How Do the Determinants of Demand for GP Visits Respond to Higher Supply? An Analysis of Grouped Counts

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1. Introduction

1.1 Objective

The purpose of this paper is to identify significant determinants of the demand for GP visits and to investigate how such demand determinants respond to higher supply.

1.2 Data

The primary data source for the analysis is the 1999–2002 Scottish Household Survey (SHS) data collected by a team from Market and Opinion Research International and Taylor Nelson Sofres (formerly NFO Social Research) on behalf of the Scottish Executive. The SHS is a nationally representative sample of 60,806 Scottish households. The first part of the survey collected information including: household composition, housing characteristics, tenure, vehicles available to the household, occupation and type of industry employing the person, highest income in the household and total household income. The second part collected

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information on an individual basis (random adult) relating housing experiences (including homelessness), qualifications, use of private and public transport, employment status, income from employment and other sources, health measures and GP visits.

Dependent Variable

The dependent variable is the number of GP visits during the last twelve months. Respondents were asked: *"In the last year, approximately how many times have you seen a GP or family doctor about your own health (either at home or at a surgery/clinic)?"* Respondents were provided with six grouped categories: none (1), one or two (2), three to five (3), six to ten (4), more than ten (5) and don't know (6). Respondents were also asked how convenient it was to use services (including GP services).

Exogenous Variables

Age, sex and two health indicators including prevalence of any limiting long-standing illness (yes/no) and self-assessed health (measured with an ordinal scale with three possible responses: not good, fairly good, and good), were used as need-determinants of GP visits. Self-reported measures of health have been found to be a good predictor of a number of health outcomes, such as subsequent use of medical care or mortality (IDLER & RONALD, 1990; IDLER & BENYAMINI, 1997; BURSTROM & FREDLUND, 2001) and morbidity (IDLER & KASL, 1995; BOBAK et al., 1998; LAURIDSEN et al., 2003). We introduced an interaction effect of having a limited long standing illness and poor self-reported general health to capture potential non-linear effects.

Accessibility to GP services: The time price of securing GP services, which depends on the travel time to a GP surgery and the wait time in the office, is a major explanatory variable in the model. GP services are free at entry in the UK National Health Service (NHS), but the people cost of visit is incorporated in travel time, cost and waiting time. For the convenience of general practitioner services respondents were asked, *"… bearing in mind where they (the general practitioner) are and your own circumstances, please tell me how convenient or inconvenient you would find it to make use of their services during their normal opening hours, assuming you needed to?"* The six possible responses provided were, *very convenient, fairly convenient, neither convenient nor inconvenient, fairly inconvenient, very inconvenient or no opinion.*

Household income: The survey also collected three household income components including: *income from paid employment and/or self-employment, benefits and pensions*. This variable summed the total income from the highest income earner and their spouse, where applicable. Income was equivalised (adjusted for household size and composition) using the McClements equivalence scale approach as suggested by Office for National Statistics (Office for National Statistics, 2003). The McClements scale is based on the assumption that smaller working households with the same income as larger households are significantly better off. The scale takes childless, two adult households as the standard (that is, they are weighted by 1) and scales up the income of households with fewer people and scales down the income of households with more. We used the logarithm of equivalised household income in our regression equation.

2. Econometric Analysis

Modelling Patterns of Utilisation of Care

A number of different econometric methodologies have been proposed in the literature for the modeling of utilisation of GP services (Cameron & Trivedi, 1986; Cameron & Trivedi, 1993; Cameron & Windmeijer, 1996; Jones, 2000; Sarma & Simpson, 2005). Most previous research has analysed GP visits using a binary variable, in which a value of one is used for those who visited their GPs during the period of interest, and zero otherwise (van der Meer et al., 1996; Abasolo et al., 2001).

In modeling the demand for GP visits, the nature of the data on utilisation determines the type of econometric methodology employed. The number of GP visits can take non-negative integer count values indicating that conventional ordinary least squares (OLS) estimation techniques are not appropriate (Greene, 1993; Cameron & Trivedi, 1998). In addition the OLS regression assumes the error term to be normally distributed with a possibility of 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.

The analysis of the GP services utilisation in this study is based on estimation of a generalisation of the Poisson regression model as discussed in Moffatt and Peters (2000). Here the essence of the approach is provided. We started with the most basic count data model, the Poisson model, where the probability of an event, Y, is determined by a Poisson distribution. Consider a discrete random variable Y_i representing the GP visit count for individual *i*. According to the Poisson model, the probability distribution of Y_i is given by:

$$P(Y_i = y) = \frac{e^{-\lambda_i} \lambda_i^{\,y}}{y_i\,!}\ , y = 0,1,2,\ldots,\infty \tag{1}$$

Where it is conventionally assumed that the Poisson mean depends on a vector of explanatory variables x_i according to:

$$\lambda_i = \exp(x_i' \beta) \tag{2}$$

Where β is a vector of parameters and the first element of the vector, *xi,* is a constant, so the first element of β is an intercept.

One feature of the GP visit data from the Scottish Household Survey requires modification of the simple Poisson process presented above. The actual GP visit count for the respondents was not observed since the response to the question was grouped. Modification to the log-likelihood function was required to account for this. It is also possible that the grouped nature of the dependent variable may have advantages from a sampling perspective by reducing potential misreporting problems where there are higher counts. In other words, respondents who incorrectly recall the actual number of counts might still get it in the correct "group" at high values of the dependent variable.

To account for grouping, the set of non-negative integers is partitioned into J mutually exclusive and exhaustive subsets $I_1,\ldots,I_J$, such that each I_j is the set of consecutive integers $\{a_j, a_{j+1},\ldots,b_j\}$, with $a_1 = 0$, $a_{j+1} = b_{j+1}$ for $j = 1,2,\ldots, J-1$, and $b_J = \infty$. The way in which the utilization of GP services question was asked results in knowledge of the set Ij to which the count belongs, but not the count itself. The probability of individual i being in group j is:

$$P(Y_i \in I_j) = \sum_{y \in Ij} P(Y_i = y) = \sum_{y \in Ij} \frac{e^{-\lambda_i} \lambda_i^{\,y}}{y_i\,!} \equiv P_j\,(X_i;\beta),\ j = 1,2,\ldots J \tag{3}$$

Let y_i be the realisation of the random variable Y_i. We define an indicator d_{ij} to take the value of one if $y_i \in Ij$, and zero otherwise. Although the y's are not fully observable, the d's are, and the log-likelihood function for a sample of size n may be constructed as follows:

$$LogL(\beta) = \sum_{i=1}^{n} \sum_{j=1}^{J} d_{ij} \log[P(Y_i \in I_j)] \tag{4}$$

The final group, group J, consists of an infinite number of integers: $a_J, a_{J+1}, \ldots, \infty$. The probability of the count falling in this final group should therefore be expressed as:

$$1 - \sum_{j=1}^{J-1} P_j(x_i; \beta)$$

in order for its evaluation to be possible.

The assumption that the mean and variance of the variable in question are equal is an assumption that is too restrictive for many scenarios and makes the Poisson model restrictive and is rarely employed in applied work. The other problem with the GP visits variable from the survey is that the responses are grouped counts and not simple counts. The alternative negative binomial model (NegBin) overcomes these two problems. A common derivation of the negative binomial model is to respecify λ to account for unobserved heterogeneity, a possible source of overdispersion in the dependent variable as follows:

$$\lambda = \exp(x_i{'}\beta)\exp(\varepsilon)$$

Where ε has a gamma distribution with a mean of one and variance α ε can be thought of as either the combined effect of unobserved variables that have been omitted from the model or as another source of pure randomness. The negative binomial probability distribution takes the form:

$$\Pr(Y = y_i / \varepsilon_i) = \frac{\exp(-\lambda(\varepsilon_i))(\lambda(\varepsilon_i))^{y_i}}{y_i!}, y_i = 0,1,2,\ldots \tag{5}$$

Unlike the Poisson model, the mean and variance of the dependent variable are now allowed to differ as follows:

$$V(y_i) = E(y_i)(1 + \alpha E(y_i)) \tag{6}$$

We built our model staring from the basic model that contained *demographic variables* (age, gender and their interaction) only. We then introduced one *socio-economic* variable at a time (from economic status, qualification, household income, and material deprivation) and examined how the model performs. Subsequent models were then adjusted for *health* indicators (self-assessed health and limiting long-standing illness) of individuals.

Variables that do not improve the model are excluded. Multivariate analysis using logistic (greater or equal to 3 visits, otherwise zero), ordered logistic and interval regressions were then performed. We performed the grouped negative binomial regression in the final model. The significance of each exogenous dummies compared to the reference group was tested using a t-test.

The first part of the paper deals with determinants of GP visits. The second part deals with determinants of poor access to GP visits, influence of lower supply (poor access) on mean GP visits, and estimates the effect of demand factors on GP visits for those with high and low supply.

To undertake this we stratified the sample into two groups based on a proxy supply indicator. These are respondents who tend to report good access (very and fairly convenient access) and those with poor access (very and fairly inconvenient access) to GP services.

First we ran a logistic regression of having inconvenient access to services, otherwise zero, on socio-demographic and health variables to identify the characteristics of individuals who are more likely to report inconvenient access to services.

We used the stratified sample to examine how the determinants of demand for GP visits respond to low and high supply of GPs compared to the rest of the population. To examine whether access influences the determinants of GP visits, grouped negative binomial regression model was run for each access group.

3. Results and Discussion

We begin by discussing results on the determinants of GP visits followed by the effects of lower supply on mean GP visits and comparing models with low and high supply of GP services.

3.1 Determinants of GP Visits

The nature of the distribution of GP visits indicated that a large proportion of observations (33%) clustered at 1–2 GP visits; and 13% of respondents reported having made more than ten visits in the previous year (Table 1). In all survey years more than eighty percent of the survey respondents reported convenient and about 14% reported inconvenient access to GP services (Table 2).
Table 3 presents the alternative estimation results for number of physician visits. We run seven multivariate regression models. These are logistic regression

Table 1: Summary Stat for the Whole Sample and by Access Groups

All respondents			Convenient access sample	
Variable	N	Mean	N	Mean
GP visits (0)	56865	0.199	45978	0.198
GP visits (1–2)	56865	0.333	45978	0.340
GP visits (3–5)	56865	0.211	45978	0.214
GP visits (6–10)	56865	0.128	45978	0.126
GP visits (11 +)	56865	0.126	45978	0.120
Demographic characteristics				
Age (sd)	58253	49.93(18.6)	46023	49.86(18.3)
female	57869	0.570	46057	0.572
Health measures				
SAH-good	57052	0.519	46096	0.537
SAH-fgood	57052	0.322	46096	0.320
SAH-ngood	57052	0.159	46096	0.143
LLSI	57051	0.249	46095	0.230
Economic status				
Self employed	57869	0.047	46057	0.048
Part time employment	57869	0.100	46057	0.106
Looking after home/family	57869	0.082	46057	0.084
Permanently retired from work	57869	0.298	46057	0.296
Unemployed and seeking work	57869	0.039	46057	0.040
At school	57869	0.009	46057	0.009
Higher/further education	57869	0.028	46057	0.027
Training scheme	57869	0.002	46057	0.002
Permanently sick or disabled	57869	0.055	46057	0.051
Unable to work	57869	0.009	46057	0.009
Others	57869	0.005	46057	0.005
Owns car	60860	0.662	46096	0.668
Log Household income (sd)	59412	9.488	45010	9.490
Survey year				
1999	60866	0.241	46096	0.244
2000	60866	0.255	46096	0.253
2001	60866	0.256	46096	0.258
2002	60866	0.248	46096	0.245

Table 1 (continued)

All respondents	Inconvenient access sample			
Variable	N	Mean	Min	Max
GP visits (0)	8662	0.192	0	1
GP visits (1–2)	8662	0.303	0	1
GP visits (3–5)	8662	0.202	0	1
GP visits (6–10)	8662	0.139	0	1
GP visits (11 +)	8662	0.161	0	1
Demographic characteristics				
Age (sd)	8672	51.75(19.6)	15	110
female	8683	0.600	0	1
Health measures				
SAH-good	8690	0.426	0	1
SAH-fgood	8690	0.333	0	1
SAH-ngood	8690	0.241	0	1
LLSI	8690	0.351	0	1
Economic status				
Self employed	8683	0.036	0	1
Part time employment	8683	0.077	0	1
Looking after home/family	8683	0.076	0	1
Permanently retired from work	8683	0.327	0	1
Unemployed and seeking work	8683	0.036	0	1
At school	8683	0.007	0	1
Higher/further education	8683	0.023	0	1
Training scheme	8683	0.002	0	1
Permanently sick or disabled	8683	0.076	0	1
Unable to work	8683	0.008	0	1
Others	8683	0.005	0	1
Owns car	8690	0.581	0	1
Log Household income (sd)	8513	9.480	6.44	14.08
Survey year				
1999	8690	0.239	0	1
2000	8690	0.272	0	1
2001	8690	0.244	0	1
2002	8690	0.244	0	1

SAH-fgood = self-assessed health fairly good; SAH-ngood = self-assessed health not good; LLSI = Limiting Long standing Illness

Table 2: Convenience of General Practitioner Services by Survey Years

Survey year	Very convenient	Fairly convenient	Neither nor	Fairly inconvenient	Very inconvenient	No opinion	Total
1999	5,428	5,817	378	1,428	649	115	13,815
%	39.29	42.11	2.74	10.34	4.7	0.83	100
2000	5,725	5,917	435	1,660	708	119	14,564
%	39.31	40.63	2.99	11.4	4.86	0.82	100
2001	6,069	5,828	487	1,504	619	133	14,640
%	41.45	39.81	3.33	10.27	4.23	0.91	100
2002	5,626	5,686	475	1,490	632	124	14,033
%	40.09	40.52	3.38	10.62	4.5	0.88	100
Total	22,848	23,248	1,775	6,082	2,608	491	57,052
%	40.05	40.75	3.11	10.66	4.57	0.86	100

(taking at least 3 or more visits, or zero otherwise), ordered logit, interval regression, Poisson and three negative binomial regressions (Nebin1, Negbi2, and grouped Negbin2) (Table 3). Interestingly we did not find substantial difference in the magnitude and significance of the parameters estimated using most of the models. In general the estimated coefficients exhibited the expected signs in each specification.

We used the log likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) to compare the performance of these models. The AIC is defined as $AIC = -2\ln L + 2k$, and the BIC is defined as $BIC = -2\ln L + k\ln(N)$, where $\ln L$ is the maximized log likelihood of the model and k is the number of parameters in the mode, and N is the sample size. We prefer the model with larger values of the log likelihood and smaller values of AIC and BIC. We present these results in Table 4. All three criteria favour the grouped count negative binomial model. Since this model is theoretically more appealing and the estimated effects are quite similar, the following discussion concentrates on the results of the estimated coefficients for the grouped count negative binomial model.

Age and gender are statistically significant predictors of the demand for primary medical care. Females are more likely to use primary medical care than males and there is a strong relationship between the number of consultations and age. Compared to the reference category (male 15–19 years), males 35–44

Table 3: Regression Results for the Determinants of Demand for GP Visits

	LOGIT b/se	Ordered logit b/se	Interval reg. b/se	Poisson b/se	Negbin1 b/se	Negbin2 b/se	Grouped Negbin2 b/se
sahfgood	1.467*	1.374*	2.046*	0.811*	0.745*	0.817*	0.815*
	(0.028)	(0.025)	(0.040)	(0.014)	(0.012)	(0.014)	(0.014)
sahngood	3.339*	3.109*	5.944*	1.460*	1.457*	1.489*	1.712*
	(0.087)	(0.050)	(0.119)	(0.017)	(0.018)	(0.018)	(0.028)
llsi	1.142*	1.127*	1.716*	0.719*	0.623*	0.726*	0.729*
	(0.066)	(0.063)	(0.110)	(0.032)	(0.031)	(0.033)	(0.036)
llsi*sahfgood	−0.475*	−0.381*	−0.156	−0.399*	−0.280*	−0.409*	−0.346*
	(0.077)	(0.071)	(0.132)	(0.035)	(0.035)	(0.036)	(0.040)
llsi*sahngood	−1.104*	−0.665*	−0.563†	−0.631*	−0.524*	−0.660*	−0.466*
	(0.117)	(0.083)	(0.176)	(0.035)	(0.035)	(0.036)	(0.048)
selfemp	−0.098	−0.113‡	−0.112	−0.052	−0.065‡	−0.053	−0.057
	(0.061)	(0.046)	(0.063)	(0.029)	(0.026)	(0.031)	(0.032)
partemp	0.129†	0.161*	0.249*	0.112*	0.097*	0.107*	0.108*
	(0.042)	(0.033)	(0.056)	(0.018)	(0.017)	(0.020)	(0.022)
homework	0.369*	0.383*	0.777*	0.214*	0.178*	0.240*	0.277*
	(0.049)	(0.041)	(0.073)	(0.018)	(0.018)	(0.021)	(0.025)
retired	0.273*	0.336*	0.642*	0.202*	0.180*	0.195*	0.224*
	(0.062)	(0.049)	(0.089)	(0.023)	(0.022)	(0.026)	(0.031)
unemp	0.159‡	0.133‡	0.189‡	0.099*	0.088*	0.091†	0.086‡
	(0.069)	(0.054)	(0.086)	(0.026)	(0.025)	(0.031)	(0.034)
school	−0.153	−0.089	−0.292	−0.117	−0.060	−0.107	−0.113
	(0.148)	(0.105)	(0.150)	(0.064)	(0.055)	(0.071)	(0.072)
h_feduc	0.006	0.067	−0.059	−0.007	0.030	−0.012	−0.019
	(0.084)	(0.062)	(0.095)	(0.037)	(0.033)	(0.040)	(0.041)
scheme	0.377	0.282	0.366	0.128	0.148	0.130	0.114
	(0.255)	(0.223)	(0.348)	(0.095)	(0.094)	(0.111)	(0.124)
permsick	0.564*	0.687*	1.328*	0.282*	0.259*	0.327*	0.443*
	(0.074)	(0.056)	(0.123)	(0.019)	(0.020)	(0.021)	(0.033)
unable	1.355*	1.157*	2.406*	0.386*	0.380*	0.476*	0.708*
	(0.192)	(0.113)	(0.259)	(0.028)	(0.030)	(0.035)	(0.068)
ecother	0.291	0.339‡	0.844*	0.261*	0.201*	0.275*	0.310*
	(0.160)	(0.144)	(0.255)	(0.060)	(0.059)	(0.073)	(0.088)
owncar	0.157*	0.151*	0.210*	0.050*	0.067*	0.049*	0.057*
	(0.029)	(0.023)	(0.041)	(0.009)	(0.010)	(0.012)	(0.014)
logequivinc	0.029	0.040‡	0.021	0.004	0.012	0.005	0.006
	(0.023)	(0.018)	(0.030)	(0.009)	(0.008)	(0.010)	(0.012)

Table 3 (continued)

	LOGIT b/se	Ordered logit b/se	Interval reg. b/se	Poisson b/se	Negbin1 b/se	Negbin2 b/se	Grouped Negbin2 b/se
Inconvenient access to GPs	−0.153* (0.033)	−0.133* (0.025)	−0.183* (0.044)	−0.045* (0.011)	−0.054* (0.011)	−0.057* (0.013)	−0.068* (0.016)
2000	−0.004 (0.033)	−0.071† (0.026)	−0.124† (0.043)	−0.028‡ (0.012)	−0.025‡ (0.011)	−0.032‡ (0.014)	−0.048† (0.016)
2001	0.014 (0.033)	−0.072† (0.026)	−0.125† (0.044)	−0.027‡ (0.012)	−0.031† (0.012)	−0.019 (0.014)	−0.035‡ (0.017)
2002	0.026 (0.034)	−0.054‡ (0.026)	−0.105‡ (0.045)	−0.019 (0.012)	−0.021 (0.012)	−0.006 (0.015)	−0.031 (0.017)
constant	−2.025* (0.249)		1.134* (0.307)	0.242‡ (0.099)	0.176 (0.093)	0.235‡ (0.113)	0.269‡ (0.125)
N	53201	53201	53201	53201	53201	53201	53201

‡ $p < 0.05$, † $p < 0.01$, * $p < 0.001$
All models are adjusted for age and sex
Sahfgood = self-assessed health fairly good;
Sahngood = self-assessed health not good;
llsi = limiting longstanding illness

Table: 4: Model Specification Testing

Model	Logit	Ologit	Intreg	Poisson	Negbin1	Negbin2	Grouped Negbin2
BIC	58852.14	145308.3	230968.7	283015.7	244059.5	240983.4	146650.7
AIC	58334.8	144764.2	230442.5	282498.3	243533.2	240457.1	146124.5
LL	−29109.4	−72321.09	−115162.2	−141191.2	−121707.6	−120169.5	−73003.23
N	55260	55260	55260	55260	55260	55260	55260

Grouped negative binomial model is preferred count regression model years old have significantly lower visits and most female groups have significantly higher likelihood of visiting their GPs over the last 12 months.

Consistent with the previous literature, the frequency of physician visits is clearly responsive to need, proxied by morbidity (Idler & Ronald, 1990; Idler & Benyamini, 1997; de Boer et al., 1997; Burstrom & Fredlund, 2001; Al Windi et al., 2002; Fernandez-Olano et al., 2006). The estimated effects for fairly good and not good general health and presence of limiting longstanding illness are all positive and significant at the 1% level, compared to those in good health without any longstanding illness.

Economic status has been shown to significantly predict primary medical health care use in Scotland. Lower economic status significantly increased the likelihood of visiting a GP. Those unable to work due to short time illness, in part-time employment, looking after home, retired, and permanently sick have significantly higher GP visits compared to full time workers. We also find a significant positive effect for individuals who own a car for personal use.

For all year dummies included, the coefficients are negative, though this is significant only for the year 2000. There is some evidence to suggest that visits to GPs reduced over the year 1999 to 2002.

We did not find significant income effect on the probability of GP visits. Similar evidence has been found in the literature by Sarma and Simpson (Sarma & Simpson, 2005) and Dev and Trivedi (Deb & Trivedi, 1998; Deb & Trivedi, 2002). However, the finding by Morris et al. (Morris et al., 2005) that low income individuals have increased probability of GP visits, showing a pro-poor distribution of general practitioner consultations in England, does not find any evidence in this study.

Finally, adjusted to need, demographic and socio economic characteristics of individuals, people with limited access to GPs remained to have lower probability of utilization.

3.2 Do Determinants of Demand Respond to Supply?

There are 8,662 (15%) individuals who reported low supply of GP services (Table 1 Column 3). Logistic regression of having low GP supply as proxied by inconvenient access to services, otherwise zero, indicated that older males and females are more likely to report inconvenient access compared to young males (15–19 years old) (Table 5 Model 1). Those with worse reported health are significantly more likely to report inconvenient access to GP services. Almost all economic status groups are less likely to report inconvenience compared to those in full-time employment, except the self employed.

Table 5 presents two models of access. Model 2 is the GP visit models for individuals who reported *convenient* access to services. Males 20–59 tend to report less GP visits compared to males 19 years old or less. Older males (above 60) and all female groups have higher GP visits, though this was statistically significant for females under 40. People with worse reported health and having any limiting longstanding illness, are more likely to utilize GP services. Self-employed have lower GP visits and those working part-time, looking after family, the retired, permanently sick and unable to work due to short term illness have higher GP visits compared to full time workers.

Table 5: Regression by Categories of Convenience

	Logit (Model 1) b/se	Convenient access (Model 2) b/se	Inconvenient access (Model 3) b/se
sahfgood	0.036 (0.034)	0.819* (0.015)	0.812* (0.038)
sahngood	−0.034 (0.075)	1.485* (0.019)	1.504* (0.043)
llsi	0.083 (0.087)	0.721* (0.035)	0.765* (0.086)
llsi*sahfgood	−0.183 (0.101)	−0.398* (0.039)	−0.461* (0.092)
llsi*sahngood	−0.161 (0.121)	−0.658* (0.039)	−0.684* (0.092)
selfemp	0.538* (0.057)	−0.061 (0.033)	−0.013 (0.086)
partemp	0.122‡ (0.051)	0.092* (0.022)	0.197* (0.053)
homework	0.370* (0.057)	0.229* (0.023)	0.310* (0.053)
retired	0.031 (0.070)	0.177* (0.029)	0.301* (0.060)
unemp	0.202‡ (0.088)	0.063 (0.033)	0.254* (0.077)
school	0.071 (0.165)	−0.136 (0.078)	0.086 (0.167)
h_feduc	−0.430* (0.125)	−0.005 (0.043)	−0.059 (0.112)

Table 5 (continued)

	Logit (Model 1) b/se	Convenient access (Model 2) b/se	Inconvenient access (Model 3) b/se
scheme	−0.682 (0.425)	−0.041 (0.126)	0.558† (0.205)
permsick	−0.083 (0.086)	0.314* (0.023)	0.381* (0.050)
unable	−0.081 (0.169)	0.452* (0.039)	0.614* (0.083)
ecother	0.363‡ (0.184)	0.266* (0.078)	0.341 (0.205)
owncar	1.112* (0.036)	0.050* (0.013)	0.042 (0.027)
logequivinc	0.006 (0.027)	0.005 (0.011)	0.009 (0.024)
2000	0.078‡ (0.038)	−0.035‡ (0.016)	−0.016 (0.032)
2001	−0.008 (0.039)	−0.015 (0.016)	−0.038 (0.034)
2002	−0.012 (0.039)	0.004 (0.016)	−0.062 (0.035)
constant	−3.036* (0.283)	0.250‡ (0.124)	0.014 (0.276)
N	55552	44745	8456

‡ $p < 0.05$, † $p < 0.01$, * $p < 0.001$
All models are adjusted for age and sex
Model 1 logit of inconvenient versus convenient access
Model 2 Grouped Negbin2 for those reporting convenient access
Model 3 Grouped Negbin2 for those reporting inconvenient access

Model 3 in Table 5 presents the GP visit model for those who say *inconvenient* access to services. Similarly all females below 40 tend to have significantly higher visits compared to the reference group. Females and males older than fifty years old tend to report higher visits, though none was significant. There is significant differences between all economic status compared to the fully-employed individuals, except those who are self-employed, in full time education which was not significant. People with worse reported health and any limiting longstanding illness have higher GP visits.

Although the effect of age, gender and health outcome measures on GP visits seem similar for the two access groups (higher versus lower supply group), there is some difference in the size of the effect of economic status. The effect of lower economic status for individuals who reported poor access is much higher than those who reported convenient access. Being unemployed has a very significant effect on GP visits to those who reported low supply. To individuals who have a high supply of GP services, being unemployed is not a significant demand factor. Those in government work/training scheme and reported worse access, for example have significantly higher visits but the same economic status who reported better access have less visits, though not significant. Those unable to work and report inconvenient access have higher odds compared to those who reported convenient access although both of them have higher visits compared to the reference group. Therefore individuals who are unable to work due to illness and have poor access to care are morel likely to see GP (regardless of the access barriers they might have or report).

4. Conclusion

The two basic questions we have tried to answer in this paper are:

1) What are the determinants of GP visits in Scotland?
2) How do the determinants of demand for GP visits respond to higher supply?

Finding answer may be crucial to improve the health system in general and particularly for resource allocation, to make it more equitable and adjusted to need. Moreover, answer can help to understand causes underlying the spectacular increase of health care public expenditure over the last two decades. In this study, we define health care consumption in terms of GP services utilization and supply of primary care is proxied by convenience to access to GP services. We included variables that represent differences in demand, such as income and economic status. We adjusted for age and gender that are significant predisposing factors. Change in utilization of GP services over time is captured by a series of year dummies with year 1999 as a base year. To address the first question, we run seven regression models and explored how alternative estimation models perform. To answer the second question, we run six regression models.

From a health policy perspective, equity of access to health care is a major issue in remote areas. We compared the demand equations for respondents with worse access to GP services to the rest of the population, taking into account differences in demographic and economic characteristics of individuals. Our pooled model demonstrated the partial significance of access and capacity measures in determining utilization.

There are limitations in this study, one being that analysis was not undertaken on the process of care (e.g., length of the consultation, waiting times and GP–patient relationships) as the survey did not ask for such information. There was also a lack of information on measures of quality of care. Incorporating evidence–based quality measures (such as in the Quality and Outcomes Framework, in the new General Medical Services contract) could enrich the analysis on the determinants of the demand for GP visits.

Another important data issue was the lack of information available on primary care teams. The data used in this study referred to general practitioners only. Information pertaining to the effect of other primary care team members (such as nurses, health visitors, and allied health professionals) on health outcomes and the utilization of primary medical care was not available. An Information Services Division Report from Scotland reviewed patient contact with the primary health care team. It indicated that GP contacts account for a little over half (59%) of all face-to-face contacts, practice nurses at approximately one-fifth (22%), district nurses (13%) and health visitors (6%) (Scottish Executive, 2005). The other important primary medical care activity missing in this analysis was the prescribing behavior of general practitioners

From a health policy perspective, our results offer an important and unique insight in that lower supply of (inconvenient access to) health care services affect utilization. Policy makers in Scotland and elsewhere need to recognize the significant negative effects limited access to GP services and morbidity have on health care utilization, in designing primary health care system.

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SUMMARY

Although there is a substantial literature on the determinants of demand for primary care, few studies have been able to examine how these determinants respond to higher supply. Some demand studies include supply variables or regional dummy variables to allow for different supply conditions. A few have tested for marginal effects of supply variables attributed at a highly aggregated geographic level. However, relatively little is known about whether there is a supply constraint and how demand responses differ across population groups. We used information from a household survey of 60,806 individuals for whom we had detailed information on supply and access conditions. As in many surveys,

the annual measure of utilisation is a grouped count and we estimate a grouped negative binomial model (NegBin2) of the determinants of demand for general practitioner (GP) visits by Maximum Likelihood. We exploit a variable on which respondents were asked to report the convenience with which they were able to access GP services. We demonstrate the significance of this variable in determining the number of GP visits. We then examine which demand determinants are correlated with reported convenience. Finally, we compare the demand equations for respondents reporting unconstrained access to GPs with respondents reporting constrained access. We find that being unemployed has a significant positive effect on GP visits for individuals who reported poor access. People who own a car and reported a good access to GPs have significantly higher visits.