EEPRU

Policy Research Unit in Economic Evaluation of Health and Social Care Interventions

Research Report

Title: Case-Mix Methodology for the NHS Outcomes Framework GP Patient Survey

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The Department of Health's Policy Research Unit in Economic Evaluation of Health and Care Interventions is a 5 year programme of work that started in January 2011. The unit is led by Professor John Brazier (Director, University of Sheffield) and Professor Mark Sculpher (Deputy Director, University of York) with the aim of assisting policy makers in the Department of Health to improve the allocation of resources in health and social care.

EXECUTIVE SUMMARY

Objective: The purpose of this paper was to expand and test the proposed methodology which could be used to determine if the health related quality of life of patients with long-term health conditions is changing over time using data collected in the GP Patient Survey (GPPS).

Methods: Data from two consecutive rounds of the GPPS were combined and cases with a complete set of responses for the variables of interest were retained. Potential relationships between explanatory variables (age, gender, ethnicity, deprivation, smoking status, limitation of activities due to recent illness, presence of long-term condition, geographical area, and survey round) and health related quality of life (HRQoL) were explored. A series of exploratory analyses were performed to examine potential relationships using the full dataset. The primary objective was to determine if relationships between the explanatory and dependent variables was constant over the two time periods, or differed across conditions and comorbidities.

Models were obtained using ordinary least square (OLS) regressions (with the EQ-5D preference based scores as the dependent variable) and polycotomous ordered logistic models (with the probability of scoring none, some or extreme problems on the EQ-5D health dimensions as the dependent variables). The approach initially proposed has been developed to incorporate separate equations for the level two and level three responses in the logistic models (partial proportional odds models (PPOM)), and where appropriate two-part models were generated to account for the proportion scoring full health, prior to generating the logistic models.

Results: When sub-grouped by health condition, with the exception of the cohort with Learning problems, the mean EQ-5D score was higher in Survey 1 than in Survey 0 and the difference was statistically significant different ($p<0.05$) in 9 of the 15 conditions. The OLS approach predicted mean scores well, but the individual predictions from the models did not represent the underlying observed distributions. This will be problematic if observed values in future Surveys are to be adjusted using predicted values as the errors in the predicted values may be systematic in that they are likely to differ in magnitude and direction at the extremes of the data. While the OLS approach appeared to capture the average effect of the Survey round for many of the conditions, the results show the effect of the Survey may not take a simple additive form and the effect varies considerably across both the health dimensions and conditions.

While not perfect, the PPOM approach produced a more accurate representation of the underlying data. However, more importantly, it allows one to examine which aspects (dimensions) of QoL have changed across the Surveys, and thus where potential interventions could be targeted to improve the QoL for patients living with long-term health conditions.

Issues and future research: there are several issues not addressed in this paper. First, it is not believed that the data collected in Survey 0 and Survey 1 are directly comparable due to potential seasonal differences and the analyses should be repeated on data collected at the same point of the year in consecutive years as opposed to consecutive surveys. Second, the results should be compared with the results obtained using the approach currently taken by the DH analysts. Third, the PPOM approach could be developed further to take account of potential conditional probabilities across the health dimensions.

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1 INTRODUCTION

1.1 Background

This paper describes developments in alternative methods to evaluate average changes in health related quality of life (QoL) observed in people with long term health conditions in England. Exploratory analyses using data from the Health Survey for England were described in a previous paper ("Case-Mix Methodology for the NHS Outcomes Framework"). The focus of the current paper is on testing and developing the methodology initially proposed, using data collected in two rounds of the General Practitioners Patient Survey (GPPS), with a view to extending and developing the proposed methodology further as additional data from future surveys become available.

Previous research proposed a case-mix adjustment methodology based on the use of ordinary least square (OLS) regressions.[1] A refinement involving a regression with fixed effects was subsequently proposed.[2] These methods use the individual level predicted EQ-5D scores to determine potential changes in case-mix adjusted QoL on the aggregate level. As discussed previously, due to the non-normal distribution of the underlying data, there are numerous fundamental theoretical issues with using OLS regressions on EQ-5D data.[3] The proposed approach evades many of the theoretical problems related to the non-normal distribution by using ordered logistic regressions and concentrating on the responses to the questions in the actual EQ-5D questionnaire as opposed to the preference-based EQ-5D scores. A similar approach has recently been proposed by Gutacker *et al*. who examined hospital provider variations in QoL for patients who have received a hip replacement, using multilevel ordered probit models to predict changes in the five EQ-5D health dimensions.[4]

1.2 Objective

The purpose of this paper was to expand and test the proposed methodology which could be used to determine if the health related quality of life of patients with long-term health conditions is changing over time using data collected in the GPPS.

1.3 Seasonal changes in QOL

Before describing the methodology and results in more detail it is worth pointing out that the data from the two GPPS surveys used in the current paper may not be directly comparable due to the differences in the timing of the surveys. There is strong evidence of seasonal variations in incidence rates and symptoms in numerous prevalent health conditions. Seasonal exposure to cold air cools the nasal epithelium which may inhibit respiratory defences against viral infections in the upper

respiratory tract, influenza and the common cold; all of these have substantially higher incidence rates in the winter months.[5,6,7] Winter incidence rates are also higher in vascular conditions such as coronary heart disease,[8] and variceal bleeding.[9] Chronic conditions characterised by intermittent periods of active disease can also exhibit seasonal trends with incidence rates and/or "flare" symptoms acerbated in winter compared to summer for ulcerative colitis ($p=0.028$),[10] and osteoarthritis.[11] The converse has been reported for Crohn's disease,[12,13] irritable bowel disease,[14] and gout[15] with increases in incidence rates and/or "flare" symptoms reported in summer compared to winter.

Seasonal fluctuations in QoL scores for the general population have been reported: the Beck Depression Inventory was reported to be higher (worse depression) in winter than summer in females;[16] the Hopkins Symptom Checklist found anxiety, depression and somatisation were twice as high in late autumn and winter months compared to the rest of the year in females;[17] the General Health Questionnaire (GHQ-12) showed seasonal differences in mental wellbeing, mood and behaviour ($p<0.001$),[18] while physical (mental) health has been reported as being worse in winter (autumn) and best in summer (spring).[19]

Although limited, seasonal changes in QoL scores have been reported for specific conditions. Physical and social problems (Ankylosing Spondylitis Arthritis Impact Measurement Scale) are reported to be worse in summer months for individuals with ankylosing spondylitis;[20] and QoL (Short Irritable Bowel Disease questionnaire) is also more impaired in summer and autumn in patients with irritable bowel disease ($p<0.05$).[14] While these two examples are potentially due to the seasonal acerbation of symptoms and flares, the QoL burden associated with common viral infections could have an effect on average QoL scores for sub-groups with specific conditions in winter months. For example, researchers found the absolute reduction in QoL (measured using the EQ-5D) attributable to influenza is 0.58 for inpatients and 0.43 for outpatients, with Pain/Discomfort and Usual Activities being the dimensions affected the most.[21] Reductions of these magnitudes are comparable with the burden of many chronic diseases and thus might be expected to contribute to dips in population level QoL scores, suggesting that data collected in one season is not directly comparable with data collected in a different season.

2 METHOD

2.1 Statistical analyses

Data from two consecutive rounds of the GPPS were combined and cases with a complete set of responses for the variables of interest were retained. Gender, ethnicity, deprivation, smoking status, limitation of activities due to recent illness and presence of long-term condition were dichotomised and treated as binary variables. Responses for the age question were assigned the mid-point values of 20, 30, 40, 50, 60, 70, 80, 90 years and treated as a continuous variable. In the logistic regressions, the five health dimensions were treated as continuous. Mean values were compared using t-tests or χ^2 where appropriate with α = 0.05 used for statistical significance. Calculations were performed using the software STATA (version 12).

2.1.1 Regressions

The models were obtained using a two-step approach. First, using the whole dataset, a series of exploratory regressions were used to examine potential relationships and to assess interactions between variables. Second, a series of models were obtained for sub-groups of respondents who indicated they had one of the 15 specified long-term health conditions (Angina, Alzheimer, Arthritis, asthma, Blindness, Cancer within the last 5 years, Deafness, Diabetes, Epilepsy, High Blood Pressure (HBP), Kidney/Liver disease (KLD), Learning difficulties, Mental Health, Neurological problems). Both sets of analyses involved generating statistical models using ordinary least squares (OLS) to predict the preference-based EQ-5D scores, and ordered logistic regressions to predict the probabilities of responses for the five health dimensions Mobility, Self-Care, Usual Activities, Pain/discomfort, and Anxiety/depression.

Simple linear regressions using OLS regression were used to obtain models of the form:

$$\text{EQ-5D} = \alpha + \beta_1 x + \beta_2 x + \ldots\ldots\ldots + \beta_n x + \varepsilon$$

whereby EQ-5D represents the EQ-5D preference-based index, α represents the constant, the β's represent the weights for the explanatory variables, and ε represents the error term.

Models obtained using OLS regressions do not deal with the non-normal characteristics typically observed in EQ-5D data,[22] hence polycotomous ordered logistic models (OLM) with three dependent variables (the probability of scoring none, some, or extreme problems) were obtained for each of the five health dimensions:

$$p(d_i = 1) = \frac{\exp\left(\beta_1^i x_1 + \beta_2^i x_2 + \ldots . \beta_n^i x_n - k_1^i\right)}{1 - \exp\left(\beta_1^i x_1 + \beta_2^i x_2 + \ldots . \beta_n^i x_n - k_1^i\right)}$$

$$p(d_i = 2) = \frac{\exp\left(\beta_1^i x_1 + \beta_2^i x_2 + \ldots . \beta_n^i x_n - k_2^i\right)}{1 - \exp\left(\beta_1^i x_1 + \beta_2^i x_2 + \ldots . \beta_n^i x_n - k_2^i\right)} - p(d_i = 1)$$

$$p(d_i = 3) = 1 - p(d_i = 1) - p(d_i = 2)$$

Here the β's reflect the weight given to the various independent variables and the *k*'s define the separation between the probabilities (or cut points). As the β's (but not the *k*'s) are the same for all values of *d*, the OLMs assume the lines are parallel. This assumption can be overly restrictive as one or more of the βs could differ across values of *d* (i.e. the regression lines may not be parallel). The brant command in STATA was used to test the parallel lines assumption for both the global model and the individual variables. William's generalised ordered logit/partial proportional odds models (PPOM) were obtained when the parallel-lines assumption was violated.[23] The formula for the PPOM is the same as that for the OLM except in the PPOM, the *k*'s (which are the negatives of the cut points) and the β's can vary for each value of *d*. If the parallel line assumption is upheld, the β's will be the same for each value of *d.* An advantage of using the PPOM is that it is more parsimonious than the generalised ordered logit model, where all the βs differ, but unlike the multinomial logit model, the order of the responses is retained.

Depending on the characteristics of the EQ-5D scores in the sub-groups, where appropriate, a probit model was used to predict the probability of scoring full health (EQ-5D = 1), followed by a PPOM (PPPM2p) to predict the probabilities for the health dimension using the data from respondents who indicated they were not in full health (EQ-5D < 1).

2.1.2 Generating expected EQ-5D scores

The expected EQ-5D scores were predicted in the normal manner using the βs in the OLS models. For the PPOMs, EQ-5D scores were obtained by estimating an expectation using the weighted average obtained from the probabilities of scoring no, some or extreme problems in each of the five dimensions, i.e. the EQ-5D scores for each of the 243 possible health states were weighted using the probabilities of being in these health states.

2.2 Case-mix approach

In addition to alternative forms of regressions, there are several different approaches which can be used to adjust for case-mix. One approach might be to use the data collected in the first survey to obtain relationships between the explanatory and dependent variables, with the objective of using these relationships to predict case-mix adjusted scores for patients in subsequent surveys. There are two key points to note relating to this methodology. Firstly, this approach by definition assumes that the individual relationships between the dependent and explanatory variables remain constant over the different surveys. Secondly, it is important that the statistical model performs well at predicting individual values across the full range of the dependent variable as opposed to on the

aggregate level, as the individual predicted scores for the subsequent surveys are used to determine any potential case-mix adjusted change in the dependent variable. Any heteroscedasticity in the residuals will translate into errors in predicted and thus case-mix adjusted values.

A second approach might be to pool data from several rounds of the surveys. The full dataset would then be used to obtain a statistical model with the survey(s) incorporated as an additional explanatory variable within the model. In a linear additive model obtained using OLS regression with the EQ-5D score as the dependent variable, the beta coefficient for the survey variable would indicate the effect of the survey. A positive coefficient would be interpreted as the average increase in QoL while a negative coefficient would be interpreted as the average decrease in QoL specifically due to the survey round after adjustment for the case-mix represented by the other explanatory variables. Using this approach one does not assume that individual relationships between the dependent and explanatory variables remain constant over the different surveys as the coefficients for these variables are derived from the full dataset. Secondly, it is less important that the statistical model predicts well on the individual level, but rather that the explanatory variables incorporated in the model are representative of the case-mix and that the model explains the variance in the dependent variable.

Because of concerns with the timing of the Surveys used in the analyses described in this paper, the analyses have been limited to the latter approach using pooled data from the two survey rounds. The former approach could be explored and results compared once the data collected in the next survey (September 2012) are available.

3 RESULTS

3.1 Summary Statistics

Data from two rounds (Survey 0 (S0) conducted in September 2011, and Survey 1 (S1) conducted in March 2012) of the GPPS were pooled and details on the socio-demographic data used in the main regressions are provided below (Table 1). A total of 795,077 respondents provided information on the full set of variables of interest. Almost two-thirds of respondents (497514/795077=63%) indicated they had at least one long-term health condition with prevalence ranging from 24% (191802/795077) for high blood pressure (HBP) to less than 1% (4993/795077) for Alzheimer.

Deprivation was equally distributed (approximately 33%) across each of the three categories with a slightly larger proportion of respondents in the least deprived category in Survey 1 than Survey 0 (35.1% vs. 32.5%, $p<0.001$). Conversely, the proportion of respondents whose activities were not limited due to a recent illness or injury was lower in Survey 1 than Survey 0 (79.6% vs.82.7%, $p<0.001$). The differences in the patients' characteristics could indicate true case-mix change across the surveys but could be due to factors that have not been considered or accounted for. For example, data inspection indicated that the GP practices involved in the two Surveys differs slightly. There were 7,727 practices common to both Surveys, 61 practices represented only in Survey 0 and 10 practices represented only in Survey 1. It is possible that this is a random difference but the effect has not been explored in this paper.

Table 1: Socio-demographic characteristics of respondents, by Survey

	Survey 0 (SO) N=410,525		Survey 1 (S1) N=384,552		
	n	%	n	%	p
Age:					
≤60 years	196,279	47.8	176,001	45.8	
>60 years	214,246	52.2	208,551	54.2	<0.001
Gender:					
Female	230,003	56.0	214,316	55.7	
Male	180,522	44.0	170,236	44.3	<0.005
Ethnicity:					
White	361,685	88.1	345,267	89.8	
Mixed	3,034	0.7	2,661	0.7	
Asian	25,959	6.3	20,617	5.4	
Black	10,644	2.6	8,700	2.3	
Other	9,203	2.2	7,307	1.9	<0.001
Deprivation:					
Least deprived	133,458	32.5	134,993	35.1	
Moderately deprived	139,568	34.0	133,359	34.7	
Most deprived	137,499	33.5	116,200	30.2	<0.001
Smoke:					
Never smoked	212,839	51.9	200,525	52.2	
Former smoker	126,401	30.8	122,668	31.9	
Occasional smoker	27,719	6.8	23,918	6.2	<0.001
Activities limited today due to recent illness or injury:					
No	339,410	82.7	305,892	79.6	
Yes, limited a little	54,156	13.2	60,789	15.8	
Yes, limited a lot	16,959	4.1	17,871	4.7	<0.001
Long-term condition:					
Alzheimer	2,516	0.6	2,477	0.6	0.078
Angina	27,274	6.6	26,273	6.8	<0.01
Arthritis	68,288	16.6	63,927	16.6	0.900
Asthma	43,850	10.7	40,917	10.6	0.551
Blindness	5,007	1.2	4,766	1.2	0.425
Cancer	15,557	3.8	15,332	4.0	<0.001
Deafness	19,641	4.8	18,739	4.9	0.066
Diabetes	35,223	8.6	33,483	8.7	<0.05
Epilepsy	4,343	1.1	4,193	1.1	0.161
High blood pressure	98,198	23.9	93,604	24.3	<0.001
Kidney/Liver disease	7,186	1.8	6,853	1.8	0.285
Learning	3,277	0.8	2,969	0.8	0.186
Back Problem	44,991	11.0	42,397	11.0	0.350
Mental Health	14,679	3.6	14,016	3.6	0.099
Neurological	7,457	1.8	7,324	1.9	<0.005
Another	51,779	12.6	49,396	12.9	<0.005
None	155,171	37.8	142,392	37.0	<0.001

3.2 Health related quality of life

Comparing across the surveys for the full dataset, although relatively small, there were statistically significant differences in the proportions of respondents who indicated they had problems on each of the five health dimensions ($p<0.05$) (Table 2). The largest difference was observed in Mobility, where 75.1% and 75.9% indicated they had no problem with Mobility in Survey 0 and Survey 1 respectively ($\chi^2=64.2$, $p<0.001$). The EQ-5D preference scores covered the full range (-0.594 to 1) and almost half of respondents indicated they were in full health (358062/795077=45%). There was a small but significant increase in the average EQ-5D score for respondents in Survey 1 compared to Survey 0 (S1: 0.804 vs. S0: 0.800; t=-6.26, $p<0.001$).

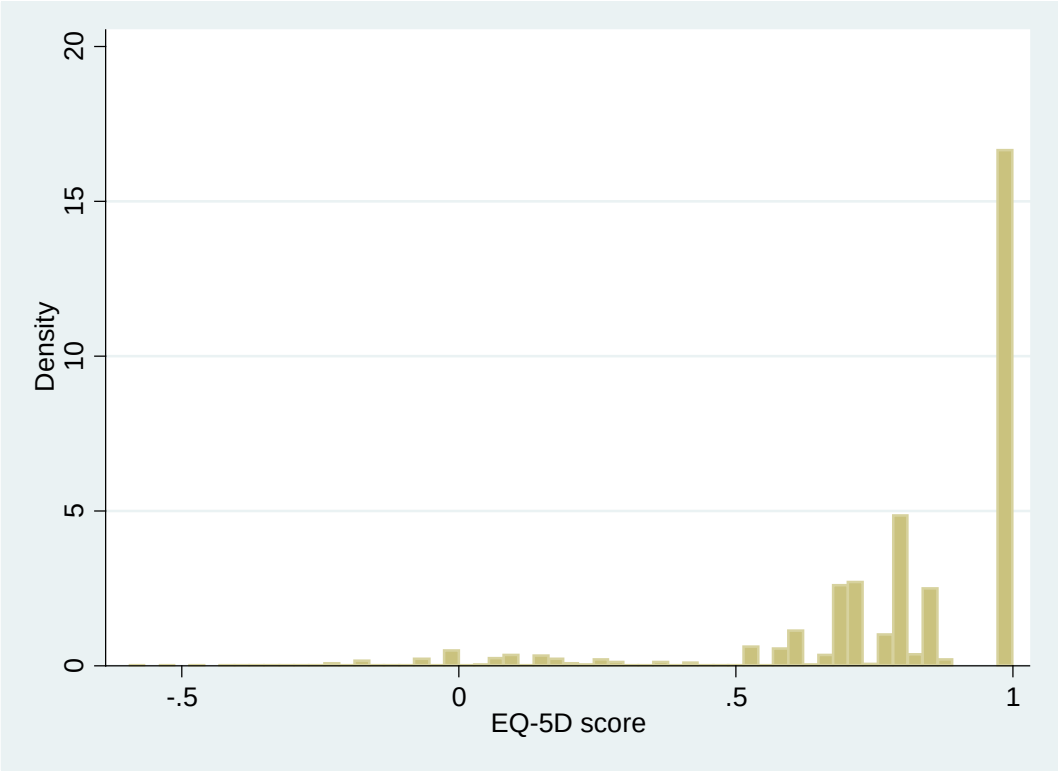
Table 2: EQ-5D scores for the full cohort by Survey

	Survey 0 N=410,525		Survey 1 N=384,552		
Mobility	n	%	n	%	p
No problems	308,319	75.1	291,710	75.9	
Moderate problems	101,125	24.6	91,780	23.9	
Extreme problems	1,081	0.3	1,062	0.3	<0.001
Self Care					
No problems	374,942	91.3	351,786	91.5	
Moderate problems	32,815	8.0	30,084	7.8	
Extreme problems	2,768	0.7	2,682	0.7	<0.05
Usual Activities					
No problems	303,418	73.9	286,244	74.4	
Moderate problems	94,819	23.1	86,847	22.6	
Extreme problems	12,288	3.0	11,461	3.0	<0.001
Pain/Discomfort					
No problems	224,195	54.6	211,796	55.1	
Moderate problems	163,012	39.7	152,195	39.6	
Extreme problems	23,318	5.7	20,561	5.4	<0.001
Anxiety/Depression					
No problems	309,632	75.4	290,349	75.5	
Moderate problems	90,155	22.0	84,564	22.0	
Extreme problems	10,738	2.6	9,639	2.5	<0.01
EQ-5D preference score					
Mean (SD)	0.8000	(0.265)	0.8037	(0.261)	t=-6.26, p<0.001
Full health (EQ-5D=1)	184,302	44.9	173,760	45.2	

p-values: χ^2 difference in proportions for Survey 0 vs. Survey 1.

The EQ-5D data were not normally distributed and exhibited the characteristics typically observed in these datasets.[22] There was a large mass at full health, a mass centred around 0.8 and a further smaller mass centred around 0.1 (Figure 1).

Figure 1: EQ-5D scores for the full cohort (n=795,077)



3.3 Long-term health conditions

3.3.1 Summary statistics by long-term health condition

When comparing across health conditions, there were some substantial differences in the socio-demographic characteristics (see Appendix). For example, the weighted average age ranged from approximately 45 years for respondents with Learning problems to approximately 77 years for respondents with Alzheimer. The proportions of male respondents ranged from 37% for Arthritis to 61% for Angina while the proportions who smoked regularly ranged from 6% for Alzheimer to 26% for Mental Health. A wide range was also observed for deprivation with 26% of respondents with Cancer in the most deprived category compared to over 50% of respondents with Learning problems. Interestingly, few respondents indicated they had just one of the specific long-term health conditions. For example, almost 90% of respondents who indicated they were Blind, and 61% of respondents with Asthma, also had additional long term conditions.

Comparing differences in socio-demographic characteristics across surveys for respondents sub-grouped by presence of the 15 health conditions, there were statistically significant differences for age (7/15), gender (3/15), smoking status (10/15), effect of recent illness or injury (13/15), ethnicity (7/15), deprivation level (14/15) and district providers (4/15). The only sub-groups with no statistically significant differences across the surveys in any of these characteristics were the respondents with Alzheimer. Without exception, the proportions in the Most Deprived categories were smaller in Survey 1 than in Survey 0 for each health condition. Similarly, the proportions who indicated their activities were not limited due to a recent illness or injury were also smaller in Survey 1 than in Survey 0 for each health condition. One would expect these differences would have converse effects on QoL with the most deprived respondents scoring lower on the EQ-5D and those in the no limitation in activities due to a recent illness or injury scoring higher on the EQ-5D.

3.3.2 Health dimension scores by long-term health condition

When comparing the proportions of respondents reporting problems in the five health dimensions for sub-groups categorised by the 15 long-term health conditions (Table 3), the proportions reporting no problems were generally largest for the dimension Self-Care and smallest for the dimensions Pain/Discomfort or Usual Activities. There were substantial differences in the proportions within a particular health dimension across the different conditions reflecting the specific aspects of health and quality of life affected by the individual conditions. For example, just 26% of Blind respondents indicated they had no problems on Mobility compared to 61% of respondents who have HBP. The proportions indicating no problems in the other health dimensions ranged from: 41% (Alzheimer) to 86% (HBP) for Self-care; 22% (Alzheimer) to 63% (HBP) for Usual Activities; 6% (Arthritis) to 46% (Learning problems) for Pain/Discomfort; and 12% (Mental Health) to 71% (HBP) for Anxiety/Depression.

The differences in the proportions of respondents who indicated problems in the health dimensions in Survey 0 and Survey 1 were statistically significant in a substantial number of the conditions for Pain/Discomfort (10/15), Mobility (9/15), and Usual Activities (7/15). Conversely, only a small number of the differences were statistically significant for the dimensions Self Care (4/15) and Anxiety/Depression (1/15). For the sub-groups with Arthritis, the differences in the proportions who indicated they had problems in Survey 0 and Survey 1 was statistically significant in all five health dimensions, while for Epilepsy, Learning, Neurological and Alzheimer, none of the differences were statistically significant.

Of particular interest, comparing respondents who indicated they had extreme problems on a health dimension, the greatest proportions were observed for the dimension Pain/Discomfort in 11 of the 15 conditions (data not shown). For the remaining four conditions, the largest proportions of respondents with extreme problems were observed in the dimension Anxiety/Depression for the sub-groups with either Learning Difficulties (14%) or Mental Health problems (33%) and in the dimension Usual Activities for the sub-groups with either Blindness (18%) or with Alzheimer (33%).

Table 3: Percentage of respondents with no problems on the health dimensions, by health condition and survey

	Mobility (%)			Self Care (%)			Usual Activities (%)			Pain/Discomfort (%)			Anxiety/Depression (%)		
	S0	S1	p	S0	S1	p	S0	S1	p	S0	S1	p	S0	S1	p
Full Survey	75.1	75.9	<0.001	91.3	91.5	<0.01	73.9	74.4	<0.001	54.6	55.1	<0.001	75.4	75.5	<0.01
Alzheimer	30.8	32.8	0.320	42.1	44.3	0.290	21.9	24.1	0.155	32.7	35.2	0.138	42.7	45.3	0.186
Angina	40.3	42.6	<0.001	76.2	77.0	<0.05	42.3	44.7	<0.001	26.6	28.3	<0.001	63.7	64.4	0.056
Arthritis	30.7	32.6	<0.001	73.6	74.1	<0.05	34.3	35.7	<0.001	5.7	6.6	<0.001	61.4	62.1	<0.05
Asthma	60.0	61.0	<0.01	83.3	83.4	0.684	58.6	59.1	0.383	41.9	42.8	<0.01	66.2	66.6	0.524
Blindness	26.1	28.5	<0.05	60.0	61.8	0.204	24.9	25.9	0.394	23.1	25.3	<0.05	53.2	54.5	0.415
Cancer	56.5	57.6	0.091	82.7	82.8	0.938	54.1	54.9	0.351	35.8	36.5	<0.05	67.2	67.5	0.845
Deafness	42.8	43.7	<0.05	76.2	76.2	0.595	45.0	46.2	0.051	27.2	28.7	<0.01	63.6	64.2	0.414
Diabetes	50.9	53.0	<0.001	80.5	81.1	<0.05	54.2	55.9	<0.001	35.4	37.3	<0.001	67.7	68.2	0.210
Epilepsy	54.9	56.5	0.227	73.9	74.8	0.480	51.3	52.9	0.212	43.5	44.8	0.400	58.1	59.9	0.240
HBP	59.0	61.1	<0.001	85.8	86.5	<0.001	61.3	62.9	<0.001	39.2	40.9	<0.001	70.8	71.2	0.186
KLD	41.2	43.1	0.062	71.0	72.1	0.276	40.6	43.0	<0.05	24.2	25.8	<0.001	56.7	57.2	0.448
Learning	51.4	52.4	0.083	58.8	58.9	0.420	39.8	39.4	0.679	46.2	46.0	0.414	44.6	46.5	0.334
Back Problem	38.2	39.8	<0.001	73.5	73.9	0.095	34.7	35.6	<0.05	6.9	7.1	<0.001	56.6	57.0	0.447
Mental Health	55.6	57.2	<0.05	72.2	72.3	0.744	38.5	40.2	<0.05	38.5	38.9	0.463	12.5	12.9	0.256
Neurological	28.5	29.6	0.303	56.8	56.1	0.636	23.8	24.7	0.200	14.8	15.8	0.120	43.6	44.2	0.269

S0 = Survey 0; S1 = Survey 1; p-values: χ^2 difference in proportions across the 3 possible responses comparing Survey 0 (S0) vs. Survey 1 (S1)

3.3.3 EQ-5D scores by long-term health condition

The mean EQ-5D scores ranged from 0.4369 (s=0.37) for respondents with Neurological problems in Survey 0 to 0.7326 (s=0.29) for respondents with HBP in Survey 1 (Table 4). The proportions who indicated they were in full health (EQ-5D=1) ranged from 4% (5603/132215) for respondents with Arthritis, to 32% for respondents with either Asthma (27328/84767) or HBP (29953/93604).

Table 4: EQ-5D scores by health condition and Survey

	Survey 0				Survey 1					
	n	FH	mean	SD	n	FH	mean	SD	Difference	p
Full Survey	410,525	45%	0.800	0.27	384,552	45%	0.804	0.26	0.004	<0.001
Alzheimer	2,516	10%	0.460	0.36	2,477	11%	0.477	0.36	0.017	0.096
Angina	27,274	18%	0.626	0.32	26,273	19%	0.638	0.32	0.012	<0.001
Arthritis	68,288	4%	0.542	0.32	63,927	5%	0.554	0.31	0.012	<0.001
Asthma	43,850	32%	0.703	0.33	40,917	32%	0.708	0.32	0.005	<0.05
Blindness	5,007	9%	0.520	0.35	4,766	10%	0.535	0.34	0.016	<0.05
Cancer	15,557	26%	0.700	0.30	15,332	26%	0.706	0.29	0.006	0.057
Deafness	19,641	18%	0.632	0.32	18,739	19%	0.637	0.32	0.005	0.145
Diabetes	35,223	27%	0.676	0.32	33,483	28%	0.687	0.32	0.011	<0.001
Epilepsy	4,343	29%	0.646	0.36	4,193	29%	0.659	0.36	0.013	0.098
HBP	98,198	31%	0.723	0.30	93,604	32%	0.733	0.29	0.010	<0.001
KLD	7,186	17%	0.573	0.36	6,853	17%	0.593	0.35	0.021	<0.001
Learning	3,277	17%	0.576	0.36	2,969	16%	0.572	0.37	-0.004	0.653
Back Problem	44,991	5%	0.518	0.34	42,397	5%	0.528	0.34	0.011	<0.001
Mental Health	14,679	6%	0.480	0.37	14,016	7%	0.490	0.37	0.011	<0.05
Neurological	7,457	6%	0.437	0.37	7,324	7%	0.446	0.38	0.009	0.138

FH= Full health (EQ-5D =1); p-value: EQ-5D Survey 0 vs. Survey 1

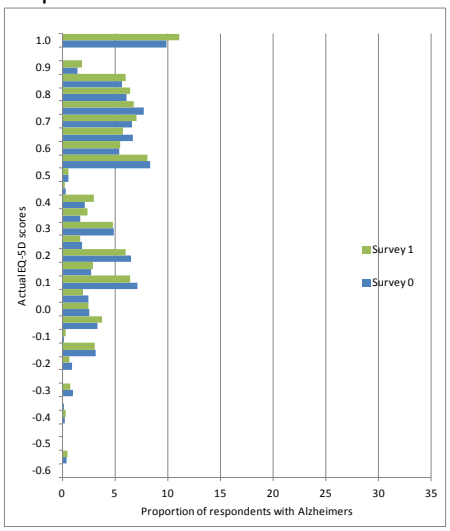
With the exception of the sub-group with Learning problems, where the mean EQ-5D score was lower in Survey 1 (decrease=-0.004 p=0.653), the mean EQ-5D scores were higher in Survey 1 compared to Survey 0 and the differences were statistically significant in 9 of the 15 conditions (Table 4). It is noteworthy that while the differences in mean EQ-5D scores were small in absolute terms relative to the EQ-5D range, the differences were large for some of the conditions. The largest difference in mean EQ-5D score was observed in respondents with KLD (increase=0.021, p<0.001). In general, the proportions scoring full health (EQ-5D=1) increased slightly in Survey 1 compared to Survey 0.

All the datasets from the sub-groups exhibited the multi-modal distributions characteristic of EQ-5D data (examples provide in Figure 2). When sub-grouped by survey the distributions of EQ-5D scores are virtually mirror images for sub-groups with the same condition, and can differ substantially when

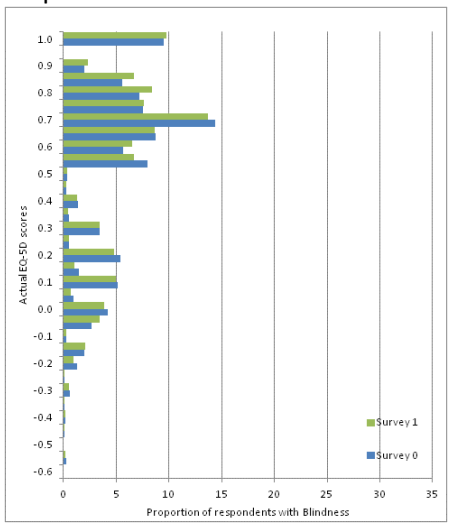
comparing across the health conditions. For example, for respondents with HBP, the skew (kurtosis) was -1.43 (4.61) and -1.49 (4.83) in Survey 0 and Survey 1 respectively while for respondents with Alzheimer the corresponding values were -0.37 (2.22) and -0.39 (2.24). These data illustrate that respondents with specific conditions are more likely to select particular sets of combinations of responses for the health dimensions. These combinations will be driven by the dimensions of health that are affected by the particular condition.

Figure 2: EQ-5D scores by long-term health condition and Survey

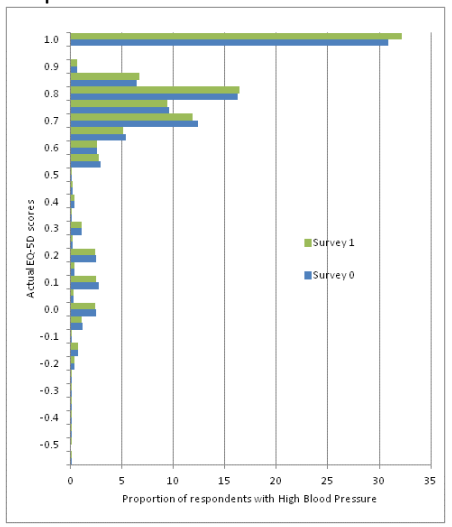
Respondents with Alzheimer



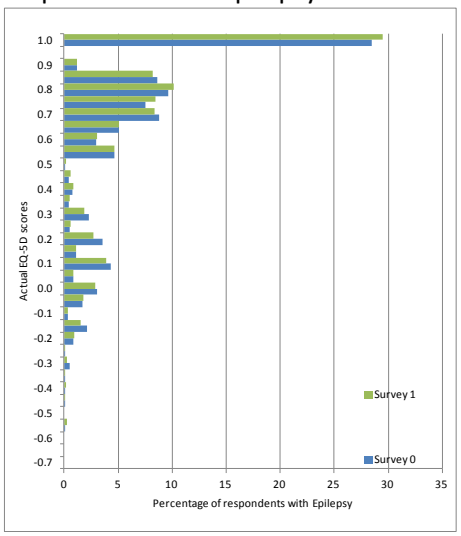
Respondents with Blindness



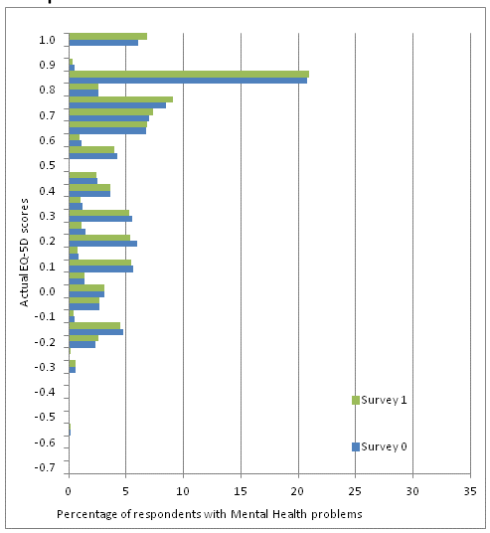
Respondents with HBP



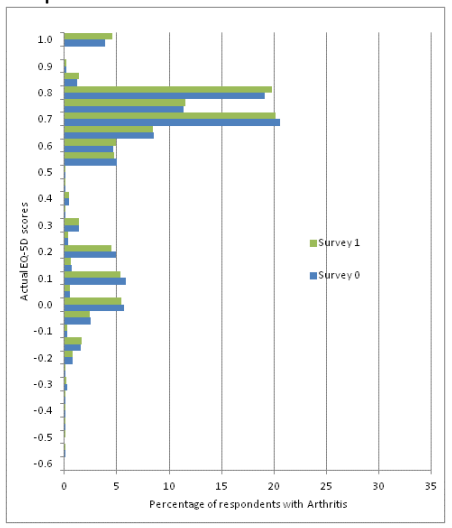
Respondents with Epilepsy



Respondents with Mental Health



Respondents with Arthritis



3.4 Exploratory regressions

A series of exploratory regressions were performed using the full dataset. The results were used to examine relationships between the proposed explanatory variables and both the EQ-5D preference-based scores (OLS models) and the five EQ-5D health dimensions (PPOM and PPOM-2p models). Models incorporating cross-products for the variables survey, comorbidities, or a specific individual condition were also obtained. The objective was to determine if the relationships with the main explanatory variables were constant over the two time periods, were affected by the number of health conditions, or differed across the specific individual conditions respectively.

3.4.1 OLS regressions

Regressing onto the EQ-5D preference scores using OLS (Main OLS model)

The effects of all the proposed explanatory variables were significant ($p<0.05$) with the exception of 3 of the 10 geographical areas. Smoking, recent illness and deprivation all had the expected effect (-ve) and increased in magnitude as expected (i.e. most deprived had a larger detriment than moderately deprived). All the long-term health conditions had negative relationships; Mental Health (Beta=-0.2383) and Neurological (Beta=-0.2321) had the largest effects while Deafness (Beta=-0.0237) and HBP (Beta=-0.0140) had the smallest. The effect of Survey 1 was significant ($p<0.001$) and positive as would be expected given that the average EQ-5D scores were higher in Survey 1.

Adding cross-products into the main OLS model to account for the interaction effects with a) Survey, b) a comorbidity, or c) an individual condition. In general, the combined effect for the explanatory variable and the corresponding Survey cross-product was in the same ball park as the effect of the explanatory variable in the main OLS model. The "order" of the magnitude of effects did not change (i.e. the Mental Health and Neurological variables had the largest effect for the conditions, as in the main OLS model). The majority of effects for the Survey cross-products were not statistically significant. However, there were exceptions including age, the effect of a recent illness or accident, one of the ethnicity variables (Other), a geographical region (North East) and four of the conditions (Arthritis, Asthma, KLD, Mental Health). The significance of the cross-products suggested that the relationships between these explanatory variables and QoL may not be constant over the two time points. For the geographical region and the four conditions, the differences could have been caused by the introduction of an intervention or health care policy. For the variable recent illness, this could be due to a particularly virulent or disabling virus during the timing of one of the Surveys, but it is less clear why the effect of age may vary across time. In the models obtained

using OLS regression the effect of the Survey is forced to be constant where the actual differences in the relationships could be of a different form.

Including comorbidity as a cross-product with the health conditions, the combined effect associated with having an additional condition was statistically significant for 12 of the 16 conditions. In half the cases the combined effect was smaller than the effect for the condition in the main model. The "order" of the magnitude of effects did not change, but some of the coefficients for the other explanatory variables changed considerably (e.g. the effect for gender was positive as opposed to negative in the main OLS model, suggesting different relationships for the presence of comorbidities).

Including the individual conditions as a cross-product with all explanatory variables, the majority of the cross-product effects were statistically significant in the 15 models (one for each condition). The results showed differing relationships in terms of both magnitude and/or direction for age, gender, and ethnicity (Mixed or Black). In particular, the effect of deprivation increased substantially for some of the conditions, and the combined effects increased the detriment on QoL for the majority of combinations.

Collectively, these results confirm that condition specific models are required to capture differing relationships between the explanatory and dependent variables. In particular, the presence of co-morbidities is likely to produce differences in the effects of the explanatory variables. Survey has a statistically significant effect in its own right, and there appear to be survey dependent relationships for some of the explanatory variables which may differ when used in individual condition models.

3.4.2 Ordered Logistic Regressions

Health dimension model using PPOM (Main PPOMs)

Using PPOM models for each of the five health dimensions (Mobility, Self-Care, Usual Activities, Pain/Discomfort, Anxiety/Depression), while the magnitude and direction of the coefficients differed across the dimensions, the effects for almost all the variables were statistically significant with the exception of the geographical areas and some of the ethnic groups. While the differences for some of these can be explained, for example one might expect the effect of age to differ across either or both dimension and condition, a plausible explanation for other variables (e.g. ethnicity) is elusive. The effects for smoking, recent illness and deprivation had the expected direction (+ve) and increased in magnitude as expected for the "worst" classes in all the models. While the majority of

the effects for the individual conditions were statistically significant, the magnitude and direction of the effects differed substantially across the five models and unlike in the OLS model, the health condition variables did not always have the largest effects. The Survey variable was statistically significant in all models (except Anxiety/Depression) but the direction and magnitude of the effects varied across the dimensions.

Adding cross-products into the main PPOMs to account for the interaction effects with a) Survey, b) comorbidity, or c) an individual condition. The effects of the Survey cross-products were not statistically significant for all variables and were dimension specific. The combined effect for the main explanatory variables and the corresponding Survey cross-product changed both the direction and magnitude of the effect for some of the variables compared to the main models. As in the OLS regressions, the effect of the age and Survey cross-product was statistically significant for two of the health dimension PPOMs (Usual Activities, Pain/Discomfort) and the magnitude of the effect changed substantially for Usual Activities suggesting the difference in the relationship may not be additive. The effects of the cross-products for recent illness or accident were statistically significant for the health dimensions Usual Activities, Pain/Discomfort and Anxiety/Depression. However, the combined effect of the main variable and the cross-products summed to approximately the same as the coefficient for the main variable in the corresponding main PPOM. Several of the effects for the Survey and health condition (Asthma, Deafness, Diabetes, Learning) cross-products were statistically significant. Again these were dimension specific and could change both the magnitude and direction of the effects (compared to the corresponding effect for the health condition in the main PPOM) (e.g. for main PPOM Pain/Discomfort, the KLD Beta=0.1019; while for the cross product PPOM Pain/Discomfort the KLD Beta=0.1681 and Survey*KLD Beta=-0.1496).

Including comorbidity as a cross-product with the health conditions, the majority of cross-products were statistically significant. In general, the combined effect of the individual condition and the comorbidity cross-product summed to approximately the same as the effect of the individual condition in the main model. However, there were exceptions where the effects differed substantially from the main model, particularly for the health dimensions Pain/Discomfort, Self-Care and Usual Activities.

Including the individual conditions as a cross-product with all explanatory variables (75 models, five models for each condition), the magnitude, direction and statistical significance of the effect of the cross-products varied substantially both by condition and health dimension. Few of the effects

of the interactions with the ethnicity, geographical area or Survey variables were statistically significant. Similarly, while the majority of the effects of the interactions with the deprivation variables were not statistically significant, the combined effects frequently changed both the direction and magnitude of the relationships compared to the results in the main models. As in the main PPOM models, the effects of the other four health dimensions were large relative to the effects of the other explanatory variables. Most of the effects of the interactions with the conditions and other health dimensions were statistically significant and the magnitude and directions were condition specific and could change substantially from the effects in the main model.

Collectively, as with the results from the OLS models, these results confirm that condition specific models are required as the relationships between the explanatory variables and the health dimensions vary substantially across the conditions. The effect of the Survey and the interactions between the Survey and other explanatory variables were both dimension and condition specific. Given that the predicted probabilities for the responses on the health dimensions are used to generate expected EQ-5D scores using the EQ-5D preference weights, where different weights are assigned to different response levels, this suggests that Survey may not have a simple linear relationship with EQ-5D.

3.5 Results of the individual condition-specific models

3.5.1 Survey effect

Individual condition specific models were generated using both OLS regressions and PPOMs with Survey included as an explanatory variable. The Survey coefficients for the OLS regressions and the corresponding differences in the observed mean EQ-5D scores (from Survey 0 and Survey 1) were directly comparable for several of the health conditions (Table 5). Specifically, the Survey coefficients in the Arthritis, Blindness, Diabetes, HBP, Back Problem and Mental Health models suggested that the average difference in EQ-5D scores after adjusting for case-mix were as observed. The Survey coefficients in the Angina and KLD models suggested that after adjusting for case-mix, the average differences in EQ-5D scores were smaller than observed. Conversely the coefficients in the Asthma, Cancer, Deafness and Neurological models suggested the average differences in EQ-5D scores were larger than observed. The effect of the Survey was not statistically significant in the Alzheimer, Epilepsy and Learning models, reflecting the non-significant difference in the observed mean scores.

Table 5: Survey coefficients from the condition specific OLS models

	n	Survey coefficient	p-value (regression)	Difference in mean observed EQ-5D scores[#]	P-value (t-test)
Alzheimer	4,993	0.010	0.243	0.017	0.096
Angina	53,547	0.008	<0.001	0.012	<0.001
Arthritis	132,215	0.012	<0.001	0.012	<0.001
Asthma	84,767	0.010	<0.001	0.005	<0.05
Blindness	9,773	0.015	<0.05	0.016	<0.05
Cancer	30,889	0.009	<0.001	0.006	0.057
Deafness	38,380	0.007	<0.01	0.005	0.145
Diabetes	68,706	0.010	<0.001	0.011	<0.001
Epilepsy	8,536	0.009	0.148	0.013	0.098
HBP	191,802	0.010	<0.001	0.010	<0.001
KLD	14,039	0.017	<0.001	0.021	<0.001
Learning	6,246	0.004	0.632	-0.004	0.653
Back Problem	87,388	0.010	<0.001	0.011	<0.001
Mental Health	28,695	0.010	<0.01	0.011	<0.05
Neurological	14,781	0.012	<0.05	0.009	0.138

[#] S1 minus S0

The effect of the Survey is not as simple to interpret in the health dimension models. None of the Survey effects were statistically significant for the conditions Alzheimer and Epilepsy, and only the Anxiety/Depression coefficient was statistically significant ($p<0.05$) for Learning difficulties, concurring with the observed non-significant differences in the mean EQ-5D scores (Table 6). Conversely, for Angina, Diabetes, HBP and Back Problem, the Survey coefficients were statistically significant ($p<0.05$) for three of the dimensions. For the remaining conditions which had a statistically significant difference in observed mean EQ-5D scores, only one or two of the Survey dimension coefficients were statistically significant. In addition, while all the Survey coefficients for Mobility and the majority of the coefficients for Pain/Discomfort (14/15) and Anxiety/Depression (13/15) had the expected negative sign (i.e. decrease the probabilities of scoring level 2 or 3) 12 of the Survey coefficients for Self Care and 5 of the Survey coefficients for Usual Activities had a positive sign.

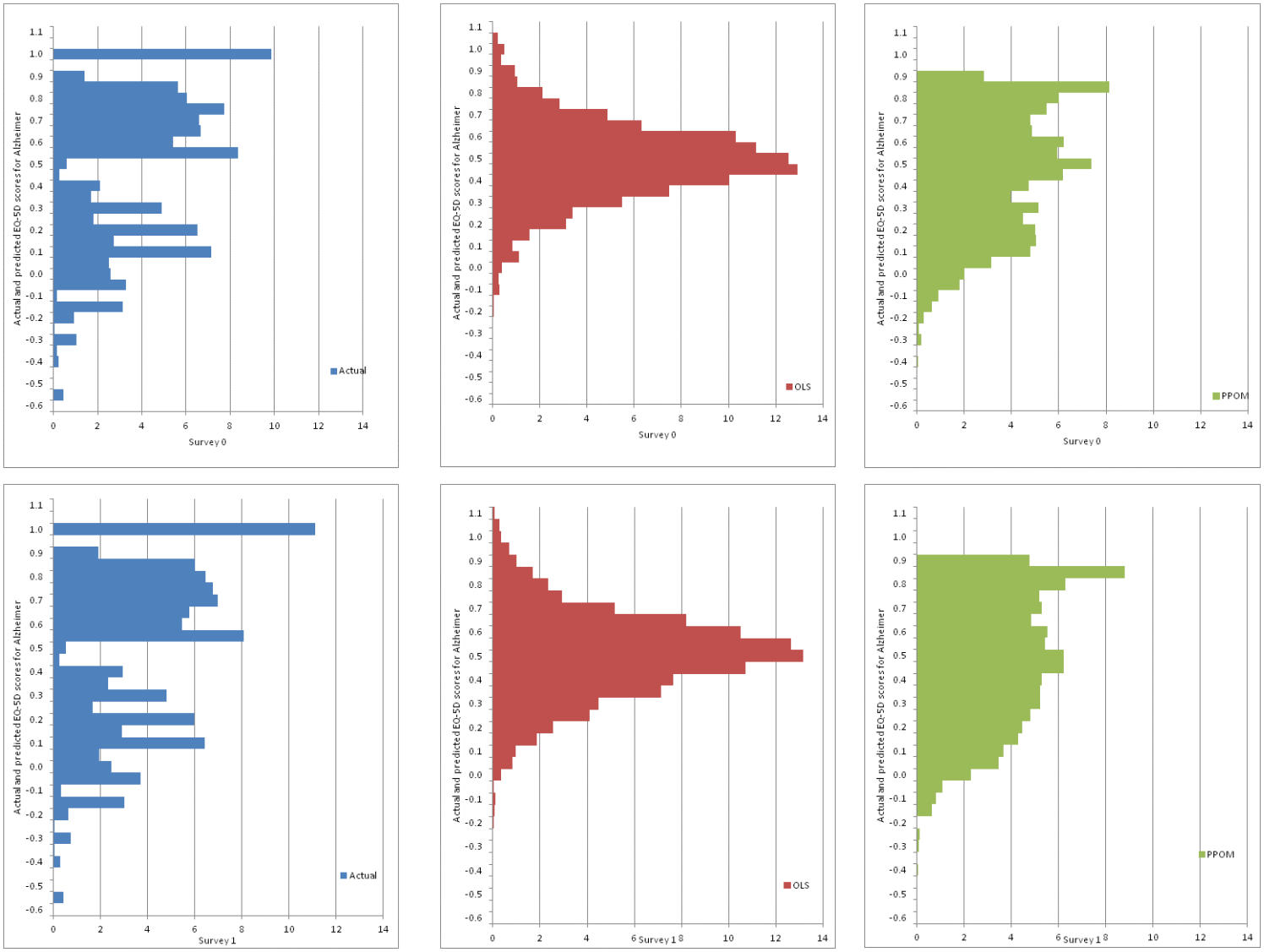
Table 6: Survey coefficients (1st equation) from the condition specific PPOM models

Condition	Probit		Mobility		Self Care		Usual Activities		Pain/ Discomfort		Anxiety/ Depression	
	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p	Beta	p
Alzheimer	Na		-0.035	0.64	-0.064	0.34	0.042	0.53	-0.077	0.22	-0.059	0.32
Angina	Na		-0.055	<0.05	0.008	0.76	-0.084	<0.001	-0.047	<0.05	-0.006	0.78
Arthritis	Na		-0.075	<0.001	0.022	0.17	-0.025	0.06	-0.139	<0.001	-0.018	0.15
Asthma	0.048	<0.001	-0.098	<0.001	0.009	0.72	-0.013	0.51	-0.101	<0.001	-0.024	0.16
Blindness	Na		-0.094	0.12	-0.019	0.70	0.015	0.75	-0.117	<0.05	-0.009	0.83
Cancer	0.040	<0.05	-0.032	0.36	0.044	0.27	-0.025	0.41	-0.077	<0.05	-0.018	0.51
Deafness	0.089	<0.001	-0.020	0.53	0.046	0.14	-0.065	<0.05	-0.123	<0.001	-0.032	0.18
Diabetes	0.073	<0.001	-0.087	<0.001	0.027	0.29	-0.042	0.05	-0.049	<0.05	0.008	0.68
Epilepsy	0.044	0.18	-0.047	0.49	0.060	0.37	-0.045	0.44	-0.028	0.62	-0.027	0.60
HBP	Na		-0.089	<0.001	0.005	0.79	-0.036	<0.05	-0.068	<0.001	-0.003	0.82
KLD	Na		-0.047	0.37	0.044	0.37	-0.098	0.06	-0.113	<0.001	0.010	0.78
Learning	-0.010	<0.001	-0.099	0.15	-0.021	0.74	0.013	0.84	0.017	0.78	-0.153	<0.05
Back Problem	Na		-0.081	<0.001	0.050	<0.05	-0.002	0.90	-0.062	<0.001	-0.008	0.57
Mental Health	Na		-0.076	<0.05	0.058	0.09	-0.042	0.13	-0.020	0.45	-0.004	0.87
Neurological	Na		-0.089	0.06	0.085	<0.05	0.017	0.67	-0.095	<0.05	-0.042	0.22

3.5.2 Distributions of actual and predicted EQ-5D scores

The distributions of the actual and predicted/estimated EQ-5D scores were plotted to assess how well the models captured the idiosyncrasies of the underlying data. As can be seen in the exemplar charts (Figure 3 with additional examples provided in Appendix), neither approach was able to accurately mirror all the characteristics observed in the actual distributions. However, it is clear that the data generated using the response mapping (PPOM and PPOM-2p) reflected the observed distributions more accurately than those generated using the results of the OLS regressions.

Figure 3: Actual and predicted EQ-5D scores for respondents with Alzheimer



4 DISCUSSION

The objective of the research described in this paper was to develop an alternative methodological approach to analyse potential differences in QoL over time in patients with long-term health conditions building on exploratory analyses presented in an earlier report. The approach initially proposed was modified by incorporating separate equations for the level two and three responses in the logistic models. Where appropriate two part models were also used whereby a probit model was used to account for the patients who scored full health, prior to obtaining PPOM models for patients who indicated they had problems on at least one of the health dimensions.

While the OLS approach predicted mean scores well (by definition this is what the methodology seeks to achieve), the individual predictions from these models did not represent the underlying observed distribution, as demonstrated graphically. This will be problematic if observed values in future surveys are to be adjusted using values predicted from models fit to data collected in earlier surveys and will introduce some substantial errors in the calculations. These errors may be systematic in that they are likely to differ in magnitude and direction at the extremes of the data.

The OLS approach also appeared to capture the average effect of the survey round for many of the conditions, but as indicated by both the exploratory analyses and the health dimension models, the effect of the Survey may not take a simple additive form for all the explanatory variables and the effect varied considerably across both the health dimensions and conditions.

While not perfect, the PPOM approach produced a more accurate representation of the underlying data. However, more importantly, it allows one to examine which aspects (dimensions) of QoL have changed across the surveys and thus where potential interventions could be targeted to improve the QoL for patients living with these long-term health conditions. For example, the results of the PPOM analyses presented in this paper suggested that there was deterioration in Self Care and Usual Activities for many of the health conditions in the second survey. Finally, as the PPOM methodology does not require the fundamental assumptions of the OLS regressions, this increases confidence in the coefficients obtained.

The GPPS data provides a valuable source of data which can be used to inform of potential changes in quality of life for patients with long-term health conditions. To our knowledge it is the largest source of this kind of data in the UK and while there are obvious limitations, including the cross-sectional survey design, these data will provide valuable information which could be used to inform

and support future policy decision making for these patients. However, the cross-sectional design is important and requires additional thought when considering differences in mean scores over time. The analyses in this paper were performed on data collected in two consecutive surveys and it may not be appropriate to directly compare these data.

4.1 Issues & future research

There are several issues that we have not addressed in this study that we would address in future work. First, because of the differences in the times of year the Surveys were conducted, we are not convinced that we are comparing like with like and it will be interesting to examine whether there are differences in QoL when comparing data collected at the same point in the year. We would hope to rerun the current analyses using data collected at the same point of the year in consecutive years as opposed to consecutive surveys. We would also like to compare results when generating models on the first survey data and predicting values for the second survey which we felt was not appropriate with the current dataset for several reasons including the statistical significance of the effects of the interactions between some of the explanatory variables and the Survey variable.

Secondly, we would like to conduct additional analyses whereby the OLS regression incorporate fixed effects for some of the variables as suggested in a meeting with analysts from the DH in 2012. This would enable us to directly compare the results of our proposed methodology with those generated using the approach currently taken by the DH analysts. This would require clarification of the exact methodology used and potential changes to the explanatory variables we have used in the current paper.

Thirdly, we currently generate the PPOM models independently for the five health dimensions and we would hope to develop the approach further to account for any potential conditional probabilities. If this were to be informative, we would also suggest that our approach could be expanded to incorporate provider variables. In the current analyses we used graphical areas as potential proxies for providers but we appreciate that these are probably not informative for local policy decision making. Finally the issue with potential differences in the GP practices involved in the Surveys requires additional exploration.

APPENDIX

Table A1: Socio-demographic characteristics sub-grouped by condition and survey

	ALZHEIMER		**ANGINA**		**ARTHRITIS**		**ASTHMA**		**BLINDNESS**		**CANCER**		**DEAFNESS**		**DIABETES**	
Survey	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1
N	2516	2477	27274	26273	68288	63927	43850	40917	5007	4766	15557	15332	19641	18739	35223	33483
Age (weighted average)	76.9	76.6	71.2	71.3	67.7	67.8	56.7	57.5	73.2	73.1	67.7	67.7	72.3	72.6	65.7	66.0
Male (%)	44.0	44.3	60.3	61.4	37.1	37.4	41.5	41.4	42.5	42.4	50.3	50.2	52.8	53.3	56.4	57.0
Never Smoke (Base)	50.3	49.4	37.1	37.5	44.8	45.0	43.5	44.8	46.4	46.8	43.2	43.9	43.4	44.1	43.9	43.6
Former Smoke	39.2	41.3	49.8	50.5	39.8	40.6	36.8	37.7	39.0	39.7	44.4	44.9	43.7	44.1	41.9	43.1
Occasional Smoke	3.5	3.2	5.2	4.8	5.7	5.4	7.5	6.3	5.2	4.8	5.3	4.5	4.6	4.4	5.1	4.9
Regular Smoke	7.1	6.1	7.9	7.2	9.8	9.1	12.2	11.2	9.4	8.6	7.2	6.7	8.3	7.4	9.1	8.4
Recent Ill Lot	12.8	12.3	9.3	10.2	9.8	10.7	7.6	9.2	12.4	12.9	7.6	8.6	8.5	9.9	8.0	8.5
Recent Ill Little	15.3	16.5	20.2	22.6	21.0	24.5	18.2	22.1	20.3	21.8	17.8	20.9	19.5	22.8	18.3	21.2
Not limited (Base)	71.9	71.2	70.5	67.2	69.3	64.8	74.2	68.8	67.3	65.3	74.6	70.5	72.0	67.3	73.7	70.3
White (Base)	91.0	91.5	93.5	94.2	92.8	93.9	90.9	92.1	89.5	91.0	95.0	95.7	95.7	96.1	83.2	85.1
Mixed	0.4	0.2	0.2	0.3	0.4	0.3	0.8	0.7	0.5	0.4	0.3	0.2	0.3	0.3	0.5	0.5
Asian	4.5	3.5	3.9	3.5	3.6	3.1	4.7	3.9	5.0	4.3	2.1	1.8	2.4	2.1	9.6	8.6
Black	1.4	1.7	0.8	0.7	1.6	1.4	1.8	1.6	2.8	2.3	1.2	1.1	0.7	0.5	3.5	2.9
Other	2.8	2.7	1.5	1.4	1.6	1.3	1.8	1.6	2.2	2.0	1.3	1.2	1.0	1.1	3.3	2.9
Most Deprived	37.4	34.6	36.6	32.5	37.7	34.5	38.4	35.0	42.3	38.4	28.7	26.5	35.9	32.4	40.7	37.1
Moderately Deprived	33.8	35.2	34.3	35.1	33.8	34.8	32.8	34.1	33.0	33.6	34.8	35.3	34.0	35.0	33.1	34.4
Least Deprived (Base)	28.8	30.2	29.2	32.5	28.5	30.7	28.9	30.9	24.8	28.0	36.5	38.3	30.1	32.6	26.2	28.5

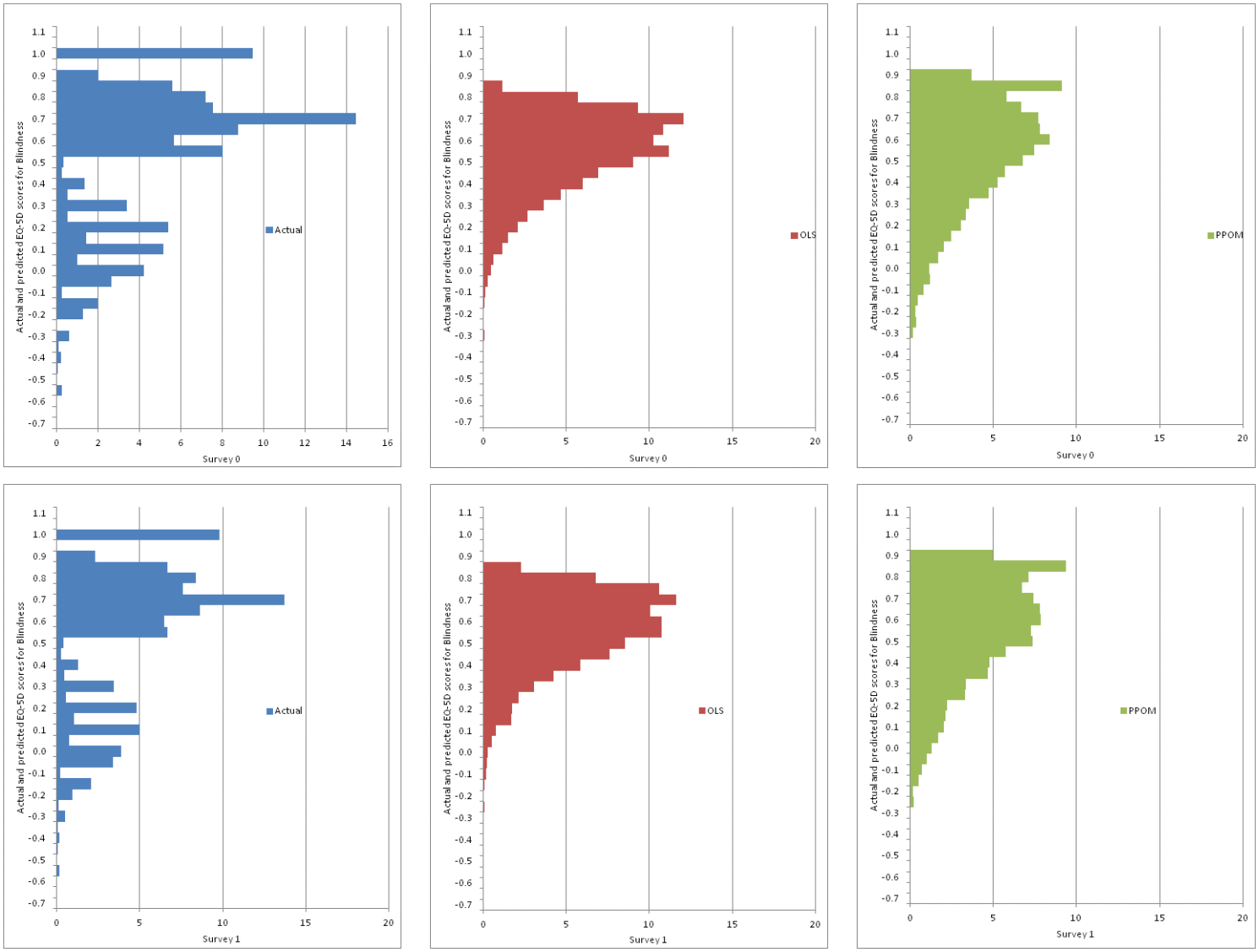
	ALZHEIMER		ANGINA		ARTHRITIS		ASTHMA		BLINDNESS		CANCER		DEAFNESS		DIABETES	
East Midland	8.0	7.6	7.8	8.0	8.0	7.8	7.8	7.9	7.7	7.9	7.7	7.8	8.1	7.7	7.8	7.8
East England	9.1	8.5	9.2	9.6	9.3	9.7	9.9	9.9	9.4	8.4	10.7	10.8	9.6	10.1	8.8	9.5
London (Base)	16.1	15.4	12.2	12.0	13.1	12.5	14.5	14.0	15.8	15.2	14.2	13.4	11.3	10.7	18.1	17.4
North East	5.5	4.8	6.6	6.3	6.5	6.4	5.5	5.3	4.9	5.4	5.2	5.1	6.6	6.4	5.2	5.0
North West	16.6	16.7	18.1	17.5	17.9	17.9	17.0	16.7	16.6	16.9	15.3	15.4	18.0	17.8	16.2	16.4
South Central	5.8	7.1	5.6	5.8	5.2	5.4	6.3	6.5	5.8	5.9	6.4	6.5	5.9	6.0	5.6	5.4
South East Coast	7.6	8.6	7.6	7.8	7.4	7.6	7.4	7.9	7.2	7.9	8.8	9.0	7.7	7.8	7.3	7.5
South West	9.4	8.9	9.9	10.2	9.5	9.7	9.7	10.2	9.2	10.0	10.6	11.1	10.1	10.4	8.7	8.8
West Midland	11.6	11.1	11.9	11.7	12.5	12.5	11.6	11.7	12.8	12.6	11.4	11.1	12.0	12.1	12.4	12.3
Yorkshire	10.3	11.2	11.2	11.2	10.8	10.6	10.4	10.1	10.6	9.8	9.7	9.7	10.7	10.9	9.9	9.8
Alzheimer			2.0	2.3	1.1	1.1	0.7	0.8	4.4	4.5	1.1	1.3	2.6	2.6	1.1	1.3
Angina	21.6	24.1			14.4	14.5	10.0	9.9	21.2	22.5	11.6	11.4	19.3	19.5	15.9	15.8
Arthritis	29.7	29.2	36.1	35.2			25.8	25.5	40.3	40.0	23.3	22.9	40.3	39.5	26.8	25.8
Asthma	11.9	13.2	16.1	15.4	16.6	16.3			18.0	18.8	11.0	10.7	16.4	16.2	12.3	12.4
Blindness	8.8	8.6	3.9	4.1	3.0	3.0	2.1	2.2			2.7	2.7	7.6	7.6	2.9	2.9
Cancer	6.8	8.0	6.6	6.7	5.3	5.5	3.9	4.0	8.4	8.8			7.2	8.0	5.4	5.6
Deafness	20.5	19.3	13.9	13.9	11.6	11.6	7.4	7.4	29.7	30.0	9.1	9.8			8.0	8.4
Diabetes	15.5	16.9	20.5	20.1	13.8	13.5	9.9	10.2	20.5	20.3	12.3	12.2	14.4	15.0		
Epilepsy	3.9	3.4	1.5	1.3	1.2	1.3	1.3	1.4	3.4	3.3	1.4	1.3	1.7	1.8	1.4	1.4
HBP	33.0	33.8	46.7	45.4	40.7	40.3	26.5	26.6	43.5	43.1	33.3	33.4	40.5	40.9	49.7	49.6
KLD	5.1	5.5	5.1	5.4	3.5	3.5	2.6	2.5	6.8	6.8	4.3	4.6	4.1	4.3	4.7	4.7
Learning	3.5	3.1	0.9	0.8	0.9	0.8	1.3	1.2	3.8	3.6	0.7	0.6	1.8	1.8	1.1	1.0
Back Problem	13.8	12.8	19.5	18.7	28.1	27.6	16.6	16.5	19.9	20.8	13.3	13.4	22.0	22.1	15.2	14.6
Mental Health	9.1	9.5	3.4	3.2	4.6	4.8	5.5	5.7	6.1	5.9	2.8	2.8	4.2	4.3	4.1	4.2
Neurological	5.6	5.6	2.9	2.7	3.0	3.2	2.2	2.5	6.1	6.0	2.6	2.5	3.3	3.4	2.6	2.5
Another	11.9	12.9	12.1	12.1	15.5	15.5	14.1	14.4	16.6	16.2	11.0	11.0	15.8	16.3	11.4	11.4
Single condition	22.5	20.5	19.2	19.8	21.8	22.3	38.5	38.2	12.0	10.8	32.9	32.4	16.2	15.6	24.4	24.5
Co-morbidity	77.5	79.5	80.8	80.2	78.2	77.7	61.5	61.8	88.0	89.2	67.1	67.6	83.8	84.4	75.6	75.5

Table A1: Socio-demographic characteristics sub-grouped by condition and survey (continued)

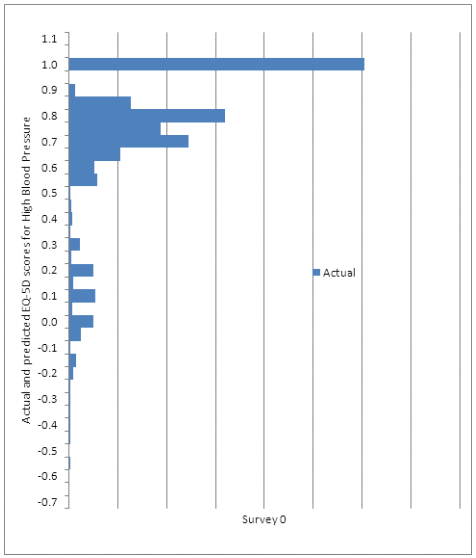
	EPILEPSY		HBP		KLD		LEARNING		BACK PROBLEM		MENTAL HEALTH		NEUROLOGICAL	
Survey	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1	S0	S1
N	4343	4193	98198	93604	7186	6853	3277	2969	44991	42397	14679	14016	7457	7324
Age (weighted average)	54.3	54.9	66.9	67.1	63.9	64.2	45.0	44.7	61.0	61.3	50.5	50.9	59.1	59.2
Male (%)	47.6	47.0	47.7	48.4	52.8	52.4	57.0	56.0	43.9	44.1	41.6	40.4	44.8	45.1
Never Smoke (Base)	50.2	51.7	47.5	47.7	42.5	41.9	61.0	62.9	42.6	42.9	38.0	39.2	45.2	45.3
Former Smoke	28.3	27.2	39.7	40.3	39.2	40.8	15.2	14.3	36.2	37.2	26.2	27.1	33.7	35.4
Occasional Smoke	6.7	6.9	4.7	4.5	6.5	5.8	7.3	6.5	7.3	6.9	9.5	9.3	7.3	7.2
Regular Smoke	14.8	14.1	8.2	7.6	11.8	11.5	16.6	16.4	13.9	13.0	26.4	24.4	13.9	12.1
Recent Ill Lot	9.2	9.4	6.0	6.5	13.5	13.3	10.3	11.3	10.9	11.9	12.1	12.9	14.2	16.2
Recent Ill Little	17.6	20.3	15.8	18.8	21.2	23.5	18.3	20.6	22.0	25.1	20.5	23.2	19.9	21.3
Not limited (Base)	73.2	70.3	78.2	74.7	65.3	63.3	71.5	68.1	67.1	62.9	67.4	63.9	66.0	62.6
White (Base)	91.7	92.9	90.3	91.5	87.3	88.0	84.1	85.4	89.7	91.0	91.0	91.7	90.6	91.7
Mixed	0.7	0.5	0.4	0.4	0.4	0.4	1.6	1.3	0.7	0.5	1.1	1.0	0.7	0.5
Asian	3.8	3.4	4.7	4.1	6.7	6.0	6.5	5.7	4.9	4.2	3.8	3.3	4.4	3.5
Black	1.8	1.6	2.8	2.5	2.4	2.1	3.0	3.3	2.1	1.9	1.7	1.7	2.0	1.9
Other	1.9	1.7	1.9	1.6	3.1	3.4	4.8	4.3	2.7	2.3	2.4	2.2	2.3	2.4
Most Deprived	43.4	38.7	34.6	31.5	42.4	39.1	54.1	49.4	39.2	36.1	47.8	44.1	36.5	33.4
Moderately Deprived	32.0	32.8	34.2	34.9	32.2	34.0	29.3	30.7	33.3	34.1	30.2	31.6	33.5	35.0
Least Deprived (Base)	24.7	28.5	31.3	33.7	25.5	26.9	16.6	19.9	27.5	29.8	22.0	24.3	30.1	31.7

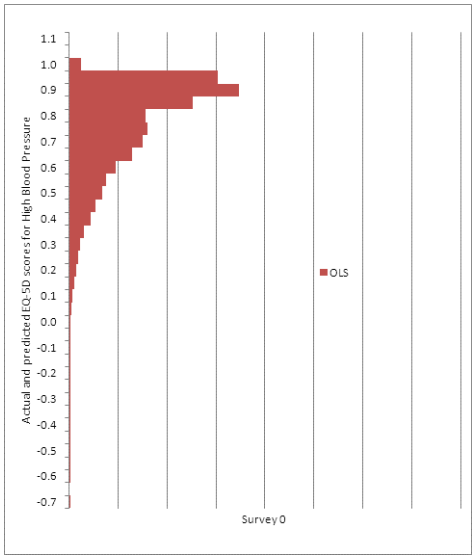
	EPILEPSY		HBP		KLD		LEARNING		BACK PROBLEM		MENTAL HEALTH		NEUROLOGICAL	
East Midland	7.6	7.7	7.7	7.8	7.8	8.0	7.6	7.1	7.6	7.8	7.6	7.9	7.7	7.8
East England	9.0	10.0	9.7	10.0	8.9	8.7	7.8	8.9	9.5	9.5	9.1	9.2	10.1	10.1
London (Base)	15.1	14.7	15.7	15.2	18.3	18.2	19.5	17.3	15.6	15.4	15.6	15.4	16.5	17.2
North East	5.6	5.2	5.6	5.3	5.3	5.3	5.3	5.2	6.1	5.9	6.2	5.8	5.2	5.0
North West	16.1	16.8	16.1	16.0	16.8	16.7	15.9	16.9	16.7	16.9	17.7	17.8	16.3	16.4
South Central	5.9	5.7	5.9	6.0	5.0	5.2	5.0	5.8	5.8	5.7	5.8	6.0	5.9	5.5
South East Coast	7.2	7.6	7.8	8.2	7.4	7.7	7.9	8.0	7.7	8.0	7.2	7.2	8.2	8.6
South West	9.0	9.6	9.4	9.6	9.3	9.7	8.9	9.1	9.4	9.5	8.6	9.2	9.6	9.6
West Midland	13.4	12.6	12.1	12.1	11.5	11.1	12.2	12.1	11.7	11.4	11.5	11.2	10.9	10.2
Yorkshire	11.3	10.1	10.0	9.7	9.7	9.5	9.9	9.8	10.0	9.9	10.9	10.4	9.7	9.6
Alzheimer	2.3	2.0	0.9	0.9	1.8	2.0	2.7	2.6	0.8	0.8	1.6	1.7	1.9	1.9
Angina	9.3	8.2	13.0	12.8	19.3	20.5	7.7	7.3	11.8	11.6	6.3	6.1	10.6	9.8
Arthritis	18.9	19.3	28.3	27.5	33.1	32.2	17.8	17.2	42.6	41.7	21.3	21.7	27.6	28.0
Asthma	13.4	13.6	11.8	11.6	16.1	15.1	17.5	16.8	16.2	16.0	16.4	16.6	13.0	13.9
Blindness	3.9	3.7	2.2	2.2	4.8	4.7	5.8	5.8	2.2	2.3	2.1	2.0	4.1	3.9
Cancer	4.8	4.7	5.3	5.5	9.2	10.3	3.1	3.0	4.6	4.9	2.9	3.1	5.4	5.3
Deafness	7.6	8.0	8.1	8.2	11.1	11.6	10.9	11.0	9.6	9.8	5.6	5.8	8.7	8.7
Diabetes	11.0	11.1	17.8	17.7	23.0	23.0	11.7	11.1	11.9	11.5	9.8	10.1	12.1	11.6
Epilepsy			1.1	1.1	2.5	2.5	12.6	12.7	1.3	1.3	2.7	2.5	6.2	5.7
HBP	24.9	25.5			51.9	51.8	19.4	20.0	33.8	33.7	20.4	20.9	29.1	29.3
KLD	4.1	4.0	3.8	3.8			4.9	5.1	3.5	3.4	3.5	3.7	4.2	4.1
Learning	9.5	9.0	0.7	0.6	2.2	2.2			1.4	1.4	5.0	4.9	3.0	3.0
Back Problem	13.3	13.2	15.5	15.2	21.8	20.8	18.7	19.7			21.1	21.4	26.4	27.1
Mental Health	9.2	8.2	3.1	3.1	7.2	7.5	22.3	23.0	6.9	7.1			10.7	10.5
Neurological	10.6	10.0	2.2	2.3	4.4	4.4	6.9	7.3	4.4	4.7	5.4	5.5		
Another	15.2	14.5	13.4	13.5	16.2	16.7	16.2	16.8	16.7	16.6	16.2	15.9	17.6	18.8
Single condition	33.7	33.2	33.5	33.8	15.7	15.6	30.5	28.2	24.1	24.3	36.0	35.7	28.2	28.1
Co-morbidity	66.3	66.8	66.5	66.2	84.3	84.4	69.5	71.8	75.9	75.7	64.0	64.3	71.8	71.9

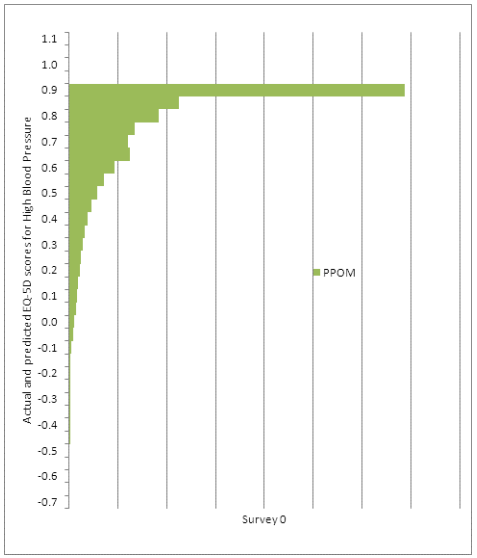
Figure A1: Actual and predicted EQ-5D scores for respondents with Blindness

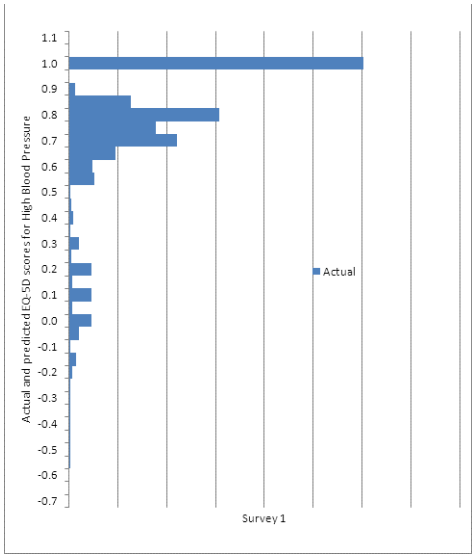


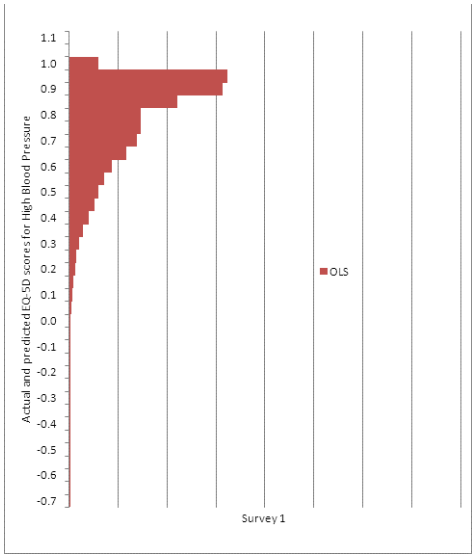
Actual and predicted EQ-5D scores for respondents with HBP

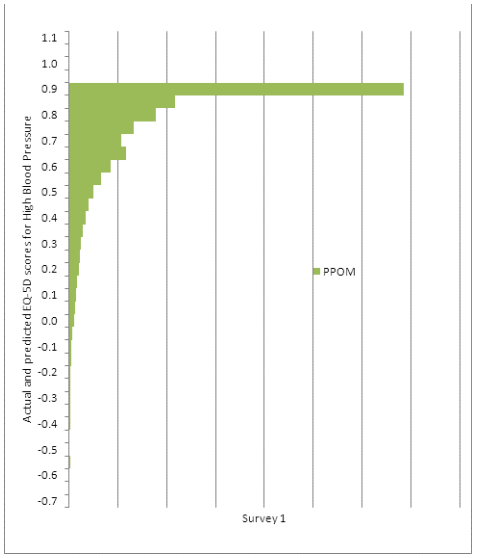




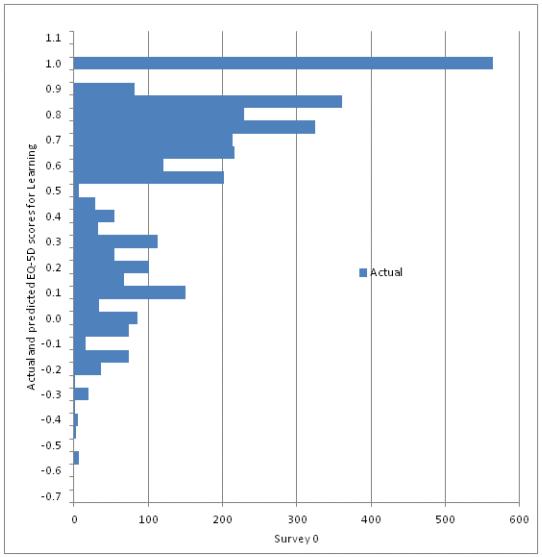


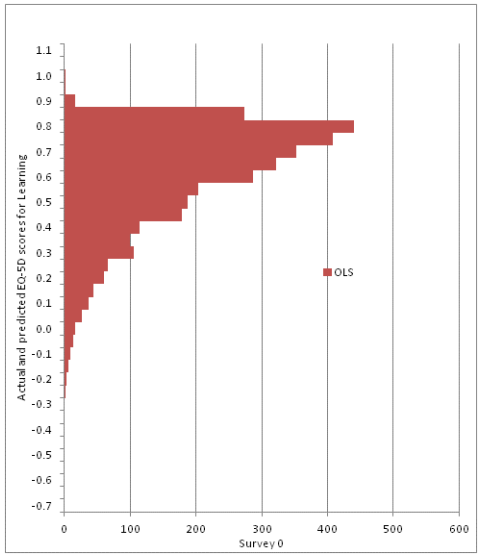


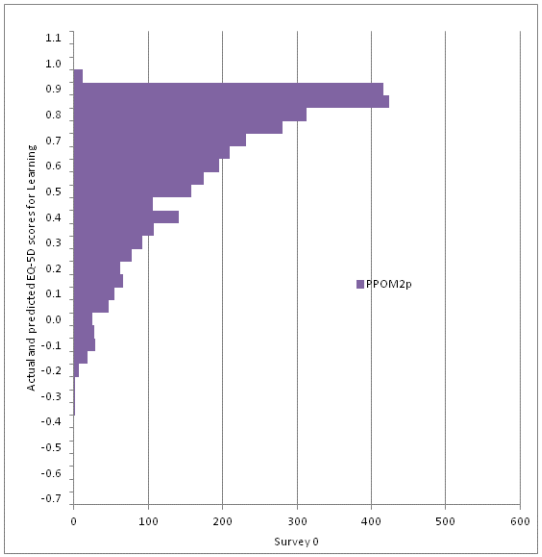


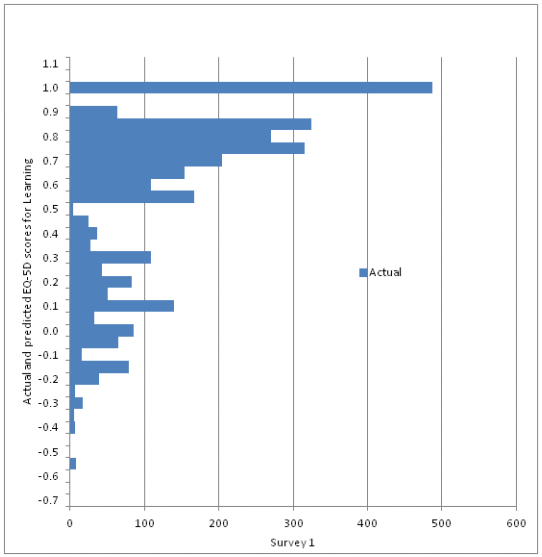


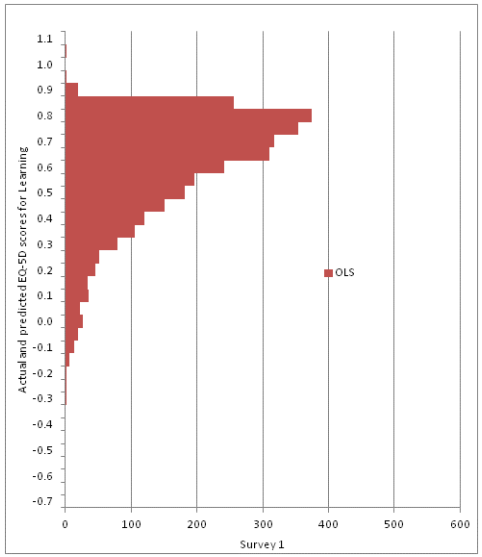
Actual and predicted EQ-5D scores for respondents with Learning

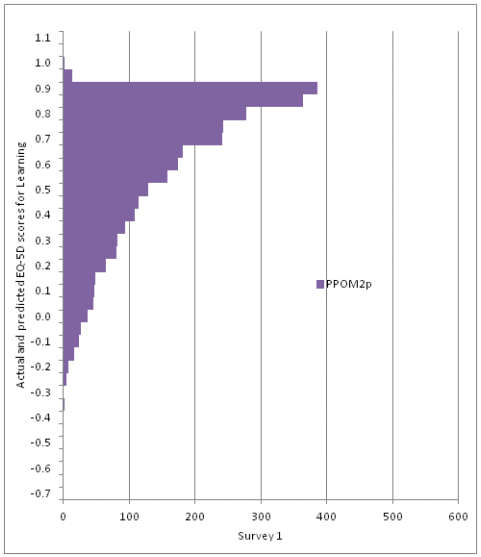




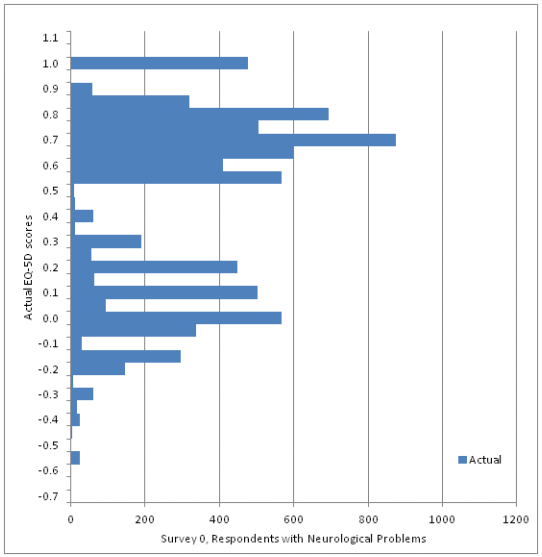


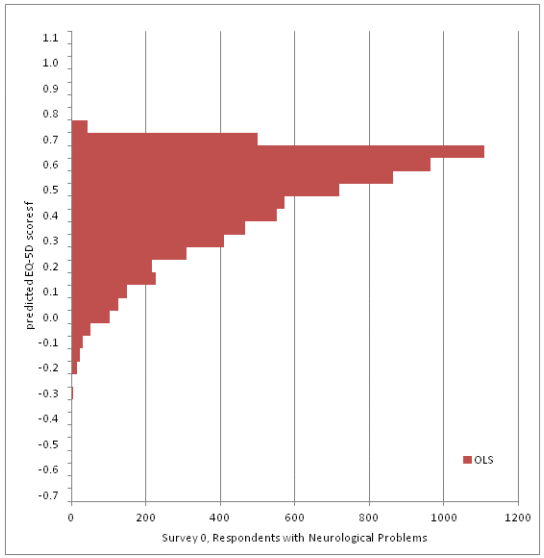


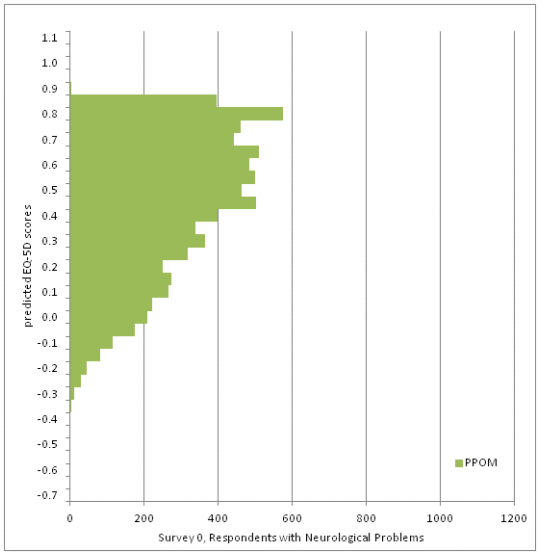


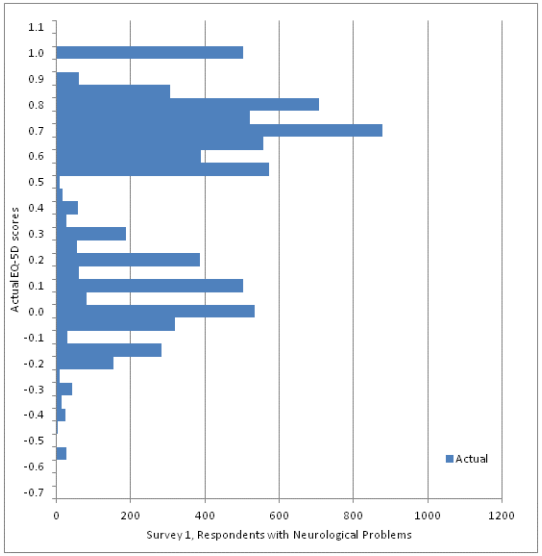


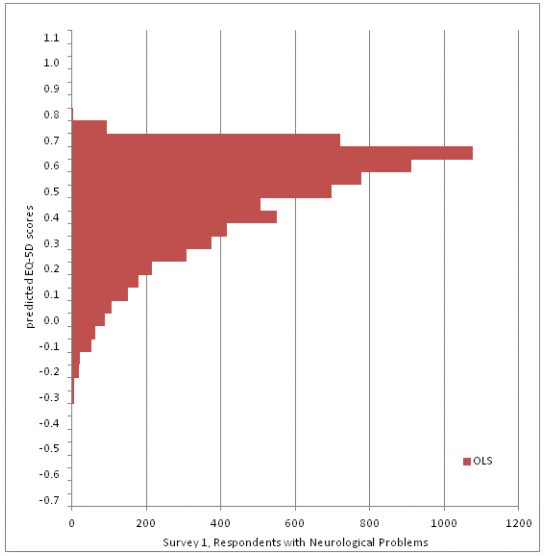
Actual and predicted EQ-5D scores for respondents with Neurological

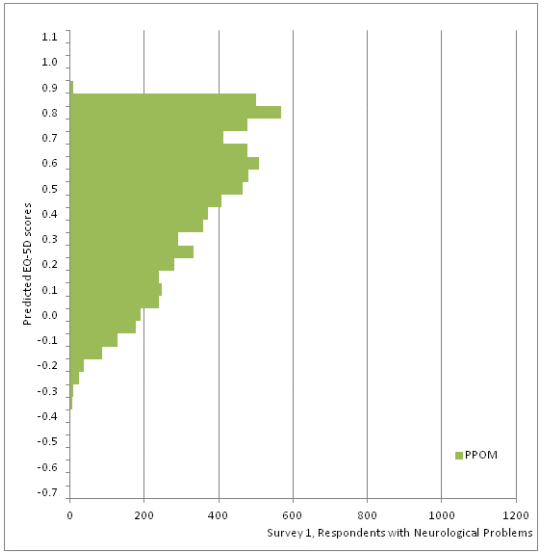












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