A Panel Data Analysis Of The Utilisation Of GP Services In Ireland: 1995-2001

Anne Nolan and Brian Nolan

Working Paper No. 13

Research Programme on "Health Services, Health Inequalities and Health and Social Gain"

This programme is supported by the Health Research Board, and is being carried out by researchers at the Economic and Social Research Institute (ESRI), University College Dublin and the University of Ulster

• Economic and Social Research Institute, 4 Burlington Road, Dublin 4, Ireland. Correspondence to: Anne Nolan, Economic and Social Research Institute, 4 Burlington Road, Dublin 4, Ireland. Email: anne.nolan@esri.ie

SUMMARY
The extent to which the cost of obtaining health care influences the utilisation of GP and other health services is a frequently analysed topic. A key issue concerns the extent to which access to private health insurance and/or eligibility for free public health services results in differences in utilisation that cannot be explained by differences in need factors such as age, gender or health status. Ireland is an interesting case study in this regard as only 30 per cent of the population are eligible for free GP consultations; the remainder of the population must pay the full price. Using panel data from 1995 to 2001 on GP visits in Ireland, this paper applies a random effects approach to count data in an attempt to determine the factors influencing GP visiting patterns, with a particular focus on the role of eligibility for free public health services.

1. INTRODUCTION

Despite the fact that hospital expenditure dominates health expenditure in most OECD countries [see OECD Health Data (2004)], there is a growing recognition that primary care services have the potential to relieve pressure on the hospital sector. In countries such as Ireland where GPs act as "gatekeepers" for the use of hospital services, the behaviour of GPs and their patients has particularly important implications for resource use in the hospital sector. In this context, it is important to understand the factors that influence GP visits and to examine the extent to which utilisation is distributed on the basis of need, rather than by ability to pay or other non-need factors such as income or area of residence.

The extent to which the cost of obtaining health care influences the utilisation of GP and other health services is particularly important in this regard. A key issue concerns the extent to which access to private health insurance and/or eligibility for free public health services distort the relative prices facing consumers and consequently result in differences in utilisation that cannot be explained by differences in age, gender or health status. Across Europe, universal entitlement to free or heavily subsidised GP services means that the role of supplementary private health insurance in determining utilisation has received most attention [see for example, Buchmueller *et al*. (2002), Cameron *et al*. (1988), Chiappori *et al*. (1998), Holly *et al*. (1998), Hurd and McGarry (1997), Jones *et al*. (2002), Schellhorn (2001), Vera-Hernandez (2001) and Waters (1999)]. In Ireland, the focus is not so much on insurance coverage as eligibility for free health services as nearly 30 per cent of the population, termed "medical cardholders", are entitled to free GP consultations and effectively face a zero monetary cost in visiting their GP. The remainder of the population however must pay out-of-pocket for GP consultations. In addition, while nearly 50 per cent of the population are covered by private health insurance, this does not cover the cost of GP consultations (except where large deductibles are exceeded) and is primarily concerned with providing cover for private or semi-private hospital care. The medical card system therefore leads to a clear differential in the economic incentives facing these two groups (and GPs) and we would expect this to lead to significant differences in utilisation, even after controlling for factors such as age, gender and health status. Using individual-level data on GP visits, a number of cross-sectional studies find that medical cardholders do indeed have a significantly higher number of GP visits than non-medical cardholders, even after controlling for a variety of demographic, socio-economic and health status characteristics [see Tussing (1985), Nolan (1991, 1993) and Nolan and Nolan (2003)].

The availability of panel data from 1995 to 2001 allows us to improve on the accuracy of previous estimates by modelling the relationship between GP utilisation and individual characteristics such as age, gender, health status and medical card eligibility at multiple points in time across the survey period. Quite apart from the increased sample size, the fact that the same individuals are repeatedly observed in a panel data set enables us to control for unobserved heterogeneity across individuals, which is impossible using cross-sectional data. Unobserved heterogeneity across individuals is represented by factors that are individual-specific but time-invariant, e.g., attitudes/preferences towards different types of medical care. However, this necessarily complicates the modelling process, as we need to take account of the fact that the random error terms will now be correlated across individuals, rather than randomly distributed as in a standard cross-sectional regression model. This rules out simply pooling repeated cross-sectional observations. Using detailed panel data from 1995 to 2001, the purpose of this paper is to examine the determinants of GP visits, in particular to analyse the impact of medical cardholder status on utilisation.

Section 2 below discusses previous research in the area and briefly outlines the Irish system of eligibility for free public health services. Section 3 describes the data-set employed in this paper and the various dependent and independent variables chosen for analysis. Section 4 discusses the econometric modelling techniques in greater detail while Section 5 presents preliminary estimation results. Section 6 concludes and details areas in need of further research.

2. GP UTILISATION IN IRELAND

All individuals who are ordinarily resident in Ireland are granted either full or limited eligibility for health care services. Individuals with full eligibility, termed “medical cardholders”, are entitled to receive all health services free of charge, including GP services, prescribed medicines, all dental, ophthalmic and aural services, maternity services, in-patient services in public hospitals and specialist treatment in out-patient clinics. The remainder of the population are entitled to free maternity services, in-patient services in public hospitals (subject to a charge per day), specialist services in out-patient clinics (again, subject to a charge per day) and assistance towards the cost of prescribed medicines over a monthly limit. They must, however, pay for all GP consultations and all dental, ophthalmic and aural treatments. Currently, approximately 30 per cent of the population are medical cardholders [Department of Health and Children (2003)]. Eligibility for a medical card is dependent upon income and is decided on the basis of a means test. Since July 2001, all those aged 70 years and older are also entitled to a medical card, regardless of income. In special circumstances such as a cancer diagnosis, a medical card may be granted to an individual who is otherwise ineligible on the basis of income or age.

In terms of the utilisation of GP services, the medical card system therefore leads to a clear differential in the economic incentives facing medical cardholders and non-medical cardholders and we would expect this to lead to significant differences in utilisation, even after controlling for factors such as age, gender and health status. Using cross-sectional individual-level data on GP services utilisation in Ireland, Tussing (1985), Nolan (1991, 1993) and Nolan and Nolan (2003) all find that medical cardholders have a significantly higher probability of visiting their GP and also a significantly higher number of GP visits. In addition, the incentives facing GPs may differ depending on the eligibility category of their patients, particularly as reimbursement methods differ between the two categories. GPs are remunerated for their medical card patients on a capitation basis, a payment which varies according to the age, sex and geographical location of their patients. Non-medical cardholder patients pay on a fee-for-service basis for each visit. GPs therefore have an incentive to encourage follow-up visits on the part of their medical cardholder patients and to discourage such visits on the part of their non-medical cardholder patients. Prior to 1989, GPs were also remunerated on a fee-for-service basis for their medical card patients. In response to the findings by Tussing (1985) in favour of demand inducement by GPs under such a system, the basis for remuneration was changed to capitation to reduce the incentives for GPs to arrange return visits. However, research by Madden *et al*. (2004) found that the differential in visiting rates between medical cardholders and non-medical cardholders did not change significantly after the change in reimbursement for medical cardholder patients in 1989. While over 50 per cent of the Irish population has private health insurance, it does not cover the cost of GP visits (except where large deductibles are exceeded) and is instead primarily taken out by non-medical cardholders to cover the cost of semi-private and private hospital cover. As such, insurance cover should not influence the utilisation of GP services in Ireland, except to the extent that insurance cover may be a proxy for other factors such as risk aversion, attitudes towards health *etc*. [see also Nolan and Nolan (2003)].

3. DATA

We use data from the Living in Ireland Survey, which was carried out by the ESRI and constitutes the Irish component of the European Community Household Panel (ECHP). The ECHP began in 1994 and ended in 2001. It involved an annual survey of a representative sample of private households and individuals aged 16 years and over in each EU member state, based on a standardised questionnaire. In terms of health information, the individual questionnaires contain information on health services utilisation in the previous year (GPs, specialists, dentists and opticians) and measures of the extent and nature of physical and psychological health problems. As the number of GP visits is not separately identified from the number of visits to medical specialists, dentists and opticians in 1994, we confine our analysis to the years 1995 to 2001 inclusive.

The panel is unbalanced and includes all adults aged 16 years and over, amounting to 42,716 observations. As Table 1 indicates, there was some attrition in the earlier years, although the representativeness of the sample was improved in 2000 with the addition of new households. After deleting observations for which information on one or more variables of interest was missing, completed observations are available for 36,418 individuals. Table 2 presents variable definitions for the various dependent and independent variables employed in this study. The dependent variable is a count variable recording the number of visits to a GP in the previous twelve months (GPVISITS). As is evident from Table 3, the standard deviation of GPVISITS is consistently larger than the mean, a feature of the data which has consequences for the choice of the most appropriate econometric methodology (see below). Schellhorn (2001) discusses the problem of reporting error that may arise when individuals are asked to recall behaviour over a long period of time. An examination of the data shows that there are clusters at certain values (e.g. 10, 12 visits), which are consistent with individuals rounding up or down the number of visits or approximating "once a month" for example. However, the percentage of individuals with such frequencies is only a small fraction of the total and is consequently not considered a problem (approximately two and six per cent report 10 and 12 visits per annum respectively).

Summary statistics for the independent variables are presented in Table 4. The demographic/socio-economic characteristics of the individual are represented by variables describing the age, gender, household location, education level, employment status, marital status, household income, medical card eligibility and private health insurance status of the individual. As the health status of the individual is consistently found to be the most significant factor explaining health services utilisation in previous studies, a number of indicators of physical and psychological health status are employed. Whether an individual gave birth during the previous twelve months is represented by a dummy variable. Individuals who report that they suffer from "*any chronic, physical or mental health problem, illness or disability*" are subsequently asked for the nature of this illness or disability; we have constructed a categorical variable with eleven categories corresponding to various medical conditions with the base category indicating that the individual did not indicate that they suffered from any chronic, physical or mental health problem, illness or disability. Scores from the General Health Questionnaire (GHQ) are used to construct an ordinal variable indicating psychological health status. The GHQ contains twelve questions relating to psychological health status. For the six positive statements (e.g. "have you recently been able to concentrate on what you're doing?"), a person scores one if they answer "less than usual" or "much less than usual" while for the six negative statements (e.g. "have you recently lost much sleep over worry?"), a person scores one if they answer "more than usual" or "much more than usual". These scores are added up and result in an ordinal variable indicating the degree of psychological distress; anyone scoring above the conventional threshold of two is considered to be in psychological distress.

Jimenez-Martin *et al*. (2002), Schellhorn *et al*. (2001), Hakkinen *et al*. (1996) and Cameron *et al*. (1988) all discuss the problem of using current measures of health status to predict past health services utilisation. Table 5 shows that there is some mobility in health status over time; for example, over the full panel, 28.3 per cent of those with no health problem in any one year reported at least one health problem the following year. An advantage of panel data is that we can use lagged values of health status instead, thus removing the potential endogeneity problem associated with using current health status to predict past GP visits. We therefore employ lagged values of the eleven health status indicators and the GHQ score.

Table 6 presents the average number of GP visits for medical cardholder and non-medical cardholder patients. As expected, medical cardholders have a higher number of annual visits to their GP than non-medical cardholders, even after controlling for age. This reflects most importantly the difference in the relative price of a consultation between the two groups and also the distribution of health status across the two groups. Across the period of the panel, the average number of GP visits stayed relatively stable for both groups of patient (see Table 3). It is the objective of the multivariate analysis undertaken described in Section 4 below to determine whether there is a significant difference between medical cardholders and non-medical cardholders in patterns of utilisation, and whether these results are affected by the choice of econometric modelling technique. Future work will examine the extent to which transitions into and out of medical cardholder status affect GP services utilisation (see also Section 6).

4. ECONOMETRIC METHODOLOGIES

In modelling the determinants of the number of GP visits, the nature of the data on utilisation influence the choice of econometric methodology. Count data modelling techniques are necessary due to the highly skewed nature of the distribution of GP visits (a large proportion of observations are clustered at zero while only a small proportion of individuals record frequent visits) and due to the fact that that number of GP visits is a variable that can take on only non-negative, integer values. An OLS regression would assume a normally distributed error term as well as predicting negative values for the dependent variable. Using a count model overcomes these problems by assuming a skewed, discrete distribution and restricting predicted values to non-negative values. While the Poisson count data model is the usual starting point for empirical research using count data, this distribution assumes that the expected number of counts is equal to the variance (Table 3 shows how this assumption is violated for our data). As an alternative, the negative binomial count data model, which allows the variance of the number of visits to exceed the mean, is commonly employed. On the basis of information criteria, the Poisson specification is rejected in favour of the negative binomial specification of the models considered below; we therefore concentrate on the negative binomial specification. For more detailed derivation and specification of count data models in a cross-sectional modelling context see for example Durkan *et al*. (1996), Gerdtham (1997), Grootendorst (1995), Hakkinen *et al*. (1996) and Pohlmeier and Ulrich (1995).

Using panel data complicates matters however, as we need to take account of the fact that the random error terms may now be correlated across individuals, rather than randomly distributed as in a standard cross-sectional regression model. However, the fact that the same individuals are repeatedly observed in a panel data set does enable us to control for unobserved heterogeneity across individuals, which is impossible using cross-sectional data. Unobserved heterogeneity across individuals is represented by factors that are individual-specific but time-invariant, e.g., attitudes/preferences towards different types of medical care. Very simply, our model takes the form:

$$y_{it} = \alpha_i + x_{it}'\beta + u_{it} \qquad (1)$$

where y_{it} represents the utilisation of GP services by individual i in time period t, α_i is the individual-specific term, x_{it} are the set of explanatory variables such as age and health status and u_{it} is the random error term. Much discussion in panel data econometrics focuses on how these unobserved individual-specific but time-invariant factors α_i should be modelled. A fixed effects formulation for the individual-specific factors assumes that the individual-specific effects are fixed, unknown parameters to be estimated within the model. The focus of such a model is on variation within individuals, e.g., why individual *i*'s utilisation of GP services in 1995 is different to individual *i*'s average level of GP utilisation over the period 1995-2001 inclusive. This formulation is most appropriate for observations that are "one of a kind" and where the object of the analysis is to explain differences within observations. In addition, the number of explanatory variables is necessarily reduced due to fact that the within transformation removes all time-invariant variables, e.g. gender, from the model. In practice, fixed effects may only work well when there are many observations and much variation within groups.[1]

The alternative formulation, the random-effects formulation, assumes that the individual effects are distributed randomly across the population, i.e.,

$$y_{it} = \mu + x_{it}'\beta + \alpha_i + u_{it} \tag{2}$$

where μ is the intercept term and $\alpha_i + u_{it}$ is treated as an error term with two components: an individual-specific component (that does not vary over time) and a remainder component that varies both over time and across individuals. The focus in such a model is on differences both within and between, but particularly between individuals, i.e., why individual *i*'s GP utilisation is different to individual *j*'s GP utilisation. It is more appropriate to consider a random effects formulation for the individual-specific effects when the observations are from a large and heterogeneous population. For this reason, we proceed with a random effects specification for the individual effects.

Following the approach of Hausman *et al*. (1984), the random effects negative binomial specification may be derived from the Poisson model. The standard Poisson model assumes that the dependent variable follows a Poisson distribution where the Poisson parameter $\lambda_{it} \sim gamma\left(u_{it}, \delta\right)$, $u_{it} = exp\left(x_{it}'\beta\right)$ and δ is the over-dispersion parameter. For the random effects negative binomial model, we allow the over-dispersion parameter to vary randomly across individuals, i.e., $\frac{\delta_i}{\left(1+\delta_i\right)} \sim beta\left(r, s\right)$ where r and s are estimated within the model, along with the coefficient vector β. The resulting density function for the random effects negative binomial model, which can be used for maximum likelihood estimation, is as follows:

[1] However, a fixed effects formulation may make sense if we are interested in explaining variations in GP utilisation at an individual level in response to changes in certain circumstances such as medical card eligibility, health status *etc*.

$$Pr\left(y_{i1},......,y_{iT} \mid x_{i1},......,x_{iT}\right) = \frac{\Gamma(r+s)\Gamma\left(r+\sum_{t=1}^{T_i} u_{it}\right)\Gamma\left(s+\sum_{t=1}^{T_i} y_{it}\right)}{\Gamma(r)\,\Gamma(s)\Gamma\left(r+s+\sum_{t=1}^{T_i} u_{it}+\sum_{t=1}^{T_i} y_{it}\right)} \prod_t \frac{\Gamma(u_{it}+y_{it})}{\Gamma(u_{it})\,\Gamma(y_{it}+1)} \tag{3}$$

A major disadvantage of the random effects formulation is that it forces the unobserved individual-specific factors (e.g. previous experience with a GP, attitudes towards medical care) to be uncorrelated with the observed independent variables (e.g. age, health status), an assumption that is too restrictive in most cases. If this assumption is violated, the random effects estimator is inconsistent. The Hausman test is rejected for the standard random effects model (see Table 7) meaning that the assumption that the individual effects are not correlated with the explanatory variables is violated for our data. One solution is to parameterise the individual-effect, i.e., to allow for correlation between the individual effects and the set of time-varying explanatory variables. We will implement this modification in a future version of the paper (see also Section 6).

5. EMPIRICAL RESULTS

As a preliminary examination of the effect of medical cardholder status, among other characteristics, on the utilisation of GP services using panel data, we estimated two specifications of the model: a simple pooled negative binomial model and a random effects negative binomial model. The results are presented in Table 7. As the likelihood ratio test favours the random effects over the pooled specifications of the model, we confine the discussion below to the random effects model. Controlling for unobserved individual effects across individuals changes the effects of some of the variables; age, rural and income become more significant, while education level becomes less significant. While not reported here, the marginal effect on medical cardholder status becomes smaller, although it still has a positive and highly significant effect.

The various demographic and socio-economic characteristics have results that are consistent with expectations. Those aged 65+years visit their GP most frequently in comparison with those aged 16-24 years, with the effect increasing as age increases. It is interesting to note that age remains significant even after medical card eligibility and health status are controlled for, reflecting perhaps a greater awareness of good health as age increases. Females visit their GP more frequently than males, even when recent maternity experience is taken into account. The results for the education level of the individual indicate that, in comparison with those with a primary level education only, those with a lower or upper secondary education visit their GP significantly less often while there is no significant difference between those with a primary level education and those with a third level education. Being either employed or unemployed reduces significantly the number of GP visits in comparison with those that are economically inactive, e.g. retired or engaged in home duties. The result for the employed is easily justified with reference to the time and effort involved in arranging time off work for a visit; the result for the unemployed is more puzzling. Consistent with the view that married or separated/divorced individuals are more likely to have children, these groups have a significantly higher number of GP visits per annum than single individuals. Once again, it is interesting that being widowed exerts a positive and significant effect on GP visits, given that age and health status have already been controlled for. As with age and gender, this may indicate that our health status variables are not adequately picking up the complex web of health status influences on visiting behaviour. However, while our measures may be crude, they are nonetheless important to include and add significantly to the explanatory power of the model [see also Tussing (1985) and Nolan (1991)].

Per capita household disposable income exerts a positive and significant effect on the frequency of GP visits, despite the fact that those on low incomes are exempt from GP charges through medical card eligibility. Gerdtham (1997) also finds that income has an impact on the utilisation of GP services and cites this as evidence in favour of horizontal inequity in the utilisation of GP services in Sweden. As expected, the effect of medical card eligibility is highly significant and positive. While it is certainly true that the difference in price faced by the two sets of patients explains this result, it is possible that medical card eligibility is also picking up other differences in health status not accounted for by our measures. Nonetheless, the results show that even after controlling for a variety of demographic, socio-economic and health status characteristics, those with medical cards have a significantly higher number of GP visits per annum. Interestingly, the effect of having private medical insurance significantly increases the frequency of visits, despite the fact that private medical insurance in Ireland does not cover the cost of GP visits, except in cases where a large deductible is exceeded. The significance of insurance in influencing the number of GP visits may reflect differences in attitudes towards health care between the two groups with those covered by private medical insurance possibly more risk averse than those without. In common with results elsewhere [see for example Jimenez-Martin *et al*. (2002), Pohlmeier and Ulrich (1995), Hakkinen *et al*. (1996), Gerdtham *et al*. (1997) and Nolan (1991)], the measures of health status are particularly significant in explaining GP services utilisation.

6. CONCLUSIONS

As a first step in analysing the determinants of GP services utilisation, with a particular emphasis on the role of medical card eligibility in this regard, this paper estimated a simple random effects model of GP services utilisation over the period 1995-2001. The availability of panel data allowed us to improve on the estimates from previous research using the data in a cross-sectional context [see Nolan and Nolan (2003)] through an increased sample size and the ability to control for unobserved individual heterogeneity.

Controlling for unobserved individual heterogeneity, medical card eligibility exerts a positive and highly significant effect on the frequency of GP visits, even after controlling for additional factors such as age, gender and health status. While medical card eligibility may also be picking up subtler differences in health status that our health status measures are not capturing, the results confirm that the differences in relative prices faced by medical cardholders and non-medical cardholders are a strong determinant of differences in visiting rates. The results also highlight other differences in visiting patterns that are not related to need factors such as age, gender or health status. For example, those on higher incomes visit their GP more frequently. This presents an interesting area for future research, i.e., to determine whether those just above the medical card income threshold are being priced out of the market for GP visits.

However, our random effects specification needs refinement in that the Hausman test rejected the assumption of no correlation between the individual effects and the explanatory variables; our next step is to follow the approach of Mundlak (1978), among others, in parameterising the individual effect to overcome this failing. While there are obvious advantages in the ability to exploit the increased sample size available in using panel data, to control for unobserved individual heterogeneity and to incorporate lagged values of health status, a fourth advantage of panel data lies in the opportunity to model dynamic behaviour at an individual level. For example, an individual's number of visits to a GP in one year may depend not only on individual characteristics such as age, gender, income and health status, but also on their visiting experience in the previous year. Panel data enable us to incorporate this additional information into our models. This necessarily complicates the estimation of the models, as we can no longer assume that the individual-specific factors are uncorrelated with the explanatory variables, irrespective of whether a fixed- or a random-effects formulation is chosen for the individual effects. In addition, panel data also allow us to model transitions into and out of different states. This is particularly useful in the context of medical card eligibility. In addition to refining the random effects specification of our models to account for the correlation between the individual effects and the independent variables and introducing a dynamic component to the model, our most immediate area of future research will involve modelling the effect on GP visiting behaviour of a change in medical card eligibility from one year to the next. In other words, does an individual's GP services utilisation change significantly when they gain/lose a medical card?

Table 1 Number of Observations

YEAR	NUMBER OF OBSERVATIONS	COMPLETED OBSERVATIONS
1995	8,530	7,023
1996	7,488	5,955
1997	6,868	5,412
1998	6,324	4,958
1999	5,451	4,271
2000	8,055	3,633
2001	6,521	5,166
Total	42,716	36,418

Note: (i) As a result of the inclusion of new households in 2000 to correct for attrition in earlier years, the number of completed observations for 2000 is much smaller than for other years.

Table 2 Variable Definitions for Dependent and Independent Variables

VARIABLE	DEFINITION
GPVISITS	Number of GP visits in the previous twelve months
Age 25-34	=1 if aged 25-34 years, =0 otherwise
Age 35-44	=1 if aged 35-44 years, =0 otherwise
Age 45-54	=1 if aged 45-54 years, =0 otherwise
Age 55-64	=1 if aged 55-64 years, =0 otherwise
Age 65+	=1 if aged 65+ years, =0 otherwise
	(Base Category = aged 16-24 years)
Female	=1 if female, =0 otherwise
	(Base Category = male)
Rural	=1 if lives in household located in open country or in a village with 200 - 1,499 inhabitants, =0 otherwise
	(Base Category = lives in a household located in a town with 1,500 – 10,000 or more inhabitants or in Waterford, Galway, Limerick and Cork cities or Dublin city and county)
Lower Secondary	=1 if highest level of education completed is lower secondary (i.e., intermediate/junior certificate), =0 otherwise
Upper Secondary	=1 if highest level of education completed is upper secondary (i.e., leaving certificate), =0 otherwise
Third Level	=1 if highest level of education completed is third level (i.e., diploma, primary degree or higher degree), =0 otherwise
	(Base Category = highest level of education completed is primary level)
Married	=1 if married, =0 otherwise
Separated/Divorced	=1 if separated or divorced, =0 otherwise
Widow	=1 if widowed, =0 otherwise
	(Base Category = never married)
Employed	=1 if employed, =0 otherwise

Unemployed	=1 if unemployed or seeking employment, =0 otherwise (Base Category = economically inactive (i.e., in education, engaged in home duties, retired, incapacitated for work *etc*.)
Income	Net Household Weekly Income in IR£[2] (adjusted for household size, inflation and divided by 100)
Medical Card	=1 if have a medical card or covered on another family member's card, =0 otherwise (Base Category = does not have a medical card and is not covered on another family member's card)

Table 2 continued

VARIABLE	DEFINITION
Insurance	=1 if insured either in own name or through another family member, =0 otherwise (Base Category = not insured in own name or through another family member)
Disease_{t-1}	=1 if nature of illness or disability is an infectious or parasitic disease or neoplasm or congenital abnormality, =0 otherwise
System_{t-1}	=1 if nature of illness or disability is an endocrine disorder, blood disorder, skin disorder or a genito-urinary problem, =0 otherwise
Mental_{t-1}	=1 if nature of illness or disability is a mental disorder, depression (defined in 2000 only) or a mental handicap (defined in 2000 only), =0 otherwise
Nervous_{t-1}	=1 if nature of illness or disability is a nervous complaint or bad nerves, =0 otherwise
Circulatory_{t-1}	=1 if nature of illness or disability is a circulatory problem, =0 otherwise
Respiratory_{t-1}	=1 if nature of illness or disability is a respiratory problem, =0 otherwise
Digestive_{t-1}	=1 if nature of illness or disability is a digestive problem, =0 otherwise
Headache_{t-1}	=1 if nature of illness or disability is headaches, =0 otherwise
$\text{Musculo-Skeletal}_{t-1}$	=1 if nature of illness or disability is a musculo-skeletal disorder, bad back or a physical handicap (defined in 2000 only), =0 otherwise
Accident_{t-1}	=1 if nature of illness or disability is an accident, =0 otherwise
Other_{t-1}	=1 if nature of illness or disability is not specified or does not fall under the above classifications, =0 otherwise (Base Category = does not have any major illness, physical disability or infirmity that has troubled the individual for the past year and is likely to go on troubling the individual in the future (1987 definition) or does not have a chronic physical or mental health problem, illness or disability (1995 and 2000 definition))
GHQ_{t-1}	Generalised Health Questionnaire Score (ranges from 1 to 12; see text for details)

Note: (i) Household income is equivalised using the following scale: 1 for the HOH, 0.66 for any other adults over the age of 14 years and 0.33 for any children under the age of 14 years.

Table 3 Summary Statistics for Dependent Variable (GPVISITS)

	1995	1996	1997	1998	1999	2000	2001	All
Mean	3.4	3.3	3.5	3.5	3.7	3.5	3.8	3.5
Standard Deviation	5.9	5.5	5.3	5.5	6.8	5.1	7.9	6.1
Minimum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum	100	100	80	90	212	70	250	250

[2] The euro was introduced in Ireland on 1 January 2002.

Table 4 Summary Statistics for Independent Variables

VARIABLE	PERCENTAGE OF SAMPLE IN EACH CATEGORY
Age 16-24	15.3
Age 25-34	16.2
Age 35-44	18.6
Age 45-54	17.6
Age 55-64	14.2
Age 65+	18.1
Female	53.0
Male	47.0
Rural	51.5
Urban	48.5
Primary	34.0
Lower Secondary	22.9
Upper Secondary	28.6
Third Level	14.5
Employed	51.3
Unemployed	4.6
Economically Inactive	44.1
Married	60.5
Separated/Divorced	2.3
Widowed	7.5
Single	29.7
Income	1.81 (1.23)
Medical Card	32.3
No Medical Card	67.7
Insurance	43.1
No Insurance	56.9
Birth	1.5
No Birth	98.5
Disease	0.6
System	1.7
Mental	1.0
Nervous	1.3
Circulatory	3.8
Respiratory	2.5
Digestive	0.9
Headache	0.2
Musculo-Skeletal	4.9

Accident	0.6
Other	0.9
No Health Problem(s)	81.6
GHQ	1.20 (2.36)

Note: (i) For Income and GHQ, the statistics are the sample mean and standard deviation (in parentheses).

Table 5 Transition Matrices for Health Status Variables

VARIABLE	0	1
At least one health problem		
0	92.4	7.6
1	28.3	71.7
Stress (i.e., GHQ score >=2)		
0	89.8	10.2
1	56.5	43.5

Note: (i) The matrices are interpreted as follows: 92.4 per cent of individuals with no health problem in any one year also reported no health problem in the following year, while 7.6 per cent reported at least one health problem in the following year.

Table 6 Average Number of GP Visits by Age and Medical Cardholder Status

AGE	MEDICAL CARDHOLDERS	NON-MEDICAL CARDHOLDERS
Age 16-24	3.4	1.6
Age 25-34	5.0	2.4
Age 35-44	4.8	2.2
Age 45-54	5.7	2.2
Age 55-64	6.4	2.8
Age 65+	7.4	3.5
All	**6.0**	**2.3**

Table 7 Estimated Coefficients for Pooled Negative Binomial and Random Effects Negative Binomial Models

	POOLED	RANDOM EFFECTS
Age 25-34	0.11 (0.05)**	0.10 (0.03)**
Age 35-44	0.05 (0.05)	0.12 (0.03)***
Age 45-54	0.04 (0.05)	0.19 (0.03)***
Age 55-64	0.17 (0.05)***	0.37 (0.04)***
Age 65+	0.33 (0.06)***	0.60 (0.04)***
Female	0.25 (0.02)***	0.27 (0.02)***
Rural	-0.01 (0.02)	-0.01 (0.01)
Lower Secondary	-0.17 (0.03)***	-0.10 (0.02)***
Upper Secondary	-0.16 (0.04)***	-0.08 (0.02)***
Third Level	-0.15 (0.04)***	-0.01 (0.03)
Employed	-0.19 (0.03)***	-0.18 (0.02)***
Unemployed	-0.11 (0.05)**	-0.11 (0.03)***
Married	0.12 (0.03)***	0.06 (0.02)**
Separated/Divorced	0.16 (0.07)**	0.12 (0.05)**
Widowed	0.10 (0.04)**	0.12 (0.04)***
Income	0.02 (0.01)**	0.03 (0.01)***

Medical Card	0.57 (0.03)***	0.46 (0.02)***
Insurance	0.06 (0.03)**	0.10 (0.02)***

Notes: (i) Standard errors, which for the pooled negative binomial model are adjusted for the clustering of observations by household, are reported in parentheses.
(ii) *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 7 continued

	POOLED	RANDOM EFFECTS
Birth	1.18	1.00
	(0.04)***	(0.03)***
Disease	0.76	0.33
	(0.09)***	(0.05)***
System	0.82	0.36
	(0.06)***	(0.03)***
Mental	0.75	0.23
	(0.08)***	(0.05)***
Nervous	0.72	0.29
	(0.06)***	(0.04)***
Circulatory	0.74	0.32
	(0.04)***	(0.02)***
Respiratory	0.75	0.33
	(0.06)***	(0.03)***
Digestive	0.79	0.34
	(0.08)***	(0.05)***
Headache	0.35	0.15
	(0.12)***	(0.11)
Musculo-Skeletal	0.67	0.27
	(0.04)***	(0.02)***
Accident	0.91	0.38
	(0.09)***	(0.06)***
Other	0.59	0.19
	(0.12)***	(0.05)***
GHQ	0.05	0.02
	(0.003)***	(0.002)***
α	0.99	
	(0.02)***	
r		3.62
		(0.08)***
s		3.55
		(0.10)***
Year Dummies?	YES	YES
Number of Observations	36,418	36,418
Log-Likelihood	-80,469.88	-76,724.71
Hausman Test		1607.74
		Rejected

Notes: (i) Standard errors, which for the pooled negative binomial model are adjusted for the clustering of observations by household, are reported in parentheses.
(ii) *** significant at 1% level; ** significant at 5% level; * significant at 10% level.
(iii) The likelihood ratio test of the pooled vs. the random effects models always rejects the pooled specification.
(iv) The one-percent chi-squared critical value for 37 degrees of freedom is 59.89.

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