)} \tag{6.1}$$

For the logit model, it can be specified as

$$\Pr\left(y_{i1=}1, y_{i2} = 0\right) = \frac{\exp\left(\alpha_i + x_{i1}^{'}\beta\right)}{1 + \exp\left(\alpha_i + x_{i1}^{'}\beta\right)} \times \frac{1}{1 + \exp\left(\alpha_i + x_{i2}^{'}\beta\right)} \tag{6.2}$$

and

$$\Pr\left(y_{i1=}0, y_{i2} = 1\right) = \frac{1}{1 + \exp\left(\alpha_i + x_{i1}^{'}\beta\right)} \times \frac{\exp\left(\alpha_i + x_{i2}^{'}\beta\right)}{1 + \exp\left(\alpha_i + x_{i2}^{'}\beta\right)} \tag{6.3}$$

Substituting (6.2) and (6.3) into (6.1), the fixed-effects α_i could be eliminated and we get

$$\Pr\left(y_{i1=}1, y_{i2} = 0 \middle| y_{i1} + y_{i2} = 1\right)$$

$$= \frac{\exp\left(x_{i1}^{'}\beta\right)}{\left\{\exp\left(x_{i1}^{'}\beta\right) + \left(x_{i2}^{'}\beta\right)\right\}}$$

$$= \frac{\exp\left\{\left(x_{i1} - x_{i2}\right)^{'}\beta\right\}}{\left[1 + \exp\left\{\left(x_{i1} - x_{i2}\right)^{'}\beta\right\}\right]} \qquad (6.4)$$

From (6.4), we could see that coefficient of time-invariant regressors are not identified resulting from $x_{i1} - x_{i2} = 0$. When there are more than two time periods, suppose T_i, α_i could be eliminated by conditioning on $\sum_{t=1}^{T_i} y_{it} = 1$ and on $\sum_{t=1}^{T_i} y_{it} = 2$,…… $\sum_{t=1}^{T_i} y_{it} = T_i - 1$. Therefore, the individuals who have constant utilisation throughout the observation periods, i.e. either $y_{it} = 0$ or $y_{it} = 1$ for all t, are dropped from the analysis because of no variation in y_{it} over t.

In the RE model, the individual-effects, α_i, are assumed to have a normal density

$$g\left(\alpha_i \middle| \sigma^2\right) = \mathrm{N}\left(0, \sigma_\alpha^2\right).$$

By integrating the α_i out, the joint density of $y_{i1}, y_{i2}, \ldots, y_{iT}$ that is conditional only on $\lambda_{i1}, \lambda_{i2}, \ldots, \lambda_{iT}$ is obtained as shown by

$$f\left(y_{it},....y_{iT} \mid \lambda_{i1},...\lambda_{iT}\right) =$$

$$\int\left[\prod_{t=1}^{T}\Lambda\left(\alpha_i + x'_{it}\right)^{y_{it}}\left\{1-\Lambda\left(\alpha_i + x'_{it}\right)^{1-y_{it}}\right\}\right]g\left(\alpha_i \middle| \sigma^2\right)d\alpha_i \tag{6.5}$$

There is no closed form expression for (6.5). In order to solve this, numerical methods can be used. In this case, 12-point Gauss-Hermite quadrature in Stata is utilised.

6.3.4.2 Fixed-Effects Poisson

In fixed-effects model (FE), x_{it} are allowed to be correlated with the time-invariant component of the error, α_i. To estimate the parameters, we have to eliminate α_i. This can be done by obtaining the joint distribution of $y_{i1}..., y_{iT_i}$ conditional on their sum (see Greene, 2008, pp. 916-918)

$$\Pr\left[y_{i1}..., y_{iT_i}\middle|\sum_{t=1}^{T_i} y_{it}\right] = \frac{\left(\sum_{t=1}^{T_i} y_{it}\right)!}{\left(\prod_{t=1}^{T_i} y_{it}!\right)}\prod_{t}^{T_i}\left(\frac{\lambda_{it}\alpha_i}{\sum_{t=1}^{T_i}\lambda_{it}\alpha_i}\right)$$

After cancelling the α_i, the equation can be simplified as

$$\Pr\left[y_{i1}..., y_{iT_i}\middle|\sum_{t=1}^{T_i} y_{it}\right] = \frac{\left(\sum_{t=1}^{T_i} y_{it}\right)!}{\left(\prod_{t=1}^{T_i} y_{it}!\right)}\prod_{t}^{T_i} P_{t=1}^{y_{it}}$$

where $P_{t=1}^{y_{it}} = \left(\frac{\lambda_{it}}{\sum_{t=1}^{T_i}\lambda_{it}}\right) = \left(\frac{\exp(x'_{it}\beta)}{\sum_{t=1}^{T_i}(x'_{it}\beta)}\right)$

The log-likelihood function of the model is therefore

$$\ln L_i(\beta) = \sum_{i=1}^{n}\left[\ln\left(\sum_{t=1}^{T_i} y_{it}\right)! - \sum_{t=1}^{T_i}\ln(y_{it}!) + \sum_{t=1}^{T_i} y_{it}\ln\left(\frac{\exp(x'_{it}\beta)}{\sum_{t=1}^{T_i}\exp(x'_{it}\beta)}\right)\right] \tag{6.6}$$

The first order conditions for conditional MLE, $\hat{\beta}_{FE}$ is obtained by differentiation (6.6) with respect to β given by

$$\sum_{i=1}^{n}\sum_{i=1}^{T_i} x_{it}\left(y_{it} - \frac{\lambda_{it}}{\overline{\lambda}_i}\overline{y}_i \right) = 0$$

where $\overline{\lambda}_i = T_i^{-1}\sum_{t=1}^{T_i}\exp\left(x_i^{'}\beta\right)$ and $\overline{y}_i = T_i^{-1}\sum_{t=1}^{T_i} y_{it}$

See also Blundell, Griffith, & Windmeijer (2000) for constructions.

6.3.4.3 Random-Effects Poisson

In the random-effects (RE) models, α_i are assumed to be is purely random and orthogonal to x_{it}. Unlike the FE model, RE model can estimate all coefficients of time-invariant regressors. To estimate the RE model, the joint probability conditioned upon the heterogeneity is formulated. By setting the density of α_i as $f(\alpha_i)$ and integrate the α_i out, the joint density of $y_{i1}, y_{i2},..., y_{iT}$ that is conditional only on $\lambda_{i1}, \lambda_{i2},..., \lambda_{iT}$ is obtained

$$\begin{aligned}\Pr\left[y_{i1}, y_{i2},...y_{iT} \,|\lambda_{i1},...\lambda_{iT} \right] &= \int_0^{\infty} \Pr\left[y_{i1}, y_{i2},...y_{iT} \,|\alpha_i, \right] f\left(\alpha_i\right) d\alpha_i \\ &= \int_0^{\infty}\left[\prod_t \Pr\left[y_{it}|\alpha_i\right]\right] f(\alpha_i) d\alpha_i \qquad (6.7)\end{aligned}$$

In order to find a closed form expression for the integral in (6.7), the Poisson-gamma mixture is used here. The random-effects α_i is assumed to be gamma distributed with parameter (δ, δ) where $\mathrm{E}[\alpha_{\mathrm{i}}] = 1$ and $\mathrm{V}[\alpha_{\mathrm{i}}] = 1/\delta$. Although gamma density also conjugates to the negative binomial model[24], it is not considered in this analysis (see Hausman et al. (1984) and Schellhorn et al. (2000) for derivation of random-effects of negative binomial model). This is because the Poisson model may be sufficient in dealing with the heterogeneity problem for panel data. As an alternative to the negative binomial specification, the cluster-robust standard errors are used to account for serial correlation and overdispersion.

By using gamma-distributed random-effects, the density of the random-effects Poisson model is specified as

$$\Pr\left[y_{i1},\ldots,y_{iT_i}\left|\lambda_{i1},\ldots\lambda_{iT}\right.\right]=\left[\prod_{t=1}^{T_i}\frac{\lambda_{it}^{\;y_{it}}}{y_{it}\,!}\right]\left(\frac{\delta}{\sum_{t=1}^{T_i}\lambda_{it}+\delta}\right)^{\delta}\left(\sum_{t=1}^{T_i}\lambda_{it}+\delta\right)^{-\sum_{t=1}^{T_i}y_{it}}\frac{\Gamma\left(\sum_{t=1}^{T_i}y_{it}+\delta\right)}{\Gamma(\delta)}$$

The first-order conditions for Poisson RE estimator, $\hat{\beta}$, is

$$\sum_{i=1}^{N}\sum_{i=1}^{T_i}x_{it}\left(y_{it}-\lambda_{it}\frac{\bar{y}_i+\delta/T_i}{\bar{\lambda}_i+\delta/T_i}\right)=0$$

where

$$\bar{\lambda}_i=T_i^{-1}\sum\nolimits_t\exp(x_{it}'\beta)$$

Other than being able to estimate all coefficients of time-invariant regressors, the RE model is more appropriate if one is interested in doing inference on the population rather than concentrating on the sample (Cameron & Trivedi, 2006).

[24] According to Greene (2008), random term, in cross-sectional data, is added to the Poisson model in which leads into the negative binomial distribution. By introducing the random effects into the negative binomial model of panel data, it resembles the same process again.

This is because the RE model utilises both within and between variations whereas the FE only uses information within the sample.

6.3.5 Correcting attrition bias

Attrition problems discussed in Section 6.3.1.4 is within the sample use in the analysis; whether balanced or unbalanced. The most important issue however is whether the *selected* sample, consisting of 16,614 observations, is representative of the original sample in the first place. Since I use wave 12 as a starting point, at this stage I assume that this sample is representative of the older population. The issue now is to check whether the *reduced* sample of 14,230 observations which is the sample I use in this study is representative of the selected sample.

To check and correct for the sample selection problem, maximum likelihood technique is used. The maximum likelihood estimation of a joint model of outcome and selection variable would produce consistent estimators (Cameron & Trivedi, 2006; Terza, 1998). This approach is more appropriate than a correction based on the inclusion of Inverse Mill's Ratio (IMR) to the conditional mean similar to the approach by Heckman (1979)[25] for a linear model.

In dealing with the possibility of sample selection problem, a Stata program called **`gllamm`** (Rabe-Hesketh, Skrondal, & Pickles, 2004) is used. This program estimates Generalised Linear Latent and Mixed Models (GLLAMMs). In this chapter a *wrapper* program of **`gllamm`**, i.e **`ssm`**[26] (Miranda & Rabe-Hesketh, 2006), is used to estimate logit (for NURSE) and Poisson (for GP and

[25] Although this approach (heckman-type) has been criticised for not leading to a correct derivation of the correction term of the nonlinear models (Cameron & Trivedi, 2006; Terza, 1998), Greene (1995; 1998) and (Orme & Peters, 2001) have found that the use of Heckman correction term is approximately correct

[26] **`ssm`** has a simple syntax that calls **`gllamm`** for estimation.

OUTPATIENT) models using maximum likelihood framework. The discussion of the models in the next two sections is based on (Miranda & Rabe-Hesketh, 2006).

Suppose for every individual i, x_i is a vector of regressors and s_i is a selection dummy (whether selected in the estimation sample) that depends on a vector of explanatory variables z_i. The fact that the model is identified through functional form, vectors z_i may contain the same elements as in x_i. However, since the complete set of regressors, x_i, are not observable if s_i = 0, a set of additional regressors, z_i, is used in the model. I use the assumption made by Wooldridge (2002) which assumes that additional variables z_i is always observed and could predict participation.

It also assumed that variables from the first period may predict the participation pattern. Hence, the additional variables which include the initial value of some regressors x_i valued at wave 11, hence prefix '11' or at any earliest participated wave are used as a set of variables that predict participation.. These variables contains no or very minimum missing values. These variables include the initial values of age (AGE11), gender (MALE), self-assessed health status (GOOD11, FAIR11, POOR11, V_POOR11) and sum of health problems (SUMHP11).

6.3.5.1 The sample selection (SS) model for nurse visits

The model for nurse visits with sample selection problem can be discussed within the latent variables framework and can be written as

$$y_i^* = x_i^{'}\beta + u_i \tag{6.8}$$

where x_i represents the covariates for individual i and β represents vector of parameters to be estimated.

The dependent variable y_i is related to y_i^* by

$$y_i = \begin{cases} 1 \; if \;\; y_i^* > 0 \\ 0 \; if \;\; y_i^* \le 0 \end{cases}$$

The latent variable for the selection dummy can be specified as

$$s_i^* = z_i^{'}\gamma + \upsilon_i \tag{6.9}$$

The variable s_i and can only be observed that linking to s_i^* by

$$s_i = \begin{cases} 1 \; if \;\; s_i^* > 0 \\ 0 \; if \;\; s_i^* \le 0 \end{cases} \tag{6.10}$$

The residual terms u_i and υ_i are assumed to have a bivariate normal distribution. The dependence between residual terms u_i and υ_i can be shown by the use of random effects, ε_i, in both equations below

$$u_i = \lambda\varepsilon_i + \tau_i$$
$$\upsilon_i = \varepsilon_i + \zeta_i$$

Suppose that u_i and υ_i are jointly normal with mean zero and covariance matrix

$$\Sigma = \begin{pmatrix} \lambda^2 + 1 & \lambda \\ \lambda & 2 \end{pmatrix}$$

and correlation coefficient

$$\rho = \frac{\lambda}{\sqrt{2(\lambda^2 + 1)}} \qquad (6.11)$$

The presented model above could be adjusted to match the familiar parameterisation in bivariate probit models where variances are set to 1. To reparameterise the model, y_i^* in (6.8) is divided by $\sqrt{\lambda^2 + 1}$ and s_i^* in (6.9) is divided by $\sqrt{2}$. All estimated regression coefficients and standard errors have been rescaled and corrected. In order to use **`gllamm`** for estimation, a mixed response variable, q_{ji}, of every individual is created. The main outcome is represented by $j = 1$ and the selection dummy by $j = 2$. The conditional mean of q_{ji}, which is π_{ji}, can be written as

$$g_j(\pi_{ji}) = d_{1ji}(x_i'\beta + \lambda\varepsilon_i) + d_{2ji}(z_i'\gamma + \varepsilon_i) \qquad (6.12)$$

where d_{1ji} is the dummies if $j = 1$ and d_{2ji} if $j = 2$.

The individuals are said to be randomly selected to the sample if λ in (6.12) equals zero which reflecting $\rho = 0$ (see 6.11).

6.3.5.2 The sample selection (SS) model for GP and outpatient visits

Suppose the frequency of GP and outpatient visits, y_i, follows a Poisson distribution

$$f(y_i | x_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}$$

where x_i (including the constant term) represents the vector of covariates for individual i and β represents vector of parameters to be estimated. The log-linear model for the mean μ_i can be written as

$$\ln(\mu_i) = x_i^{'}\beta + \varepsilon_i$$

where ε_i is the unobserved heterogeneity term. The selection model is specified as

$$s_i^* = z_i^{'}\gamma + \lambda\varepsilon_i + \zeta_i$$

$$s_i = \begin{cases} 1 \ if \ s_i^* > 0 \\ 0 \ if \ s_i^* \le 0 \end{cases}$$

The error term ζ_i is assumed to have a standard normal distribution with mean 0 and variance 1, $\zeta_i \sim N(0,1)$ and independent of ε_i. The variance of ε_i is not set to constant here as it reflects the amount of overdispersion in count data. The variance of ε_i is therefore $\sigma^2, \mathrm{V}(\varepsilon_\mathrm{i}) = \sigma^2$. To adjust this parameterisation to the one in Terza (1998) which set the variance equals to 1, the regression coefficients from this model is divided by $\sqrt{\lambda^2\sigma^2 + 1}$.

For estimation using **`gllamm`** a mixed response variable, q_{ji}, of every individual is created as in (6.9). The mean of mixed-response variable q_{ji}, i.e. π_{ji}, can be written as

$$g_j(\pi_{ji}) = d_{1ji}(x_i^{'}\beta + \varepsilon_i) + d_{2ji}(z_i^{'}\gamma + \lambda\varepsilon_i)$$

6.4 RESULTS

This section starts with the descriptive statistics of both dependent and independent variables in Section 6.4.1. In Section 6.4.2, results from both fixed and random-effects models are presented and discussed. At this stage, it is assumed that there is no bias due to attrition or sample selection problems. Results from maximum likelihood estimation of sample selection models are discussed in Section 6.4.3 and Section 6.4.4 summarises the finding of selected models.

6.4.1 Descriptive analysis

6.4.1.1 Summary statistics of dependent variables

Table 6.5 exhibits the definition and summary statistics of health services whose utilisations will be modelled in this chapter.

Table 6.5 Definition and summary statistics of dependent variables

Variables	Definitions	Mean	Std. Dev.	Min	Max
NURSE	Whether have used nurse/health visitor services in the last year	0.11	0.31	0	1
GP	Number of GP or family consultations in the last year (excluding hospital visits)	4.30	3.64	0	12
OUTPATIENT	Number of outpatient visits in the last year	2.13	2.94	0	12

6.4.1.2 Frequency distribution of dependent variables

As outlined in Section 6.3.3, this section starts by discussing the frequency distributions of nurse, GP and outpatient use as shown in Figures 6.1 to 6.3. As mentioned before, the frequency of utilisations for GP and outpatient use has been recoded from interval data to a single count variable: 1-2 (2), 3-5 (4), 6-10 (8), and more than 10 (12). However, the use of interval frequency is more appropriate here to reduced measurement error. This is because for 12-months reference period, it is difficult for the respondents to recall the exact number of visits. Though the interval frequencies are not shown in Figures 6.2 to 6.3, they are used for the discussion in this section.

From the histograms, it shows that the frequencies of non-users among the elderly for nurse and outpatient services are greater than for GP. There are around 85% of non-users for nurse, 48% for outpatient and only 15% for GP visits. Most observations, presenting 32% of the sample, have between one and two of GP visits. Only 12% of observations have visited GP more than 10 times. Similar patterns are observed in outpatient visits except for zero visits. Zero visits are the highest frequencies for outpatient, but not for GP use.

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Figure 6.1 Frequency distribution of district nurses/health visitor's use by the elderly

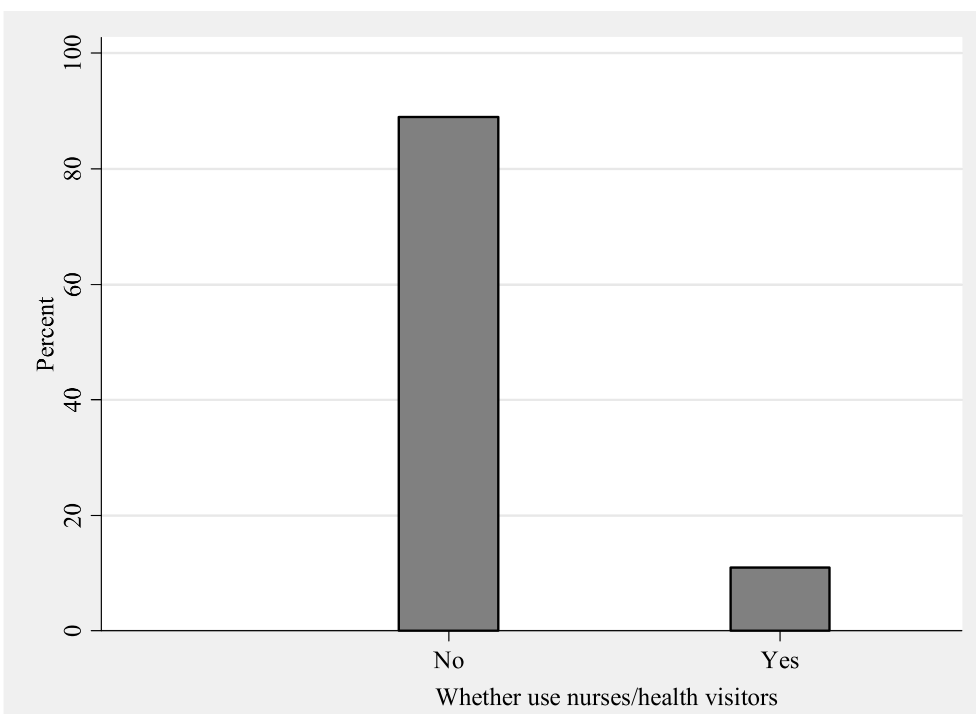


Figure 6.2 Frequency distribution of GP use by the elderly

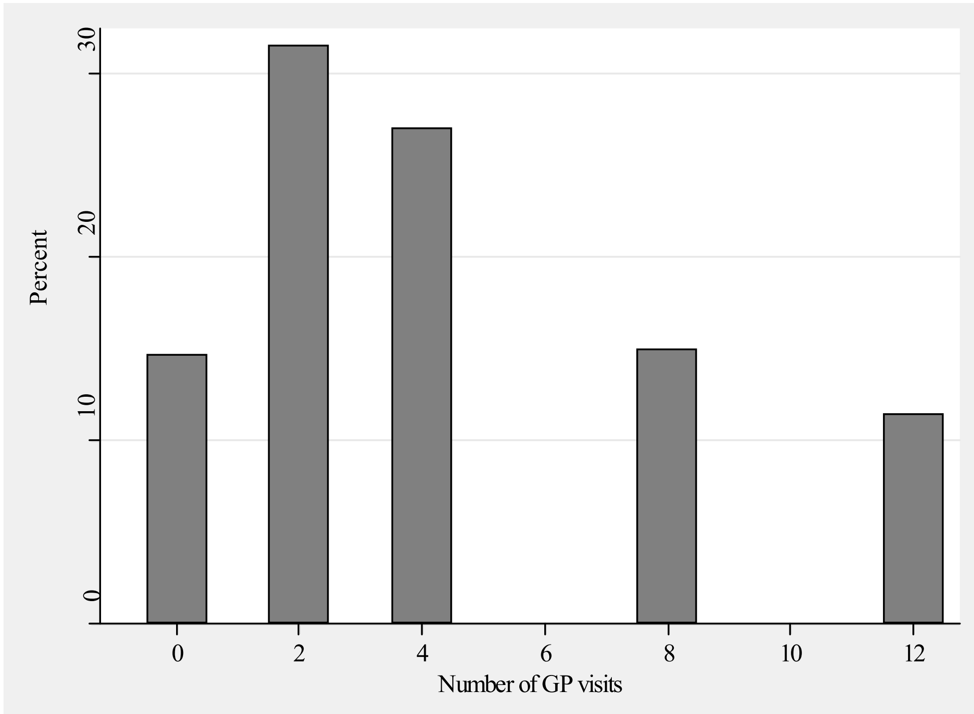
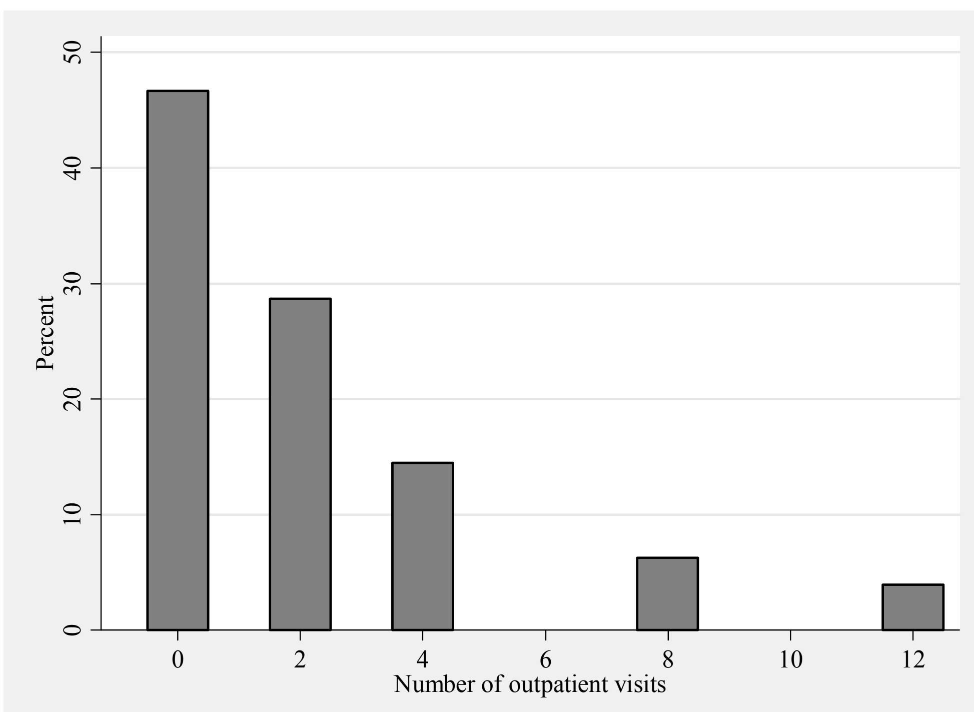


Figure 6.3 Frequency distribution of outpatient visits by the elderly



6.4.1.3 Transitions of visits

Tables 6.6 to 6.8 show, year-to-year, the transitions of use in a percentage. The columns show the current frequencies while the rows represent frequencies for the next year. The 'total' represents the percentage of use in the next periods (percentage of whether have utilised the services or not for nurse).

As for nurse visits, as shown in Table 6.6, 92.99% who have no visit in one year remain as non-users in the next year, while for those who have nurse visits in one year, 54.49% have switched to non-users in the next year. As shown in Table 6.7 at least 29% of the observations have the same GP use in the next year (shown in the shaded area). For example, 44.07% who did not have contact with a GP in one year remain as non-users in the next year while 46.45% retain to have twelve utilisations in the next year.

Most respondents (67.27%) who have zero visits for outpatient care in one year continue to have zero utilisation in the next year. Only around 11% have moved from zero visits to between four to twelve outpatient visits in the next year. The differences in care patterns may be explained by different specific initial diagnoses. Apart from zero visit, other frequencies for outpatient visits do not show a substantial year to year consistency as shown in Table 6.8.

Table 6.6 Transitions of nurse visits

Nurse visits	No	Yes	Total
No	92.99	7.01	100.00
Yes	54.49	45.51	100.00
Total	89.19	10.81	100.00

Table 6.7 Transitions of GP visits

Frequencies	0	1-2	3-5	6-10	>10	Total
0	44.07	39.58	11.68	3.03	1.64	100.00
1-2	18.27	49.11	22.26	7.16	3.20	100.00
3-5	5.40	28.43	40.61	17.69	7.87	100.00
6-10	2.80	14.32	33.79	29.88	19.21	100.00
>10	1.51	7.45	18.44	26.15	46.45	100.00
Total	14.59	32.35	26.94	14.82	11.30	100.00

Table 6.8 Transitions of outpatient visits

Frequencies	0	1-2	3-5	6-10	>10	Total
0	67.27	22.09	7.27	2.02	1.35	100.00
1-2	34.70	41.47	15.92	5.17	2.74	100.00
3-5	21.26	31.05	30.03	12.84	4.82	100.00
6-10	14.31	23.03	28.62	22.53	11.51	100.00
>10	13.42	15.34	19.73	21.37	30.14	100.00
Total	46.37	28.77	14.68	6.34	3.85	100.00

6.4.1.4 Mean of visits by age categories and gender

Figure 6.4 and 6.5 exhibit the mean visits for GP and outpatient by age categories and gender at 95% confidence interval. Age is divided into four categories- between 60-69 (1); 70-79 (2); 80-89 (3); and 90-99 (4). The mean of use for GP, in every year, is greater for those between age 80-89 compared to other age groups. The mean is quite stable for group 2 as compared to other groups, particularly group 4. The overall mean, however, has decreased over the years except in 2006 where it reaches its maximum level. On average, as shown in Figure 6.5, females have more GP use than males every year. This may be because women live longer, so are likely to have utilised more health care as age increases. Conversely, the mean for hospital visits for males is greater than for females. The elderly in age group 3 also have, on average, the highest hospital visits.

Figure 6.4 Mean of GP visits by age category

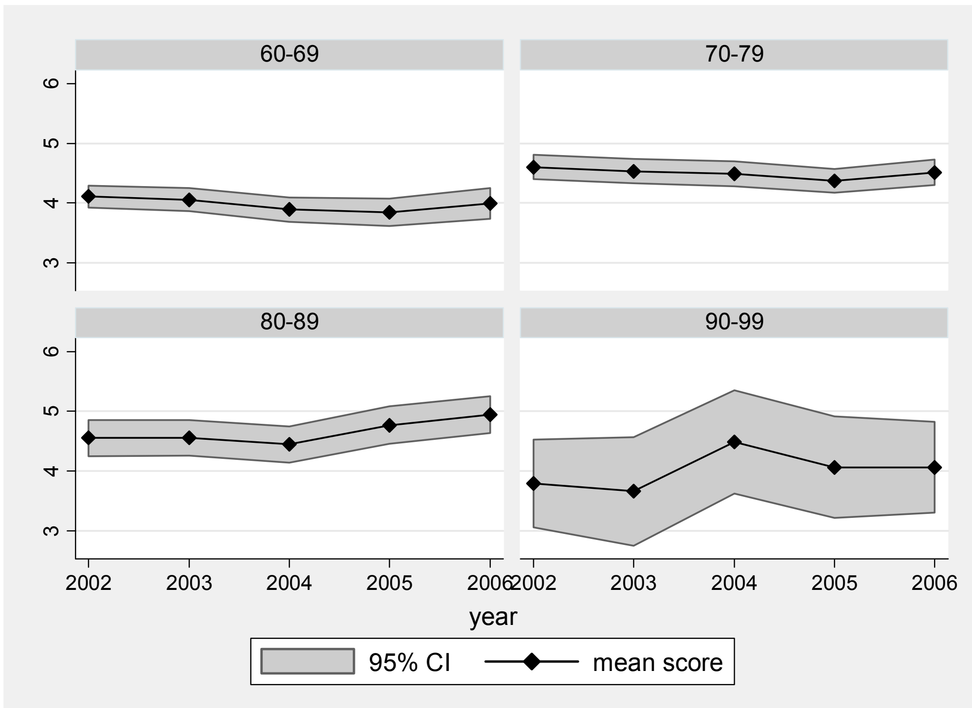


Figure 6.5 Mean of GP visits by gender

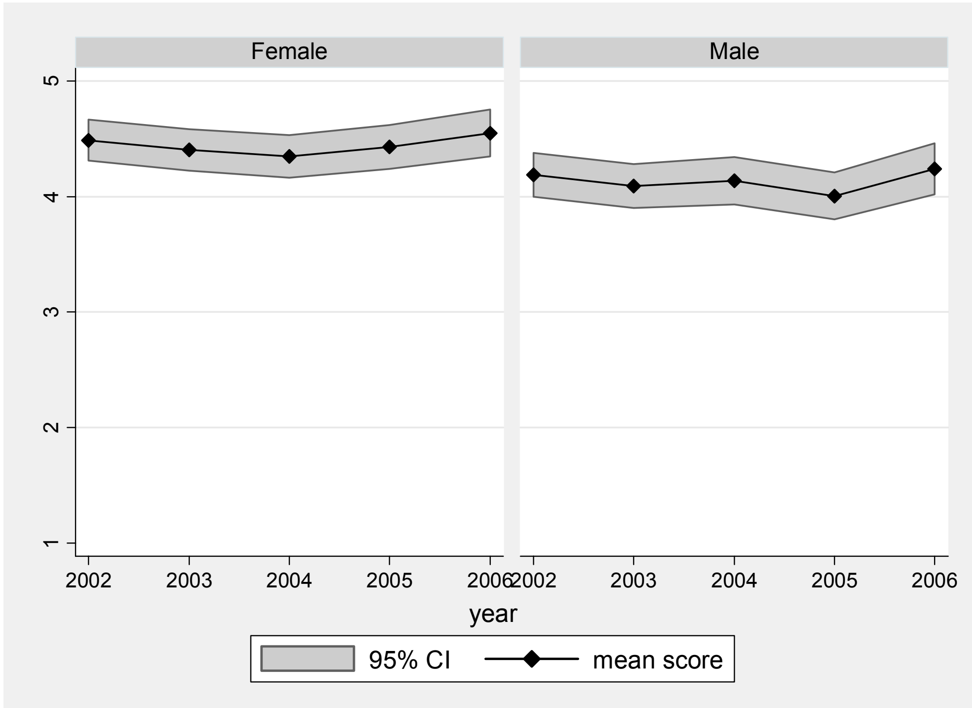


Figure 6.6 Mean of outpatient visits by age category

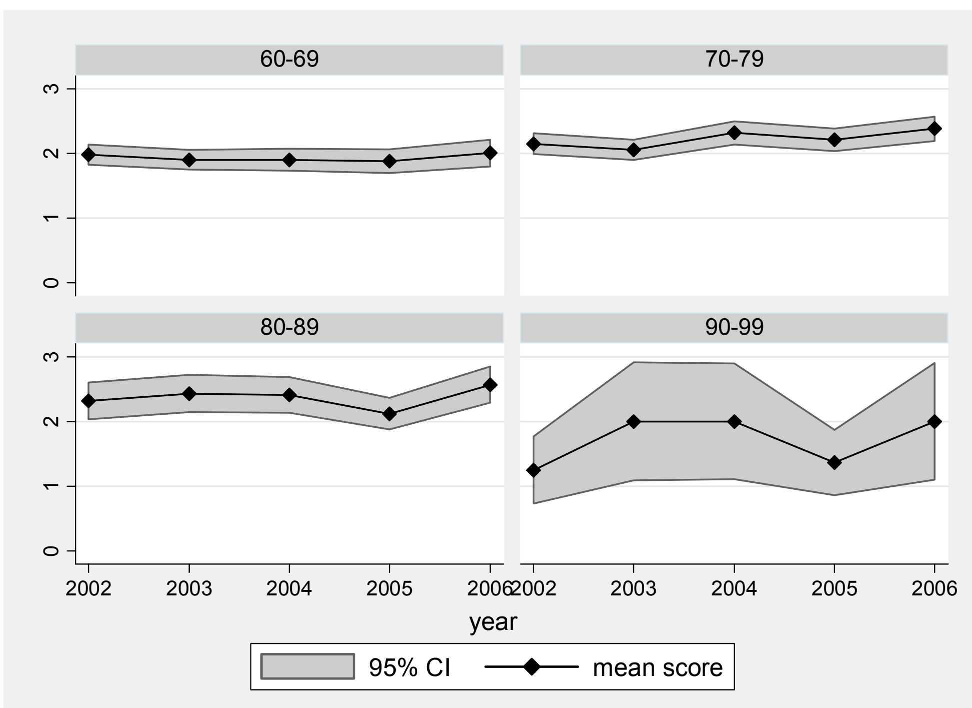


Figure 6.7 Mean of outpatient visits by gender

6.4.1.5 Summary statistics of independent variables

Figure 6.8 shows the frequency distribution of health status while Table 6.9 shows its year-to-year transitions. Most of the respondents, which are 44% of them, perceive their health status as “good”. Only 12% regard their health as “poor” or “very poor”. The remaining 15% have “excellent” while 29% have “fair” status. Referring to Table 6.8, 54.62% respondents with “excellent” status in one period remain “excellent” while 39.13% have moved from “excellent” to “good” in the next period. Only 0.26% moved from “excellent” in one period to “very poor” in the next. In all cases, the level of health status tends to transit to the nearest level (either lower or upper level) in the next period and only a small percentage has a drastic change. As discussed in section 6.3.2.2, independents variables are divided into three main categories as shown in Table 6.10. The summary is obtained from 14,069 observations from year 2002 to 2006.

Figure 6.8 Frequency distribution of self-assessed health status

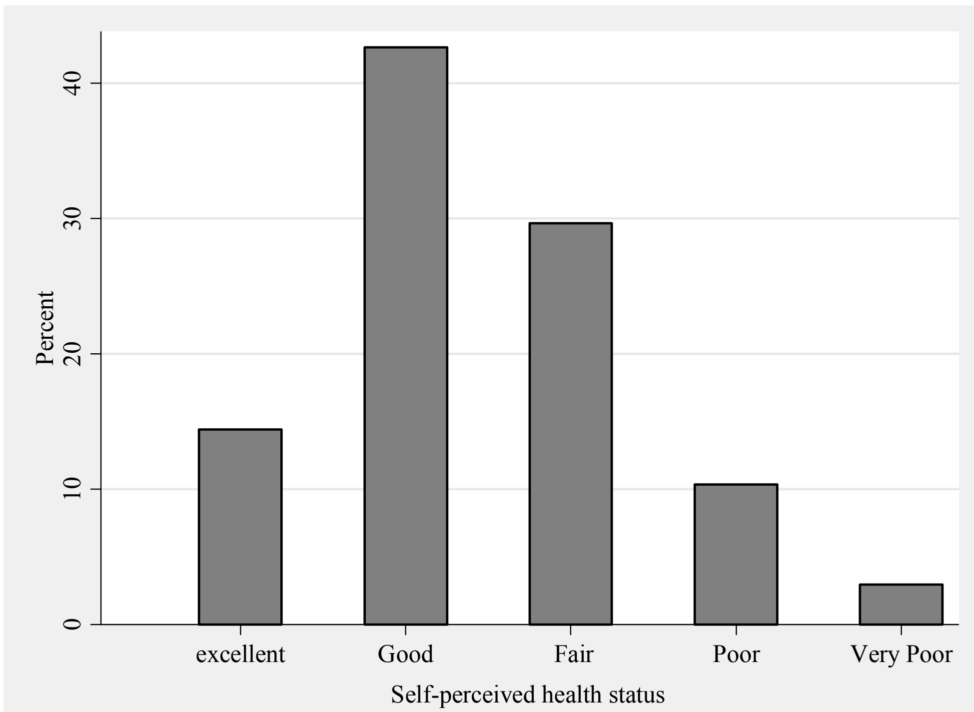


Table 6.9 Transitions of health status

Status	Excellent	Good	Fair	Poor	Very poor	Total
Excellent	54.62	39.13	4.88	1.11	0.26	100.00
Good	12.39	63.84	2.09	3.13	0.54	100.00
Fair	1.65	28.57	54.81	12.34	2.63	100.00
Poor	0.62	9.09	38.22	41.74	10.33	100.00
Very poor	0.00	7.57	19.52	39.04	33.86	100.00
Total	14.09	43.41	29.67	9.99	2.83	100.00

Table 6.10 Definition and summary statistics of independent variables

Variable	Definition	Mean	Std. Dev.	Min	Max
I. Personal Characteristics					
AGE	Age in year	72.93	7.146	61	99
AGESQ	Square of age in year	5370	1070	3721	9801
MALE	1 if gender is male, 0 if female	0.443	0.497	0	1
SINGLE	1 if never married, 0 otherwise	0.060	0.238	0	1
COUPLE	1 if living as a couple, 0 otherwise	0.013	0.114	0	1
MARRIED	1 if married, 0 otherwise	0.576	0.494	0	1
SEPARATED	1 if separated, 0 otherwise	0.007	0.081	0	1
DIVORCED	1 if divorced, 0 otherwise	0.051	0.22	0	1
WIDOWED	1 if widowed, 0 otherwise	0.293	0.455	0	1
II. Health status and health related variables (Lagged)					
Self-perceived health status and limitation					
EXCELLENT_L	1 if has excellent health status over the last 12 months, 0 otherwise	0.150	0.357	0	1
GOOD_L	1 if has good health status over the last 12 months, 0 otherwise	0.434	0.496	0	1
FAIR_L	1 if has fair health status over the last 12 months, 0 otherwise	0.294	0.456	0	1
POOR_L	1 if has poor health status over the last 12 months, 0 otherwise	0.097	0.295	0	1
V_POOR_L	1 if has very poor health status over the last 12 months, 0 otherwise	0.025	0.155	0	1
LIMIT_L	1 if health limits daily activities, 0 otherwise	0.325	0.468	0	1
Reported health problem excluding temporary conditions					
ARMS_L	1 if reported arms, legs, hands problems, 0 if not	0.536	0.499	0	1
SIGHT_L	1 if reported sight problems, 0 if not	0.117	0.322	0	1
HEAR_L	1 if reported hearing problems, 0 if not	0.219	0.414	0	1
SKIN_L	1 if reported skin conditions/allergy, 0 if not	0.099	0.298	0	1
CHEST_L	1 if reported chest/breathing problems, 0 if not	0.181	0.385	0	1
HEART_L	1 if reported having heart/blood pressure, 0 if not	0.455	0.498	0	1
STOMACH_L	1 if reported having stomach or digestion problems, 0 if not	0.119	0.324	0	1
DIABETES_L	1 if reported having from diabetes, 0 if not	0.095	0.293	0	1
ANXIETY_L	1 if reported suffering from anxiety/ depression, 0 if not	0.073	0.261	0	1

Table 6.10 Definition and summary statistics of independent variables

Variable	Definition	Mean	Std. Dev.	Min	Max
ALCOHOL_L	1 if reported having alcohol or drugs problems, 0 if not	0.002	0.047	0	1
EPILEPSY_L	1 if reported suffering from epilepsy, 0 if not	0.007	0.086	0	1
MIGRAINE_L	1 if reported suffering from migraine, 0 if not	0.051	0.22	0	1
CANCER_L	1 if reported suffering from cancer, 0 if not	0.034	0.181	0	1
STROKE_L	1 if reported suffering from stroke, 0 if not	0.035	0.183	0	1
OTHER_L	1 if reported other problems, 0 if not	0.049	0.217	0	1
Health service use					
NURSE_L	1 if has health district nurse/health visitor visit in the last 12 months, 0 otherwise	0.101	0.302	0	1
GP_L	1 if has GP or family doctor contact in the last 12 months, 0 otherwise	0.851	0.407	0	12
III. Socioeconomic Status					
Education and Income					
HIGH_EDU	1 if has higher qualification, 0 otherwise	0.246	0.431	0	1
OTHER_EDU	1 if has other qualification, 0 otherwise	0.274	0.446	0	1
NO_EDU	1 if has no qualification, 0 otherwise	0.48	0.5	0	1
INCOME	Log of equivalised and adjusted household annual income	9.755	0.713	0	12.354
Housing tenure					
OWNED	1 if owned outright, 0 otherwise	0.694	0.461	0	1
MORTGAGE	1 if owned with mortgage, 0 otherwise	0.079	0.269	0	1
LOCAL_RENT	1 if local authority rented, 0 otherwise	0.142	0.349	0	1
OTHER_RENT	1 if other rented, 0 otherwise	0.086	0.28	0	1
Current economic activity					
SELF_EMP	1 if self employed, 0 otherwise	0.023	0.149	0	1
EMPLOYED	1 if employed, 0 otherwise	0.06	0.238	0	1
UNEMPLOYED	1 if unemployed, 0 otherwise	0.002	0.048	0	1
RETIRED	1 if retired altogether, 0 otherwise	0.857	0.35	0	1
HOME	1 if looking after family or home, 0 otherwise	0.037	0.189	0	1

Table 6.10 Definition and summary statistics of independent variables

Variable	Definition	Mean	Std. Dev.	Min	Max
SICK	1 if long term sick or disable, 0 otherwise	0.018	0.132	0	1
OTHER	1 if other -apart from above, 0 otherwise	0.003	0.053	0	1
Country					
ENGLAND	1 if live in England, 0 otherwise	0.457	0.498	0	1
WALES	1, if live in Wales, 0 otherwise	0.2	0.4	0	1
SCOTLAND	1, if live in Scotland, 0 otherwise	0.186	0.389	0	1
N.IRELAND	1, if live in Northern Ireland, 0 otherwise	0.156	0.363	0	1
Time					
t	time-continuous	3.86	1.409	2	6

6.4.2 Findings from the FE and RE model

The results of the FE and RE models are reported in Tables 6.11 to 6.13. The number of observations in the FE model had reduced considerably, especially for nurse visits because of several reasons as noted below Tables 6.11 to 6.13. In the FE model, coefficients of the time-invariant variables are not identified and they are subsequently dropped from the model. These variables include MALE and N.IRELAND. The individuals that have unvarying utilisation over the years are also dropped from the FE estimation. Due to this reason, of 14,230 observations, only 3440 left for analysis in the model for nurse visits. The loss of observations leads to larger standard errors in the FE model of nurse visits (FE_NURSE) than those in the RE model (RE_NURSE).

All variables in the FE_NURSE are not significant. In many cases, the direction of coefficients changes between models. For example, in the FE_NURSE, the effects of ARMS_L and DIABETES_L are negative but in the RE_NURSE models there are positive. Based on the FE_NURSE, these results suggests that those who suffer from arms, legs and hands problems and diabetes utilise less health care than those without these problems. These effects, however, are not significant. This may be because the utilisation of those left in the sample of FE_NURSE have not being influenced by their health problems, thus it may not indicate the true effects of health problems on the use of nurse service.

The FE model also requires an individual to be observed for at least two years so that the variation within-individual can be identified. Due to only one year participation, 344 individuals are dropped from the FE model of GP visits (FE_GP). Nevertheless, the observations left in the FE_GP are considerably greater than those of nurse visits. The effects of self-assessed health status are significant in both FE and RE models of GP visits and the sign of significant coefficients of health problems are comparable between the FE and RE models except for HEART_L. On balance, these effects suggest that suffering from health problems have increased the frequency of GP visits except for STROKE_L where the effect is negative. The direction of coefficients of marital status and current economic activities are also comparable between the FE_GP and RE_GP while the effects of other significant variables such as age, education and country vary between models.

As for outpatient visits, the direction of coefficients of marital status dummies are comparable between the FE and RE models. Those who are coupled have less outpatient visits than those singles (never married) but have more visits if separated. These effects are significant in FE model (FE_OUTPATIENT). Like in the GP model, the effects of self-assessed health status are significant in both FE and RE model for outpatient visits. The sign of coefficients are similar between models.

The directions of some significant coefficients are different between the FE_OUTPATIENT and RE_OUTPATIENT. This is similar case like in the nurse visits model because FE and RE approach works differently. For instance, the variation between individuals is completely ignored in the FE model. However, by ignoring the between-variation, the possibility to get unbiased estimates is greater. This is because the variation between individual are exposed to distortion by unobserved effects that are correlated with the regressors. Therefore, the choice between FE and RE models involves the trade-off between bias and variation of the sample. By referring to the panel summary statistics in *Appendix 6-IV*, pp. 204-206, in all cases, except for time (t), the 'between' variations are greater than 'within' variations. Since the FE estimators are more relevant in explaining the heterogeneity within the sample, it may not produce efficient results for this case. Furthermore, the FE model is appropriate if one is more interested in understanding the sample rather than the population (Cameron & Trivedi, 2006).

6.4.3 Findings from the sample selection (SS) model

This section reports the estimation results by assuming that there is sample selection bias in the data due to attrition or item-non response. Results are reported in the last columns of Tables 6.11 to 6.13. Most of the variables used to predict participation are significant that includes age, self-assessed health and the sum of health problems at wave 11. The sign of significant coefficients in SS and RE models are identical, except for some. However the value of effects is different between competing models. From the SS model, the null hypothesis that there is no sample selection bias can be tested. If $\rho = 0$, there is evidence of no sample selection problem in the data, thus the FE or RE models could be used for discussion. Based on the p-value of ρ, the null hypothesis of no sample selection bias is rejected for outpatient visits but not for nurse and GP visits. Therefore, the SS model is used for discussion for outpatient visits.

Table 6.11 FE, RE and SS estimates for nurse visits

	FE		RE		SS	
	coef.	s.e	coef.	s.e	coef.	s.e
AGE	-0.364	0.309	0.036	0.106	0.014	0.035
AGESQ	0.001	0.002	0.000	0.001	0.0002	0.0002
MALE			-0.144	0.102	-0.068**	0.033
COUPLED	-13.511	715.941	-0.423	0.515	-0.047	0.167
MARRIED	1.327	1.300	-0.008	0.197	-0.017	0.063
SEPARATED	2.016	2.103	0.524	0.536	0.207	0.166
DIVORCED	1.665	1.322	0.187	0.265	0.030	0.087
WIDOWED	1.574	1.278	0.254	0.199	0.104*	0.063
GOOD_L	-0.029	0.190	0.331**	0.153	0.122***	0.058
FAIR_L	0.160	0.211	0.686***	0.164	0.282***	0.062
POOR_L	0.110	0.236	1.090***	0.186	0.543***	0.072k
V_POOR_L	0.295	0.297	1.762***	0.233	0.927***	0.092
LIMIT_L	0.028	0.111	0.638***	0.090	0.319***	0.036
ARMS_L	-0.068	0.125	0.322***	0.089	0.154***	0.034
SIGHT_L	-0.147	0.141	0.023	0.107	0.033	0.041
HEAR_L	-0.087	0.147	0.084	0.095	0.057*	0.035
SKIN_L	-0.235	0.171	0.029	0.124	0.052	0.047
CHEST_L	0.142	0.147	0.279***	0.099	0.086***	0.037
HEART_L	-0.094	0.117	0.073	0.083	0.055*	0.031
STOMACH_L	-0.021	0.140	0.053	0.110	-0.005	0.043
DIABETES_L	-0.168	0.267	0.467***	0.132	0.209***	0.045
ANXIETY_L	-0.075	0.164	0.090	0.129	0.063	0.050
ALCOHOL_L	0.787	0.643	0.833	0.601	0.069	0.247
EPILEPSY_L	0.569	0.929	0.409	0.446	0.163	0.149
MIGRAINE_L	-0.042	0.222	0.011	0.169	0.013	0.065
OTHER_L	-0.145	0.168	0.222	0.147	0.143***	0.060
CANCER_L	-0.201	0.206	0.240	0.173	0.148	0.069
STROKE_L	0.029	0.207	0.575***	0.163	0.317***	0.065
GP_L	0.035	0.098	0.106	0.088	0.0004	0.021
OTHER_EDU	-0.542	1.363	-0.109	0.138	-0.047	0.045
NO_EDU	-0.527	1.622	-0.100	0.128	-0.063	0.042
INCOME	-0.078	0.078	-0.049	0.053	-0.023	0.020
MORTGAGE	-0.013	0.313	-0.058	0.176	-0.016	0.061
LOCAL_RENT	0.124	0.423	0.455***	0.124	0.159*	0.041
OTHER_RENT	-0.046	0.352	0.106	0.148	-0.026	0.051
EMPLOYED	0.636	1.240	0.015	0.488	0.075	0.176
UNEMPLOYED	0.543	1.645	0.128	1.031	0.108	0.412
RETIRED	0.904	1.220	0.326	0.433	0.150	0.154
HOME	0.421	1.260	0.349	0.480	0.156	0.171
SICK	0.832	1.252	0.881*	0.487	0.514	0.175
OTHER	0.788	1.835	0.054	0.981	0.061	0.351
WALES	1.384	1.266	0.171	0.126	0.044	0.041
SCOTLAND	14.421	1435.988	0.657***	0.124	0.260***	0.040
N.IRELAND			0.270*	0.140	0.109***	0.044
t	0.314	0.137	-0.061**	0.025	-0.029***	0.011
CONSTANT			-9.105**	4.094	-3.748***	1.351

Table 6.11 FE, RE and SS estimates for nurse visits

	FE		RE		SS	
	coef.	s.e	coef.	s.e	coef.	s.e
Selection						
AGE11					-0.020***	0.002
MALE					-0.004	0.025
GOOD11					0.006	0.037
FAIR11					-0.121***	0.041
POOR11					-0.464***	0.050
V_POOR11					-0.616***	0.078
SUMHP11					0.036***	0.009
CONSTANT					2.520***	0.119
σ						
ρ					0.036	0.031
					P>=chi2=0.245	
Log likelihood	1234.27		3931.03		11196.91	
No. of Obs.	3440		14230		16614	

Note:
1. The symbols ***, ** and * denote 1, 5 and 10% level of significance, respectively
2. In FE model:
   - multiple positive outcomes within group encountered
   - 2768 groups (10790 observations) dropped because of all positive or negative outcome
   - MALE omitted because of it is constant within group
   - N.IRELAND omitted because of it is constant within group

Table 6.12 FE, RE and SS estimates for GP visits

	FE		RE		SS	
	coef.	s.e	coef.	s.e	coef.	s.e
AGE	-0.13***	0.040	0.039	0.025	0.070***	0.017
AGESQ	0.0005**	0.0002	-0.0002	0.0002	0.0005***	0.0001
MALE			-0.024	0.018	-0.032**	0.015
COUPLED	0.077	0.157	0.055	0.072	0.127*	0.066
MARRIED	0.217*	0.129	0.102***	0.035	0.123***	0.029
SEPARATED	0.435**	0.191	0.191**	0.091	0.111	0.081
DIVORCED	0.157	0.134	0.069	0.055	0.024	0.040
WIDOWED	0.223*	0.125	0.091**	0.038	0.085***	0.030
GOOD_L	0.058***	0.022	0.160***	0.029	0.261***	0.023
FAIR_L	0.094***	0.025	0.260***	0.030	0.460***	0.025
POOR_L	0.125***	0.029	0.331***	0.033	0.607***	0.032
V_POOR_L	0.115***	0.038	0.333***	0.038	0.566***	0.047
LIMIT_L	0.007	0.014	0.062***	0.015	0.116***	0.017
ARMS_L	0.034**	0.014	0.096***	0.016	0.167***	0.015
SIGHT_L	-0.005	0.018	0.023	0.014	0.041**	0.020
HEAR_L	0.004	0.018	0.028*	0.015	0.069***	0.016
SKIN_L	-0.004	0.020	0.025	0.020	0.046**	0.022
CHEST_L	0.030*	0.018	0.103***	0.014	0.175***	0.017
HEART_L	-0.008	0.014	0.085***	0.016	0.265***	0.014
STOMACH_L	0.022	0.017	0.060***	0.018	0.162***	0.020
DIABETES_L	0.011	0.031	0.126***	0.029	0.210***	0.022

Table 6.12 FE, RE and SS estimates for GP visits

	FE		RE		SS	
	coef.	s.e	coef.	s.e	coef.	s.e
ANXIETY_L	0.011	0.021	0.046**	0.023	0.134***	0.024
ALCOHOL_L	0.082	0.101	0.072	0.113	-0.050	0.132
EPILEPSY_L	0.352	0.111	0.211	0.140	0.014	0.075
MIGRAINE_L	0.009	0.027	0.020	0.030	0.000	0.030
OTHER_L	-0.001	0.022	0.027	0.025	0.118***	0.029
CANCER_L	-0.038	0.029	-0.003	0.031	0.089**	0.035
STROKE_L	-0.046*	0.028	-0.021	0.035	0.005	0.034
NURSE_L	-0.019	0.017	0.003	0.019	0.013	0.022
OTHER_EDU	-0.119	0.132	0.053**	0.022	0.029	0.019
NO_EDU	-0.151	0.166	0.040*	0.023	-0.007	0.018
INCOME	0.005	0.009	0.001	0.010	-0.005	0.010
MORTGAGE	-0.039	0.033	0.001	0.032	0.021	0.026
LOCAL_RENT	0.066	0.050	0.057**	0.028	0.001	0.020
OTHER_RENT	-0.006	0.043	0.029	0.031	0.031	0.024
EMPLOYED	0.039	0.065	0.040	0.074	-0.010	0.056
UNEMPLOYED	0.313***	0.120	0.267**	0.104	0.198	0.144
RETIRED	0.172***	0.060	0.186***	0.057	0.109**	0.049
HOME	0.162**	0.070	0.150**	0.059	0.020	0.060
SICK	0.125*	0.070	0.177**	0.073	0.126*	0.066
OTHER	0.172	0.118	0.153	0.142	0.008	0.137
WALES	-0.032	0.146	0.058**	0.023	0.034*	0.018
SCOTLAND	0.357	0.646	0.053**	0.025	0.056***	0.019
N.IRELAND			0.073**	0.029	0.092***	0.020
t	0.073***	0.021	-0.007	0.005	-0.011**	0.005
CONSTANT			-0.822	0.959	-2.267***	0.636
Selection						
AGE11					-0.020***	0.002
MALE					-0.004	0.025
GOOD11					0.006	0.037
FAIR11					-0.122***	0.041
POOR11					-0.463***	0.050
V_POOR11					-0.613***	0.078
SUMHP11					0.036***	0.009
CONSTANT						
σ					0.604***	0.007
ρ					0.021	0.042
					P>=chi2=0.626	
Log likelihood	-20964.94		-33828.54		-43480.46	
No. of Obs.	13625		14230		16614	

Note:
1. The symbols ***, ** and * denote 1, 5 and 10% level of significance, respectively
2. In FE model:
   - 344 groups (344 observations) dropped because of only one observation per group
   - 66 groups (261 observations) dropped because of all zero outcome
   - MALE omitted because of it is constant within group
   - N.IRELAND omitted because of it is constant within group

Table 6.13 FE, RE and SS estimates for outpatient visits

	FE		RE		SS	
	coef.	s.e	coef.	s.e	coef.	s.e
AGE	-0.028	0.057	0.059	0.052	0.121***	0.031
AGESQ	0.0003	0.0003	0.000	0.000	-0.0008***	0.0002
MALE			0.049	0.032	0.033	0.027
COUPLED	-0.497**	0.227	-0.172	0.168	0.204*	0.118
MARRIED	0.031	0.184	0.090	0.078	0.116	0.052
SEPARATED	0.612**	0.262	0.417	0.299	0.194	0.147
DIVORCED	0.220	0.197	0.154	0.116	-0.003	0.074
WIDOWED	-0.040	0.181	-0.003	0.080	0.007	0.054
GOOD_L	0.084**	0.033	0.202***	0.044	0.345***	0.042
FAIR_L	0.189***	0.036	0.360***	0.044	0.608***	0.046
POOR_L	0.200***	0.041	0.431***	0.056	0.883***	0.058
V_POOR_L	0.275***	0.053	0.509***	0.056	0.976***	0.084
LIMIT_L	0.014	0.020	0.091***	0.029	0.214***	0.031
ARMS_L	0.005	0.021	0.078***	0.030	0.211***	0.027
SIGHT_L	-0.036	0.024	0.014	0.029	0.203***	0.036
HEAR_L	-0.048*	0.026	0.010	0.037	0.162***	0.029
SKIN_L	0.042	0.028	0.066*	0.035	0.063	0.040
KCHEST_L	-0.029	0.025	0.043	0.037	0.165***	0.032
HEART_L	0.012	0.021	0.057*	0.031	0.153***	0.025
STOMACH_L	0.037	0.024	0.091**	0.039	0.286***	0.036
DIABETES_L	0.062	0.044	0.211***	0.048	0.480***	0.039
ANXIETY_L	-0.022	0.030	0.001	0.045	-0.002	0.045
ALCOHOL_L	0.257*	0.142	0.226	0.206	0.050	0.236
EPILEPSY_L	0.121	0.139	0.156	0.132	0.167	0.133
MIGRAINE_L	-0.087**	0.040	-0.062	0.059	-0.056	0.055
OTHER_L	0.017	0.028	0.070*	0.040	0.362***	0.052
CANCER_L	-0.001	0.035	0.083**	0.042	0.637***	0.060
STROKE_L	-0.057	0.039	-0.026	0.050	0.012	0.063
NURSE_L	0.013	0.023	0.046	0.042	0.163***	0.039
OTHER_EDU	-0.365**	0.173	-0.017	0.055	-0.043	0.034
NO_EDU	-0.380	0.236	-0.102	0.045	-0.210***	0.033
INCOME	0.021	0.015	0.030	0.019	0.046***	0.018
MORTGAGE	-0.056	0.047	-0.050	0.058	-0.030	0.047
LOCAL_RENT	0.026	0.077	0.008	0.047	-0.093**	0.037
OTHER_RENT	-0.112*	0.064	-0.085	0.057	-0.096**	0.044
EMPLOYED	0.002	0.098	0.007	0.151	-0.048	0.102
UNEMPLOYED	0.335*	0.188	0.276	0.267	0.135	0.268
RETIRED	0.180*	0.092	0.222	0.138	0.168*	0.089
HOME	0.172	0.107	0.178	0.159	0.088	0.109
SICK	0.308***	0.104	0.382**	0.160	0.255**	0.119
OTHER	-0.007	0.185	0.053	0.387	-0.203	0.262
WALES	-0.558**	0.228	-0.036	0.047	-0.071**	0.033
SCOTLAND	1.513***	0.561	-0.049	0.048	-0.066*	0.034
N.IRELAND			-0.020	0.046	-0.014	0.036
t	0.022	0.027	0.014**	0.007	0.005	0.009
CONSTANT			-2.719	1.977	-5.857***	1.174

Table 6.13 FE, RE and SS estimates for outpatient visits

	FE		RE		SS	
	coef.	s.e	coef.	s.e	coef.	s.e
Selection						
AGE11					-0.020***	0.002
MALE					-0.004	0.025
GOOD11					0.006	0.037
FAIR11					-0.121***	0.041
POOR11					-0.464***	0.050
V_POOR11					-0.613***	0.078
SUMHP11					0.036***	0.009
CONSTANT					2.517***	0.119
σ					1.129***	0.013
ρ					0.045**	0.022
					P>=chi2=0.041	
Log likelihood	-17221.17		-28232.02		-35247.255	
No. of obs.	11774		14230		16614	

Note:
1. The symbols ***, ** and * denote 1, 5 and 10% level of significance, respectively
2. In FE model:
   - 344 groups (344 observations) dropped because of only one observation per group
   - 51 groups (2112 observations) dropped because of all zero outcome
   - MALE omitted because of it is constant within group
   - N.IRELAND omitted because of it is constant within group

6.4.4 Summary of findings of the preferred model

This section presents the effects of the variables of interest on health care used based on the random-effects models for nurse and GP visits and sample selection model for outpatient visits.

6.4.4.1 Personal characteristics

Age has no significant effect in determining nurse and GP visits among the elderly but has a non-linear in outpatient visits with a maximum turning point at age 75. Male is less likely to have nurse and GP visits but more outpatient visits. However the effect of gender is not significant in all equations. Marital status has no significant role in explaining use of nurse services but those who have been married, separated or widowed, however, has more GP visits than those who have never been married. Marital status also has a limited role in determining the utilisation of outpatient services.

6.4.4.2 Health, health related and health care

Self reported health status is very significant in determining use. Respondents, who perceived their health status as very poor, poor, fair and good, use health care more than those who regard their health as excellent. These effects are similar between models. This finding is not surprising as people would be unlikely to use health services if they were not worried about their health. However, some services are provided for all healthy adults over 60 (e.g. flu immunization), therefore some use of services by healthy people would be expected. Those with limitation in doing daily activities due to health conditions tend to use more health care.

Problems with arms, legs and hands (ARMS_L), CHEST_L and DIABETES_L contributed significantly to the increase in use for all services considered here. Besides three problems above, respondents who suffered from a stroke are more likely to have more nurse visits while health problems like HEART_L, STOMACH_L and ANXIETY_L have significantly increased GP use. After dealing with sample selection problem, SIGHT_L and HEAR_L become significant in determining outpatient visits. Suffering from cancer and other health problems has also significantly contributed to the increase in outpatient use.

The use of nurse visits in the previous period (NURSE_L) does not significantly influence the current use of GP but NURSE_L is an important factor for outpatient visits with a positive effect. As for nurse model, whether the respondents have GP visits in the previous wave do not show any major influence on current use of the nurse. This is because a one year lagged or sometimes more, might be quite long to see any significant relationship between two types of health services.

6.4.4.3 Socioeconomic

Levels of education do show some important roles in determining GP and outpatient visits. Those with no education (NO_EDU) having less outpatient visits but more GP visits than those who had higher education (HIGH_EDU). Respondents with OTHER_EDU also visit more GP than those HIGH_EDU.

Individuals who rented their house from local authority (LOCAL_RENT) are more likely to utilise nurse and GP services than those who are house owners as four outpatient service, the effect are opposite. Those who rented their house from local authority, or having any other type of house arrangements, utilised more outpatient service.

Respondents who are unemployed, retired, sick or disabled and looking after the family at home visit the GP more than those who are self-employed. However, only SICK and RETIRED are significant for outpatient visits while other economic activities show no significant difference from being self-employed for nurse visits. Elderly people in Wales, Scotland and Northern Ireland had significantly higher nurse and GP use but less outpatient visits than those in England.

6.5 DISCUSSION

We have to be very careful of making generalisations from the findings of this study because of some data limitations. This study only focuses on the sample of older people that can be observed. Those who are in an institution or being hospitalised, for example, are not considered here in the analysis. Nevertheless, I believe that the elderly in an institution may have different needs for health care where special analysis may be more appropriate depending on the questions policy makers might have[27]. Despite these limitations, I try to reduce sample selection problem by using a specific model that could deal with sample selection bias. However, there is no evidence in this study that the sample selection bias exists in nurse and GP demand model.

Age is not a significant determinant for primary care utilisation among the elderly. Once health status is controlled for, this finding is quite common (Schellhorn et al., 2000). Gender does not show any significant effect but the direction of its coefficient is similar to that found in the study by Deb & Trivedi (1997). It is suggested that males utilise less primary care but more outpatient services than women. One possible explanation to this trend is males are less likely to seek medical care until the problems become serious which later requires more outpatient and inpatient care.

From the estimation results, it is difficult to distinguish the role of partner, through marital status, in influencing contact with health care among the elderly. Therefore, the informal roles of partner as a compliment or substitute to formal health care by the older age groups cannot be established in this study. Of 15 self-

[27] A separate analysis for the elderly in the institutions also seems to be more appropriate as there are a different range of options in different countries, and people with same staff category do different things in different places.

reported health problems, ARMS which include arms, legs, and hands problems, chest problems and suffering with diabetes have affected the utilisation of all services considered here. As problems with arms, legs, hands, etc. are natural among older people, we may expect that health care demand will rise in the future as people live longer. More health education is needed that could influence lifestyle and later prevent problems like diabetes, chest, heart and blood pressure. Other problems like alcohol, epilepsy, and migraine does not show enough evidence to influence demand.

Besides health status and health related variables, other variables have also influenced health care utilisations by the elderly where effects vary across services. Level of education is important determinant of GP and outpatient visits. Those who have had higher education, utilise less GP service but more outpatient. This effect for outpatient is similar with those in Chapter 5, although using a different dataset with different age categories. The reason behind this may be similar as discussed in Chapter 5 that higher educated individual are better informed and utilise more consultative outpatient services than other groups. As most of the people of an older age have retired, or are unemployed, stay at home or are even unwell, the effects of these economic activities is not surprising in GP model. On balance personal characteristics and socioeconomics factors have less influence than health conditions in determining health care utilisation.

The level of income does not show any significant influence in determining the frequency of GP and outpatient use or the probability of utilising district nurse or health visitor's services. This is one of the indicators of equitable health system as people with same need should receive the same amount of care regardless of other factors. The significant role of the district nurse as a substitute or complement to GP services has however failed to be proved.

6.6 CONCLUSION

This study is motivated due to the increase of the number of people in older age groups over time. It has been drawn to our attention before that the objectives of health care consumption to the consumers is to increase their utility, and the objective of the health system is to achieve equitable distribution of health care using the most efficient system. The change of age composition in the society may contribute to the change of utilisation pattern for health care. For a health system to be responsive to the needs of the nation, it requires understanding of the demand process, specifically on the factors affecting demand.

In this study, data from the British Household Panel Survey is used to model health care demand by individuals aged 60 and over. The influence of personal characteristics, health and health related and socioeconomic factors on health care utilisation are identified by using random-effects model, and in the existence of sample selection bias, the sample selection model is used. A new set of evidence of the roles of these factors on health care use by the elderly may provide some information for policy analysts in designing health and health care policy.

CHAPTER SEVEN

7 CONCLUSION

7.1 CONCLUSION

This thesis has provided new evidence on factors determining demand for health care services within the UK system. Demand has been proxied by the frequency of utilisation of health services. There are four types of health services considered in this study: General Practitioner (GP), outpatient, inpatient and in the last empirical chapter, I also include the utilisation of district nurse or health visitor service. Prior to the empirical investigation, a set of empirical studies has been systematically reviewed. I have underlined three questions to be answered from the review.

First is what types of econometric models are employed in estimating health care demand. The literature review reveals that most studies reviewed, work within a count data framework which is consistent with the type of data used since it typically involves a non-negative integer valued dependent variable. The Poisson model is the natural starting point for this type of analysis and could be extended to the negative binomial model if there is evidence of overdispersion in the data. While understanding the empirical specification used in these l studies, I have also identified how these studies deal with endogeneity problems of the regressors. Two regressors that are potentially endogenous in health care demand models are insurance status and self-assessed health status. These two variables are exposed to a self-selection problem, where their values may be influenced by other unobserved characteristics which in turn affect health care use. The review reveals that some studies have neglected these problems and treated these variables as exogenous which may produce biased results.

The aim of second question is to help me to identify a set of explanatory variables used in health care demand model. These variables can be divided into several broad categories which are socioeconomic; health and health related; and supply side variables. Due to data limitation, most of the studies concentrate on the first two types of variables. Although supply side variables like density of doctors or health facilities, are not included in the analysis, some proxies like region and urbanisation level are used to represent supply-side variables as region or urbanisation level could be linked to the supply of health facilities.

The third question aims to increase understanding about the effects of health status, income and education on the use of General Practitioner (GP) services. Health status proves to be the main determinant of GP use regardless the role of GP as a gate-keeper or not. The effects are consistent across selected studies in the literature review, and suggest that people with poor health status utilise the service more than those who have good health status. On the other hand, effects of income and education level and are not consistent between studies. Due to this fact we are not able to make any generalisation of the impacts of income and education factors on GP use. Therefore, for more understanding and policy implications, more empirical research within a specific country is needed. From the review, only three studies are set within the context of the United Kingdom and all three concentrate on demand for GP services. For that reason, this thesis aims to extend the work of current existing studies to other services in the UK which includes outpatient, inpatient, and district nurse services. In pursuing this, I divided the empirical part of the thesis into three main chapters (Chapters 4-6).

Although Chapters 4 to 6 have their own specific objectives, the main objective of the thesis is to identify how personal characteristics, health and health related variables and socioeconomic variables affect demand for specific type of health services by using econometric models and using available data from national services. The findings from this study provide new evidence of the effects of these variables on health care demand in the UK which could be considered by policy analysts in designing health and health care policy.

While developing the demand model for each service, I have dealt with some econometric issues like endogeneity of the regressor and sample selection bias. The theoretical framework used in all empirical analyses here is based on the most influential work on health and health care demand by Grossman (1972). In simple terms it suggests that an individual demand for health care is a 'derived demand' in order to achieved 'good health' which in turn affects individual's utility level.

The first empirical study is presented in Chapter 4. This study is a cross-sectional analysis which utilises data from the General Household Survey 2004/2005. Apart from identifying the determinants of health care utilisation, this chapter specifically deals with the potential endogeneity problem of the regressors; in this case, self-assesesed health status. I am building up the model by first assuming the exogeneity of health status and later followed by treating it as an endogenous variable. Self-assessed health status is treated as endogenous based on the fact that it is a self selected variable and its value is likely to be determined by other unobserved individual characteristics. Besides, there may be simultaneity problems between recent health care use and the assessment one makes of her long term health status. Based on FIML model, the exogeneity of health status is rejected for GP services but not for outpatient and inpatient. Thus, neglecting the endogeneity of the self-assessed health status in GP equation would cause the model to be inconsistently estimated.

So far, the utilisation of health services in Chapter 4 has been modelled based on the assumption of a single data generating process (DGP) whereby the DGP between users and non-users are assumed to be the same. However, it might not be the case here. There are a large proportion of zero-count in the data and the DGP between zero and positive counts might be different. The next empirical chapter deals with this issue.

Chapter 5 is a continuation of the empirical work from Chapter 4. It utilises the same dataset and based on the same main objective that is to identify the determinants of the demand for health services. This chapter concentrates on the modelling part when utilisation data contains excess zeros and the DGP between users and non-users are expected to be different. The analysis is still within a count data framework, and includes, in addition to standard Poisson and negative binomial models, zero-inflated, two-part, and latent class models. Two model selection criteria are used to select the best-fitting model – the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Based on these criteria, it is established that the standard count model is not sufficient in explaining the data. The zero-inflated negative binomial (ZINB) model is the best model for GP and inpatient use while the latent class negative binomial two-component model (LCNB-2) is preferred for outpatient visits. As for both GP and inpatient use, effects are appear to differ between 'non-users' and 'potential users' while for outpatient episodes the populations are separated into two groups labelled as 'infrequent' and 'frequent' users.

In agreement with other studies, health and health related variables remain as the main factors determining use of health services but effects vary depending on class. For example, whether the populations are users or potential users for GP and inpatient services; or infrequent or frequent users for the utilisation of outpatient services. Age, gender education level, GP density and country also have some influences especially for outpatient visits. Marital status and income does not appear to have a major effect on utilisation in this cross-sectional study. Some effects vary quite markedly between the different competing models, underlining the importance of finding the best-fitting model for consistent estimation.

In Chapter 6, I focus on health care use by a specific group of individuals aged 61 and over. The literature review (in Chapter 3) shows that empirical studies for health care use among the elderly are dominated by studies within the context of the United States. Therefore, in Chapter 6, I have empirically identified the determinants of health care utilisation among people in older age groups in the UK. By identifying these factors, it is hoped that the health system can be made more responsive to the needs of the older society. Apart from the utilisation of

GP and outpatient services, this study also includes the utilisation of district nurse or health visitor services (known as 'nurse' throughout the thesis) as one of the key players in elderly health. The use of GP and outpatient is measured by the frequency of use while for nurse, it is measured by whether there is use of service or not, thus data is in a binary form.

The data used for this study are in the form of panel data of wave 12 to 16 from British Household Panel Survey (BHPS). Based on the nature of the data, for nurse and GP service, the random-effects Poisson model is used while for outpatient visits, I used the sample selection model. Besides identifying the factors affecting use, the problem of sample selection bias is specifically discussed in Chapter 6, a problem that had not been discussed before in health care demand studies that use data from BHPS (Allin, Masseria, & Mossialos, 2006; Bago d'Uva, 2005).

Health status, which is proxied by self-assessed health status, remains the major influence for health care use among the elderly. As for health problems, suffering from arms legs and hands problems, chest or breathing problems and diabetes have shown the greatest impacts on all services considered in the chapter (Chapter 6).

Education does not influence the contact with nurse but has some impact for GP and outpatient visits. In agreement with finding in the previous chapter, people with higher education, utilise more outpatient care than those with no education. Although other socioeconomic variables, like housing tenure and economic activity have influenced utilisation, the effects are limited when compared to health status and other health factors.

Income shows no significant influence in determining health care use among the elderly for all types of care. The inclusion of country dummies is intended to pick up the effects of different health system and other country related factors. There is an interesting pattern of these effects, which suggest that older people in Wales, Scotland, and Northern Ireland utilise more GP but less outpatient than those in England.

Taking an overview of all three empirical chapters, two categories of findings are brought to our attention. Firstly, there are applied findings which focus on the factors that affect health care utilisation of health services. Secondly, there are findings concerning econometric methodology in developing the models for health care use. As for applied findings, while there are variables that show almost consistent effects across models, like the effects of health status on health care use, other variables may have different effects depending on data use and types of model.

There is no evidence of income-related inequity of health care demand in all empirical analyses in this thesis. This study also shows that, besides health status, the effects of socioeconomic factors on health care demand for older age groups may be different from the rest of the population. Therefore, it justifies the importance of identifying new evidence on determinants of use for older age groups as the proportion of them in the society has increased over time.

As far as econometric methodology is concerned, the selection of the best-fitting model to the data used is vital because results vary across models. Two econometric problems that have been dealt with in this study include endogeneity issue of the regressors and sample selection problem. From the analyses, it shows that ignoring these problems may lead to different results and incorrect interpretation.

7.2 POLICY IMPLICATIONS

Findings from this study may provide some information for policy analysts who work closely with the policy makers in designing health and health care policy. In the UK, health care resources are allocated according to measures of population need (McGregor, McKee, & O'Neill, 2008). In individual data, health status may represent health care need of an individual. Health care need is also reflected by factors such as age and gender. For instance, children at certain age are required for immunisations and women are subjected to some health screenings, e.g cervical screening for detecting cervical cancer.

The key finding of this thesis would be the effects of health status in determining health care use. If the objective of the policy is to control health care use in the future, an overall improvement of health status of society is one of the options to control health care use. From the analysis in Chapter 4, I found evidence that age, gender, education, economic status, ethnicity and housing tenure have determined health status. Among factors that determine health status that can be altered by public policy would be education and income. From the health demand model in Chapter 4, income and education level are found to have positive impacts on health status. However, from the empirical analysis in Chapter 5 regarding health care demand, I found no evidence that income has a significant net effect in determining health care use. For education, results suggest that people with higher education are more likely to visit GP and outpatient department. Education has no significant effect in the use for inpatient service.

From the analyses in this thesis, it is apparent that health and other health related variables are important in determining health care utilisation. Therefore, in order to improve health status of the population that in turn may also control health care use in the future, policy analysts may consider alternatives on how to improve health status through health, social or education policy. They may concentrate on policies that involve in health promotion that include health education, prevention and protection.

A thorough study on health promotion that relevant to health promotion policy was done by Kiiskinen (2003) by using structural equation model on Finnish health examination survey. It was found that health knowledge would increase the ability of individuals in producing health in the long run. From the study, it is also established that participation in health education would increase health knowledge of individuals while formal education improves the efficiency of producing the knowledge. Collaboration between health and education sectors in promoting health is not a new concept. School is identified as key setting for health promotion (Secretary of State for England as cited in Denman, 1999).

In school, health knowledge is built and disseminated through the integration between health education curriculums, social and physical environment, and active involvements from parents and community (Denman, 1999). Besides teaching health related subjects in classes, introducing healthy options in school meals and promoting healthy packed lunches are one of the strategies of health promotion in school. For a health-promoting school program to be effective and successful, it requires research evidence from both sectors to be utilised, as to ensure that both sectors achieve the desired outcomes (Rowling & Jeffreys, 2006).

However, how far health promotion could contribute to the change of individuals' behaviour is not easy to measure, let alone to identify its roles in determining health. Evidence of effective health promotion may sometimes lead to incorrect conclusions by the policy analysts regarding its effectiveness.

Three possible reasons for false conclusion of the effectiveness of the health promotion programs as outlined by Speller, Learmonth, & Harrison (1997) are - (1) Problem in reaching agreement about what type of promotional activity; (2) Problem regarding evidence to use in measuring effectiveness of promotional activities and (3) different views on tools for reviewing process. Therefore, in dealing with these problems, an appropriate and a good quality tool is vital in assessing the effectiveness of health-promoting programs.

Formal schooling or education increases efficiency of producing health knowledge (Kiiskinen, 2003) and health stock (Grossman, 1972). Health knowledge can be translated to a better life-style, being well informed on medical conditions and needs, consuming good diet and exercise, etc. Therefore, as found in this study, the effects of formal education on health care use may be of both directions. Besides health promotion policy, education policy that could promote people to pursue higher education could be considered in both cases. If everyone has the same opportunity to pursue higher education and can equally accessed to the health information, we could relieve the health care system from being exploited by just higher educated individuals.

In Chapter 6, I focus on health care demand by the older age group. Due to the availability of health related variables in the BHPS, more of them are included in the demand models in Chapter 6 than in Chapters 4 and 5. Besides self-assessed health status, variables that indicate whether the respondents suffer from specific health problems have been included in the models. As found in Chapters 4 and 5, health status proves to be the most influential variable in health care use. Therefore, the previous discussion on how to improve the health status of the population is applicable for the elderly health as well. More specific policy may be designed to control specific health problems that significantly affect health care use among older age groups. Two health problems that show significant effects for all services considered for elderly health care demand in this thesis are problems with arms, legs and hands, and diabetes. Despite the debates of finding good evidence of the effectiveness of health promotion on health (Speller et al., 1997), health-promoting programs may help reduce older people from encountering these health problems.

One of the measures that can be considered to control health care use due to diabetes in the future is the screening of type 2 diabetes[28]. There is evidence that for people at risk of diabetes, screening for impaired glucose tolerance and when needed, together with intervention of lifestyle and pharmacological is cost effective. Early intervention may control or delay the development of diabetes and may also may increase the quality of life of a patient (Gillies et al., 2008; Schwarz, Li, & Bornstein, 2009). Understanding the determinants for district nurses or health visitors' use is also important in designing public health policy, specifically for the elderly. Their roles in promoting health is sometimes uncertain (Gott & O'Brien, 1990; Wilhelmsson & Lindberg, 2009). As the UK government is encouraging 'self-care' initiative for individuals who are suffering

[28] Type 2 diabetes is a condition where the body does not respond to the insulin produced. Insulin is required to move glucose into cells in order to produce energy.

from chronic illness or disability, the role of community nursing in supporting self and home care is expected to intensify as the population becomes older and more prone to health problems.

What is considered essential now is a ‘evidence-based’ guideline regarding the role of effective community nursing (which includes district nurse and health visitor services) within the system and how they integrate with other players within the primary care groups. Although, from this study I found no significant net effect of nurse utilisation on GP visits their roles in promoting health is undeniable.

While findings from this study may provide some information for policy analysts in designing health or health care policy, country specific research is needed to provide more evidence concerning the role of health and socioeconomic factors on health care use. It requires policy analysts to synthesis existing theory and research findings and comparing alternative policies to ensure that they come up with a sound public policy based on the specific objectives that the system wants to achieve.

7.3 LIMITATIONS

In this section I aim to outline the limitations in completing the thesis by chapters, beginning with Chapter 3 which is the review of the literature. In this review, due to time and financial constraints, despite the existence of many databases, I have had to concentrate on two databases which cover a large proportion of published empirical health care research only - Social Science Citation Index (SSCI) and EconLit. Studies that are not in English language are also excluded this time.

In Chapter 4 and 5, the analyses are limited to the availability of the data. As with any other empirical analyses that utilise secondary datasets, the variables used in the demand models are restricted to what is available in the datasets. The use of self reported health variables may have some limitations as the reliability can be questioned.

Despite these limitations, these self-reported variables are the best available proxies as the 'true' values of health status are difficult to observe. Qualities of data for answering questions on utilisation are also subject to criticism. One instance is the use of two weeks reference period for GP visits in General Household Survey used in these two chapters may influence the number of visits reported. The short reference period has contributed to many zero count in the dataset.

In Chapter 6, the non-response and attrition problems of panel data may have affected the results. In addition, the elderly who are in institution were not considered in the analysis.

7.4 FURTHER RESEARCH

In gathering recent evidence on this subject, the review can be updated over time by replicating the same review protocol. It could also be improved by including more databases which could contribute to more relevant studies. Econometric modelling in Chapter 4 could be extended by considering the original nature of the endogenous variable, i.e. self-assessed health status that has originally three categories. In the analyses in Chapters 4 and 5, I have recoded self-assessed health status into two categories only. In the future, the random-effects Poisson models in Chapter 6 could also be extended using a more appropriate econometric model for grouped data of health care visits, where the log-likelihood function is derived using a logarithmic link of the Poisson mean (see Moffatt, 1995; Moffatt & Peters, 2000). When individual data are accessible to the researchers, the empirical work could be extended within the context of other countries, especially the developing countries where these types of research are still very limited.

8 APPENDICES

Appendix 3-I
List of Studies for Systematic Review

Atella, V., Brindisi, F., Deb, P., & Rosati, F. C. (2004). Determinants of access to physician services in Italy: a latent class seemingly unrelated probit approach. *Health Economics, 13*(7), 657-668.

Bago d'Uva, T. (2005). Latent class models for use of primary care: evidence from a British panel. *Health Economics, 14*(9), 873-892.

Bago d'Uva, T. (2006). Latent class models for utilisation of health care. *Health Economics, 15*(4), 329-343.

Carlsen, F., & Grytten, J. (1998). More physicians: Improved availability or induced demand? *Health Economics, 7*(6), 495-508.

Carrin, G., & Vandael, J. (1984). An Empirical-Model of the Demand for Health-Care in Belgium. *Applied Economics, 16*(3), 317-334.

Chiappori, P. A., Durand, F., & Geoffard, P. Y. (1998). Moral hazard and the demand for physician services: First lessons from a French natural experiment. *European Economic Review, 42*(3-5), 499-511.

Deb, P., Li, C. H., Trivedi, P. K., & Zimmer, D. M. (2006). The effect of managed care on use of health care services: Results from two contemporaneous household surveys. *Health Economics, 15*(7), 743-760.

Deb, P., Munkin, M. K., & Trivedi, P. K. (2006). Private insurance, selection, and health care use: A Bayesian analysis of a Roy-type model. *Journal of Business & Economic Statistics, 24*(4), 403-415.

Deb, P., & Trivedi, P. K. (1997). Demand for medical care by the elderly: A finite mixture approach. *Journal of Applied Econometrics, 12*(3), 313-336.

Deb, P., & Trivedi, P. K. (2002). The structure of demand for health care: latent class versus two-part models. *Journal of Health Economics, 21*(4), 601-625.

Deb, P., & Trivedi, P. K. (2006). Specification and simulated likelihood estimation of a non-normal treatment-outcome model with selection: Application to health care utilization. *Econometrics Journal, 9*(2), 307-331.

Erbsland, M., Ried, W., & Ulrich, V. (1995). Health, Health-Care, and the Environment - Econometric Evidence from German Micro Data. *Health Economics, 4*(3), 169-182.

Geil, P., Million, A., Rotte, R., & Zimmermann, K. F. (1997). Economic incentives and hospitalization in Germany. *Journal of Applied Econometrics, 12*(3), 295-311.

Gerdtham, U. G. (1997). Equity in health care utilization: Further tests based on hurdle models and Swedish micro data. *Health Economics, 6*(3), 303-319.

Gerdtham, U. G., & Trivedi, P. K. (2001). Equity in Swedish health care reconsidered: New results based on the finite mixture model. *Health Economics, 10*(6), 565-572.

Gurmu, S. (1997). Semi-parametric estimation of hurdle regression models with an application to Medicaid utilization. *Journal of Applied Econometrics, 12*(3), 225-242.

Gurmu, S., & Elder, J. (2000). Generalized bivariate count data regression models. *Economics Letters, 68*(1), 31-36.

Holly, A., Gardiol, L., Domenighetti, G., & Bisig, B. (1998). An econometric model of health care utilization and health insurance in Switzerland. *European Economic Review, 42*(3-5), 513-522.

Hunt-McCool, J., Kiker, B. F., & Ng, Y. C. (1995). Gender and the Demand for Medical-Care. *Applied Economics, 27*(6), 483-495.

Jimenez-Martin, S., Labeaga, J. M., & Martinez-Granado, M. (2002). Latent class versus two-part models in the demand for physician services across the European Union. *Health Economics, 11*(4), 301-321.

Kenkel, D. S. (1994). The Demand for Preventive Medical-Care. *Applied Economics, 26*(4), 313-325.

Koc, C. (2005). Health-specific moral hazard effects. *Southern Economic Journal, 72*(1), 98-118.

Lee, M. J., & Kobayashi, S. (2001). Proportional treatment effects for count response panel data: Effects of binary exercise on health care demand. *Health Economics, 10*(5), 411-428.

Lindelow, M. (2005). The utilisation of curative healthcare in Mozambique: Does income matter? *Journal of African Economies, 14*(3), 435-482.

Liu, G. G., Wu, X. D., Peng, C. Y., & Fu, A. Z. (2003). Urbanization and health care in rural China. *Contemporary Economic Policy, 21*(1), 11-24.

Lopez-Nicolas, A. (1998). Unobserved heterogeneity and censoring in the demand for health care. *Health Economics, 7*(5), 429-437.

Lourenco, O. D., & Ferreira, P. L. (2005). Utilization of public health centres in Portugal: effect of time costs and other determinants. Finite mixture models applied to truncated samples. *Health Economics, 14*(9), 939-953.

Madden, D., Nolan, A., & Nolan, B. (2005). GP reimbursement and visiting behaviour in Ireland. *Health Economics, 14*(10), 1047-1060.

Mangalore, R. (2006). Income, health and health care utilization in the UK. *Applied Economics, 38*(6), 605-617.

Mocan, H. N., Tekin, E., & Zax, J. S. (2004). The demand for medical care in urban China. *World Development, 32*(2), 289-304.

Munkin, M. K., & Trivedi, P. K. (2003). Bayesian analysis of a self-selection model with multiple outcomes using simulation-based estimation: an application to the demand for healthcare. *Journal of Econometrics, 114*(2), 197-220.

Mwabu, G., Ainsworth, M., & Nyamete, A. (1993). Quality of Medical-Care and Choice of Medical-Treatment in Kenya - an Empirical-Analysis. *Journal of Human Resources, 28*(4), 838-862.

Nandakumar, A. K., Chawla, M., & Khan, M. (2000). Utilization of outpatient care in Egypt and its implications for the role of government in health care provision. *World Development, 28*(1), 187-196.

Nolan, A. (2007). A dynamic analysis of GP visiting in Ireland: 1995-2001. *Health Economics, 16*(2), 129-143.

Pohlmeier, W., & Ulrich, V. (1995). An Econometric-Model of the 2-Part Decision-Making Process in the Demand for Health-Care. *Journal of Human Resources, 30*(2), 339-361.

Santos-Silva, J., & Windmeijer, F. (2001). Two-part multiple spell models for health care demand. *Journal of Econometrics, 104*(1), 67-89.

Sarma, S., & Simpson, W. (2006). A microeconometric analysis of Canadian health care utilization. *Health Economics, 15*(3), 219-239.

Schellhorn, M. (2001). The effect of variable health insurance deductibles on the demand for physician visits. *Health Economics, 10*(5), 441-456.

Schellhorn, M., Stuck, A. E., Minder, C. E., & Beck, J. C. (2000). Health services utilization of elderly Swiss: Evidence from panel data. *Health Economics, 9*(6), 533-545.

Schneider, H., & Mathios, A. (2006). Principal agency theory and health care utilization. *Economic Inquiry, 44*(3), 429-441.

Van Houtven, C. H., & Norton, E. C. (2004). Informal care and health care use of older adults. *Journal of Health Economics, 23*(6), 1159-1180.

Vera-Hernandez, A. M. (1999). Duplicate coverage and demand for health care. The case of Catalonia. *Health Economics, 8*(7), 579-598.

Windmeijer, F., Gravelle, H., & Hoonhout, P. (2005). Waiting lists, waiting times and admissions: an empirical analysis at hospital and general practice level. *Health Economics, 14*(9), 971-985.

Windmeijer, F. A. G., & Santos Silva, J. (1997). Endogeneity in count data models: An application to demand for health care. *Journal of Applied Econometrics, 12*(3), 281-294.

Winkelmann, R. (2004a). Co-payments for prescription drugs and the demand for doctor visits - Evidence from a natural experiment. *Health Economics, 13*(11), 1081-1089.

Winkelmann, R. (2004b). Health care reform and the number of doctor visits - An econometric analysis. *Journal of Applied Econometrics, 19*(4), 455-472.

Winkelmann, R. (2006). Reforming health care: Evidence from quantile regressions for counts. *Journal of Health Economics, 25*(1), 131-145.

Yen, S. T., Tang, C. H., & Su, S. J. B. (2001). Demand for traditional medicine in Taiwan: A mixed Gaussian-Poisson model approach. *Health Economics, 10*(3), 221-232.

Zimmer, D. M., & Trivedi, P. K. (2006). Using trivariate copulas to model sample selection and treatment effects: Application to family health care demand. *Journal of Business & Economic Statistics, 24*(1), 63-76.

Scoring Criteria for Methodology Quality by Canadian Council on Learning

Table A3II-1 Scoring Criteria for Methodology Quality

Study Category	Score 1 Criteria	Score 2 Criteria	Score 3 Criteria
Quality of Data			
Data Source	All data sources are not documented.	The sources of data are not clearly documented.	The sources of data are clearly documented.
Data Completeness	A substantial amount of data is missing- seriously affects the study results.	Explanation of missing data is provided. The missing data is not discussed, but is believed not to seriously affect the study result.	There are no missing data.
Representative Sample	The chosen sample is a poor representation of the population of interest.	It is uncertain whether the chosen sample can serve as a good representation of the population of interest.	The chosen sample serves as good representation of the population of interest.
Data Description	The variables used are not described.	The variables used are described but not clear.	The variables used are clearly described.
Quality of Model			
Type of Analysis	The study does not employ any econometric method- relies solely on descriptive analysis.	The study only uses econometric methods for estimating results.	The study is a mix of quantitative and any other type of analysis (experiment or qualitative) for enhancement.
Model Assumptions	Assumptions are unreasonable. Assumptions are made without any explanation.	Assumptions are not relevant to the study. Assumptions are non-intuitive. Assumptions are not clearly discussed.	Assumptions are intuitive. Assumptions are used in other relevant studies. Assumptions are necessary and important for the study and a reasonable explanation is provided.

Table A3II-1 Scoring Criteria for Methodology Quality

Study Category	Score 1 Criteria	Score 2 Criteria	Score 3 Criteria
Model Specification	The specification is uncommon and without/poor explanation. The chosen specification does not account for the issues regarding the type of data used.	The specification is common in relevant studies. The specification is consistent with the type of data used.	The validity of the functional form specification is tested by the researcher (s). The specification used in the study is justified with reference to reliable sources. The specification is a good match of the type of data used.
Choice of Variables	Many of important factors are not included in the model. Proxy variables, if any, are not relevant to their underlying factors. Instrument variables, if any, are weak.	Many important factors are included in the model. Proxy variables, if any, are relevant to their underlying factors. Instrument variables, if any, are adequate.	All important variables are included in the model. Proxy variables, if any, are highly relevant to their underlying factors. Proxy variables, if any, are strong.
Quality of Results			
Statistical Significance	Estimates that capture statistical significance are not reported. Results are not discussed in terms of statistical significance.	Estimates that capture statistical significance are reported, but researcher(s) does not discuss the result in terms of statistical significance.	Estimates that capture statistical significance are reported. Results are discussed in terms of statistical significance.
Estimation Bias	The results are biased.	The results may be biased, but the direction of the effects should be reliable.	The results are unbiased.
Objectivity of the Discussion	The researcher (discusses) the results in a subjective manner. Implications and inferences are made beyond the estimated results. The discussion substantially overstates the estimated results.	The discussion slightly overstates the estimated result.	The researcher (discusses) the results in a objective manner, such that implications and inferences are made on the basis of the estimated results.

Source: Canadian Council on Learning (2006)

Table A4I-1 GHS2004/2005: Summary statistics from original sample

Variables	Observation	Mean	Std Dev	Min	Max
AGE	20421	38.870	22.938	0	99
AGESQ	20421	20.370	19.216	0	98
MALE	20421	0.485	0.500	0	1
COHAB	20421	0.100	0.301	0	1
MARRIED	20421	0.569	0.495	0	1
GOODHLTH	19156	0.647	0.478	0	1
LIMITACT	20096	1.091	3.392	0	14
LONG_ILL	20091	0.479	0.877	0	6
OTHER_EDU	16547	0.499	0.500	0	1
NO_EDU	16547	0.204	0.403	0	1
INCOME	17775	5.013	1.076	0	9.607
WALES	20421	0.048	0.214	0	1
SCOTLAND	20421	0.095	0.294	0	1
GPPOP	20421	0.639	0.047	0.583	0.745

Table A4I-2 GHS 2004/2005: Summary statistics from reduced sample

Variables	Observation	Mean	Std Dev	Min	Max
AGE	14706	34.316	19.666	0	69
AGESQ	14706	15.643	13.721	0	47
MALE	14706	0.480	0.500	0	1
COHAB	14706	0.114	0.317	0	1
MARRIED	14706	0.575	0.494	0	1
GOODHLTH	14706	0.681	0.466	0	1
LIMITACT	14706	0.941	3.101	0	14
LONG_ILL	14706	0.413	0.808	0	6
OTHER_EDU	14706	0.503	0.500	0	1
NO_EDU	14706	0.201	0.401	0	1
INCOME	14706	5.054	1.089	0	9.607
WALES	14706	0.041	0.198	0	1
SCOTLAND	14706	0.100	0.300	0	1
GPPOP	14706	0.640	0.048	0.583	0.745

A. Dependent Variables

Doctor Consultations (nchats) –rename as GP

It refers to the number of consultations with NHS or private general practitioners during the two weeks before interview. It includes visits to surgery, home visits, and telephone conversation but exclude contacts with receptionist only. It includes 0 count by the person with no consultation *(doctalk*=0)[29], but exclude consultations made on behalf of other person aged 16 or over.

Outpatient attendances (ntimsop)-rename as OUTPATIENT

It refers to the number of outpatient attendances (casualty or outpatient department) in the last 3 months at NHS or private hospitals other than as inpatient. Consultative outpatient attendances, casualty attendance and attendance at ancillary department are all included. It includes 0 count by the person with no visit (*outpatnt=0*).

Inpatient stays (nstays)-rename as INPATIENT

It refers to number of separate overnights or longer stays in the hospital in the past one year before the interview. All type all cases except maternity stays. It includes 0 count by the person with no overnight or longer stays (*inpatnt=0*).

B. Independent Variables

age (age)

Age in years. Age squared is the square of age divided by 100.

male (gender)

male….1
female..2

Recode male=1, female=0

[29] All 'NO'=2 in the original dataset have been recoded to 0

Living Arrangements (de facto marital status- dvmardf)

Married ………….1

Cohabiting……… 2

Single ……………3

Widowed ……......4

Divorced …………5

Separated ………...6

Same sex couple …7

Marital status for children is based on marital status of the Household Reference Person (HRP)(*hrpmar*) (replace *dvmardf=hrpmar* if age<16). Recode Widowed, Divorced, Separated, Same sex couple=0; cohabiting=1; married=2. Rename dummies as **SINGLE** (single), **COHAB** (cohabiting), **MARRIED** (married)

Self-Perceived General Health (genhlth)-rename as GOODHLTH

Self-perceived health states, on the whole in the last 12 months.

Good………..1

Fairly good….2

Not Good…...3

Recode Good=1; Fairly Good *plus* Not Good=0

Number of days with activities prevented (ndyscutd)-rename as LIMITACT

It refers to the number of days with normal activities (house/work/school/free time) prevented because of illnesses or injuries including Saturday and Sundays in the last two weeks before the interview. It include 0 count by the person without activities cutdown (*cutdown=0*)

Number of longstanding illness (lmatnum)-rename as LONG_ILL

It refers to the number of longstanding illnesses (up to the most important six illnesses), disabilities or infirmities that causes problems over a period of time. It also include 0 count by the person with no longstanding illness (*illness=0)*.

Education Level (edlev7)

Higher qualification...1

Other qualification….2

No qualification …... 3

Higher qualification includes higher degree, first degree, teaching qualification, other higher qualification, and nursing qualification Other qualifications include GCE A level in two or more subjects, GCE A level in one subject, GCSE/O LEVEL, standard grades, GCSE/O LEVEL, GCSE below grade 1, GCSE below grade c, apprenticeship and other vocational, professional or foreign qualifications.

Education level for children is recoded based on education level of HRP *(hrpedlev1)* (replace *edlev7=hrpedlev1* if age<16). Rename dummies as **HIGH_EDU** (Higher qualification), **OTHER_EDU** (Other qualification), **NO_EDU** (No qualification)

Net Weekly Equivalised Household Income in pence (nthheq)- rename INCOME

Weekly household income that includes all type of earnings, benefits, pension, dividends, interest and other regular payments, after deductions, received by all adults in the household.

INCOME= log(1+(nthheq/100))

Country (country2)

England …1

Wales……2

Scotland…3

Rename dummies **ENGLAND** (England), **WALES** (Wales), **SCOTLAND** (Scotland),

Ratio GP per thousand populations (GPPOP)

Population number is based on the Government Office Region (GOR). The number of General Practitioners by GOR is retrieved from *Regional Trends 2006* edition.

GPPOP=Number of GPs/Number of population('000)

Economic Status of HRP (hrpilo5)

Working ……………. 1

Unemployed ………... 2

Other unemployed 3

Economic inactive …. 4

Working is defined as worked for wages, salary or other form of cash payment. Full time students are classified according to their own reports of what they were doing during the reference week. Unemployed person is a person who was out of work but actively looking for work in the four weeks before interview. Economically inactive includes people who are neither working nor unemployed by the ILO measures (e.g. looking after a home or retired). Rename dummies as **WORKED** (Working), **UNEMPLOYED** (Unemployed), **O_UNEMPLOYED** (Other unemployed), **INACTIVE** (Economic Inactive) There is no O_UNEMPLOYED in the dataset.

Ethnic origin (ethnic2)-rename as NONWHITE

White…………1

Non white…....2

Recode White=0, Non white=1

Tenure1

Owned………..1

Social renters…2

Private renter…3

Rename dummies as **OWNED** (Owned), **SOCIAL** (Social renters), **PRIVATE** (Private renters)

Definition of Variables from British Household Panel Survey (BHPS)

A. Dependent Variables

Doctor Consultations (hl2gp) – rename as GP

It refers to the number of consultations with a GP or family doctor for the past 12 months regarding own health. It does not include any hospital visits. The frequencies are in interval.

None …… 0

1 or 2 …… 1 – recode as 2

3 – 5 ……..2 – recode as 4

6 – 10 ……3 – recode as 8

> 10 …….. 4 – recode as 12

Outpatient attendances (hl2hop) – rename as OUTPATIENT

It refers to the number of outpatient attendances as an outpatient or day patient for the past 12 months . It does not include visit to Accident and Emergency (A&E).

None …… 0

1 or 2 …… 1 – recode as 2

3 – 5 ……..2 – recode as 4

6 – 10 ……3 – recode as 8

> 10 …….. 4 – recode as 12

Health visitor/district nurse use (hlsva) – rename as NURSE

It refers to whether these services have been utilised in the last year.

No …..0

Yes ….1

B. Independent Variables

AGE (age)

Age in years. Age squared (**AGESQ**) is the square of age**.**

MALE (sex)

Female …. 0

Male …….1

Current legal marital status (mastat)

Married ………. 1 – recode 3
Coupled ……… 2
Widowed …..... 3 – recode 6
Divorced ……... 4 – recode 5
Separated …….. 5 – recode 4
Never married ... 6 – recode 1

Generate and rename dummies as **SINGLE** (Never married), **COUPLED** (Coupled), **MARRIED** (married), **SEPARATED** (Separated), **DIVORCED** (Divorced), **WIDOWED** (Widowed)

Self-assessed health (hlstat)

It refers to how the respondents self-assessed their health as a whole over the last 12 months has been compared to other people of their age.

Excellent ….. 1

Good ……… 2

Fair ………... 3

Poor ……….. 4

Very poor …. 5

Generate and rename dummies as **EXCELLENT** (excellent), **GOOD** (Good), **FAIR** (Fair), **POOR** (Poor), **V_POOR** (Very poor).

Health limits (hllt) – rename as LIMIT

Whether health conditions limit daily activities compared to others of the same age.

No …. 0

Yes …. 1

Reported health problems excluding temporary conditions (hlpr)

HLPRBA – Rename as **ARMS**

Problems or disability concerning arms, legs, hands, feet, back or neck. This include arthritis and rheumatism.

HLPRBB – Rename as **SIGHT**

Problems in seeing other than needing glasses to read normal size print.

HLPRBC – Rename as **HEAR**

Difficulty in hearing

HLPRBD – Rename as **SKIN**

Problems with skin or suffering from skin allergies

HLPRBE – Rename as **CHEST**

Problems with chest/breathing, asthma, bronchitis.

HLPRBF – Rename as **HEART**

Problems with heart/blood pressure or blood circulation problem

HLPRBG – Rename as **STOMACH**

Problems with stomach/liver/kidneys or digestion

HLPRBH – Rename as **DIABETES**

Suffering from diabetes

HLPRBI – Rename as **ANXIETY**

Suffering from anxiety, depression or bad nerves

HLPRBJ – Rename as **ALCOHOL**

Problems with alcohol or drug/drug related

HLPRBK – Rename as **EPILEPSY**

Suffering from epilepsy

HLPRBL – Rename as **MIGRAINE**

Suffering from migraine or frequent headache

HLPRBM – Rename as **OTHER**

Other health problems

HLPRBN – Rename as **CANCER**

Suffering from cancer

HLPRBO – Rename as **STROKE**

Suffered from stroke

Highest educational qualification (qfedhi)

No qualification ……….. 1

Other qualification …….. 2

Higher Qualification ….. 3

Other type of education includes British School exams or equivalent, commercial qualification, apprenticeship and other qualifications. Higher education includes higher degree, first degree, teaching and nursing qualification and other higher qualifications. Generate and rename dummies as **HIGH_EDU** (Higher qualification), **OTHER_EDU** (Other qualification), **NO_EDU** (No qualification).

Annual Equivalised Household Income (fihhyr/fieqfca) – rename LOGINC

Annual household income that includes all type of earnings, benefits, pension, dividends, interest and other regular payments received by all adults in the household divided by household equivalence scale after housing costs.

LOGINC = log(1 + (fihhyr/fieqfca))

Current economic activity (jbstat)

Self employed ……………… 1

In paid employment ……….. 2

Unemployed ……………….. 3

Retired from paid work ……. 4

On maternity leave ………… 5 – recode 7

Looking after family/home…. 6 – recode 5

Full time student/ at school … 7 – recode 7

Long term sick/disabled ……. 8 – recode 6

On government training …... . 9 – recode 7
scheme

Generate and rename dummies as **SELF_EMP** (self employed), **EMPLOYED** (employed), **UNEMPLOYED** (Unemployed), **RETIRED** (retired), **HOME** (Looking after family/home), **SICK** (Long term sick/disable), OTHER (On maternity leave, student, on government training scheme).

Region/metropolitan area (region)

Inner London …………………1	Region of North West …………...11
Outer London …………………2	Region of South Yorkshire …….. 12
Region of South East …............3	Region of West Yorkshire ………13
Region of South West …………4	Region of York & Humberside 14
Region of East Anglia ………....5	Tyne & Wear ……………………15
Region of East Midlands …… 6	Region of North England ……... 16
West Midlands conurbation …...7	Wales ……………………………17
Region of West Midlands ……..8	Scotland …………………………18
Greater Manchester ……………9	Northern Ireland ………………...19
Merseyside ……………………10	

Recode 1- 16 to 1; 17 to 2; 18 to 3; and 19 to 4. Generate and rename dummies as **ENGLAND** (all area in category 1), **WALES** (Wales), **SCOTLAND** (Scotland), **N.IRELAND** (Northern Ireland)

Time (t)

Time measured as a continuous variable.

Appendix 6-II

Comparison of summary statistics between selected sample and reduced sample using data from British Household Panel Survey (BHPS)

Table A6II Summary statistics of selected sample and reduced sample using data from BHPS

Variable	Obs		Mean		Std. Dev.		Min		Max	
NURSE	15766	*14230*	0.115	*0.110*	0.319	*0.313*	0	*0*	1	*1*
DOCVIS	15722	*14230*	4.337	*4.304*	3.662	*3.649*	0	*0*	12	*12*
OUTPATIENT	15728	*14230*	2.129	*2.129*	2.944	*2.939*	0	*0*	12	*12*
AGE	16614	*14230*	73.205	*72.934*	7.367	*7.146*	61	*61*	99	*99*
AGESQ	16614	*14230*	5413.19	*5370.38*	1108.36	*1069.98*	3721	*3721*	9801	*9801*
MALES	16614	*14230*	0.441	*0.443*	0.497	*0.497*	0	*0*	1	*1*
COUPLED	16614	*14230*	0.014	*0.013*	0.116	*0.114*	0	*0*	1	*1*
MARRIED	16614	*14230*	0.566	*0.576*	0.496	*0.494*	0	*0*	1	*1*
SEPARATED	16614	*14230*	0.007	*0.007*	0.081	*0.081*	0	*0*	1	*1*
DIVORCED	16614	*14230*	0.050	*0.051*	0.218	*0.220*	0	*0*	1	*1*
WIDOWED	16614	*14230*	0.303	*0.293*	0.459	*0.455*	0	*0*	1	*1*
GOOD_L	16342	*14230*	0.423	*0.434*	0.494	*0.496*	0	*0*	1	*1*
FAIR_L	16342	*14230*	0.299	*0.294*	0.458	*0.456*	0	*0*	1	*1*
POOR_L	16342	*14230*	0.104	*0.097*	0.306	*0.295*	0	*0*	1	*1*
V_POOR_L	16342	*14230*	0.030	*0.025*	0.170	*0.155*	0	*0*	1	*1*
LIMIT_L	16266	*14230*	0.345	*0.325*	0.475	*0.468*	0	*0*	1	*1*
ARMS_L	16255	*14230*	0.539	*0.536*	0.499	*0.499*	0	*0*	1	*1*
SIGHT_L	16255	*14230*	0.121	*0.117*	0.326	*0.322*	0	*0*	1	*1*
HEAR_L	16255	*14230*	0.219	*0.219*	0.414	*0.414*	0	*0*	1	*1*
SKIN_L	16255	*14230*	0.097	*0.099*	0.296	*0.298*	0	*0*	1	*1*
CHEST_L	16255	*14230*	0.184	*0.181*	0.387	*0.385*	0	*0*	1	*1*
HEART_L	16255	*14230*	0.451	*0.455*	0.498	*0.498*	0	*0*	1	*1*
STOMACH_L	16255	*14230*	0.120	*0.119*	0.325	*0.324*	0	*0*	1	*1*
DIABETES_L	16255	*14230*	0.095	*0.095*	0.293	*0.293*	0	*0*	1	*1*
ANXIETY_L	16255	*14230*	0.076	*0.073*	0.265	*0.261*	0	*0*	1	*1*
ALCOHOL_L	16255	*14230*	0.003	*0.002*	0.051	*0.047*	0	*0*	1	*1*
EPILEPSY_L	16255	*14230*	0.008	*0.007*	0.086	*0.086*	0	*0*	1	*1*
MIGRAINE_L	16255	*14230*	0.050	*0.051*	0.217	*0.220*	0	*0*	1	*1*
CANCER_L	16255	*14230*	0.035	*0.034*	0.184	*0.181*	0	*0*	1	*1*
STROKE_L	16255	*14230*	0.038	*0.035*	0.191	*0.183*	0	*0*	1	*1*
OTHER_L	16255	*14230*	0.053	*0.049*	0.224	*0.217*	0	*0*	1	*1*
NURSE_L	15784	*14230*	0.108	*0.101*	0.310	*0.302*	0	*0*	1	*1*
OTHER_EDU	15556	*14230*	0.270	*0.274*	0.444	*0.446*	0	*0*	1	*1*
LOW_EDU	15556	*14230*	0.493	*0.480*	0.500	*0.500*	0	*0*	1	*1*

Table A6II Summary statistics of selected sample and reduced sample using data from BHPS

Variable	Obs		Mean		Std. Dev.		Min		Max	
INCOME	16130	*14230*	9.743	*9.755*	0.755	*0.713*	0	*0*	12.35	*12.35*
MORTGAGE	16205	*14230*	0.083	*0.079*	0.276	*0.269*	0	*0*	1	*1*
LOCAL_RENT	16205	*14230*	0.145	*0.142*	0.352	*0.349*	0	*0*	1	*1*
OTHER_RENT	16205	*14230*	0.088	*0.086*	0.283	*0.280*	0	*0*	1	*1*
EMPLOYED	16603	*14230*	0.058	*0.060*	0.234	*0.238*	0	*0*	1	*1*
UNEMPLOYED	16603	*14230*	0.002	*0.002*	0.049	*0.048*	0	*0*	1	*1*
RETIRED	16603	*14230*	0.852	*0.857*	0.355	*0.350*	0	*0*	1	*1*
HOME	16603	*14230*	0.038	*0.037*	0.192	*0.189*	0	*0*	1	*1*
SICK	16603	*14230*	0.023	*0.018*	0.150	*0.132*	0	*0*	1	*1*
OTHER	16603	*14230*	0.003	*0.003*	0.059	*0.053*	0	*0*	1	*1*
WALES	16614	*14230*	0.200	*0.200*	0.400	*0.400*	0	*0*	1	*1*
SCOTLAND	16614	*14230*	0.183	*0.186*	0.386	*0.389*	0	*0*	1	*1*
N.IRELAND	16614	*14230*	0.173	*0.156*	0.378	*0.363*	0	*0*	1	*1*
t	16614	*14230*	3.869	*3.860*	1.412	*1.409*	2	*2*	6	*6*

Note:
Values in *italics* are from the reduced sample

Table A6III RE estimates: Comparison between alternative recoding

	RE_GP1[1]		RE_GP2[2]	
	coef.	s.e	coef.	s.e
AGE	0.030	0.021	0.028	0.022
AGESQ	-0.0002***	0.0001	-0.0002***	0.0001
MALE	-0.024	0.023	-0.024	0.025
COUPLED	0.052	0.083	0.016	0.085
MARRIED	0.099**	0.043	0.100**	0.046
SEPARATED	0.191*	0.110	0.225**	0.114
DIVORCED	0.065	0.056	0.072	0.059
WIDOWED	0.090**	0.044	0.097**	0.047
GOOD_L	0.159***	0.020	0.148***	0.020
FAIR_L	0.259***	0.022	0.245***	0.022
POOR_L	0.331***	0.026	0.314***	0.026
V_POOR_L	0.333***	0.035	0.321***	0.034
LIMIT_L	0.060***	0.013	0.058***	0.013
ARMS_L	0.095***	0.013	0.094***	0.013
SIGHT_L	0.023	0.016	0.017	0.016
HEAR_L	0.028	0.016	0.025	0.015
SKIN_L	0.025	0.018	0.020	0.018
CHEST_L	0.102***	0.016	0.103***	0.016
HEART_L	0.084***	0.013	0.070***	0.013
STOMACH_L	0.061***	0.016	0.057***	0.015
DIABETES_L	0.122***	0.024	0.120***	0.024
ANXIETY_L	0.046**	0.019	0.042**	0.018
ALCOHOL_L	0.072	0.096	0.074	0.092
EPILEPSY_L	0.210**	0.087	0.286***	0.088
MIGRAINE_L	0.020	0.025	0.026	0.024
OTHER_L	0.024	0.021	0.024	0.020
CANCER_L	-0.004	0.027	-0.006	0.026
STROKE_L	-0.022	0.026	-0.037	0.025
NURSE_L	0.003	0.016	0.005	0.015
OTHER_EDU	0.054*	0.030	0.068**	0.032
NO_EDU	0.044	0.028	0.066**	0.030
INCOME	-0.001	0.008	-0.002	0.008
MORTGAGE	0.001	0.027	-0.001	0.027
LOCAL_RENT	0.059**	0.027	0.079***	0.028

Table A6III RE estimates: Comparison between alternative recoding

	RE_GP1[1]		RE_GP2[2]	
	coef.	s.e	coef.	s.e
OTHER_RENT	0.028	0.028	0.020	0.028
EMPLOYED	0.040	0.056	0.048	0.056
UNEMPLOYED	0.266**	0.113	0.301***	0.111
RETIRED	0.185***	0.051	0.206***	0.051
HOME	0.150***	0.060	0.166***	0.060
SICK	0.177***	0.061	0.189***	0.060
OTHER	0.152	0.111	0.174	0.109
WALES	0.057**	0.028	0.067**	0.031
SCOTLAND	0.054*	0.030	0.056*	0.032
N.IRELAND	0.072***	0.031	0.077**	0.033
CONSTANT	-0.460	0.805	-0.332	0.831
Log likelihood	-33830.665		-36062.035	
No. of obs.	14230		14230	

Note:
The symbols ***, ** and * denote 1, 5 and 10% level of significance, respectively
[1] RE_GP1 – recode > 10 visits equal 12
[2] RE_GP2 – recode > 10 visits equal 15

Panel summary of dependent and independent variables using data from British Household Panel Survey (BHPS)

Table A6IV Panel summary of dependent and independent variables using data from BHPS

Variable		Mean	Std. Dev.	Min	Max	Observations
NURSE	overall	0.11019	0.31314	0	1	N = 14230
	between		0.25797	0	1	n = 3566
	within		0.21707	-0.6898103	0.9101897	T-bar = 3.99047
GP	overall	4.30443	3.64880	0	12	N = 14230
	between		3.05077	0	12	n = 3566
	within		2.19309	-4.695573	13.90443	T-bar = 3.99047
OUTPATIENT	overall	2.12987	2.93878	0	12	N = 14230
	between		2.33351	0	12	n = 3566
	within		1.97627	-5.870134	11.72987	T-bar = 3.99047
AGE	overall	72.93359	7.14648	61	99	N = 14230
	between		7.32304	61	97.5	n = 3566
	within		1.34650	64.68359	76.68359	T-bar = 3.99047
AGESQ	overall	5370.37700	1069.984	3721	9801	N = 14230
	between		1102.975	3721	9507.5	n = 3566
	within		196.44400	4041.627	5985.627	T-bar = 3.99047
MALE	overall	0.44322	0.49678	0	1	N = 14230
	between		0.49707	0	1	n = 3566
	within		0.00000	0.4432186	0.4432186	T-bar = 3.99047
MARITAL STATUS	overall	3.85264	1.53969	1	6	N = 14230
	between		1.52765	1	6	n = 3566
	within		0.35163	-0.1473647	7.852635	T-bar = 3.99047
HEALTH STATUS (SAH)	overall	2.41096	0.93977	1	5	N = 14230
	between		0.83935	1	5	n = 3566
	within		0.50659	0.2109628	5.610963	T-bar = 3.99047
LIMIT_L	overall	0.32509	0.46842	0	1	N = 14230
	between		0.39176	0	1	n = 3566
	within		0.28421	-0.4749122	1.125088	T-bar = 3.99047
ARMS_L	overall	0.53619	0.49871	0	1	N = 14230
	between		0.41795	0	1	n = 3566
	within		0.28532	-0.2638089	1.336191	T-bar = 3.99047
SIGHT_L	overall	0.11736	0.32186	0	1	N = 14230
	between		0.25900	0	1	n = 3566

Table A6IV Panel summary of dependent and independent variables using data from BHPS

Variable		Mean	Std. Dev.	Min	Max	Observations
	within		0.21100	-0.6826423	0.9173577	T-bar = 3.99047
HEAR_L	overall	0.21911	0.41366	0	1	N = 14230
	between		0.36355	0	1	n = 3566
	within		0.21512	-0.5808855	1.019115	T-bar = 3.99047
SKIN_L	overall	0.09859	0.29813	0	1	N = 14230
	between		0.23923	0	1	n = 3566
	within		0.18636	-0.7014055	0.8985945	T-bar = 3.99047
CHEST_L	overall	0.18110	0.38511	0	1	N = 14230
	between		0.33885	0	1	n = 3566
	within		0.20278	-0.6189037	0.9810963	T-bar = 3.99047
HEART_L	overall	0.45467	0.49796	0	1	N = 14230
	between		0.42570	0	1	n = 3566
	within		0.27201	-0.3453268	1.254673	T-bar = 3.99047
STOMACH_L	overall	0.11876	0.32352	0	1	N = 14230
	between		0.25636	0	1	n = 3566
	within		0.21155	-0.6812368	0.9187632	T-bar = 3.99047
DIABETES_L	overall	0.09459	0.29266	0	1	N = 14230
	between		0.27737	0	1	n = 3566
	within		0.11060	-0.7054111	0.8945889	T-bar = 3.99047
ANXIETY_L	overall	0.07330	0.26063	0	1	N = 14230
	between		0.21082	0	1	n = 3566
	within		0.17029	-0.7267041	0.8732959	T-bar = 3.99047
ALCOHOL_L	overall	0.00225	0.04737	0	1	N = 14230
	between		0.03413	0	1	n = 3566
	within		0.03669	-0.7977512	0.8022488	T-bar = 3.99047
EPILEPSY_L	overall	0.00745	0.08599	0	1	N = 14230
	between		0.07691	0	1	n = 3566
	within		0.03445	-0.7925509	0.8074491	T-bar = 3.99047
MIGRAIN_L	overall	0.05123	0.22047	0	1	N = 14230
	between		0.17784	0	1	n = 3566
	within		0.13353	-0.7487702	0.8512298	T-bar = 3.99047
OTHER_L	overall	0.04933	0.21657	0	1	N = 14230
	between		0.13815	0	1	n = 3566
	within		0.17350	-0.7506676	0.8493324	T-bar = 3.99047
CANCER_L	overall	0.03394	0.18109	0	1	N = 14230
	between		0.14254	0	1	n = 3566
	within		0.12743	-0.7660576	0.8339424	T-bar = 3.99047

Table A6IV Panel summary of dependent and independent variables using data from BHPS

Variable		Mean	Std. Dev.	Min	Max	Observations
STROKE_L	overall	0.03472	0.18306	0	1	N = 14230
	between		0.13871	0	1	n = 3566
	within		0.13226	-0.7652846	0.8347154	T-bar = 3.99047
NURSE_L	overall	0.10134	0.30178	0	1	N = 14230
	between		0.24662	0	1	n = 3566
	within		0.21172	-0.6986648	0.9013352	T-bar = 3.99047
GP_L	overall	0.85102	0.40675	0	12	N = 14230
	between		0.28832	0	4.666667	n = 3566
	within		0.30326	-2.815648	9.101019	T-bar = 3.99047
EDUCATION	overall	1.76634	0.81916	1	3	N = 14230
LEVEL	between		0.80964	1	3	n = 3566
	within		0.05617	0.5663387	3.366339	T-bar = 3.99047
INCOME	overall	9.75500	0.71319	0	12.35351	N = 14230
	between		0.59057	0	11.98174	n = 3566
	within		0.42960	1.878416	16.40304	T-bar = 3.99047
TENURE	overall	1.62038	1.01736	1	4	N = 14230
	between		1.00503	1	4	n = 3566
	within		0.28888	-0.7796205	4.020379	T-bar = 3.99047
ECONOMIC	overall	3.89051	0.75409	1	7	N = 14230
ACTIVITY	between		0.64456	1	7	n = 3566
	within		0.40180	0.490513	8.390513	T-bar = 3.99047
COUNTRY	overall	2.04090	1.12549	1	4	N = 14230
	between		1.14955	1	4	n = 3566
	within		0.03019	1.0409	3.0409	T-bar = 3.99047
t	overall	3.85987	1.40930	2	6	N = 14230
	between		0.70777	2	6	n = 3566
	within		1.32635	1.52654	6.193207	T-bar = 3.99047

Note: For simplicity, variables for marital status, self assessed health status, education level housing tenure, economic activity and country have been treated as continuous instead of dummies

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