A PANEL DATA ANALYSIS OF GP VISITING IN IRELAND: 1995-2001[*]

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SUMMARY

This paper examines the determinants of GP visiting in Ireland, using panel data from the Living in Ireland Survey (LIIS) from 1995-2001. While cross-sectional studies provide important information on GP visiting patterns at a certain point in time, with panel data we can identify the impact of observed individual characteristics while also controlling for unobserved individual heterogeneity, as well as identify whether it is the same individuals who consistently visit their GP year on year, or whether there is more mobility in GP visiting. We therefore estimate dynamic panel models of GP utilisation, and attempt to decompose the observed variation in GP visiting into components attributable to unobserved individual heterogeneity, state dependence and observed individual characteristics such as age or health status.

KEYWORDS: GP Utilisation; Economic Incentives; Random Effects Negative Binomial Model

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1 INTRODUCTION

1.1 Context

This paper examines the determinants of GP visiting in Ireland, using panel data from the Living in Ireland Survey (LIIS) from 1995-2001. To date, GP visiting in Ireland has been studied using cross-section data [see Tussing (1985), Nolan (1991, 1993), Kelleher and McElroy (2002), Nolan and Nolan (2003) and Madden *et al*. (2005)], and has concentrated on the role of economic incentives (principally, means-tested eligibility to free care) in determining differences in GP visiting patterns across the population. The extent to which differences in the cost of seeking care (either through private insurance cover or eligibility for free care) distort the relative prices facing consumers and consequently results in differences in utilisation that cannot be explained by differences in age, gender or health status is a common theme in cross-sectional studies of health services utilisation. Across Europe, universal entitlement to free or heavily subsidised GP services means that the role of supplementary private health insurance in determining differences in GP 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 (1999) 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 ("non-medical cardholders") must pay out-of-pocket for the full cost of GP consultations.[1] 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

[1] The Irish healthcare system is a mixture of a universal public health service and a fee-based private system. In addition to GP services, medical cardholders are entitled to receive all public health services free of charge, including prescribed medicines, all dental, ophthalmic and aural services, maternity services, in-patient services in public hospitals and specialist treatment in out-patient clinics of public hospitals. Non-medical cardholders are entitled to free public maternity services, in-patient services in public hospitals (subject to a €55 charge per day), specialist services in out-patient clinics (again, subject to a €55 charge per day), assistance towards the cost of prescribed medicines over a monthly limit and assistance towards the cost of prescribed medicines for certain chronic conditions or high cost treatments. They must, however, pay for all GP consultations and all dental, ophthalmic and aural treatments. Eligibility for a medical card is dependent upon income and is decided on the basis of a means test with the income thresholds set nationally and updated annually. From 1st July 2001, all individuals aged 70 years and over are also entitled to a medical card, regardless of income. In special circumstances such as a cancer diagnosis, an individual who is otherwise ineligible on the basis of income or age may be granted a medical card.

semi-private hospital care.[2] 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 GP utilisation. Irish studies using cross-sectional data 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), Nolan and Nolan (2003) and Madden *et al*. (2005)].

1.2 Objectives

Panel data allow us to extend previous cross-sectional analyses of GP visiting behaviour in Ireland to consider the impact of state dependence and unobserved individual heterogeneity on visiting, as well as the impact of observed individual characteristics such as age, gender and health status. Controlling for state dependence means that we can determine the degree of persistence or mobility in GP visiting at the individual level over time. For example, studies of poverty dynamics often find that poverty is a more common experience when examined using longitudinal rather than cross-sectional data [see for example Layte and Whelan (2002) and Jenkins (2000)]. A similar picture emerges when examining the extent of GP visiting using both cross-sectional and longitudinal data; if we treat each of the seven waves of the LIIS as an independent cross-section, approximately 30 per cent of individuals report no GP visits in any one year but when examining the data on a longitudinal basis, only 2.5 per cent of individuals present in all seven waves report no GP visits across the seven years of the panel. This suggests that there is considerable mobility in GP visiting, with the vast majority of individuals having at least one visit to their GP over the period of the panel.

Panel data are thus essential in order to determine whether it is the same individuals who consistently visit their GP year on year, or whether there is more mobility in GP visiting. In addition, panel data afford us the opportunity to control for time-invariant but unobservable individual characteristics such as attitudes towards medical care, time preference rates *etc*. Controlling for state dependence and unobserved individual heterogeneity necessarily complicates the estimation of the models, and Section 4 deals in detail with the appropriate specification and estimation of the models employed.

[2] In very recent years, the two main private health insurance providers have provided limited cover for primary care expenses, but neither scheme was in operation for the period under review in this paper.

1.3 Previous Literature

In contrast to the extensive literature using cross-section data to analyse the utilisation of health services, previous research on the dynamics of health services utilisation has been limited. However, Schellhorn *et al*. (2000) examine the utilisation of primary physician and specialist services among elderly Swiss using a three-year panel and Van Ourti (2004) analyses the utilisation of GP, specialist and hospital services using Belgian panel data from 1994-1997. In addition, there is an extensive literature examining the dynamics of self-reported health status; for example, Jones and Rice (2004), Contoyannis *et al*. (2004) and Hauck and Rice (2004) all use the British Household Panel Survey (BHPS) to examine the dynamics of self-reported physical and mental health status. This paper draws on the methodologies and techniques employed in many of these studies (see also Section 3).

1.4 Paper Structure

We therefore estimate dynamic panel models of GP utilisation, and attempt to decompose the observed variation in GP visiting into components attributable to state dependence (i.e., the effect of GP visiting in the previous period on the current number of visits), unobserved individual heterogeneity (factors that are individual specific but time-invariant, e.g. attitudes/preferences towards different types of medical care) and observed individual characteristics such as age, health status or entitlement to free care. With cross-section data we are only able to identify the influence of the latter set of factors. Section 2 describes the data set employed in this paper and presents some descriptive statistics on GP utilisation patterns from both a cross-sectional and longitudinal perspective. Section 3 discusses the econometric modelling techniques employed while Section 4 presents estimation results. Section 5 concludes and details areas in need of further research.

2 DATA, VARIABLES AND DESCRIPTIVE STATISTICS

2.1 Data Source

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 (GP, specialist, dentist and optician visits as well as number of nights in hospital) 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.

We base our analysis on the unbalanced sample of individuals aged 16 years and over, which amounts to 49,237 observations. As Table 1 indicates, there was some attrition in the earlier years of the LIIS, although the representativeness of the sample was improved in 2000 with the addition of new households [see also Russell *et al*. (2004)]. We delete observations for which information on variables of interest are missing, as well as observations where GP visits in excess of 104 per annum were recorded, and as we use lagged values of the dependent variable and some of the independent variables in estimation (see below), this reduces the size of the final sample for estimation to 29,262.

2.2 Dependent Variable

The dependent variable (*gpvisits*) is a count variable recording the number of visits to a GP in the previous twelve months. As illustrated in Table 2, the average number of GP visits per annum stayed relatively stable at approximately 3.4 visits per annum across the period 1995-2001, while the proportions reporting no visit in any one year declined from 31.5 per cent in 1995 to 27.2 per cent in 2001 (based on the unbalanced sample).

However, such cross-sectional snapshots provide no guidance as to whether it is the same individuals who are visiting their GP repeatedly each year, or whether there is mobility among individuals over time in visiting. Table 3 suggests that the latter may be the case. While the proportion of the balanced sample reporting no GP visit in any one year ranges from 30.4 per cent in 1995 to 23.6 per cent in 2001, the proportion of the sample reporting no GP visits over the entire seven waves of the panel falls to 2.5. In other words, when viewed longitudinally, the vast majority of individuals have some contact with their GP. There is also considerable mobility in crude GP visiting, with 60.2 per cent of the balanced sample making at least one move from no visits to positive visits, or vice versa, over the period of the panel.

Looking at transitions between different levels of visiting in more detail, Table 4 presents the transition matrix for GP visits classified into five categories (0, 1-2, 3-5, 6-10 and 11+ visits per annum). The rows represent the category of visiting in year *t* while the columns represent the category of visiting in year *t+1*. Each element represents the proportion of individuals in a particular category in time period *t* who move to the same or a different category in time period *t+1* (figures in bold represent the proportion who remain in the same category over the two years). It is not surprising that the majority of transitions occur on the diagonal or just off it, with the most persistence in GP visits observed for those with no visits or 11+ visits per annum, where over 50 per cent of individuals in these categories remain in the same category of visiting the following year. However, it is notable that 13.0 per cent of those with no GP visits in one year move to 3 or more visits the following year, and 11.3 per cent with 11 or more visits in one year move to 2 visits or fewer the following year. For those with 1-2, 3-5 and 6-10 visits, transitions to the next category down are more common than transitions to the next category up. However, such patterns are sensitive to the definition of the categories and the relative size of the groups (Hauck and Rice, 2004); if we divide visiting into more equal group sizes (0, 1, 2, 3-5, 6+ visits per annum) as in Table 5, the patterns are broadly similar. However, there is now more movement, both upwards and downwards, among the 1 and 2 categories and in particular, a greater proportion of those visiting once in time period *t* move down to no visits than stay on one visit in time *t+1*. While transition matrices are a useful descriptive tool, random effects models offer the opportunity to identify persistence/mobility more accurately through the inclusion of a lagged value of the dependent variable in the model (see Section 3).

2.3 Independent Variables

Independent variables correspond to the demographic/socio-economic characteristics of the individual, as well as their observed health status. Age is represented by a categorical variable with six indicators of 10-year groups (*age 16-24*, *age 25-34*, *age 35-44*, *age 45-54*, *age 55-64*, *age 65+*). Gender is represented by a dummy variable (*female*). Household location is summarised by a dummy variable (*rural*), which classifies individuals based on the location of their household (rural households are those that reside in open countryside or a village with 200-1,499 inhabitants while urban households are those that reside in towns with 1,500 or more inhabitants or in the major cities of Dublin, Cork, Galway, Waterford or Limerick). A four-category variable summarises the highest level of education obtained by the individual: primary level education (the reference category), lower second level (*lower secondary*), upper second level (*upper secondary*) and third level (*third level*). All individuals are classified into three mutually exclusive employment status groups, namely full- or part-time employees (*employed*), unemployed (*unemployed*) and students, retired, economically inactive and engaged in home duties (the reference category). We use a categorical indicator of present marital status that distinguishes between being married (*married*), separated or divorced (*separated/divorced*), widowed (*widowed*) and never married (the reference category). Income is real net household income in Irish pounds, adjusted for the size and composition of the household using equivalence scales[3]. While Pohlmeier and Ulrich (1995) state that in the presence of a high degree of free public health provision and coverage by private medical insurance, income may more accurately reflect a difference in opportunity costs rather than an income effect in the traditional sense (i.e., not picking up ability to pay in the monetary sense as few people incur the monetary costs of health services use), this is not so in Ireland where approximately 70 per cent of the population must pay out-of-pocket for GP visits. Medical card eligibility (*medical card*) and private insurance cover (*insurance*) are represented by dummy variables. Medical card eligibility is included as a proxy for the price of services and also for the attitudes of the doctor. For example, a GP may feel it easier to encourage follow-up visits if an individual faces a zero monetary cost in doing so. Conversely, the remuneration system in operation for medical cardholder patients in Ireland (capitation) may mean that a GP is more likely to encourage follow-up visits for non-medical cardholder patients (who pay a fee-for-service for each visit).

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 (*birth*). A binary variable (*ill-health*) identifying individuals who report that they suffer from "*any chronic, physical or mental health problem, illness or disability*" is included with the reference 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 a dichotomous variable indicating psychological health status (*stress*). 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

[3] 1 for the HOH, 0.66 for adults aged 14+ years and 0.33 for children under the age of 14 years.

and anyone scoring above the conventional threshold of two is considered to be in psychological distress and is given the value one.

Jimenez-Martin *et al*. (2002), Schellhorn *et al*. (2000), 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 6 shows that there is some mobility in health status over time. For example, over the full panel, 7.8 per cent of those with no health problem in year *t* report at least one health problem in year *t+1*, and 26.7 per cent with a health problem in year *t* reported no health problem in year *t+1*. Similarly, for psychological health status, 10.1 per cent scoring below the threshold in year *t* move above the threshold in year *t+1*, while 56.5 per cent of those above the threshold in year *t* move below the threshold in year *t+1*. An advantage of panel data is that we can use lagged values of health status, thus removing the potential endogeneity problem associated with using current indicators of health status to predict past GP visiting. We therefore employ lagged values of the health status and psychological stress variables in our analysis.

3 ECONOMETRIC MODELING

3.1 Model Specification

In modelling the utilisation of GP services, we estimate a dynamic negative binomial model[4]. To investigate the effect of unobserved individual heterogeneity and state dependence on GP visiting, we also estimate two static versions of the model. Assuming for the moment a linear specification, our model takes the following form:

$$y_{it} = \alpha_i + x_{it}'\beta \ + \ \varepsilon_{it} \tag{1}$$

where y_{it} represents the utilisation of GP services by individual i in time period t, α_i is the individual-specific intercept term (which represents individual heterogeneity), x_{it} are the set of independent 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 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

[4] The choice of the negative binomial estimation method is discussed further in Section 3.3.

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 the 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.

The random-effects specification, on the other hand, assumes that the individual effects are distributed randomly across the population, i.e.,

$$y_{it} = \mu + x_{it}'\beta + \alpha_i + u_{it} \qquad (2)$$

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 represents unobserved individual heterogeneity) 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 differs from 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, and due to the fact that we can also infer the effect of time-invariant independent variables, we proceed with a random effects specification for the individual effects.

Introducing a dynamic component to the model involves adding a lagged value of the dependent variable to the model as follows:

$$y_{it} = \mu + x_{it}'\beta + y_{t-1}\delta + \alpha_i + u_{it} \qquad (3)$$

where y_{t-1} is the level of visiting in the previous time period *t-1.* δ, the estimated coefficient on the lagged value of GP visiting, can interpreted as a measure of persistence or mobility in visiting. A coefficient close to zero indicates high mobility in visiting since the level of visiting in the previous period does not affect current visiting. If the coefficient on lagged visiting is positive and large, individuals are characterised by relatively low mobility in visiting. A negative coefficient would indicate cyclical fluctuations in visiting over time.

3.2 *Correlated Individual Effects, State Dependence and Initial Conditions*

A major failing of the random effects specification is the assumption that the unobserved individual effects must not be correlated with the observed independent variables. Otherwise, parameter estimates are inconsistent. To allow for the possibility of correlated individual effects, we parameterise the individual effects as suggested by Mundlak (1978) and Wooldridge (2002). This involves specifying an auxiliary distribution function for the individual effects as follows:

$$\alpha_i = \alpha_0 + \bar{x}_i'\alpha_1 + e_i \qquad (4)$$

where $\bar{x}_i$ is the vector of within-individual means for time-varying independent variables. In addition, controlling for state dependence by estimating a dynamic specification of the model means that we also take account of the problem of initial conditions. In a series where the observations are unlikely to be serially independent and where the first observation (i.e., 1995) is not the true beginning of the process, we cannot assume that the initial conditions are exogenous. To overcome this problem, Wooldridge (2002) suggests adding the initial condition to the auxiliary distribution specified above as follows:

$$\alpha_i = \alpha_0 + \bar{x}_i'\alpha_1 + y_{i0}\alpha_2 + e_i \qquad (5)$$

where y_{i0} is the initial level of visiting, i.e., the level of visiting in the first observation of the panel (1995).

We therefore estimate three specifications of the model in an attempt to investigate the separate contributions of unobserved individual heterogeneity and state dependence. We begin by estimating specification (2), which is a simple static model, which does not take account of the problem of correlated individual effects. We then control for correlated individual effects by substituting (4) into (2). This will indicate the importance of correcting for correlation between the individual effects and our observed independent variables. Finally, we analyse the contribution of state dependence by substituting (5) into (3).

3.3 *Count Data Methodology*

In modelling the utilisation of GP services, the nature of the data on utilisation determines the type of econometric methodology employed. 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) means that conventional OLS estimation techniques are inappropriate. In addition, the 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 2 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).[5]

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:

[5] A number of authors (Buchmueller *et al*. (2002), Van Doorslaer *et al*. (2002), Hurd and McGarry (1997), Gerdtham *et al*. (1997), Hakkinen *et al*. (1996), Pohlmeier and Ulrich (1995), Nolan (1991, 1993) and Tussing (1985)) have argued that two-step or hurdle approaches are more appropriate in accounting for the nature of the decision-making process underlying the decision to visit a GP. They argue that different variables may affect the decision to visit a GP and secondly, the decision about frequency of visits. In addition, the same variables may affect the two stages of the decision-making process in different ways. In cross-section models, the first stage is modelled using a binary choice model (logit or probit) while a variety of techniques are used for the second stage, including truncated OLS, Poisson and negative binomial models. Estimating the second stage using panel data is more complicated, although van Ourti (2004) employs a two-step model in estimating the utilisation of health services using Belgian panel data; however, we leave this an avenue in need of further research.

$$Pr\left(y_{i1},......,y_{iT} \mid x_{i1},......,x_{iT}\right) = \frac{\Gamma(r+s)\Gamma\left(r+\sum_{t=1}^{T_i} u_{it}\right)\Gamma\left(s+\sum_{t=1}^{T_i} y_{it}\right)}{\Gamma(r)\,\Gamma(s)\Gamma\left(r+s+\sum_{t=1}^{T_i} u_{it}+\sum_{t=1}^{T_i} y_{it}\right)} \prod_t \frac{\Gamma(u_{it}+y_{it})}{\Gamma\,(u_{it})\,\Gamma\,(y_{it}+1)} \qquad (6)$$

3.4 Attrition

When using panel data, the possibility of attrition bias, whereby individuals drop out of the panel in a non-random manner, must be considered. In particular, our results may be biased by health-related attrition whereby those who remain in the panel are likely to be younger and healthier on average. To test for attrition, we apply tests suggested by Verbeek and Nijman (1992) and applied by Contoyannis *et al*. (2003). We add an indicator of whether the individual responds in the following wave (*next wave*), an indicator of whether the individual responds in all seven waves (*all waves*) and a count of the number of waves observed for each individual (*count waves*) to our model in an attempt to indicate whether attrition bias is an issue for our sample. The results of these variable addition tests are presented in Table 8 and discussed in Section 4.2. While all coefficients are statistically significant at the one per cent level, there is little substantive difference in the marginal effects.

4 EMPIRICAL RESULTS

4.1 Pooled and Random Effects Negative Binomial Models

Table 7 presents marginal effects and standard errors for the three specifications of the model:
(a) static random effects model, i.e., specification (2)
(b) static random effects model with correlated individual effects, i.e., specification (2) with substitution of (4)
(c) dynamic random effects model with correlated individual effects, i.e., specification (3) with substitution of (5)

The difference in effects between specifications (a) and (b) will indicate the importance of controlling for correlation between the unobserved individual effects and any time-varying independent variables, and the difference between specifications (b) and (c) will indicate the importance of controlling for state dependence and initial conditions. Using likelihood ratio tests, the random effects specifications are always preferred to the pooled specification of the model, and the final specification of the model, the dynamic specification controlling for state dependence, initial conditions and correlated individual effects, is preferred to the two static specifications.

Focussing on the results from the final random effects specification, GP visiting is an increasing function of age, although the effect is only significant after age 55 years. 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. Moving from the basic static random effects specification, (a), to the static specification controlling for correlated individual effects, (b), reduces the size and significance of the age effects, and when we move to the dynamic model controlling for state dependence, initial conditions and correlated individual effects, (c), the effects fall slightly again. Females visit their GP more frequently than males, even when recent maternity experience is taken into account. As with age, the major change in effect is when we control for correlation between the individual effects and time-invariant variables (although neither age nor gender are included in the vector of within-individual means). Accounting for state dependence and initial conditions does little to change these results.

Household location, education level, marital status and income are all insignificant in determining differences in GP visiting across the population. However, research by Madden *et al*. (2005) on pooled Irish data from 1987, 1995 and 2000 found that those with lower levels of education, married or separated/divorced and with higher incomes had a significantly higher number of GP visits than the reference category. Looking in more detail at the results shows that it is the correction for correlated individual effects that makes these variables insignificant; in other words, once correlation between education, marital status and income and unobserved time-invariant individual characteristics is taken into account, the effects become insignificant. Being employed reduces significantly the number of GP visits in comparison with those that are economically inactive, reflecting the time and effort involved in arranging time off work for GP visits. As with age and gender, accounting for state dependence hardly changes the results for education, marital status, income and employment status.

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. Without any information on the "right" or most appropriate level of visiting from either a medical or cost-effectiveness point of view, it is difficult to say whether medical cardholders are "overconsuming" GP services or non-medical cardholders "underconsuming" GP services, or indeed both. However, given the size of the gap between these two groups after controlling for a variety of demographic, socio-economic and health status characteristics, it is likely that neither level of visiting is optimal. Insurance exerts an insignificant effect, consistent with our expectations as private health insurance is primarily taken out to provide cover for hospital expenses.

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), Nolan (1991, 1993) and Madden *et al*. (2005)], our indicators of recent birth and physical health status are particularly significant in explaining GP services utilisation. However, psychological health status is an insignificant determinant. As with the other demographic and socio-economic characteristics such as education, marital status and income, a substantial drop in the size of the marginal effects for physical and psychological health status is evident when we move from model (a) to model (b). This suggests that a large part of the health status effect resulting from the random effects model is in fact due to time-invariant individual characteristics, rather than health status *per se*.

While the number of past visits exerts a highly significant effect on current visiting, the effect is small in magnitude. In comparison with the effects of other variables such as age 65+, medical card eligibility and recent birth (which increase the number of visits by 1.3, 0.9 and 4.5 visits per annum respectively), an additional visit in the previous year only increases the number of visits by 0.02 in the current year. In other words, while the positive and significant sign suggests that there is indeed some habit or persistence in GP visiting from year to year, the effect is very small in comparison with other influences on visiting. This is consistent with the change in effects noted for the other variables; controlling for state dependence and initial conditions, while adding significantly to the explanatory power of the model, does not change substantially either the magnitude or significance of the other effects.

4.2 Tests for Attrition

Table 8 presents the coefficient estimates for the variable addition tests for attrition suggested by Verbeek and Nijman (1992). All three indicators (*next wave*, *all waves* and *count waves*) are significant, suggesting that GP visiting varies non-randomly by individual response characteristics. However, the inclusion of each of these variables does not change the effects of any of the other variables, either in significance or magnitude. We therefore do not attempt to correct for attrition in the sample.

5 SUMMARY AND CONCLUSIONS

This paper analysed the determinants of GP visiting in Ireland, using panel data for the period 1995-2001. The availability of panel data allowed us to improve on the estimates from previous Irish research using cross-sectional data [see Tussing (1985), Nolan (1991, 1993), Nolan and Nolan (2003) and Madden *et al*. (2005)] through an increased sample size and the ability to control for state dependence and unobserved individual heterogeneity. While previous cross-sectional analyses highlighted significant differences in visiting due to non-need factors such as education level, employment status, marital status, income and medical card eligibility, the panel results suggest that the only significant non-need factors are medical card eligibility and employment status. In common with the cross-sectional results, need factors such as age, gender and health status are particularly significant. However, the effects of physical and psychological health are much reduced in magnitude once we take account of individual heterogeneity and the correlation between this unobserved heterogeneity and our observed independent variables.

As with previous research, a particular focus of the paper was the analysis of the medical card effect and as expected, medical card eligibility exerts a positive and highly significant effect on GP visiting, even after controlling for additional factors such as age, gender and health status. While medical card eligibility may also be picking up more subtle 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 final specification of the model suggests that medical cardholders have 0.9 extra GP visits per annum than non-medical cardholders, and this is the third highest effect after recent birth and age 65+ years (4.5 and 1.3 extra GP visits per annum respectively).

State dependence, as captured by the level of visiting in the previous year, was highly significant although the effect was small in size in comparison with other effects. This suggests that while there is some persistence or habit in GP visiting from one year to the next, it is not an important determinant in comparison with other effects such as age or medical card eligibility. Future work will investigate this effect in more detail. In particular, we may expect persistence in GP visiting to be more pronounced for different individuals, e.g., the elderly or those with medical cards, and it may be informative to estimate the models based on these separate sub-samples. Indeed, preliminary investigations suggest that the effect of state dependence is larger and more significant for medical cardholders than non-medical cardholders. In addition, we intend to exploit the panel nature of the data and attempt to model the impact of transitions into and out of medical card eligibility at the individual level on GP visiting. In other words, does an individual's GP visiting change significantly when they gain/lose a medical card? Preliminary analyses of the data suggest that the average number of GP visits per annum falls when individuals lose a medical card, and the number of visits increases when individuals gain a medical card. However, it will be important to examine the relative importance of changes in medical card eligibility on visiting in comparison with changes in other characteristics such as health status or age.

TABLES

Table 1 Sample Sizes

Year	Full Sample	Estimation Sample
1995	8,530	
1996	7,488	5,907
1997	6,868	5,393
1998	6,324	4,951
1999	5,451	4,261
2000	8,055	3,632
2001	6,521	5,118
Total	49,237	29,262

Note: (i) The estimation sample includes lagged values of the dependent variable and the health status and psychological stress variables, and excludes observations where GP visits exceed 104 per annum, and where information is missing on any of the variables of interest.

Table 2 Average number of GP Visits per annum, 1995-2001

	1995	1996	1997	1998	1999	2000	2001	1995-2001
Mean	3.4	3.3	3.4	3.5	3.5	3.5	3.4	3.4
Std. Dev.	5.9	5.9	5.7	5.7	5.5	5.8	5.4	5.7
Minimum	0	0	0	0	0	0	0	0
Maximum	100	100	100	104	100	104	100	104
% zeros	31.5	32.3	29.1	28.8	28.8	29.0	27.2	29.7

Table 3 Proportion with at least one GP Visit per annum by year, and longitudinally

	1995	1996	1997	1998	1999	2000	2001	Panel
0	30.4	30.2	26.8	25.7	26.5	25.1	23.6	2.5
1	69.6	69.8	73.2	74.3	73.5	74.9	76.4	37.3
>0 and <1								60.2

Note: (i) Based on the balanced sample of individuals

Table 4 Transition Matrix for GP Visits, 1995-2001

	0	1-2	3-5	6-10	11+	Total
0	**56.3**	30.9	8.1	3.2	1.6	100.0
1-2	26.5	**48.3**	17.4	5.4	2.5	100.0
3-5	11.7	29.9	**35.2**	15.2	8.1	100.0
6-10	7.6	16.5	28.7	**28.8**	18.5	100.0
11+	3.5	7.8	15.9	19.7	**53.0**	100.0
Total	28.7	32.8	18.9	10.2	9.5	100.0

Table 5 Transition Matrix for GP Visits, 1995-2001

	0	1	2	3-5	6+	Total
0	**56.3**	19.4	11.5	8.1	4.8	100.0
1	32.7	**28.9**	20.1	12.8	5.5	100.0
2	20.0	20.0	**27.5**	22.2	10.3	100.0
3-5	11.7	10.2	19.7	**35.2**	23.3	100.0
6+	5.6	4.4	7.8	22.4	**59.8**	100.0
Total	28.7	16.5	16.3	18.9	19.7	100.0

Table 6 Transition Matrices for Physical and Mental Health Status, 1995-2001

Ill-health	0	1
0	92.2	7.8
1	26.7	73.3
Stress		
0	89.9	10.1
1	56.5	43.5

Table 8 Attrition Tests

	Estimated Coefficient and Standard Error
All waves	-0.05
	(0.02)***
Next wave	-0.05
	(0.02)***
Count waves	-0.02
	(0.01)***

Note: (i) From the random effects negative binomial model controlling for correlation between the individual effects and time-varying independent variables, state dependence and initial conditions, i.e., specification (c).

Table 7 Marginal Effects and Standard Errors for the Random Effects Models

	Static	Static with correlated individual effects	Dynamic with correlated individual effects
Age 25-34	0.33	0.16	0.09
	(0.10)***	(0.09)*	(0.09)
Age 35-44	0.45	0.18	0.06
	(0.12)***	(0.11)*	(0.10)
Age 45-54	0.60	0.31	0.21
	(0.13)***	(0.12)***	(0.11)*
Age 55-64	1.25	0.73	0.63
	(0.16)***	(0.14)***	(0.13)***
Age 65+	2.17	1.36	1.26
	(0.18)***	(0.16)***	(0.15)***
Female	0.78	0.67	0.63
	(0.06)***	(0.06)***	(0.05)***
Rural	-0.13	0.02	0.03
	(0.05)**	(0.10)	(0.10)
Lower Secondary	-0.27	-0.11	-0.12
	(0.06)***	(0.08)	(0.07)
Upper Secondary	-0.26	-0.08	-0.10
	(0.07)***	(0.10)	(0.10)
Third Level	-0.11	-0.08	-0.11
	(0.08)	(0.14)	(0.13)
Employed	-0.55	-0.46	-0.44
	(0.06)***	(0.08)***	(0.07)***
Unemployed	-0.31	-0.01	-0.01
	(0.10)***	(0.12)	(0.12)
Married	0.16	0.32	0.27
	(0.08)**	(0.25)	(0.24)
Separated/Divorced	0.40	0.61	0.56
	(0.19)**	(0.44)	(0.42)
Widowed	0.44	0.28	0.20
	(0.13)***	(0.32)	(0.31)
Income	0.06	0.04	0.03
	(0.02)***	(0.02)*	(0.02)
Medical Card	1.52	0.89	0.87
	(0.07)***	(0.09)***	(0.08)***
Insurance	0.24	0.13	0.12
	(0.06)***	(0.09)	(0.09)
Birth	5.22	4.51	4.47
	(0.29)***	(0.28)***	(0.27)***
Ill-Health	1.16	0.22	0.16
	(0.06)***	(0.06)***	(0.05)***
Stress	0.30	0.07	0.04
	(0.05)***	(0.05)	(0.04)
GP visits$_{t-1}$			0.02
			(0.00)***
GP visits$_{95}$			0.07
			(0.01)***
r	3.86	4.42	5.00
s	3.49	4.05	4.94
NT	29,262	29,262	29,262
Log-Likelihood	-61746	-61262	-61052
LR Test vs. pooled	5551	5422	4239

Notes: (i) Year dummies are included in all models.
(iii) *** significant at 1 per cent level; ** significant at 5 per cent level; * significant at 10 per cent level.

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