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Inequality in consultations with general practitioners

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Abstract. Using data from a survey of patients from a sample of 60 English general practices in 1998/9 we estimate a demand function for GP consultations, allowing for selective non-response to the income question by the Heckman procedure and for simultaneity bias by two stage least squares. Rich white men have fewer visits other things equal. Allowing for selective non response tends to reduce the negative effect of income on visits and allowing for simultaneity to increase it. Demand is higher for patients with lower levels of self reported health, more free time, more access to cars, and for those with higher levels of trust in their GP. Practices with more highly deprived patients and younger GPs have more visits. The negative effect of income on visits is smaller in fundholding practices.

PRELIMINARY DRAFT – This is work in progress. Please check with the authors before citing: the results may have changed.

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1 Introduction

One of the principles of the British National Health Service (NHS) is that access to health care should depend only on need. Ninety per cent of patient contacts with the NHS are made via primary care. Patients are registered with a general practice and their general practitioners (GPs) act as gatekeepers, controlling non emergency access to the rest of the NHS. Most GPs are independent contractors, rather than employees. Even with recent attempts to introduce greater regulation, GPs have considerable freedom in the services they choose to provide to their patients and in the way they organise their practices to do so. Hence it is of interest to examine whether practice policies and organisation have any effect on inequalities in the use of health care

In this paper we concentrate on the effect of income on utilisation and consider whether the effect varies across practices and if so whether it is related to characteristics of practices, especially those which may be amenable to policy.

The basic approach is to estimate a regression of utilisation (consultations with a GP) on income, on personal characteristics such as age, gender, and ethnicity, and on the characteristics of the practice to which the patient belongs. A positive or negative coefficient on income indicates whether there is pro rich or pro poor income related inequality in utilisation. To investigate if inequality differs across practices we interact income with practice dummies and test whether constraining all income coefficients to be equal leads to a significant reduction in the performance of the regression. We then investigate whether differences in the effect of income across practices are explained by characteristics of practices, such as the number of GPs or various indicators of practice quality. We do so in two ways. In the first method we estimate an individual patient level regression of utilisation which includes practice dummy variables interacted with patient income, to obtain estimated income-utilisation slope coefficients for each practice. Then we regress the estimated income slope coefficients for practices on practice characteristics. The second method is more direct: we regress individual utilisation on individual characteristics, income, and the interaction of income with practice characteristics.

The analysis raises two issues which have not previously attracted much attention in the extensive literature on income related inequality in health care (Wagstaff and van Doorslear, 2000). The first arises because individuals are more reluctant to answer questions about income than about their health, utilisation or other personal characteristics. If income non response is non random or selective there are two potentially damaging implications. First, attempts to increase the effective sample size by estimating income for non responders will yield biased income estimates if non response is related to income. Second, even if analysis is restricted to those who report income, the estimated effect of income on utilisation will be biased if non-response is related to utilisation because the same unobserved factors influence both the response to the income question and utilisation.

The second issue is simultaneity: health affects income and utilisation, utilisation affects health, and income affects utilisation and health. Thus utilisation also affects income via its effect on health. The standard procedure in analysis of income related inequality is to regress utilisation on income but this will yield biased estimates of the effect of income. The estimate may be useful if one is only interested in measuring the overall correlation of income and utilisation. For policy it is useful to know how much of the correlation is due to the effect of income on utilisation and how much to the effect of utilisation on income (via the effect of health on income) since different types of policy are required to change the two relationships.

2 Data

2.1 Patient characteristics

The General Practice Assessment Survey (GPAS) (*www.gpas.co.uk*) asks patients about their use of general practice, their views on its accessibility and quality of care. We used an augmented version of GPAS, with additional questions on income, employment status and various aspects of health. The sample was selected by multistage stratification (Campbell et al, 2001). At the final stage approximately 200 adult patients were randomly selected from the lists of 60 practices in 1998/9 (the last year of fundholding). The sample was not self-weighting because the probability of an individual being selected depended on the size of the practice. We have not used sampling weights which are less efficient and no more unbiased in a regression model intending to determine the causal relationship between income and health (Deaton, 1997). The practices are in six Health Authorities and we include Health Authority dummy variables in the regressions as fixed effects to capture, inter alia, any survey design effects. We also allow for the clustering of errors within practices by using robust standard errors (Stata Corporation, 2001).

There were 4462 returned questionnaires, giving an overall response rate of 37%. There was a slight overrepresentation of females (59%) compared with practice populations and those over the age of 65 (27% actual against an expected 19%). Since the regression analysis conditions on observable characteristics of the sample respondents, the representativeness of the sample with respect to observable characteristics is not an important issue.

We had to drop two practices from the analysis because of lack of data on some practice characteristics. Some 3225 respondents in the remaining 58 practices completed all items on the questionnaire except the income question, and 2283 of them completed all items (an item non response rate of 29%). After estimating income we therefore had a sample for analysis of the effects of practice characteristics of 3225. The patient variables are summarised in Table 1.

The health measure used in the analysis is based on the SF-6D questionnaire included in GPAS. It covers six dimensions of health: physical functioning, role limitation, social functioning, pain, mental health, and vitality. Each dimension has between two and six levels. Weights were applied to responses to construct a single health measure (Brazier et al, 2001) with 1 corresponding to the best possible health state and 0 to the worst.

Household income was reported in bands and we calculate equivalised income for each individual by taking the mid point of the reported band and calculating

Income = Household income/√(adults+0.5*children).

The variable *Freetime* measures the patient's freedom from work or education commitments which we expect to reduce the opportunity cost of visits to the GP. Since the visits question asked about the number of visits in the last year we also include a dummy variable *New Patient* for patients who have been with the practice less than a year.

2.2 Practice characteristics

Data on the characteristics of practices were obtained from the QUASAR study of practice quality (Campbell et al, 2001) and from the Department of Health's General Medical Statistics database. We also had information from the Index of Multiple Deprivation (DETR, 2001) on indices of a number of domains of deprivation (education, employment, access) at electoral ward level. We linked these to practices using the post code of the practice from the GMS database. Summary statistics for practice data are shown in Table 2.

Some of the practice characteristics measure various aspects of practice quality, for example the proportion of GPs who are recognised trainers, or the antibiotic prescribing rate or the provision of maternity services. Some, such as the list size per GP reflect the workload of the practice. Others, such as the proportion of GPs over 60 and the proportion of female GPs, measure practice characteristics derived from the type of GPs in the practice. Finally, some of the practice characteristics, such as the proportion of patients in various deprivation bands are derived from the characteristics of the practice population.

3 Methods

3.1 Simultaneous relationship between utilisation, health and income

The basic model was assumed to be

$$v = D(h, y, x, \varepsilon^{v}) \qquad (1)$$

$$h = h(v, y, x, \varepsilon^{h}) \qquad (2)$$

$$y = y(h, x, \varepsilon^{y}) \qquad (3)$$

where v is number of consultations by a patient, h is health, y is income, x is a vector of individual and practice characteristics and ε^{j}, $j = v, h, y$ are error terms. Since the main interest is income related inequality in visits we need to take account of potential simultaneity bias arising because visits depend on income, health depends on income and income depends on health. Estimates of (1) which do not allow endogeneity of health and income will yield biased estimates of the effect of income on health.

We include in the estimated utilisation regression all variables that are thought to have a direct effect on utilisation. These include age, gender and race and marital status. We also include variables related to the accessibility of the practice: the number of cars available to the patient and an index of the patient's assessments of a number of dimension of accessibility of the practice. We include the patient's rating of the extent trust they have in their GP since this may affect the patient's expected benefits from a consultation.

The model was estimated by two stage least squares by predicting income and health and then including their predicted values in the utilisation equation. We regressed income and health on all the exogenous regressors in the utilisation regression and a set of instrumental variables. The instruments were both individual level (smoking behaviour, number of children in the household, accommodation ownership type) and practice level (DETR index of education deprivation for the electoral ward of the patient's practice.)

3.2 Selection bias due to income non-response

To allow for possible selection bias arising from non response to the income question we used the Heckman two step procedure for the income equation. We ran a probit regression of the decision to report income or not on all the explanatory variables used in the utilisation model. We then included the inverse Mills ratio generated by the income response model as one of the explanatory variables when estimating income for the 2SLS model of visits. We also include the inverse Mills ratio in the health equation. Since the ratio reflects the propensity to report income its inclusion in the health equation will allow for any possible correlation of the error term and non-response (Angrist, 1997)

4 Results

4.1 Selection and endogeneity

Table 3 reports four estimated visits equations to show the effects of selection and endogeneity. To ensure comparability all the models are estimated on the sample of 2283 patients who provided a full set of answers. Model 1 is a simple OLS model with no allowance for selection in income reporting or for endogeneity. Model 2 allows for selection by including actual income and the inverse Mill ratio from the Heckman selection model for income reporting. Model 3 allows for simultaneity by using predicted income and predicted health and model 4 allows for both simultaneity and selection.

We do not show the results for the income and health equations (available from mad105@york.ac.uk). The instruments used in the income and health equations are significantly correlated with income and health, though more weakly with health than with income. We included both actual and predicted values of health and income in a visits regression to test for endogeneity bias. All had negative signs. The coefficients on predicted income and predicted health had t-statistics of -.11 and –2.05 respectively suggesting that there was significant bias in respect of the health variable. Finally, as suggested by Smith and Blundell (1988) we regressed the residuals from a visits regression containing actual and predicted health and income on all the explanatory variables in the visits equation including the instruments from the health and income equations. We were unable to reject the null hypothesis of no correlation between the residuals and the instruments, suggesting that our instruments were indeed valid.

A comparison of the models in Table 3 suggests that selection and endogeneity do affect the coefficients in the visits equation. Selection has a larger impact on the coefficients on the gender dummy than does endogeneity (compare the differences between models 2 and 1, models 4 and 3 with the differences between models 3 and 1, 4 and 2). Allowing for selection increases the effect of gender on visits, whilst allowing for endogeneity reduces it but only slightly. Allowing for selection increases the positive effect of being non-white whereas allowing for endogeneity reduces it. Allowing for selection alone has a negligible effect on the negative income coefficient whereas allowing for endogeneity alone more than doubles the effect. There also marked effects on other coefficients (for example allowing for endogeneity nearly doubles the negative coefficient on health).

4.2 Practice characteristics and demand for visits

Table 4 shows the results from three visit demand equations. Because we allow for simultaneity by using estimated income all the models are estimated on the sample of 3225 patients for whom income could be estimated. Model 1 is intended to test whether practice characteristics have any impact on the number of visits and is estimated allowing for selection and simultaneity. It differs from model 4 in Table 3 in the sample size. We started with a general model which included the full set of practice characteristics from Table 2 and proceeded to eliminate insignificant practice characteristics until the final set of four reported here were left.

The rich have fewer GP visits, though the coefficient is not quite significant at the 5% level. Women patients have more visits, as do non-white patients and the effects of gender and ethnicity on the number of visits is similar: about 0.5 visits each year (compared to an overall mean number of visits of 3.4). The effect of ethnicity is only significant at the 10% level. In short, rich white men have fewer GP visits than would be expected given their health and other characteristics.

The other effects are plausible: those who make more visits are less healthy, have more free time, have a more favourable view of practice accessibility, access to more cars and trust their GP more. The *New patient* variable was included to allow for the fact that patients registered for less than a year are likely to have fewer visits to their current practice in the last year and it has the expected negative sign.

Four of the practice characteristic seem to have a significant effect on visits after allowing for individual characteristics. The *Drug_Costs* variable is positively correlated with visits. One would expect the number of visits and the level of prescribing to be highly correlated, so that one interpretation of the positive coefficient on the average level of prescribing in the practice is that it is capturing an aspect of the practice population or the practice which is not otherwise reflected in the other variables and which increases the number of visits. The positive coefficient on the proportion of the practice's patients who live in highly deprived areas may arise for similar reasons. The effects of the other practice characteristics have a more direct interpretation. The proportion of GPs offering minor surgery may reflect higher quality services and patients may feel that that a consultation with a GP over 60 may be of less benefit.

Model 2 drops practice characteristics and instead uses practice fixed effects to test if there are additive differences in demand functions across practices. We do not report the coefficients on the practice dummy variables but we can reject the null hypothesis that there are no additive differences across practices (F(57, 3143) = 2.08, P = 0.0000). The inclusion of additive practice effects has little overall effect on the pattern of coefficients but it does alter the magnitude and significance of some of them (for example the income coefficient). However, because the practice fixed effects are perfectly collinear with the DETR deprivation variable used in the income and health regressions we have to drop it from these regressions and so the estimated health and income variables in the visits equation differ from those in model 1 in the table.

The third set of results in Table 3 are from a model with both practice fixed effects and practice dummy variables are interacted with income. The model is used to test for differences in the effect of income on visits across practices. We can reject the null hypothesis that there are no differences in income slopes across practices (F(57,3088) = 1.53, P = .0069). Figure 1 shows the across practice distribution of the coefficients on income. The mean slope is negative but there are some practices with positive coefficients on income.

4.3 Explaining differences in the visits-income relationship

We explore the reason for differences in the relationship between visits and income in two ways. First we take the estimated coefficients on income in each practice from the third model in Table 4 and regress them on the full set of practice coefficients in Table 2. Proceeding from the general to the specific by dropping insignificant variables we get the results reported in Table 5. Seven of the eight variables measure characteristics of a practice's patients, some of which are also measured indirectly by the characteristics of individual patients which were included in the patient level regression which generated the income slope dependent variable in the practice level regression. For example, the generally negative effect of income on the number of visits is reduced when the practice has a higher proportion of female patients. One possible explanation is that the effects of income on visits differ for men and women. In the absence of an interaction term between gender and income in the individual level visits equation the proportion of female patients may then explain some of the variation in income slopes across practices. Similarly, the fact that the proportion of patients under 16 affects the income slope suggests that the effect of an individual's income on the demand for visits may depend on the number of children they.

The effects of the proportions of patients in different deprivation bands are difficult to interpret since the coefficients do not display any consistent pattern with respect to sign or size. One possibility suggested by the coefficients, together with the coefficient on the needs variable, is that the individual level relationship between income and visits may be non-linear. Similarly the significance of the rurality variable may indicate that the effects of distance or accessibility are also more complicated than our simple linear model.

In fundholding practices the negative effect of income on the number of visits is reduced, so that in such practices the rich account for a higher proportion of visits than in non-fundholding practices.

Our second method of investigating the practice level determinants of the relationship between income and the number of visits is more direct: we estimate an individual level demand function for visits and interact income with practice characteristics. The results from two such models are reported in Table 6. The first model in the Table 6 is estimated by OLS and the second model results from using a random effects estimator which allows for heterogeneous unobserved practice characteristics. Both models allow for selection and endogeneity.

In both cases we started with a specification which included the practice characteristics found in Tables 3 and 4 to affect the number of visits and added the practice characteristics found to affect practice income slopes in Table 5. The latter were included both by themselves and interacting with the income variable. Their main effects were insignificant were dropped, leaving only their interactions in the final models shown in Table 6.

The results are from the two models are very similar. Comparing Table 6 with Table 4 we see that allowing for interaction of the income variable with practice characteristics does not alter the pattern of the coefficients of the main effects of individual and practice characteristics. The interactions of practice characteristics and income also confirm the results in from the two step approach reported in Table 6. The sign and significance pattern of coefficients on the practice variables affecting the income slope are very similar.

5 Conclusions

The paper has attempted to make both a methodological and a substantive contribution. The methodological contribution is to examine the implications of selective non response to income questions and of simultaneity in the relationship between utilisation of health care, health and income when investigating the determinants of utilisation and. We found that simultaneity and selection had opposite effects on the coefficients of the explanatory variables in the demand for visits equation but that allowing for simultaneity made the biggest difference.

The substantive results on the effects of patient characteristics are plausible and in line with previous findings. Rich white men have fewer visits other things equal. Allowing for selective non response tends to reduce the negative effect of income on visits and allowing for simultaneity to increase it. Demand is higher for patients with lower levels of self reported health, more free time, more access to cars, and for those with higher levels of trust in their GP.

We also found that practice characteristics affected both the number of visits and the relationship between income and visits. For example, patients in practices with more highly deprived patients, offering minor surgery and having younger GPs make more visits. The negative effect of income on visits is smaller in fundholding practices. We could find no effect of measures of practice quality on the number of visits or on the effects of income on the demand for visits.

This is work in progress. Whilst we feel that the results concerning the implications of selection and simultaneity and the effects of individual patient characteristics are robust, we are less sure about the effects of practice characteristics, especially their impact on the relationship between income and visits. We intend in further work to investigate whether the practice characteristics which are based on the practice population are picking up possible misspecifications of the functional form for the individual level variables or whether they reflect genuine contextual effects. We will also investigate whether practice characteristics alter the relationships between visits and gender and between visits and ethnicity.

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Table 1. Patient characteristics

Variable	Mean	SD	Min	Max	Definition
GPVisit	3.42	2.44	0	8	Times patient has seen a GP from their practice in past 12 months
Income	18100	16701	316	114754	Equivalised household income
Health	80.6	11.0	35.1	100.0	SF-6D health state valuation
Female	0.6125				Female
Age	49.93	16.7	18	99	Age in years
Non_white	0.0653				Race other than White European
Married	0.732				Married (baseline category)
Single	0.115				Single
Separate	0.076				Separated
Widowed	0.075				Widowed
Freetime_O	0.418				Full time employment, education or training (baseline)
Freetime_H	0.147				Occupied in employment part time
Freetime_F	0.435				Not occupied in employment, education or training.
New patient	0.021				Registered with practice for less than a year
Access	61.8	18.9	5	100	Patient's score on GPAS access scale rating of practices
Trust_1-3	0.165				Patient's rating of trust in their GP
Trust_4	0.193				from 1(not at all) to 10 (completely).
Trust_5	0.113				Category 1-3 combines ratings 1 – 3.
Trust_6	0.060				
Trust_7	0.058				
Trust_8	0.024				
Trust_9	0.027				
Trust_10	0.360				Baseline category
No cars	0.234				No car available for use (baseline)
Cars_1	0.540				One car available for use
Cars_2	0.226				At least two cars available for use
Never_Smoked	0.487				Never smoked for more than a year
Children_0	0.670				No one under 18 in household (baseline)
Children_1	0.129				One person under 18 in household
Children_2	0.134				Two people under 18 in household

Children_3	0.052		Three people under 18 in household
Children_4	0.011		Four people under 18 in household
Children_5	0.004		Five or more people under 18
Owner_occup	0.800		Owner
Rent_LA	0.135		Accommodation rented from local authority/housing association
Rent_Private	0.046		Accommodation rented from private landlord
Other	0.019		Other arrangement
Invmills	0.190	0.079	Inverse Mills ratio from income response equation

Table 2. Practice characteristics

Variable name	Mean	SD	Min	Max	Definition
High_Deprived	0.014323	0.088039	0	0.678868	Proportion patients living in highly deprived ward
GPs_Over61	0.041131	0.152016	0	1	Proportion of GPs in practice over 60
Minor_Surgery	0.814544	0.32358	0	1	Proportion of GPs performing minor surgery.
Drug_Costs	20.69488	4.423524	12.585	34.959	Prescribing costs per patient
Patients_Under15	0.200276	0.051498	0.122528	0.354128	Proportion of practice population under 15
Female_Patients	0.495665	0.045558	0.345348	0.59783	Proportion of female patients
Deprivation_Band1	508.0508	762.6618	0	3579	Number of band 1 deprived patients
Deprivation_Band2	213.2034	361.2557	0	2082	Number of band 2 deprived patients
Deprivation_Band3	96.74576	280.5792	0	1828	Number of band 3 deprived patients
Needs_Index	0.062003	0.160129	0	0.742812	Deprivation index score
Rural_Patients	4.059492	5.191995	0	16.44	% patients living $\geq$ 3 miles from practice
Fundholder	0.5	0.50422	0	1	Fundholding practice
DETR_Education	0.293793	1.113956	-1.66	2.53	DETR Education deprivation score
DETR_Employment	13.23948	7.560641	4.15	33.35	DETR Employment deprivation score
DETR_Access	-0.48569	0.781692	-1.66	1.47	DETR Access deprivation score
DETR_Multiple	30.11638	21.62827	4.74	72.48	DETR Overall index of multiple deprivation
Training	0.120	0.209	0	1	Proportion of GPs accredited as trainer.
FemaleGP	0.298	0.288	0	1	Proportion of female GPs
Out_hours	0.972	0.135	0	1	Proportion of GPs with out of hours responsibility
WTEGP	2.820	1.868	1	8	Number of WTE GPs
List_WTEG	2.152	0.525	0.991	3.524	Patients per WTE GP (000s)
Maternity	0.954	0.164	0	1	Proportion of GPs providing maternity services
Antibiotic	0.070	0.020	0.041	0.145	Rate of antibiotic prescribing
Disable_score	83.436	16.545	33.33	100	QUASAR disability access index

Table 3. Demand for visits: effects of selection and endogeneity

	Allowing for selection and endogeneity			
	Neither	Selection	Endogeneity	Selection and endogeneity
Income	-0.15633	-0.15229	-0.35904	-0.2658
	[3.037]**	[2.958]**	[2.508]*	[1.939]
Female	0.596863	0.71031	0.570156	0.705945
	[5.447]**	[4.921]**	[4.695]**	[4.571]**
Non_white	0.400874	0.449895	0.286529	0.361813
	[1.938]	[2.103]*	[1.413]	[1.748]
Health	-0.0668	-0.06701	-0.11023	-0.12291
	[14.388]**	[14.539]**	[3.889]**	[4.530]**
Age	-0.22597	-0.30061	-0.28746	-0.40558
	[3.431]**	[3.180]**	[3.479]**	[3.869]**
Age2	0.003977	0.00552	0.005216	0.007603
	[3.057]**	[2.906]**	[3.217]**	[3.634]**
Age3	-2.3E-05	-3.2E-05	-3.1E-05	-4.5E-05
	[2.792]**	[2.772]**	[3.003]**	[3.488]**
Single	-0.28827	-0.29216	-0.27498	-0.35047
	[1.990]	[2.028]*	[1.457]	[1.891]
Separate	0.086002	-0.03404	-0.05369	-0.28104
	[0.432]	[0.150]	[0.223]	[1.082]
Widowed	0.081296	0.044146	0.152624	0.057158
	[0.314]	[0.166]	[0.585]	[0.211]
Freetime_H	0.477856	0.55967	0.361793	0.494185
	[3.016]**	[3.211]**	[2.173]*	[2.697]**
Freetime_F	0.768828	0.868461	0.354941	0.457633
	[6.488]**	[6.151]**	[1.713]	[1.984]
New patient	-0.48306	-0.5168	-0.57529	-0.63656
	[1.436]	[1.536]	[1.665]	[1.805]
Access	0.003709	0.003192	0.004512	0.00414
	[1.290]	[1.083]	[1.516]	[1.379]
Trust_1-3	-0.4884	-0.52503	-0.63006	-0.73476
	[1.629]	[1.758]	[1.828]	[2.136]*
Trust_4	-0.12692	-0.17976	-0.14381	-0.24466
	[0.460]	[0.619]	[0.535]	[0.836]
Trust_5	-0.22554	-0.21419	-0.27308	-0.28913
	[0.909]	[0.868]	[1.086]	[1.140]
Trust_6	-0.52208	-0.49298	-0.49629	-0.47017
	[2.578]*	[2.480]*	[2.332]*	[2.217]*
Trust_7	-0.45192	-0.49231	-0.37625	-0.44939
	[2.836]**	[3.008]**	[2.238]*	[2.601]*
Trust_8	-0.41749	-0.48594	-0.37126	-0.4763
	[3.127]**	[3.126]**	[2.780]**	[3.009]**
Trust_9	-0.13558	-0.17945	-0.1298	-0.21856
	[0.880]	[1.086]	[0.856]	[1.288]
Cars_1	-0.00206	-0.02802	0.148795	0.114651
	[0.017]	[0.230]	[1.110]	[0.845]
Cars_2	0.209299	0.15825	0.470386	0.389291
	[1.508]	[1.090]	[2.884]**	[2.296]*
High_Deprived	0.798655	0.889905	0.593655	0.758884
	[2.683]**	[2.960]**	[1.962]	[2.347]*
GPs_Over61	-0.51281	-0.59452	-0.37496	-0.46795
	[2.595]*	[2.841]**	[1.609]	[1.941]

Drug_Costs	0.033092	0.034189	0.026685	0.027417
	[2.272]*	[2.332]*	[1.735]	[1.775]
Minor_Surgery	0.345448	0.340573	0.407361	0.401678
	[2.713]**	[2.664]*	[3.278]**	[3.364]**
Invmills		-0.75964		-1.00066
		[1.044]		[1.310]
Observations	2283	2283	2283	2283
Adjusted R-squared	0.205	0.205	0.166	0.148

Robust t statistics in brackets. * significant at 5%; ** significant at 1%

HA fixed effects included in regression but not reported

Table 4. Demand for visits allowing for practice characteristics or practice effects

	Practice characteristics	Fixed effects	Practice effects with income interactions
	1[1]	2[2]	3
Income	-0.24998	-0.13722	-0.14562[3]
	[1.939]	[0.933]	
Female	0.59826	0.66687	0.663495
	[4.481]**	[4.746]**	[4.617]**
Non_white	0.465147	0.158993	0.159131
	[1.746]	[0.761]	[0.729]
Health	-0.11218	-0.11905	-0.11078
	[3.864]**	[4.501]**	[4.121]**
Age	-0.30657	-0.38006	-0.35238
	[2.913]**	[3.497]**	[3.176]**
Age2	0.005623	0.006977	0.006439
	[2.686]**	[3.237]**	[2.926]**
Age3	-3.3E-05	-4E-05	-3.7E-05
	[2.579]*	[3.091]**	[2.787]**
Single	-0.48114	-0.56048	-0.57667
	[2.782]**	[3.226]**	[3.285]**
Separated	-0.17631	-0.27201	-0.21834
	[0.712]	[1.141]	[0.911]
Widowed	-0.01329	-0.09207	-0.06894
	[0.068]	[0.430]	[0.318]
Freetime_H	0.522587	0.628694	0.609994
	[3.035]**	[3.692]**	[3.535]**
Freetime_F	0.559924	0.64043	0.683196
	[2.864]**	[2.903]**	[3.041]**
New patient	-0.51622	-0.60528	-0.53256
	[1.416]	[2.102]*	[1.827]
Access	0.005963	0.006844	0.00681
	[1.839]	[2.236]*	[2.203]*
Trust_1	-0.72033	-0.88541	-0.79578
	[2.190]*	[2.765]**	[2.435]*
Trust_4	-0.4413	-0.58322	-0.52647
	[1.593]	[1.948]	[1.720]
Trust_5	-0.29359	-0.3285	-0.26038
	[1.348]	[1.687]	[1.335]
Trust_6	-0.37105	-0.35908	-0.34273
	[2.158]*	[2.076]*	[1.954]
Trust_7	-0.34808	-0.44267	-0.42021
	[2.219]*	[2.808]**	[2.630]**
Trust_8	-0.38149	-0.46475	-0.42106
	[2.850]**	[3.251]**	[2.901]**
Trust_9	-0.09633	-0.16385	-0.10806
	[0.626]	[1.170]	[0.764]
Cars_1	0.102694	0.101624	0.090057
	[0.954]	[0.813]	[0.717]
Cars_2	0.323506	0.295765	0.321303
	[2.310]*	[1.676]	[1.787]
High_Deprived	1.471214		
	[3.476]**		
GPs_Over61	-0.82301		

	[3.933]**		
Drug_Costs	0.027318		
	[1.886]		
Minor_Surgery	0.45691		
	[2.987]**		
Invmills	-0.92581	-1.53691	-1.40032
	[1.251]	[1.982]*	[1.767]
Observations	3225	3225	3225
$\bar{R}^2$	0.13	0.14	0.142

Robust t statistics in brackets
* significant at 5%; ** significant at 1%

[1] Health Authority effects included in the regression but not reported
[2] Estimates with practice fixed effects omit the DETR practice level variables as exclusion restrictions for the selection and the instrumental variables estimation.
[3] Mean income effect across practices
Practice fixed effects and income*practice effects not reported.

Table 5. Determinants of practice specific effect of income on visits

Patients_Under15	-6.69146
	[3.299]**
Female_Patients	3.755461
	[2.137]*
Deprivation_Band1	-0.00057
	[4.786]**
Deprivation_Band2	0.000902
	[3.708]**
Deprivation_Band3	0.000448
	[2.071]*
Needs_Index	-1.38363
	[3.765]**
Rural_Patients	0.054063
	[2.265]*
Fundholder	0.307321
	[2.142]*
Constant	-0.89556
	[1.290]
Observations	58
Adjusted R-squared	0.369

Robust t statistics in brackets
* significant at 5%; ** significant at 1%

Table 6. Effect of practice characteristics on effect of income on visits

Dependent variable: visits	OLS	Random effects
Income	-0.2425201[1]	-0.229691
	[1.986]	[1.729]
Female	0.546646	0.5626045
	[4.128]**	[4.179]**
Non_white	0.3151256	0.3087258
	[1.333]	[1.553]
Health	-0.1046784	-0.1091962
	[3.638]**	[4.446]**
Age	-0.2617808	-0.2859465
	[2.588]*	[2.764]**
Age2	0.0047185	0.0051795
	[2.342]*	[2.502]*
Age3	-0.0000273	-0.00003
	[2.214]*	[2.368]*
Single	-0.4730206	-0.4966876
	[2.739]**	[2.849]**
Separate	-0.1031097	-0.1354002
	[0.418]	[0.596]
Widowed	0.0077768	-0.0082623
	[0.039]	[0.043]
Freetime_H	0.488031	0.5039474
	[2.898]**	[3.208]**
Freetime_F	0.5358001	0.5389471
	[2.687]**	[2.746]**
New patient	-0.4489345	-0.4579957
	[1.246]	[1.551]
Access	0.0058472	0.0064173
	[1.838]	[2.405]*
Trust_1	-0.7121258	-0.7469096
	[2.238]*	[2.574]*
Trust_4	-0.4093566	-0.4394755
	[1.476]	[1.539]
Trust_5	-0.2853388	-0.2944621
	[1.334]	[1.534]
Trust_6	-0.3812787	-0.3765401
	[2.237]*	[2.002]*
Trust_7	-0.352408	-0.3671088
	[2.262]*	[2.381]*
Trust_8	-0.3392679	-0.3569789
	[2.571]*	[2.605]**
Trust_9	-0.0587863	-0.071155
	[0.380]	[0.532]
Cars_1	0.119253	0.1184438
	[1.065]	[1.020]
Cars_2	0.3716499	0.3691738
	[2.471]*	[2.259]*
High_Deprived	2.6424156	2.6891555
	[5.581]**	[2.315]*
GPs_Over61	-0.8121159	-0.842033
	[3.924]**	[2.356]*
Drug_Costs	0.0356695	0.0333727
	[2.533]*	[2.214]*

Minor_Surgery	0.4492376	0.4614684
	[3.124]**	[2.336]*
Invmills	-0.5438769	-0.7101267
	[0.738]	[1.068]
Patients_Under15*Income	-7.627627	-7.7490759
	[4.325]**	[3.676]**
Female_Patients*Income	5.4624183	5.2051916
	[3.352]**	[2.864]**
Deprivation_Band1*Income	-0.0002006	-0.0002461
	[1.228]	[1.502]
Deprivation_Band2*Income	0.0001126	0.0002014
	[0.404]	[0.624]
Deprivation_Band3*Income	0.0009177	0.0008776
	[3.511]**	[2.053]*
Needs_Index*Income	0.0255284	0.0303006
	[1.109]	[1.160]
Rural_Patients*Income	-1.182955	-1.2055685
	[4.050]**	[2.475]*
Fundholder*Income	0.4103736	0.3997994
	[3.532]**	[2.600]**
Constant	9.8509353	10.3096643
	[3.876]**	[4.674]**
Observations	3225	3225
Adjusted R-squared	0.138	0.1484

Robust t statistics in brackets
* significant at 5%; ** significant at 1%

[1.] Income effect evaluated around the means of all practice characteristics

Figure 1: Variation in the relationship between income and utilisation across practices