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Night Visits in General Practice:

Practice Organisation and Patient Demand

Antonio Giuffrida

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Night Visits in General Practice: Practice Organisation and Patient Demand

Antonio Giuffrida[*]

Abstract

This paper presents estimates of the impact of practice organisation and patients' characteristics on the number of night visits made in English general practices. In the analysis we use a statistical methodology that recognises that the dependent variable is a non-negative count of events and we consider the possibility of sample selection and the potentially endogenous nature of some of the covariates. It is found that the zero-inflated negative binomial model is the preferred econometric specification and that there is no evidence of selection bias. Our finding suggest that general practices formed by 4 or more GPs provide more night visits than smaller practices, and that exists an inverse U relationship between the average age of the GPs and the number of night visits provided. In addiction, female GPs provide, *ceteris paribus*, less night visits that male GPs. In relation to the characteristics of the patients we found that the proportion of very young and very old patients and measures of morbidity and deprivation are positively associated with the number of night visits.

Keywords: primary care; night visits; out of hours care; count data models

JEL codes: I11

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[*] Inter-American Development Bank, Social Development Division, Stop W0502, 1300 New York Avenue, NW, Washington, DC 20577, USA. Tel: +1-202-623 1735; Fax: +1-202-623 1576; Email: antoniogi@iadb.org.
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1. Introduction

In the British National Health Care System General Practitioners (GPs) are personally responsible for the primary care of their patients on a 24 hour basis. A recent review of GPs terms and conditions introduced significant changes in the way GPs are remunerated for out of hours services (Hurwitz, 1995). Under the new out of hours arrangement introduced in April 1996, GPs receive for each face to face consultation carried out between the 20:00-8:00 hours a £20.80 fee and £2,078 as an annual fixed payment.[1] GPs receive the fee whether or not the visit is performed by a GP from the same practice or by a commercial deputising service. Therefore, the new system erased the previous two tier system which provided a high fee for night visits made by GPs and a low fee for visits made by commercial deputising services.

In the new out of hours arrangement, provision is made to enable GPs to transfer part or all out of hours obligations. However, the Health Authority (HA) decides whether or not to approve it, taking into account the interest of the GP's patients as well as the practicability of the proposed arrangement. Another important initiative was the provision of a £45 million development fund directed to the reorganisation of out of hours services. Thanks to the new regulation the number of co-operatives devoted to cover the out of hours commitment of its members, rose from six in 1990 to 124 in October 1996 (Jessopp et al., 1997).[2]

Night visit rates vary widely between general practices for reasons that are not altogether clear (see Hallam, 1994). The majority of previous studies analysed variation at the level of the administrative unit for primary care, the Family Health Service Authorities (FHSAs), where data are more readily available. Buxton et al. (1977), Baker and Klein (1991) and Banker et al. (1994) found that characteristics of FHSAs populations which were positively associated with night visit rates included the proportion of the population in lowest social class (social class V), the standardised mortality ratios, and the proportion of elderly patients. Practice characteristics such as the proportion of GPs aged over 65, the ratio of practice nurses to GPs, and the proportion of practitioners with list size below 1000 patients, were negatively related with night visiting rates. Conversely, practice characteristics positively associated with these rates included the proportion of GPs with permission to use deputising services.[3] Giuffrida and Gravelle (1999) presented a modelling framework to examine factors influencing the supply of and the demand for out of hours care in primary care. Their empirical analysis, based on a panel of data aggregated at FHSAs covering the 1984-85 to 1994-95 period, found evidence that the 1990/1 increase in fees for night visits by GPs led to large increases in the number of visits made by relative to visits made by deputies. In addition, demand for night visits was not significantly affected by the proportion of visits made by deputies, and GPs actively managed the demand from their patients rather than passively meeting it.

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[1] The 1st of April 1997 the annual payment for night visit rose to £2,165 and the consultation fee to £21.65.

[2] GP co-operatives are non-profit making organisations entirely owned and medically staffed by GPs practising in the area.

[3] Similarly Sheldon and Harris (1984) and Cragg et al. (1997) argued that the use of commercial deputising services is related with increases in night visit rates.

Few studies have examined night visits variation at general practice level. Majeed et al. (1995) analysed night visits made by GPs in London, finding a positive relationship with the proportions of patients aged less than five years, and chronically ill. Whynes and Baines (1996) examined night visits made in general practices in Lincolnshire, showing a positive relationship with the number of maternity claims, GPs' list size, home visit rates, the number of other practices within a one mile radius, and unemployment rate.

The main purpose of this paper is to improve the understanding of the determinants of night visits in English general practice. This study makes a number of contributions. Firstly, to our knowledge, it is the first examination since the new out of hours arrangement introduced in April 1996 and our dataset has the great advantage of including the majority of general practices in England. Secondly, we use an econometric model that recognises that the dependent variable is a non-negative count event and we test for the possibility of sample selection and for the endogeneity of some of the covariates.

The structure of the paper is as follows. In the next section we present the methodology used. Section 3 describes the data set used. Section 4 reports the results and section 5 concludes the paper.

2. The empirical model

In analysing night visits at practice level statistical problems may arise, as the event we want to model is a non-negative count event with a skewed distribution. Statistical methods have been developed to deal with this type of data (see Cameron and Trivedi, 1998).[4] In our analysis, the dependent variable, y_i, is a count event measuring the number of claims made by the i-th practice for night visits made during previous 6 months. The aim of the analysis is to identify factors explaining the observed number of night visits. Formally, our objective is to identify the qualitative relationship between the dependent variable and a set of characteristics **x** within a probabilistic system of the form

$$y_i = f(\mathbf{x}_i), \quad \mathbf{x}_i \in \Re \ , y \in \{0,1,2,...\}. \tag{1}$$

Poisson specification

The basic parametric count data model is the Poisson regression model. Let Y be a random variable with a discrete distribution that is defined on {0,1,2,...} and this follows a Poisson distribution with parameter λ_i. The Poisson regression model is derived from the Poisson distribution by specifying λ_i to depend upon a k-dimensional vector set of covariates, $\mathbf{x}_i$. Typically we have n independent observations, the i-th of which is (y_i, $\mathbf{x}_i$). The Poisson regression model specifies the conditional mean of the dependent variable, y_i, as a log-linear function of $\mathbf{x}_i$ and a vector β

$$E(Y_i = y_i | \mathbf{x}_i) = \exp(\mathbf{x}_i \beta) . \tag{2}$$

The exponential shape implies that an increase in $\mathbf{x}_i\beta$ necessary to obtain a unit increase in $E(Y_i = y_i|\mathbf{x}_i)$, is smaller the further one moves away from zero. The Poisson distribution has only one parameter, λ_i, which determines simultaneously the conditional mean and the variance

[4] For a review of count data models with specific emphasis to applications in health care see Jones (2000).

$$E(Y_i = y_i|\mathbf{x}_i) = \exp(\mathbf{x}_i\beta) = Var(Y_i = y_i|\mathbf{x}_i) = \lambda_i . \quad (3)$$

This characteristic is usually referred to as equidispersion. The merits of this stochastic specification are various. Firstly, we note that the exponential use of $\mathbf{x}_i\beta$ ensures that the mean parameter λ_i is non-negative, which captures the discrete and non-negative nature of the data. Secondly, this specification implies a particular form of heteroskedasticity due to equidispersion, which may account for the heteroskedastic and skewed distribution inherent to non-negative data. The standard estimator for this model is the maximum likelihood estimation.[5] Given n independent observations, the log-likelihood function to maximise is

$$\ln L(\beta) = \sum_{i=1}^{n}[y_i\mathbf{x}_i\beta - \exp(\mathbf{x}_i\beta) - \ln y_i!] . \quad (4)$$

Negative binomial model

The Poisson regression model imposes the assumption of equidispersion. In empirical application, the data almost always reject this restriction and exhibit overdispersion (i.e. the conditional variance exceeds the conditional mean) and the erroneous assumption of Poisson distribution has similar qualitative consequences to failure of the assumption of homoskedasticity in the linear regression model (Cameron and Trivedi, 1998, p. 77). Thus, the estimation yields consistent estimates of the mean parameters (Winkelmann, 1997, p. 79), but the magnitude of the effect on reported standard errors and t-statistics can be much larger.

The standard model to account for overdispersion is the Negative Binomial (NB) regression model. The NB model maintains the assumption that $\lambda_i = E(y_i|\mathbf{x}_i) = \exp(\mathbf{x}_i\beta)$, but the variance is modelled as a function of the mean and of a scalar parameter α, which has to be estimated

$$Var(y_i \mid \mathbf{x}_i) = \varpi_i = \lambda_i + \alpha\lambda_i^p \quad (5)$$

where p is a specified constant. The analysis is usually restricted to two special cases, $p = 1$ and $p = 2$. We note that if we impose the restriction $\alpha = 0$, the NB model reduce to the Poisson. Therefore, a sound practice is to estimate both the Poisson and the NB model and then to test the null hypothesis Ho: $\alpha = 0$ against the alternative $\alpha > 0$.

Zero Inflated count data model

Real data often display overdispersion through an excess of zeros. This refers to observing more zeros than what is consistent with standard count regression models like the Poisson or the NB models. Zero Inflated (ZI) Poisson or NB models allow for systematic differences in the statistical processes governing observations with zero and observations with one or more counts. This is achieved by combining a dichotomous model governing the binary outcome of the count being zero or positive and a truncated-at-zero model for strictly positive outcomes. A binary selection variable c_i allows for a separate treatment

[5] Other suitable estimators are the Generalised Linear Model and the Generalised Method of Moments.

of zeros and strictly positive outcomes. Then we observe the underlying count data variable y_i^*, only if $c_i = 1$

$$y_i = \begin{cases} y_i^* & \text{if } c_i = 1 \\ 0 & \text{if } c_i = 0 \end{cases}. \tag{6}$$

If the probability that $c_i = 1$ is denoted by p_i, the probability function of y_i takes the form

$$g(y_i) = (1 - p_i)^{1-c_i} + p_i f(y_i) \tag{7}$$

Therefore, in the ZI count data models there are two types of zeros: one type is obtained as $c_i = 0$; the other as $c_i = 1$ and $y_i^* = 0$.[6] Lambert (1992) introduced the ZI model together with a logit model for c_i in order to capture the influence of covariates.[7]

Sample selection

Sample selection bias, usually introduced by a departure from simple random sampling, is an important issue in econometrics (Heckman, 1979). The importance of selection bias in the estimation of medical care demands has been suggested by a number of authors (see Zimmerman-Murphy, 1987; Hunt-McCool et al., 1994). In our analysis, it is possible that zero events may represent situations where the practice did not claim the fees for the night visits made. Therefore they may be missing observations rather that true zero. If zeros are not a random event, we may incur into a sample selection problem.

Strictly speaking, sample selection occurs if data are generated in such a way that we do not observe the underlying count data variable y_i^*, but rather a censored count y_i. The potential bias exists because observations can be censored at zero depending on the outcome of another variable c_i, and this may not be independent of y_i^*. Therefore, the essential element is that there is a latent process

$$c_i^* = \mathbf{z}_i \gamma + v_i \tag{8}$$

which generates the binary indicator variable c_i where

$$c_i = \begin{cases} 1 & \text{if } c_i^* \geq 0 \\ 0 & \text{if } c_i^* < 0 \end{cases}. \tag{9}$$

Sample selection may arise when potentially important variables, u_i, are omitted and correlated with the selection rule (8)

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[6] Another model which captures the excess of zeros is the hurdle count data model introduced by Mullahy (1986). The hurdle model has an interpretation as a two-part model. The first part models the probability that the threshold is crossed (in principle, the threshold need not to be zero). The second part is a truncated count data model.

[7] Applications of ZI models in the health economics literature are given in Grootendorst (1995) and Street et al. (1999) on pharmaceutical utilisation.

$$E(y_i^*|\mathbf{x}_i, u_i) = \exp(\mathbf{x}_i\beta + u_i)\ . \tag{10}$$

We can model the correlation between c_i and y_i^* through the correlation of the error terms of the equations (8) and (10) and assume that u_i and v_i are jointly normal distributed with mean vector zero and covariance matrix

$$\Sigma = \begin{bmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{bmatrix} \tag{11}$$

where ρ is the coefficient of correlation and σ^2 is the variance of u_i. This specification allows for sample selection in the sense that unobserved factors affecting c_i also affect y_i^*. The effects of selectivity in count data models are similar to those found in the linear regression model, i.e. by ignoring this correlation the model will be misspecified with the possibility of inconsistent parameter estimates (Winkelmann, 1998).

A model for incidental truncation is proposed in Greene (1998). Greene's model is a direct analogue to Heckman's (1979) two-step estimation. The first step is to estimate by maximum likelihood the probit model of the selection equation $\mathrm{Prob}(c^* > 0) = \Phi(\mathbf{z}_i\gamma)$ and to compute for all observations for which $z_i = 1$ (i.e., for observations with non-zero data) the Mill's ratio $\hat{M}_i = \phi(\mathbf{z}_i\hat{\gamma}) / \Phi(\mathbf{z}_i\hat{\gamma})$. The second step consists in estimating the parameters (β, θ) of the "mean corrected" count data model

$$E(y_i|\mathbf{x}_i, c_i = 1) = \exp(\mathbf{x}_i\beta + \theta\hat{M}_i)\ . \tag{12}$$

However, if the original model were a Poisson regression, the Poisson distribution would surely not apply in the selected subpopulation. Thus, Greene suggests using the Poisson model and to fit equation (12) by Non-linear Least Squares (NLS). Greene (1998) applied this model to a study of the determinants of credit card default, where c_i indicates credit card approval.

3. Data

The data analysed here are from the October 1997 GP Census partnership level database. This database was provided by the General Medical Services STATS division of the English NHS Executive and collects information about all general practices in England. The GP Census includes the number of night visit fees paid to each partnership in England. Because, the terms and conditions regulation provides that night visits fees are payable only to practitioners with whom the patients are registered, even if GPs opted out from the provision of night visits, they would still receive the fees for the night visits made on their behalf. Therefore, the figures in the dataset represent the number of night visits provided to patients registered in the practices.

The GP census indicates that in October 1997 there were 27,200 GPs practising in England, organised in 9,102 general practices. A substantial number of practices were excluded from the analysis because their postal addresses were incomplete and they could not be matched with the information derived from the 1991 Census of Population. Therefore, the dataset used in the analysis covered 6,513 general practices.[8] Table 1 presents the definition and the summary statistics of all the variables used in the analysis.

3.1 Dependent variable

Our dependent variable is the number of night visit fees claimed by general practices over the six months period from the 1st of April 1997 to the 31 September 1997. The implied annual night visits rate in England is 397 per 10,000 population.[9]

The inspection of the variable reveals that 390 of the 6,513 practices included in the analysis did not claim any night visit fee over the last 6 months. The relative large cluster of observations not presenting night visits highlights the problem of overdispersion in the form of excess zeros.

3.2 Explanatory variables

Since the dependent variable measures the number of night visits made in the general practice, we have to consider the size of the practice, i.e. the number of patients registered. This variable is entered logarithmically, as it reflects the amount of "exposure" over which the dependent variable events were observed for each observation. Therefore, we expect that the estimated coefficient will be close to unity.

Supply side factors

The supply side factors affecting the number of night visits relate to the fee paid to GPs and the characteristics of general practice organisation, which may affect the propensity to provide them. In relation to the first factor, night visit fee is fixed centrally by the Department of Health and since does not vary across areas cannot be included in the empirical analysis.

The literature on the empirical analyses of variations in night visit rates suggests that important supply side factors are the age of the practitioners, the percentage of female practitioners, the size of the practice, and the percentage of practitioner with authorisation to use deputising services.

We expect the relationship between GPs' age and their propensity to provide night visits either to be positive or to follow an inverse "U" shaped function. This relationship is expected to arise because of family responsibilities and health reasons. The youngest GP in the dataset is 29 years old. Around this age, individuals are more likely to have young children and important family commitments. Therefore they may find it more difficult to provide night visits. Getting older, GPs may have less family commitment and be more willing to provide night visits.[10] The positive relationship between GP's age

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[8] We compared the practises included in the analysis with the practices there were excluded because of incomplete observations using the Mann-Whitney test. Though there were not statistically significant differences in the number of night visits made and the demographic characteristics of the patients' population. The sample used in the analysis comprised practices that were, on average, smaller, with a lower proportion of female GPs, with older GPs and a larger proportion of practitioners authorised to use deputising services.

[9] The annual rate is calculated using data from all 9,102 general practices.

[10] Scott (1999) found evidence of a positive relationship between GP's age and willingness to provide night visits.

and willingness to provide night visits may hold up to a certain point. Older GPs may find heavier the burden of night visits and be forced to work only at regular hours (Myerson, 1991). In general, we expect to find an inverse "U" shaped relationship between age and family responsibilities related to marriage and children, which suggest that the relationship between age and number of night visits may be convex. In addiction, traditionally, family responsibilities are more likely to affect female GPs. Hence, we expect that female GPs may provide less night visits than male practitioners, as found in previous studies (Whynes and Baines, 1996; Scott 1999).

To measure the effect of practice size we constructed dummy variables indicating whether or not the practice was composed by a solo practitioner, by two or three GPs or by 4 or more GPs.[11] We expect a positive relationship between the number of GPs in the practice and the number of night visits, because *ceteris paribus*, GPs working in larger partnership may find it easier to arrange a rota within their practice.

In relation to the authorisation to use commercial deputising services, previous studies have generally found a positive relationship between this variable and the number of night visits provided (see Buxton et al., 1977; Sheldon and Harris, 1984; and Cragg et al., 1997). The use of deputising services has been interpreted as a "supply" factor, but it is important to recognise the potential endogeneity of this variable, because, if patients care about who provides the night visits, demand and supply equations would become determined simultaneously and this could cause problems in the estimation. Therefore, we choose Instrumental Variable (IV) technique to test and to correct for the potentially endogenety of this variable.

Demand side factors

Previous literature has identified three main factors affecting the patients' demand for night visits: the age structure, and various measures of morbidity and deprivation among the patients in the practice. In relation to the first factor, various studies (e.g. Baker et al., 1994; Buxton et al., 1977; Majeed et al., 1995) have showed that some age groups, notably the very young and the very old, express higher demand for night visits. Therefore, in the empirical specification we included the proportion of individuals in the practice list aged five or younger, and aged 75 or older expecting positive coefficients for these two variables. We also expect a positive relationship between night visits and morbidity among the patients in the practice list. In specifying the relevant variables, we had not direct measures of morbidity among the patients in the practice, but we had only information derived from the 1991 Population census. The morbidity measure used in the analysis is defined as the percentage of adult population reported to be permanently sick among the population living in the electoral ward where the practice is located.

The most commonly used measure of deprivation is the Jarman (1983) score. The Jarman index is used to identify areas of high GP workload and combines eight factors: overcrowding, unemployment, lone parent families, mobility, manual worker, elderly living alone, ethnic minority, children under the age of 5. Rather that using the Jarman index, which aggregate these factors using *a priori* weights, we prefer to

[11] In the regression analysis the baseline was practices with two or three GPs.

include its raw components. We also included variables measuring the proportion of car ownership,[12] and the lack of central heating in the area in order to capture other important aspects of social deprivation. In addiction, we include the proportion of persons with some qualification to verify if education was associated with the use of out of hours primary care services.

Patients do not face charge for night visits but their demand will depend on the cost of alternative sources of out of hours of care, for example the travelling, waiting and treatment time necessary for a visit at the pharmacy or at the accident and emergency department. *Ceteris paribus*, we expect that in areas with larger population density (i.e. urban areas) individuals have easier access to alternative sources of out of hours care, therefore the effect on the demand would be negative. However, in areas with higher population density, the travel time and travel cost for GPs to reach patients would be lower, therefore the effect of this variable would be positive. Therefore, we include in the model the population density, measured by the ratio between the population in the electoral ward and the area of the ward in hectares. Since the estimated coefficient is the result of demand and supply side effects, the expected sign of this variable is unclear.

4. Results

Table 2 presents the estimates of the Poisson and NB models. The estimates are broadly in line with the expectations, but the extremely large goodness of fit statistic (χ^2 (6491) = 390629) indicates that the Poisson model is not appropriate and that it is advisable to estimate also the NB model.[13] The Poisson model is a special case of the NB. The restriction α = 0, is tested using a likelihood-ratio test and the χ^2 (1) value of 357000, indicates that the probability that we would observe these data conditional on the process being Poisson, is virtually zero.[14]

In relation to the issue of the interpretation of the regression coefficients, we note that the coefficient of the number of patients represents the elasticity, since this variable has been entered logarithmically. The number of patients in the practice is a measure of "exposure". Therefore, as expected the elasticity of this variable is close to unity. The estimated coefficient of the remaining variables, which are entered in the regression in their original scale, can be interpreted as semielasticity. In other words, the coefficient β_j equals the proportionate change in the conditional mean if the j-th regressor change by one unit.

The estimates of the NB model suggest that both solo GPs and practices with 4 or more GPs, provide more night visits that practices with 2 or 3 GPs. Practices constituted solely by female GPs provide, on average, 23% less night visits than practices formed entirely by male practitioners. Practices whose members are all authorised to use deputising services provide, on average, 9.6% more night visits than those practices whose members are not authorised. In relation to the average age of the partners, we

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[12] Car ownership is included in the deprivation index developed by Townsend (1979).

[13] The Chi-squared goodness of fit test compares the fitted probability with actual frequencies, where the fitted frequencies distribution is computed as the average over observations of the predicted probabilities fitted for each count (Cameron and Trivedi, 1998, p. 155).

[14] However, the estimates of the NB model are not qualitatively much different from the estimates of Poisson model. The Hausman test did not report systematic differences between the two models: χ^2 (20) = 10.43 (p-value = 0.960).

observe an inverse "U" shaped relationship, which indicates that practices whose partners are on average 53 years old, provide more night visits than practices whose partners are, on average, either younger or older.

Among the demand side factors we notice that practices that have a larger percentage of patients aged 0-4 years and aged 75 or older supply more night visits. Also our measure of morbidity presents a positive and highly significant relationship with night visits.

The variables measuring deprivation among the population do not show a clear relationship with the number of night visits. The unemployment rate and the proportion of households whose head is classified in manual class, are positively related with night visits. On the other hand the presence of single parent families and ethnic minorities are negatively related with the dependent variable. This may be explained by the existence of a "confounding relationship", e.g. these socio-economic variables measure interrelated aspects, therefore, the estimated coefficients counterbalance each other.

Zero Inflated model

The presence of overdispersion, although consistent with the NB specification, does not necessarily imply that the NB specification is the best model. A plausible alternative is the Zero Inflated (ZI) model. For instance, it may be possible that the sample under analysis may represent a mixture of two types of GPs, a first type who always claim the number of night visits made to the HA and second type who never report these claims. The ZI model allows for systematic differences between these two groups and may help in explaining the observed large number of zeros.

Table 3 presents the estimate of the ZI model, in which the probability of a nonzero count is modelled as logit function and the number of positive counts is assumed to follow a NB distribution.[15] The Likelihood ratio tests prefer the ZI NB model over the NB model, the ZI Poisson model and the Poisson model.

The estimates of the ZI NB model for the non zero outcomes are similar to the previous model.[16] The main difference is that the elasticity of the number of patients in the practice is now significantly smaller than unity. A plausible interpretation of this finding is that, *ceteris paribus*, GPs may be willing to supply less night visits when the demand increases, because of the increasing disutility in providing these services. We note some interesting differences in the relationship with the average GPs age. The logit function, which models the probability to observe a zero number of night visits, shows a strong "U" shaped relationship. The minimum is among practices whose GPs' average age is 51 years. However, the estimate of the ZI NB model for the non zero outcome is only marginally significant, though the coefficients suggest an "U" shaped relationship with the maximum at 52 years, which is similar to the estimate of the NB model.

[15] Since the ZI model assumes the correlation between the two regressions to be zero, the covariate lists of the two models can be identical.

[16] Altogether the estimates of the ZI NB model differ only marginally from the estimates of the NB model. The Hausman test comparing the two models produces a χ^2 (20) statistic of 28.65 (p-value = 0.0948).

4.1 Endogeneity and sample selection

Endogeneity

The ZI NB model suggests that, *ceteris paribus*, practices whose members are all authorised to use deputising services provide 8.5% more night visits than those practices where no members are authorised. This variable may be endogenous as GP's decision to seek authorisation to use deputising services may be correlated with unobservables. In this case, the assumption of statistical independence between regressors and the error term will break down and standard estimation methods like maximum likelihood will not generally be consistent. The generic solution to this problem is a nonlinear IV approach as described in Mullahy (1997) and Windemeijer and Santos Silva (1997).[17]

The instruments used include variables that explain GPs' choice to gain permission to use deputising services, but they are not likely to determine the number of night visits directly. These variables are the proportion of patients on the practice list eligible for rural practice payments, (i.e. patients who are more than 3 miles distant from the partnership's main surgery), the proportion of patient on the practice list for whom drugs are dispensed by the GP, and the average patients list size. The F-test of joint significance of the instruments in the first stage regression has the value of 20.49 (p-value = 0.00). In comparison, this test statistic in the Poisson model with the potentially endogenous variable included, is equal to 5.26 (p-value = 0.155). This result indicate that the instruments do explain the proportion of GPs having the authorisation to use deputising services, but not the number of night visits other than via the potentially endogenous variable and the overidentifying (OID) restriction test is not significant.

Sample selection

The last issue we consider is the possibility of sample selection. Empirical studies estimating expenditure for health care services have been criticised for not having examined the correlation between the equation modelling the probability of consuming health care and the equation describing the level of consumption (see Maddala, 1985), and the same criticism can be applied to count data models. To understand which approach is more appropriate Jones (2000, p. 16) suggests to ask whether or not the zero observations do "represent an actual choice. If the answer is no, the problem is one of non-observable response and a sample selection model is potentially appropriate". In our data set, we cannot rule out the possibility that zero events represent, at least in some cases, situations where the GPs in the practice made some night visits, but they did not claim the fees from the Health Authority. If this is the case, the underlying demand for night visits in those practices is non-observable. Therefore, if there is a correlation between the probability that the practice did not report the number of night visits and the underlying number of night visits made, a sample selection model may be correct specification.

The models we have presented so far could be specified either with a Poisson or with a NB distribution. However, the estimation of sample selection models must assume a Poisson distribution. The NB distribution is no longer suitable in the context of sample selection, since the resulting model suffers from

[17] An interesting issue is the choice between multiplicative and additive specifications in the context of simultaneous equations model for count data. In what follows we adopt a linear specification since the overidentifying restriction test does not reject this specification.

overparametrisation (Winkelmann, 1997, p. 112). However, the use of a Poisson distribution does not reinstate the assumption of equidispersion, because the selection model builds overdispersion into the structure as it is (Greene, 1997).

Table 4 presents the nonlinear IV estimates of the model accounting for both endogenity and sample selection.[18] The exogeneity test rejects the null hypothesis that the variable indicating the proportion of GPs authorised to use deputising services is not endogenous but only marginally (p-value = 0.092). However, the effect on the endogenous variable is considerable, as the coefficient is substantially smaller and it is not statistically significant. The estimated coefficient on the Mill's ratio is not statistically significant, which indicates that the estimation is not affected by sample selection bias. Since the endogeneity is only marginally significant and sample selection does not appear to be an issue, the estimates are not altogether much different. We note that the significance level of the estimated parameters are lower than the previous models as the NLS method is less efficient than maximum likelihood.[19]

5. Conclusion

In this paper we have examined the variation in the number of night visits made in English general practices. This study represents the first analysis since the new out of hours arrangement was introduced in April 1996. The econometric analysis is performed using a statistical model that recognises the nature of the dependent variable as a non-negative count event. The results from the standard count data models suggest that the ZI NB model is the best specification. We also considered the possibility of sample selection. In addiction, we investigated whether the number of night visits is affected by the use of commercial deputising service in the practice accounting for the potential endogeneity of this variable. This approach produced some interesting results, as the coefficient of the endogenous variable estimated with nonlinear IV was smaller and no longer statistically significant. This result suggests that patient' demand for night visits is not affected by the use of deputising services.

Other substantive results are that large practices formed by 4 or more GPs provide more night visits to the patients on their list. This suggests that larger practice may be able to deliver out of hours primary care more efficiently than smaller practices in England. Also the age and the gender of the GPs appeared to be related with the provision of night visits. We found an inverse U relationship between the average age of the GPs in the practice and the number of night visits provided. Moreover, female GPs provide, on average, less night visits that male GPs.

In relation to patients' characteristics (i.e. the demand side variables), we note that very young and very old patients require much more night visits than the rest of the population. In addiction, morbidity measure and socio-economic characteristics like the proportion of households lacking of central heating, unemployment rate and the proportion of manual workers are positively related with a higher demand for night visits.

[18] The regression model uses the predicted values of the endogenous variable.

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[19] We have also tried to estimate a full maximum likelihood sample selection model (Greene, 1997), unfortunately in our sample the estimator did not prove to be computationally manageable.

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Table 1 **Description of the variables**

Variable name	Description	Mean	Std. Dev.	Min	Max	Sources or census table	Construction of the census variables
Night visits	Number of night visits claimed from the 1st of April 1997 to the 31 September 1997	108.7935	131.308	0	4941	GMS census	
No. of patient	Total number of patients in the practice	5188.981	3415.465	1	28688	GMS census	
Solo GP	Solo practitioner	0.3485	0.4765	0	1	GMS census	
Large practice	Practice with 4 or more GPs	0.3075	0.4615	0	1	GMS census	
% female GPs	% of female GPs in the practice	0.2547	0.2867	0	1	GMS census	
% GP with deputies	% of GPs who had the authorisation to use deputising services	0.7399	0.4127	0	1	GMS census	
Age	Average age of partners in years	46.9630	7.2479	29	68	GMS census	
Population density	Ratio persons to area	33.7151	30.0200	0.042	202.730	Table S01 [a]	64/Hectares
Patients 0-4	Percentage of patients aged 4 or under	0.0606	0.0210	0	0.75	GMS census	
Patients 75+	Percentage of patients aged 75 or older	0.0720	0.0355	0	0.947	GMS census	
Permanently sick	Percentage of adult population permanently sick	0.0413	0.0216	0.005	0.178	Table S08 [a]	(122+276)/(1+155)
No central heating	Percentage in households lacking central heating	0.1896	0.1299	0.001	0.805	Table S20 [a]	(171+201)/141
With qualification	Percentage of persons aged 18+ with some qualification	0.1308	0.0838	0.004	0.639	Table S84 [a]	4/1
With no car	Percentage in households with no car	0.2854	0.1542	0.020	0.812	Table S20 [a]	150/141
Crowded accommodation	Percentage in households in crowded accommodation (>1 per room)	0.0578	0.0538	0.001	0.570	Table S23 [a]	(43+44)/41
Unemployment	Percentage of economically active unemployed	0.1090	0.0629	0.014	0.439	Table S08 [a]	(78+232)/(12+166)
Lone parents	Percentage of families which are lone parent with dependent child(ren)	0.1384	0.0800	0.017	0.476	Table S89 [a]	1/12
Moving	Percentage of residents with different address to one year ago	0.1038	0.0390	0.031	0.414	Table S151 [a]	S151/S02 1
Manual class	Percentage of persons in households with head in manual classes	0.4309	0.1194	0.094	0.738	Table S90 [a]	(22+27+32)/2
Elderly living alone	Percentage of those of pensionable age living alone	0.3544	0.0638	0.152	0.642	Table S47 [a]	(15+29+43+57+71+85)/169
Ethnic minority	Percentage in non-white ethnic groups	0.0915	0.1418	0	0.902	Table S06 [a]	(2-1)/1

a: Table from the 1991 Census of the Population.

Table 2 **Estimates of the Poisson and Negative Binomial models**

	Poisson		Negative Binomial	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
ln(*No. of patient*)	0.9428***	0.054	0.9163***	0.047
Solo GP	0.0813	0.053	0.0915*	0.053
Large practice	0.0579	0.038	0.0726*	0.042
% female GPs	-0.1854***	0.071	-0.2267***	0.073
% of GP using deputies	0.0700	0.043	0.0958**	0.043
Age	0.1071***	0.022	0.0817***	0.023
Age2	-0.0010***	0.000	-0.0008***	0.000
Population density	0.0004	0.002	0.0019	0.002
Patients 0-4	7.4861***	1.110	6.7334***	1.606
Patients 75+	2.7027***	0.845	2.0307**	0.997
Permanently sick	4.4532***	0.891	4.8210***	1.081
No central heating	0.2424*	0.131	0.2183	0.173
With qualification	0.3327	0.281	0.3158	0.261
With no car	-0.2332	0.451	-0.6307	0.566
Crowded accommodation	0.5373	0.999	1.8357	1.178
Unemployment	1.2109*	0.708	1.6667**	0.780
Lone parents	-0.8748**	0.422	-0.9683**	0.459
Moving	0.4354	0.622	0.8177	0.859
Manual class	0.8740***	0.245	0.8537***	0.234
Elderly living alone	-0.0559	0.336	-0.0479	0.394
Ethnic minority	-0.3615	0.419	-0.8890**	0.433
Intercept	-7.4198***	0.797	-6.4651***	0.807
ln(α)	-	-	-0.1636***	0.072
Log-likelihood	-214085		-35796.5	
Goodness of fit test [χ^2 (1)]	390629***			
Likelihood ratio test of α= 0 [χ^2 (1)]			357000***	

*** indicates $p \leq 0.01$; ** indicates $0.01 < p \leq 0.05$; * indicates $0.05 < p \leq 0.1$
Standard errors adjusted for clustering on Health Authorities

Table 3 Estimates of the Zero Inflated Negative Binomial models

	Non zero outcome		Zero outcome	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
ln(*No. of patient*)	0.8669***	0.048	-0.6007***	0.140
Solo GP	0.0460	0.052	-0.6251***	0.188
Large practice	0.1330***	0.043	0.8462***	0.159
% female GPs	-0.2374***	0.072	-0.2615	0.220
% of GP using deputies [a]	0.0852**	0.038	-0.1941	0.226
Age	0.0403*	0.023	-0.5309***	0.083
Age2	-0.0004*	0.000	0.0052***	0.001
Population density	0.0023	0.002	0.0060**	0.003
Patients 0-4	7.4420***	1.515	2.0395	2.117
Patients 75+	2.4228**	1.014	1.7688	1.107
Permanently sick	4.5958***	1.053	-4.3653	5.485
No central heating	0.1935	0.167	-0.2560	0.571
With qualification	0.4805*	0.260	1.4561	1.419
With no car	-0.6074	0.509	0.0179	2.612
Crowded accommodation	1.7459	1.150	-1.0176	1.847
Unemployment	1.6821**	0.716	0.6462	3.683
Lone parents	-0.9102**	0.416	0.7704	1.549
Moving	0.8796	0.812	1.0085	1.960
Manual class	0.9128***	0.224	0.6107	1.206
Elderly living alone	-0.0344	0.371	0.4071	1.652
Ethnic minority	-0.8876**	0.428	-0.1023	0.669
Intercept	-5.1130***	0.837	14.2816***	2.661
ln(α)	-0.7349***	0.184	-	-
Log-likelihood	-34738			
Likelihood ratio test				
Inflate = 0 [χ^2 (22)]	2117***			
α= 0 [χ^2 (1)]	270811***			
NB vs. Poisson [χ^2 (23)]	358693***			

*** indicates $p \leq 0.01$; ** indicates $0.01 < p \leq 0.05$; * indicates $0.05 < p \leq 0.1$
Standard errors adjusted for clustering on Health Authorities
a: Predicted values

Table 4 Estimates of the nonlinear IV model

Variable	Coefficient	Standard Error
ln(*No. of patient*)	0.9120***	0.077
Solo GP	-0.0310	0.078
Large practice	0.1549*	0.088
% female GPs	-0.1884***	0.060
% of GP using deputies	0.0181	0.035
Age	0.0530	0.057
Age2	-0.0005	0.001
Population density	0.0006	0.001
Patients 0-4	11.0010***	0.901
Patients 75+	3.9420***	0.523
Permanently sick	3.7038***	0.845
No central heating	0.2305**	0.094
With qualification	0.5233	0.334
With no car	-0.2961	0.293
Crowded accommodation	-0.4643	0.470
Unemployment	1.6608***	0.485
Lone parents	-0.6546**	0.280
Moving	0.0720	0.578
Manual class	0.9866***	0.235
Elderly living alone	-0.0010	0.269
Ethnic minority	-0.0918	0.182
Intercept	-6.1259***	1.974
R^2-adjusted	0.6141	
Mills ratio	-0.6959	0.910
Exogeneity test	0.2784*	0.165
OID restrictions test $\chi^2(2)$	0.572	
1st stage F-test	20.45***	

*** indicates $p \leq 0.01$; ** indicates $0.01 < p \leq 0.05$; * indicates $0.05 < p \leq 0.1$
The sample includes observations with non zero night visits.