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Developing a PBRA formula for allocations in 2012/13

Update for ACRA

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Summary

Final Models

- PBRA3 models explain around 15% of the variation in next year's costs at person level and 86% of the variation at practice level. This is slightly better than the results for PBRA2.

- Models using person-based needs variables and area-based (attributed) needs variables perform better than models only using area-based (attributed) needs variables.

- Person-based need variables (morbidity) have been refined in PBRA3 relative to PBRA2. In PBRA3 models the following improved the goodness of fit of the models:
    - using only the first six diagnostic fields to define morbidity flags
    - a count of morbidities as well as the morbidity flags
    - interaction terms for morbidities in different ICD chapters along with morbidity counts (increases the goodness of fit only slightly . However it ensures that none of the morbidity flags are negative and statistically significant).

- Other person based variables that could plausibly signify need that were tested and if included improved model fit were: a new variable to denote if a patient was newly registered in a practice; and (as in the case of PBRA2) whether the person had used privately funded care within NHS facilities in the previous two years.

- Using age-stratified models (different models for 3 age groups (0-14,15-64,65+) increases the model complexity but also improves the model fit and leads to a plausible pattern of coefficients on attributed needs.

- Over 300 attributed needs and supply variables were tested in PBRA3 including a number that were not tested in PBRA2

- Provider dummy variables did add to the explanatory power of the model but they were not strongly correlated with the other variables (so freezing them had little impact on practice needs). They were therefore dropped from the analysis.

- Running updated data (2009/10 dependent variable, morbidity variables from 2008/09 and 2007/08 and updated attributed needs and supply variables) through PBRA2 models results in similar but slightly better performance compared to PBRA2 models using older data (2007/08 for the dependent variable and 2006/07 and 2005/06 and not updating the attributed variables).

- The effect of a range of different PBRA3 models on expected costs relative to observed costs per practice in 2009/10 was very similar. We will report on risk sharing analyses separately.

Key decisions/choices

In selecting a preferred PBRA3 model we suggest:

- The adoption of Model 9b which differs from PBRA2 models in that it:
  - Uses up to six diagnoses to assign a binary morbidity flag
  - Adds a variable with the count of the number of morbidities
  - Adds morbidity interaction variables based on ICD chapters
  - Uses different coefficients for three age bands (0-14,15-64,65+)
  - Uses a wider set of attributed needs and supply variables

- Adopting age -stratified models

- Adopting models in which attributed needs variables are dropped if they are not statistically significant for a particular age group

- The proportion from black and minority ethnic groups has a negative coefficient in the all-age model and the model for ages 15-64 years. It has a positive and significant coefficient in the model for ages 0-14 years. We propose that the negative coefficients should be interpreted as an indication of differentially met need and that its effect should not be included when calculating needs-based predictions at practice level.
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- The variable to indicate whether a practice is serving significant population of students to be the proportion of the practice registered list aged 20-24 (as a continuous variable). This recommendation was reached after empirical testing and avoids cliff-edges, so that the calculations can be easily updated for practices that merge and de-merge.

Background

This project has two main aims. The first is to develop an improved person-based resource allocation (PBRA) formula for the NHS in England, based more on the health needs of individual patients, for allocations in 2012/13 from PCTs or PCT clusters to their constituent practices. We are assuming that the CARAN formula will apply to PCTs or PCT clusters in 2012/13.

The second is to begin to develop an empirical basis for sharing financial risk amongst commissioning entities in the NHS - between the proposed NHS Commissioning Board and Clinical Commissioning Groups (CCGs) and between CCGs and their constituent practices - and thus make suggestions on how financial risks might best be mitigated.

The scope of the formula covers allocations for inpatient care, outpatient care, and A&E care. It excludes funding for mental health and maternity care. It also excludes funding for the care of individuals in the following categories: unregistered, homeless, members of the armed forces – we were asked to advise on allocations for individuals in these categories outwith the PBRA formula.

Both arms of the project use electronic data that are routinely collected on each unique individual using the NHS (in a way which protects patient confidentiality), on the supply of health services available to the individual, and on the characteristics of the community in which the individual lives. In arm 1, using these data, statistical models have been developed which predict the cost of hospital care of individuals in the next financial year. The greater the health needs of the individual, the greater the likely future cost of hospital care. These models can then be used to predict the expenditure on hospital care for all the patients registered with each general practice in England. From these models, a 'weighting' for each practice in a primary care trust based on the need of the registered population is generated - the higher the weighting the higher the share of the PCT commissioning budget will go to the practice.

In arm 2, the models have been used to predict expected costs in practices (or PCTs or shadow consortia) in the next financial year. This was compared with an estimate of ‘actual’ costs by these entities for the same year. The impact of a variety of approaches to risk sharing have been investigated, for example by ‘carving out’ the costs of specific services (eg specialised services), by increasing the population size covered by the commissioning entity, by extending the breakeven period of a budget beyond one year, or by modeling a ‘stop-loss’ arrangement whereby practices are at risk to a maximum ceiling of cost per year for each patient (eg £20K).

The PBRA3 project began in October 2011 and included work to:

1. Update the existing ‘PBRA2’ methodology using the most recently available data (completed Nov 2010)
2. Develop an improved ‘PBRA3’ formula for use in allocations to practices in 2012/13)
3. Develop and model options for risk sharing approaches that could be used by practices and shadow Consortia (by Sept 2011)
4. Suggest broad options for resource allocation for unregistered populations (by Sept 2011).

This note updates ACRA on 2. It does not describe work we have done (are doing) in relation to:

- Updating PBRA2 needs estimates
- Undertaking risk analysis
- Analysis of unregistered populations and the generation of small area files
- Creation of allocation outputs from PBRA3 using new models
- Definition of specialised services.

The final report will include the full analyses in these areas.

Broad modeling strategy and results

Previous briefings to ACRA (see PBRA3 note June 2011) have outlined the approach taken to develop the models (these are not repeated here). This section summarises the measures used to assess performance of the models, the broad modeling strategy, the main models that have emerged and their performance. All models shown below use 2009/10 as the dependent variable, and draw person-level needs variables from the two preceding years.

All PBRA3 models exclude specialized services, mental health and maternity care. All PBRA3 models include critical care costs in the dependent variable and A&E costs. All PBRA3 models truncated costs at £100K – this means that all costs per person (in the dependent variable) were included up to 100K, but excluded after that ceiling, but all morbidity variables that related to these high cost patients were included. The models refer to people registered in any general practice in England as of 1st April 2009. The models exclude all practices with a registered list size of 1000 or less. The above also applied to PBRA2 models rerun with updated ('PBRA3') data to allow the necessary comparisons.

Measures of performance

The relative performance of different models was measured using a range of metrics estimated at person and practice level (Table 1).

Table 1 Goodness of fit and redistribution metrics calculated for each model

Level of analysis	**Person level**	**Practice level**
Samples	Estimation sample Validation sample	Practice sample
Goodness of fit measures	R-squared Mean Absolute Prediction Error (MAPE) for: • all persons • zero cost persons • deciles of non-zero cost persons	R-squared Mean Absolute Prediction Error (MAPE) for: • all practices • deciles of observed costs within 10%
Redistribution measures	-	Redistribution Index (RI) Mean Absolute Percentage Change In Share (MAPCIS) Percentage of Practice Shares Substantially Affected (PopShaSA)

The **R-squared** statistic measures the amount of variation in the dependent variable that is explained by the model (better models have higher R2 values:.

The **mean absolute prediction error (MAPE)** measures the average absolute difference between observed cost and the expected (predicted) cost. Better models have a lower MAPE. The 'within

10%' measure represents the proportion of expected (predicted) values that lie within 10% of the observed values. Better models have a higher value on the 'within 10%' measure.

Within the practice sample, we also include statistics which can be used to compare against a base model. These statistics indicate how material the impact of including specific variables will be on the target shares of resources for each practice. These metrics require a reference model for comparison. The **redistribution index** (RI) is the percentage of total resources that would be reallocated from the 'losers' to the 'gainers'. The **mean absolute percentage change in share** (MAPCIS) summarises the average magnitude of the changes in practice shares. The **percentage of practices shares substantially affected** (PoPShaSA) shows how many practices have their shares changed by more than 5%.

Analysis of person-level variables

In previous papers to ACRA on PBRA3, we presented findings on testing models using different person-level variables. We concluded that it was appropriate to include in models:

- 37 binary variables for 38 age-sex categories (omitted category is male, <1 years old)
- binary **diagnostic flags** to denote if a recorded inpatient diagnosis was in one of 150 diagnostic groups developed by the NHS Information Centre
- 5 binary variables for morbidity counts of: 2; 3; 4; 5; 6+.

We then investigated the impact of adding in other variables that may denote person-level need: interaction terms (32 interactions terms between ICD-10 main chapters the number of diagnoses recorded); use of privately funded care within NHS facilities; and a variable denoting that the patient was newly registered with a practice.

We began by taking the updated attributed needs and supply variables from PBRA2, and altered the person-level needs variables in the models to study the marginal impact of these morbidity variables. We started with a basic specification of just 38 age/sex categories, and systematically introduced more variables, ultimately leaving us with the complete model using the PBRA2 (updated) attributed needs and supply variables. In model 7, we removed all of the person level needs variables (associated with diagnostic information) to test the performance without them. In model 8 we included all of the updated attributed needs and supply variables (over 300) from the PBRA2 model. For PCT dummies, 151 binary variables for 152 PCTs (omitted category is NHS Hampshire) were used.

The models had the specifications shown in Table 2 below.

Table 2 Specification of the main models

Model	Specification
1	38 Age-sex categories
2	38 Age-sex categories, 150 Morbidity flags
3	As Model 2, but adding 6 morbidity counts, new registration marker, any private utilisation and 32 significant ICD10 chapter interaction terms
4	As Model 3, but adding dummies for 152 PCTs
5	As Model 4, but adding attributed needs variables
6	As Model 5, but adding PBRA2 parsimonious set of updated attributed supply variables
7	As Model 6, but removing morbidity flags, ICD10 chapter interaction terms and 6 morbidity counts.
8	As Model 7 but including the PBRA2 full set of updated attributed needs and supply variables.

For the metrics in the practice sample which require a reference category (RI, MAPCIS, PoPhaSA), each model becomes the reference model for the next model. For example, model 1 is the reference model for model 2, model 2 is the reference model for model 3, and so on. For model 1 we use as a reference model a totally naïve model where all persons are assigned the mean cost across the whole sample. This represents an unweighted per capita allocation.

The summary results are shown in Table 3. Models 1 and 2 improve on the previous models substantially. They have substantial improvements in R^2 and high values for all other practice level metrics. Including morbidity counts, significant main chapter interactions, new registration marker and private attendances have little effect on practice level predictions where the R^2 metric falls slightly and there is no substantial percentage change in practice shares.

Including the PCT dummies improves the goodness of fit and has a large redistribution effect, greatly affecting the shares allocated to practices. This improvement in goodness of fit is continued when the attributed needs and supply variables were introduced where ultimately Models 5 and 6 explain 85% of practice variation. The attributed supply variables add very little (model 6 over model 5) at individual or practice level, but the PCT dummies add a lot particularly at practice level (model 4 compared to model 3).

Removing the diagnostic information from the estimation (Model 7 relative to 6) reduces the goodness of fit substantially at individual level. At practice level, the R^2 falls from 85.4% to 76.2%.

Table 3 Goodness-of-fit of different models

	Estimation Sample n=5,276,253		Validation Sample n=5,271,858		Practice Sample, n=798				
					Full predictions				
	R2	MAPE	R2	MAPE	R2	Within 10%	RI	MAPCIS	PopShaSA
Naïve	0		0		0	35.34	Ref.	Ref.	Ref.
Model 1.	0.0592	568.9	0.0591	567.4	0.3360	40.85	0.061	12.85	0.741
Model 2.	0.1470	521.4	0.1480	520.2	0.6468	55.39	0.030	6.340	0.519
Model 3.	0.1488	521.0	0.1498	520.0	0.6473	55.64	0.002	0.339	0
Model 4.	0.1493	520.5	0.1503	519.5	0.8151	72.81	0.036	7.474	0.580
Model 5.	0.1493	520.2	0.1506	519.2	0.8536	76.57	0.015	3.146	0.217
Model 6.	0.1496	520.2	0.1506	519.2	0.8542	76.69	0.001	0.192	0
Model 7.	0.0611	566.9	0.0611	565.4	0.7616	68.17	0.014	3.140	0.400
Model 8.	0.0614	566.7	0.0613	565.3	0.7845	70.43	0.017	3.671	0.267

We concluded that the person level variables best to include in the models were:
- 37 binary variables for 38 age-sex categories (omitted category is male, <1 years old)
- 150 binary morbidity flags
- 5 binary variables for morbidity counts of: 2; 3; 4; 5; 6+
- 32 interactions terms between ICD-10 main chapters
- new registration with the GP practice in the last year

- a variable denoting whether the person had used privately funded care within NHS facilities in the previous two years privately funded episode of care in the previous 2 years .

Selection of attributed needs and supply variables

In the above analysis we had simply used the set of attributed needs and supply variables from the PBRA2 study. In this stage a new set of these variables were selected. To select attributed needs and supply variables, we adopted three methods. We combined the selections from these processes, and made the final selection of variables from that smaller set of variables as described below.

Method 1

The first method of the variable selection process is similar to the selection process made in the PBRA2 study. It involves modelling the dependent variable is individual level costs (not practice level). The process begins by including all the available attributed needs and supply variables with age/gender, morbidity markers and PCT dummy variables as the explanatory variables.   The all age models were used in the first phase of variable selection. We then followed these steps:

1. Estimate the full model
2. Re-estimate full model after removing attributed needs and supply variables with absolute t-ratio less than 0.2
3. Re-estimate model in (2) after removing attributed needs and supply variables with absolute t-ratio less than 0.4
4. Continue this selection process until only variables with absolute t-ratio of 2 remain.
5. Inspect the coefficients on the attributed needs and supply variables and remove variables with "incorrect/unexpected" signs.
6. Re-estimate the model with variables left in (5) and inspect the coefficients on the attributed needs and supply variables and remove variables with "incorrect/unexpected" signs.
7. Re-estimate the model with variables left in (6) and inspect the coefficients on the attributed needs and supply variables and remove variables with "incorrect/unexpected" signs
8. Repeat this process until all variables have "correct/expected" sign
9. Re-estimate the model with remaining attributed needs and supply variables and remove attributed needs and supply variables with absolute t-ratio of less than 2.2
10. Continue process (9) until the model contains only attributed needs and supply variables with t-ratio of 2.58 remain.

Methods 2 and 3

The second and third methods for variable selection were undertaken at practice level since the primary aim is to maximise explanatory power at practice level. We initially ran a regression with age/gender, morbidity markers, 6 morbidity counts, 32 co-morbidity interaction terms, any private episode, new GP registration marker and dummy variables for each GP practice as the explanatory variables. We then extracted the unexplained practice level variation. These practice level variables were then treated as the dependent variable in a second stage regression. In this second stage regression we include 151 PCT dummy variables and selected significant attributed needs and supply variables using forwards stepwise (Method 2) and backwards stepwise (Method 3) variable selection procedures.

Once all selection procedures have finished, we took all the selected attributed needs and supply variables from the three methods and ran the estimations again, with age/gender, morbidity markers, new practice registration, any private episodes, 6 morbidity counts and 32 co-morbidity interaction terms as explanatory variables. We kept all attributed needs and supply variables with absolute t-ratio values greater than 2.58.

Throughout these variable selection processes, if one sub category of ONS classification remained as significant, we included all the ONS sub categories in the model. The approach is similar to that used for the morbidity flags as these are comprehensive classifications – if one group is included they all are. Table 9 lists all the categories in the final model – not all these are significant.

Stratifying by age

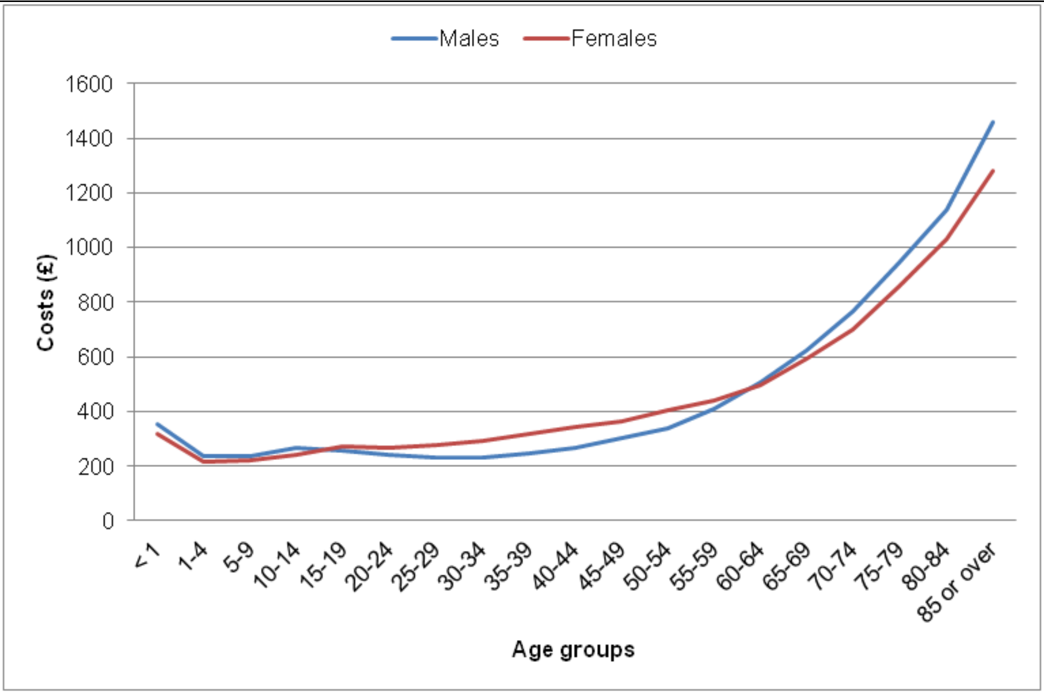
The next step was to test the impact of stratifying the models by age, that is where the coefficients were estimated separately for the three age bands. Five separate models were tested, each with the specification shown in the table below. The person-level variables and PCT dummy variables were the same in each. The PBRA 2 set of attributed variables is the updated parsimonious set. The PBRA3 set is those selected as described in the section above. Model 9b uses a subset of these attributed variables selected where the non significant coefficients for selected age bands were dropped. This is the preferred model that emerged from the selection process.

Table 4Modeling strategy to test the impact of age stratifying the main models

Model	Attributed needs and supply variables	Age Structure
NP1	PBRA 2 set	All age model
NP2	PBRA 2 set	Age stratified model (ages <16, 16-64, 65+)
NP3	PBRA 3 set	All age model
NP4	PBRA 3 set	Age stratified model (ages <16, 16-64, 65+)
Model 9b	PBRA-3 subset	Age stratified model (ages <16, 16-64, 65+)

Figure 1 shows the estimated coefficient for specific ages (derived from model NP3 – the all age model). As expected there is an increase in costs with age, with slightly higher weights attached to older men. The coefficients for the specific age groups in Model 9b are shown in Table 5 below

Figure 1 The estimated coefficient for specific ages (derived from model NP3)



Note: The reference category is males <1. The value shown for males <1 is the mean value for this age group. Values for other age groups are coefficients added to the mean value for males <1.

Table 5 Coefficients for the three specific age groups using Model 9b

	Model 9 b					
	Age group 0-14		Age group 15-64		Age group 65+	
	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic
Age Sex Categories						
male aged < 1						
male aged 1-4	-120.7	(-16.47)				
male aged 5-9	-130.6	(-17)				
male aged 10-14	-104.2	(-13.48)				
male aged 15-19						
male aged 20-24			-13.0	(-4.96)		
male aged 25-29			-22.8	(-8.88)		
male aged 30-34			-20.9	(-7.95)		
male aged 35-39			-7.8	(-2.93)		
male aged 40-44			12.7	(4.53)		
male aged 45-49			45.5	(14.71)		
male aged 50-54			79.9	(22.21)		
male aged 55-59			148.5	(35.93)		
male aged 60-64			236.9	(50.16)		
male aged 65-69						
male aged 70-74					144.6	(14.8)
male aged 75-79					323.0	(27.2)
male aged 80-84					517.3	(33.03)
male aged 85 or over					838.8	(41.29)
female aged < 1	-37.2	(-3.92)				
female aged 1-4	-145.3	(-19.47)				
female aged 5-9	-147.2	(-19.08)				
female aged 10-14	-126.8	(-16.41)				
female aged 15-19			14.2	(5.25)		
female aged 20-24			12.6	(4.92)		
female aged 25-29			24.1	(9.12)		
female aged 30-34			39.4	(14.44)		
female aged 35-39			62.8	(21.94)		
female aged 40-44			84.7	(28.06)		
female aged 45-49			106.2	(32.96)		
female aged 50-54			141.0	(37.44)		
female aged 55-59			174.6	(41.53)		
female aged 60-64			229.6	(50.98)		
female aged 65-69					-21.7	(-2.67)
female aged 70-74					85.3	(9.4)
female aged 75-79					242.1	(22.96)
female aged 80-84					416.0	(32.83)
female aged 85 or over					660.3	(45.96)

The goodness of fit metrics for the five models shown above are given in table 5. As shown, age-stratified models produce a better goodness of fit. Model NP4 - the age stratified models with PBRA3 variables - results in the greatest level of fit. Our preferred Model 9b, increases the model complexity but also improves the model fit at practice level and leads to a plausible pattern of coefficients on attributed needs.

Looking at the R^2 metric, the best fitting models explain around 15% of individual level variation on both estimation and validation samples, and around 85%-86% of practice level variations. Unlike the case with PBRA2 we also show the R^2 for the needs only predictions (ie with attributed supply variables and PCT dummy variables frozen) which shows slightly lower values.

Of the morbidity flags 88% of them had coefficients that were positive and statistically significant, indicating a tendency to increase costs and were statistically significant (see table 9 for a selection). A small proportion (around 3%) of the morbidity flags were negative ie associated with lower future costs in hospital care. These can be explained either as conditions that are associated with death; some conditions whereby treatment reduces the likelihood of further problems eg removal appendix, some infectious diseases or conditions where costs from the dependent variable may have been excluded, mental health, specialist care

The impact of the variables that count different morbidities are negative (see Table 8) indicating that the additional costs of having more than one condition is less than the sum of cost of the two individual components.

Table 6 Goodness of fit of the final models

	Estimation Sample, N=5,588,669		Validation Sample N=5,588,547		Practice Sample, N=815									
					Full predictions					Needs only predictions				
	R2	MAPE	R2	MAPE	R2	Within 10%	RI	MAPCIS	PopShaSA	R2	Within 10%	RI	MAPCIS	PopShaSA
Model														
NP1	0.1494	521.5	0.1495	521.1	0.855	76.2	Ref.	Ref.	Ref.	0.7448	62.8	Ref.	Ref.	Ref.
NP2	0.1526	520.5	0.1519	520.2	0.8589	77.6	0.0037	0.8256	0.8589	0.7456	62.6	0.0022	0.4909	0
NP3	0.1495	521.4	0.1496	521	0.8598	77.8	0.0073	1.674	3.926	0.7291	61.6	0.0119	2.684	13.13
NP4	0.1527	520.3	0.1519	520.2	0.8625	77.2	0.0085	1.934	6.012	0.7325	62.2	0.0111	2.506	11.90
Model 9b	0.1527	520.4	0.1519	520.2	0.8621	77.2	0.0084	1.901	6.012	0.7344	62.8	0.0110	2.488	11.90

Table 7 Examples of coefficients on values for morbidity flags (highest and lowest)

	Model 9b					
	Age group 0-14		Age group 15-64		Age group 65+	
	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic
C81-C96 - Malignant neoplasms of lymphoid, haematopoietic & rel. tiss.	8774.5	(5.48)	3821.6	(18.53)	2921.3	(21.76)
C45-C49 - Malignant neoplasms of mesothelial and soft tissue	11075.7	(2.18)	2302.1	(5.29)	1598.5	(5.21)
C60-C63 - Malignant neoplasms of male genital organs	11762.3	(1.47)	787.6	(7.19)	655.5	(9.3)
C40-C41 - Malignant neoplasm of bone and articular cartilage	5574.9	(1.49)	4031.8	(3.55)	1695.8	(2.37)
F00-F03 - Dementia	10870.7	(8.11)	-52.1	-(0.18)	-249.8	-(4.43)
C51-C58 - Malignant neoplasms of female genital organs	7547.4	(1.15)	1503.5	(9.48)	1104.1	(7.21)
I00-I09 - Rheumatic heart disease	7710.1	(1.57)	509.7	(2.22)	993.7	(7.26)
C69-C72 - Malignant neoplasms of eye, brain & other parts of CNS	4163.1	(3.11)	1897.1	(6.43)	1035.1	(2.56)
N17-N19 - Renal failure	1946.1	(2.32)	3333.7	(21.75)	1375.3	(19.72)
F04-F09 - Other organic including symptomatic mental disorders	5996.8	(0.91)	-26.3	-(0.11)	244.5	(1.71)
C73-C80, C97 - Malignant neoplsm. of thyroid and oth. endo. Glands etc.	2234.1	(0.82)	2085.6	(18.72)	1343.0	(14.38)
J60-J70 - Lung diseases due to external agents	3846.1	(2.31)	1114.6	(3)	667.2	(3.37)
C15-C26 - Malignant neoplasm of digestive organs	687.2	(0.1)	2502.7	(16.04)	1306.5	(13.53)
A15-A19 - Tuberculosis	3427.8	(1.25)	68.3	(0.44)	986.3	(1.95)
A80-A89 - Viral infections of the central nervous system	-558.5	-(1.72)	-129.4	-(1.34)	606.0	(1.2)
K35-K38 - Diseases of appendix	95.3	(2.14)	18.7	(0.88)	-407.1	-(2.53)
A50-A64 - Infections with predominantly sexual mode of transmission	313.2	(2.15)	304.4	(2.68)	-1034.6	-(1.38)
K65-K67 - Diseases of peritoneum	-1712.4	-(3.05)	635.7	(5.27)	395.9	(2.27)
P05-P96 - Other conditions originating in the perinatal period	383.4	(8.81)	-172.1	-(0.97)	-1143.3	-(4.21)
A90-A99 - Arthropod-borne viral fevers & viral haemorrhagic fevers	-97.4	-(1.49)	-528.6	-(2.23)	-639.0	-(0.91)
C00-C14 - Malignant neoplasm of liporal cavity and pharynx	-3471.7	-(0.92)	1015.5	(4.47)	1103.5	(4.09)
B50-B64 - Protozoal diseases	155.3	(0.19)	-352.3	-(2.44)	-1462.4	-(5.4)
B20-B24 - Human imrnunodeficiency virus [HIV] disease	-1639.2	-(2.07)	-666.7	-(5.5)	-942.2	-(1.85)

Table 8 Morbidity counts: table of coefficients, t-ratios and mean values.

	Model 9 b					
	Age group 0-14		Age group 15-64		Age group 65+	
	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic
Morbidity Counts						
2	-229.8	(-10.64)	-238.1	(-16.64)	-8.9	(-0.5)
3	-383.9	(-10.49)	-409.2	(-18.52)	-97.5	(-4.02)
4	-514.1	(-9.69)	-565.6	(-18.64)	-186.4	(-6.08)
5	-624.2	(-8.46)	-665.7	(-16.84)	-268.7	(-7.18)
6	-653.2	(-6.91)	-863.2	(-15.02)	-311.0	(-6.17)

Finalising the models

The last stage of modeling involved examining closely the set of attributed needs variables described above and used in model NP4.

Several variants of NP4 were developed, each one testing different variations in the attributed needs variables that had been selected. For example we explored a number of different ways of capturing student practices. This is important as these practices can often be atypical in terms of their list and expected needs. Our first choices was to use a binary flag to indicate practices in the top 5% based on % of list aged 15-24. This definition had been used in some sensitivity testing in the prescribing formula analysis during the RAMP Review, though not used in the final model. However one problem with this is that it has a threshold value which creates a cliff-edge in the practice need calculations; two practices with very similar proportions aged 20-24 years will receive allocations that differ by £11 per capita. After some debate and empirical testing we have proposed using an indicator based on the % of list aged 20-24 as a continuous variable.

Table 9 summarises the attributed need and supply variables included in Model 9b.

It is important to reiterate that in this variant Model 9b:

a. The variable on ethnicity is positive (ie tending to increase costs) in the 0-14 age band but negative (ie tending to decrease costs) in the 15-64 age band and not significant in the older age groups.
b. Needs/supply variables that were not significant for each respective age band have been excluded.

The black and minority ethnic group proportion has a negative coefficient for age group 15-64. We treat this as an indication of differentially met need and do not include its effect when calculating needs-based predictions at practice level as it would lead to lower (all else equal) allocations for practices with a higher proportion of ethnic minorities.

Table 9 Summary of needs and supply variables used in Model 9b

	Age group 0-14 Coefficient	T-Statistic	Age group 15-64 Coefficient	T-Statistic	Age group 65+ Coefficient	T-Statistic
New GP Registration	8.2	(3)	24.7	(13.17)	-78.4	(-4.52)
Whether had a private episode	-137.9	(-4.05)	-324.8	(-14.49)	-535.6	(-11.51)
ONS classification (Reference = Urban commuters)						
Countryside Communities	-18.0	(-1.78)	-7.4	(-0.9)	-47.2	(-1.47)
Rural Economies	-3.9	(-1.02)	-5.6	(-1.88)	-5.9	(-0.47)
Farming and Forestry	-2.7	(-0.47)	-6.3	(-1.31)	22.6	(1.11)
Educational Centres	-1.8	(-0.17)	-8.2	(-1.86)	-66.9	(-1.87)
Young City Professionals	-24.2	(-3.35)	-23.3	(-4.72)	-79.3	(-2.26)
Mature City Professionals	-16.6	(-2.84)	-10.9	(-2.96)	-40.5	(-1.94)
Affluent Urban Commuter	-3.7	(-0.93)	-13.0	(-4.55)	-19.8	(-1.51)
Well off Mature Households	1.0	(0.23)	-6.1	(-2.04)	5.4	(0.41)
Young Urban Families	-8.0	(-1.85)	-2.5	(-0.73)	18.6	(1.09)
Mature Urban Households	-4.4	(-0.96)	-6.3	(-1.71)	17.5	(1.06)
Multicultural Inner City	-20.2	(-2.63)	-10.5	(-1.83)	-27.9	(-0.72)
Multicultural Urban	-11.2	(-1.44)	-1.5	(-0.28)	-66.3	(-2.89)
Multicultural Suburbia	-9.8	(-1.59)	-10.0	(-2.24)	-6.4	(-0.24)
Struggling Urban Families	0.6	(0.09)	-8.8	(-1.85)	-34.0	(-1.34)
Blue Collar Urban Families	-6.3	(-1.27)	-5.1	(-1.17)	-29.6	(-1.36)
Suburbia	-5.2	(-1.05)	-1.7	(-0.45)	13.7	(0.7)
Resorts and Retirement	-13.8	(-2.78)	-6.3	(-1.66)	-1.5	(-0.08)
Urban Terracing	-3.0	(-0.57)	-0.1	(-0.03)	29.2	(1.48)
Small Town Communities	-7.4	(-1.59)	-8.5	(-2.27)	8.6	(0.48)
Attributed Needs Variables						
Census - Proportion of people from black and minority ethnic groups	0.3	(2.51)	-0.3	(-3.09)		
y0809_QOF asthma prevalence	2.3	(3.14)	3.2	(5.65)		
Percentage of persons in social rented housing			0.2	(3.49)	1.2	(3.13)
Disability living allowance claimants as proportion of population	182.3	(3.78)	212.1	(3.22)		
Census - Student away from home proportion	-345.0	(-2.36)	-447.0	(-4.15)	-2119.6	(-3.92)
y2005_Modelled proportion consuming fruit and veg	48.3	(2.14)			-293.2	(-3.52)
ADS_ONS - Log population variance of ADS compared to ONS MYE	-17.2	(-1.8)	-36.0	(-6.52)	-96.7	(-2.19)
Census - People aged 16-74 Semi-routine occupations	174.3	(4.25)	289.5	(10.32)		
y0809_QOF hypothyroidism prevalence	378.1	(2.75)	268.1	(2.67)		
Census - Persons aged 75 and over living alone					179.6	(2.85)
DWP - laimants of DLA mobility award at higher rate			560.1	(4.45)	867.5	(2.27)
Proportion of population aged 20-24			-52.4	(-4.97)		

Attributed Supply Variables						
ip0809_proportion seen in less than 3 months			-28.9	(-2.45)	-152.7	(-2.45)
y0809_average distance travelled to OP	-0.5	(-3.47)	-0.4	(-3.95)		
asthma weighted population achievement			-38.6	(-4.64)		
Number of operating theatres - gravity model power 2					744451	(2.38)
hypothyroidism unweighted population achievement			-89.9	(-2.33)		

Predicted variation in needs at practice level: PBRA3 compared with PBRA2 and CARAN

The model outputs have been applied to all practices for 2009/10 to derive a relative measure of need that can be compared to the observed costs for 2009/10. In each case the models freeze the attributed supply variables and the PCT dummies. These outputs were compared to the equivalent values calculated from the PBRA2 model (updated to 2009/10) and from the CARAN model applied at practice level. (Observed costs in this instance are not 'real' costs, but activity multiplied by tariff/reference cost – the same method to calculate costs for the dependent variable. In reality PCTs may negotiate different costs than tariff or national average reference costs).

The degree of variation observed with the PBRA models is less than that seen when the CARAN weights were applied at practice level, and the crude correlation with observed costs was not as strong (Table 10).

Table 10 Summary statistics on ratio of observed costs and predicted needs based costs for 3 different models.

	Mean	Median	St Dev	RMS	% within 5%	% within 10%	Rsqd
PBRA3 Model 9	1.38%	0.60%	11.83%	11.91%	36.72%	64.31%	0.73569
PBRA2 updated	-0.25%	-0.32%	11.96%	11.96%	36.05%	63.81%	0.74166
CARAN	-1.48%	-1.84%	13.13%	13.21%	32.10%	58.87%	0.57627

Figure 2 shows at practice level the ratio between observed and predicted costs per person based on the needs variables only. The overall plot shows the expected funnel shape with high variability for smaller practices. Overall these values fit with the values observed in the samples used to develop the models (see earlier Table 6) with approximately 64% of practices observed costs being within +/- predicted costs. (Note these values have not been adjusted to account for area differences in the level of expenditure. This is important as clearly some area will in reality be over target and thus likely to generate more observed costs.)

Figure 2. Difference between observed costs and predicted needs based costs per person (national baseline) at practice level by practice size (2009/10) (excluding practices <1000) n=8,163.

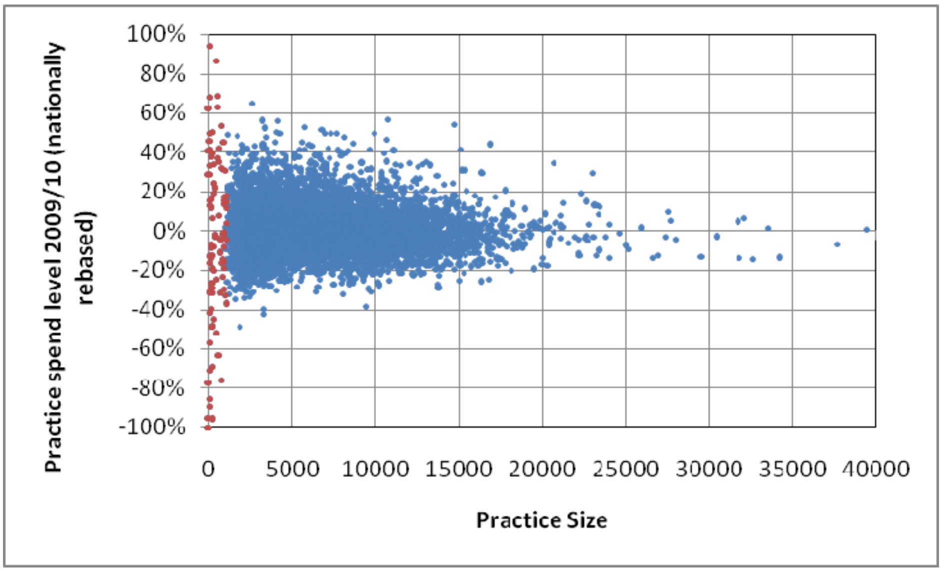


Figure 3. shows the equivalent values but rebased relative the PCT total costs. These effectively removes the variability generated by differences at the PCT level – which are indicative of fundamental differences in supply and historic patterns of care. In looking at variability between observed and predicted costs at practice level these regional effects are very strong.

Figure 3. Difference between observed cost and predicted needs based costs per person (from PCT baseline) at practice level by practice size (2009/10) (excluding practices <1000) n=8,163.

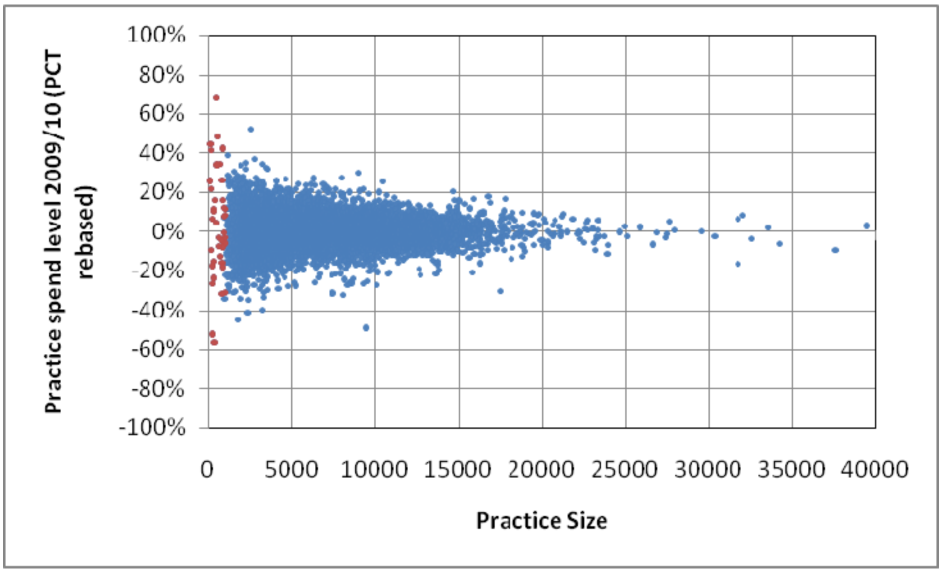


Table 11 shows the same findings, comparing the needs-based predicted costs rebasing to national costs, or at PCT level. It shows that rebasing to PCT level just over 80% of practices the observed costs will be within 10% of the expected.

Table 11 Comparing the distribution of differences in observed and predicted needs based cost when expressed relative to national total, or PCT total

	Mean	Median	St Dev	MAPE	RMS	Pracs % within 5%	Pracs % within 10%	N underspnd > 10%	N underspnd > 5%	N overspnd > 5%	N overspnd > 10%	Rsqd
Nationally rebased	0.79%	0.01%	11.76%	8.90%	11.78%	37.08%	64.56%	1378	2590	2618	1555	0.73569
PCT rebased	-0.21%	-0.16%	8.17%	6.30%	8.17%	50.93%	80.72%	842	2077	1950	740	0.86771

5. Next Steps

We have defined the key elements of our preferred model and subject to agreement on some specific questions we will use this to estimate practice level allocations. We have already agreed the format for sharing these output files at practice level and have already shared results from earlier model.

A draft final report on the modelling, and all other elements of the study will be sent to XXXX at the end of September for comment, with a final report ready by mid October.