Private healthcare remittal provisional findings report

Appendices and glossary

Shares of supply in central and Greater London

Table 1: Central London aggregate shares of supply, 2011*

	Inpatient admissions	*Inpatient revenue*	*Total admissions*	*Total revenue*
				%
HCA	[✂]	[✂]	[✂]	[✂]
TLC	[✂]	[✂]	[✂]	[✂]
BMI	[✂]	[✂]	[✂]	[✂]
The Bupa Cromwell Hospital	[✂]	[✂]	[✂]	[✂]
Aspen	[✂]	[✂]	[✂]	[✂]
Hospital of St John & St Elizabeth	[✂]	[✂]	[✂]	[✂]
King Edward VII's Hospital Sister Agnes	[✂]	[✂]	[✂]	[✂]
Total private hospitals	**85**	**89**	**86**	**86**
Imperial College Healthcare NHS Trust	[✂]	[✂]	[✂]	[✂]
Royal Free London NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
Royal Brompton and Harefield NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
The Royal Marsden NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
King's College Hospital NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
Guy's & St Thomas' Trust	[✂]	[✂]	[✂]	[✂]
Total PPUs	**15**	**11**	**14**	**14**

Source: CC analysis.
*All revenue and admissions figures include international patients. When excluding international patients from our data for central London operators, we obtain similar results: HCA's share of total admissions in central London does not change ([✂]%) and HCA's share of total revenue in central London drops by one percentage point ([✂]).
Note: Total admissions include inpatient and day-case. Total revenue includes inpatient, day-case and outpatient.

Table 2: Shares of capacity of private hospitals in central London, 2011

	Overnight beds (including PPUs)		*Theatres*		*Consulting rooms*		*Critical care beds level 3*	
	Numbers	*%*	*Numbers*	*%*	*Numbers*	*%*	*Numbers*	*%*
Aspen								
Highgate Hospital	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
BMI								
Blackheath	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Fitzroy Square	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
London Independent	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Weymouth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Total BMI	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
HCA								
Harley Street Clinic	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Lister Hospital	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
London Bridge Hospital	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Portland Hospital	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Princess Grace Hospital	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Wellington Hospital	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
NHS ventures UCLH	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Total HCA	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
St John & St Elizabeth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
King Edward VII's Sister Agnes	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
The Bupa Cromwell	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
TLC	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Total private hospitals	**1,318**	**82.8**	**80**		**430**		**85**	
Guy's & St Thomas' Trust	[✂]	[✂]	N/A		N/A		N/A	
Imperial College Healthcare NHS Trust	[✂]	[✂]	N/A		N/A		N/A	
King's College Hospital NHS Foundation Trust	[✂]	[✂]	N/A		N/A		N/A	
Royal Brompton and Harefield NHS Foundation Trust	[✂]	[✂]	N/A		N/A		N/A	
Royal Free London NHS Foundation Trust	[✂]	[✂]	N/A		N/A		N/A	
The Royal Marsden NHS Foundation Trust	[✂]	[✂]	N/A		N/A		N/A	
Total PPUs	**274**	**17.2**						

Source: CC analysis.
Note: N/A = not available.

Table 3: London (inner London and outer London) aggregate shares of supply, 2011

%

	Inpatient admissions	*Inpatient revenue*	*Total admissions*	*Total revenue*
HCA	[✂]	[✂]	[✂]	[✂]
TLC	[✂]	[✂]	[✂]	[✂]
BMI	[✂]	[✂]	[✂]	[✂]
The Bupa Cromwell Hospital	[✂]	[✂]	[✂]	[✂]
Aspen	[✂]	[✂]	[✂]	[✂]
Hospital of St John & St Elizabeth	[✂]	[✂]	[✂]	[✂]
King Edward VII's Hospital Sister Agnes	[✂]	[✂]	[✂]	[✂]
Spire	[✂]	[✂]	[✂]	[✂]
St Anthony's Hospital	[✂]	[✂]	[✂]	[✂]
The New Victoria Hospital	[✂]	[✂]	[✂]	[✂]
Total private hospitals	**87**	**90**	**88**	**87**
Imperial College Healthcare NHS Trust	[✂]	[✂]	[✂]	[✂]
Royal Free London NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
Royal Brompton and Harefield NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
The Royal Marsden NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
King's College Hospital NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
Guy's & St Thomas' Trust	[✂]	[✂]	[✂]	[✂]
NorthWest London Hospitals NHS Trust	[✂]	[✂]	[✂]	[✂]
EN Hertfordshire Trust	[✂]	[✂]	[✂]	[✂]
Total PPUs	**13**	**10**	**12**	**13**

Source: CC and CMA analysis.
Note: Total admissions include inpatient and day-case. Total revenue includes inpatient, day-case and outpatient.

Table 4: Area within M25 (London and four hospitals outside London) aggregate shares of supply, 2011

%

	Inpatient admissions	*Inpatient revenue*	*Total admissions*	*Total revenue*
HCA	[✂]	[✂]	[✂]	[✂]
TLC	[✂]	[✂]	[✂]	[✂]
BMI	[✂]	[✂]	[✂]	[✂]
The Bupa Cromwell Hospital	[✂]	[✂]	[✂]	[✂]
Aspen	[✂]	[✂]	[✂]	[✂]
Hospital of St John & St Elizabeth	[✂]	[✂]	[✂]	[✂]
King Edward VII's Hospital Sister Agnes	[✂]	[✂]	[✂]	[✂]
Spire	[✂]	[✂]	[✂]	[✂]
St Anthony's Hospital	[✂]	[✂]	[✂]	[✂]
Ramsay	[✂]	[✂]	[✂]	[✂]
The New Victoria Hospital	[✂]	[✂]	[✂]	[✂]
Total private hospitals	**88**	**91**	**89**	**87**
Imperial College Healthcare NHS Trust	[✂]	[✂]	[✂]	[✂]
Royal Free London NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
Royal Brompton and Harefield NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
The Royal Marsden NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
King's College Hospital NHS Foundation Trust	[✂]	[✂]	[✂]	[✂]
Guy's & St Thomas' Trust	[✂]	[✂]	[✂]	[✂]
NorthWest London Hospitals NHS Trust	[✂]	[✂]	[✂]	[✂]
EN Hertfordshire Trust	[✂]	[✂]	[✂]	[✂]
Total PPUs	**12**	**9**	**11**	**13**

Source: CC and CMA analysis.
Note: Total admissions include inpatient and day-case. Total revenue includes inpatient, day-case and outpatient.

HCA business cases

No.	Date	Facility	Title
1*	[✂]	[✂]	[✂]
2*	[✂]	[✂]	[✂]
3	[✂]	[✂]	[✂]
4*	[✂]	[✂]	[✂]
5*	[✂]	[✂]	[✂]
6*	[✂]	[✂]	[✂]
7	[✂]	[✂]	[✂]
8	[✂]	[✂]	[✂]
9	[✂]	[✂]	[✂]
10*	[✂]	[✂]	[✂]
11*	[✂]	[✂]	[✂]
12	[✂]	[✂]	[✂]
13	[✂]	[✂]	[✂]
14*	[✂]	[✂]	[✂]
15	[✂]	[✂]	[✂]
16*	[✂]	[✂]	[✂]
17	[✂]	[✂]	[✂]
18	[✂]	[✂]	[✂]
19*	[✂]	[✂]	[✂]
20*	[✂]	[✂]	[✂]
21	[✂]	[✂]	[✂]
22*	[✂]	[✂]	[✂]
23	[✂]	[✂]	[✂]
24	[✂]	[✂]	[✂]
25*	[✂]	[✂]	[✂]
26*	[✂]	[✂]	[✂]
27*	[✂]	[✂]	[✂]
28*	[✂]	[✂]	[✂]
29*	[✂]	[✂]	[✂]
30	[✂]	[✂]	[✂]
31	[✂]	[✂]	[✂]
32	[✂]	[✂]	[✂]
33	[✂]	[✂]	[✂]
34	[✂]	[✂]	[✂]
35	[✂]	[✂]	[✂]
36	[✂]	[✂]	[✂]
37	[✂]	[✂]	[✂]
38	[✂]	[✂]	[✂]
39	[✂]	[✂]	[✂]
40	[✂]	[✂]	[✂]
41	[✂]	[✂]	[✂]
42	[✂]	[✂]	[✂]
43	[✂]	[✂]	[✂]
44	[✂]	[✂]	[✂]
45	[✂]	[✂]	[✂]
46*	[✂]	[✂]	[✂]
47	[✂]	[✂]	[✂]
48*	[✂]	[✂]	[✂]
49	[✂]	[✂]	[✂]
50	[✂]	[✂]	[✂]
51	[✂]	[✂]	[✂]
52	[✂]	[✂]	[✂]
53	[✂]	[✂]	[✂]
54	[✂]	[✂]	[✂]
55	[✂]	[✂]	[✂]
56	[✂]	[✂]	[✂]
57	[✂]	[✂]	[✂]
58	[✂]	[✂]	[✂]
59	[✂]	[✂]	[✂]
60	[✂]	[✂]	[✂]
61	[✂]	[✂]	[✂]
62	[✂]	[✂]	[✂]
63	[✂]	[✂]	[✂]
64	[✂]	[✂]	[✂]
65	[✂]	[✂]	[✂]

No.	Date	Facility	Title
66	[✂]	[✂]	[✂]
67*	[✂]	[✂]	[✂]
68	[✂]	[✂]	[✂]
69	[✂]	[✂]	[✂]
70	[✂]	[✂]	[✂]
71	[✂]	[✂]	[✂]
72	[✂]	[✂]	[✂]
73	[✂]	[✂]	[✂]
74	[✂]	[✂]	[✂]
75	[✂]	[✂]	[✂]
76	[✂]	[✂]	[✂]
77	[✂]	[✂]	[✂]
78	[✂]	[✂]	[✂]
79	[✂]	[✂]	[✂]
80	[✂]	[✂]	[✂]
81	[✂]	[✂]	[✂]
82	[✂]	[✂]	[✂]
83	[✂]	[✂]	[✂]
84	[✂]	[✂]	[✂]
85	[✂]	[✂]	[✂]
86	[✂]	[✂]	[✂]
87	[✂]	[✂]	[✂]
88	[✂]	[✂]	[✂]
89	[✂]	[✂]	[✂]
90	[✂]	[✂]	[✂]
91	[✂]	[✂]	[✂]
92	[✂]	[✂]	[✂]
93	[✂]	[✂]	[✂]
94	[✂]	[✂]	[✂]
95	[✂]	[✂]	[✂]
96	[✂]	[✂]	[✂]
97	[✂]	[✂]	[✂]

Source: CMA and HCA.
*Indicates full cases which were submitted and considered during the original inquiry.

Minimum episode threshold

Minimum episode threshold for treatments included in the IPA

1. We have used the raw data from Healthcode to form a data set that consists of data at the patient episode level across different treatments and insurers for each year between 2007 and 2011. In the IPA methodology for a specific treatment for a specific insurer in a specific year, we explain episode prices as a function of several patient characteristics. In order to estimate a regression model, we need a minimum number of observations (episodes of a specific treatment at the insurer-year level), which corresponds to the number of variables in the regression.[1] In this section we discuss our reasoning behind providing results for both a 5- and 30-minimum patient threshold.

2. In the Final Report, we reported results – both for the estimated price differences between HCA and TLC and for the statistical significance testing of these price differences – based on a minimum of 5 episodes per treatment per insurer per year per hospital operator.

3. As set out in the Final Report, we checked the sensitivity of these results using a 30-episode threshold, which, as reported in the Final Report, showed lower price indices for both HCA and TLC compared with using a 5-episode threshold, while the price differences were broadly similar.[2]

4. The Final Report set out briefly the relative merits of using a 5-episode threshold and of using a 30-episode threshold:

   (a) In relation to the 5-episode threshold, the Final Report stated that:

   > … because negotiations between a PMI and a hospital operator focus on all of a PMI's expenditure, we thought it was more appropriate to compare prices over as wide a range of treatments as possible.[3] For the same reasons, we did not separately examine inpatient and day-case treatments. Note that as part of our sensitivity analysis, one analysis considered only those treatments with more than 30

---

[1] Note that we are talking about a minimum of observations in order to estimate the coefficient in the model.
[2] The results of the 30-episode sensitivity are presented in the Final Report, Appendix 6.12, Annex B, Figure 2 and are compared with the 5-episode results presented in Appendix 6.12, Figure 1.
[3] Looking at those treatments where there are at least 5 episodes per treatment per year per hospital operator provides us with a larger data set than when we restrict this to only those treatments that meet a 30-episode threshold.

patients per operator for a given PMI in a given year, and these results are therefore relevant to the more common treatments.[4]

(b) On the 30-episode sensitivity, the Final Report stated that: '…a higher threshold of 30 patient episodes … allows for a higher number of observations per regression and as a result may mitigate the impact of any outlying or extreme price observations and produce more precise price predictions …'[5]

5. Bearing these points in mind, we have further considered whether we should continue to treat the results based on the 5-episode threshold as our main analysis, while using the 30-episode threshold as a sensitivity check, when coming to a view on any price difference between HCA and TLC. We have decided that we should place reliance on both sets of results in our analysis of the price difference (and not rely on the 30-episode threshold as a sensitivity as we did in the Final Report). We set out below two main reasons for this decision.

6. First, the 5-episode threshold includes treatments with very low patient volumes, which has the advantage of increasing the number of different treatments included in the common basket. However, this approach has the disadvantage of not allowing us to be as confident as we could that the treatment-level regressions in the IPA precisely identify the relationship between patient characteristics and the episode prices.[6] Increasing the minimum number of episodes per treatment increases our confidence that we are getting more precise estimates of the relationship between patient characteristics and prices.

7. Second, increasing the minimum number of episodes per treatment to 30 increases the reliability of our statistical significance testing of any estimated price differences. The more observations that are available for a given treatment, the more information there is about the underlying true distribution of the episode prices for that treatment. This means that we are able to estimate the standard errors of our estimated price differences through the bootstrapping procedure (as set out in Appendix F below) with a higher degree of accuracy.[7] Thus the precision and reliability of our statistical

[4] Final Report, Appendix 6.12, footnote 16.
[5] Final Report, Appendix 6.12, paragraph 25 (c).
[6] Having larger sample sizes – in our case, analysing treatments with higher numbers of patients being treated – leads to better estimates. In technical terms, larger sample sizes improve the consistency of our estimates meaning that the larger the sample, the less risk that the estimates that are produced will be biased.
[7] The principle of the bootstrap assumes that the observed distribution of the data in our sample is the best approximation for the true underlying distribution in the population. This may be a questionable assumption for

significance testing improves when we apply a higher minimum threshold for the number of episodes per treatment.

8. We also recognise that while increasing the threshold to a minimum of 30 episodes increases the precision and reliability of our methodology, it reduces the size of the common baskets considered and the number of insurers we are able to consider. In particular, when increasing the threshold to a minimum of 30 episodes, we are able to conduct the statistical significance test for only 23 out of 36 insurer-year observations. We cannot do so in relation to the price differences for the remaining 13 insurer-year pairs because of insufficient number of observations due to low patient volumes for these smaller insurers.

9. Looking at the issue of coverage – which is relevant both to this issue of the minimum episode threshold and to the issue of the representativeness of the IPA data – we set out below four measures (all in terms of nominal revenue):

   (a) The proportion of the hospital operators' revenue from insured patients that is covered in the Healthcode raw data.

   (b) The proportion of the Healthcode raw data that is included in the final cleaned data set that we use in our analysis.

   (c) The proportion of this final cleaned data set that we use in our IPA – both the 5- and 30-episode analyses.

   (d) The proportion of spend of the two major insurers in the final data set that is included in the IPA – again both 5- and 30-episode analyses.

10. These figures are set out in Tables 1 and 2 below.

11. Looking at 2011, we note that the Healthcode data set accounts for approximately [✂]% of HCA's insured revenue, while for TLC the equivalent figure is [✂]%. The final cleaned version of the data set that we use in our IPA includes invoices accounting for [✂]% (for both HCA and TLC) of the hospital operators' insured revenue covered by the Healthcode data.

12. Our IPA analysis is based on a smaller subset of this data set for two reasons. First, we are comparing the price of HCA and TLC and so can only conduct our analysis on treatments that both HCA and TLC provide – the 'common basket'. Second, our IPA analysis only covers those treatments where at least

---

treatments in which we observe very small numbers of patient episodes. For the bootstrap, it is, therefore, preferable to use those treatments with a higher number of observations, and thus have a higher threshold, in order to obtain more robust results.

5 episodes are observed per treatment per insurer per year per hospital operator, which reduces the coverage of the sample further.[8]

13. The IPA based on the 5-episode threshold covers episodes accounting for [✂]% of HCA's revenue in the final data set, while for TLC it accounts for [✂]%. Looking at the IPA conducted using the 30-episode threshold, the data set is further reduced, as treatments with lower patient volumes are no longer included. Overall this reduces the activity covered by the common basket, with the data set used in the 30-episode analysis accounting for [✂]% of HCA's revenue in the final cleaned data set and [✂]% of TLC's.

Table 1: Share of insured revenue included in the IPA

		%
	HCA	*TLC*
Healthcode data as a share of insured revenue, 2011*	[✂]	[✂]
Final data set that we use as a share of Healthcode data, 2011	[✂]	[✂]
Data used in the IPA (5-episode) as a share of final data set, all years	[✂]	[✂]
Data used in the IPA (30-episode) as a share of final data set, all years	[✂]	[✂]

Source: CMA analysis.
*HCA's and TLC's insured revenues for 2011 are presented in the Final Report, Tables 3.3 and 3.6 respectively.

14. Table 2 below sets out the share of insurer spend at HCA and TLC in our final cleaned data set that is used in our IPA analysis. Looking at the two main insurers, our IPA (based on 5 episodes) uses data representing, for example, [✂]% of Bupa's spend with HCA that is contained in the final cleaned data set, while for AXA PPP the equivalent share is [✂]%. Applying the 30-episode threshold, the coverage of the IPA falls, as lower volume treatments are no longer included in the analysis.

Table 2: Share of insured revenue included in the IPA, Bupa and AXA PPP

				%
	HCA		*TLC*	
	Bupa	*AXA PPP*	*Bupa*	*AXA PPP*
5-episode IPA as a share of final data set, all years	[✂]	[✂]	[✂]	[✂]
30-episode IPA as a share of final data set, all years	[✂]	[✂]	[✂]	[✂]

Source: CMA analysis.

[8] Our regression approach (see Appendix G, paragraph 34 onwards) covers a larger proportion of the Healthcode data, as it includes all treatments with at least two episodes.

15. Based on these figures, the IPA covers less than [✂]% of the revenue accounted for by the Healthcode data for both TLC and HCA. We do not consider that this invalidates our analysis, for a number of reasons.

16. First, looking again at the revenue coverage of our IPA, we consider that the most relevant measure of its coverage is to focus on the 'overlap' treatments which both HCA and TLC provide to insured patients. For HCA, the IPA (5-episode version) accounts for [✂]% of the revenue generated by overlapping treatments in the final cleaned data set, while for TLC the equivalent figure is [✂]%. As such, our analysis does cover a substantial proportion of those treatments for which a price comparison between HCA and TLC is meaningful.

17. Second, and more importantly, in order to make a meaningful comparison between HCA and TLC prices we only compare those treatments that are provided by both operators. Given that the range of services that HCA and TLC provide is not identical, there are treatments which HCA provides that TLC does not and vice versa. Therefore, there are many treatments that HCA and TLC provide, and which generate insured revenue for them, which are not relevant to our analysis.

18. We are comparing prices in those treatments where HCA and TLC overlap and, hence, actually or potentially compete for insured patient business. Comparing price differences for those treatments where HCA and TLC do not overlap would be impossible. Furthermore, to the extent that we consider TLC to be HCA's closest competitor, we would expect a comparison of prices in those treatments where they overlap to be representative of HCA's pricing more generally and to be a reasonable proxy for HCA's relative market power.

Conclusion on minimum episode thresholds

19. As presented in Table 1 above, there is a reduction in the coverage of the common baskets used in the IPA when we use the 30-episode minimum threshold. However, this higher threshold has clear advantages in terms of statistical robustness, as set out above. Therefore, we have decided that we should place reliance on both sets of results in our analysis of the price difference (and not rely on the 30-episode threshold as a sensitivity as we did in the Final Report).

Treatment-level regressions

1. In this appendix we comment on coefficient estimates for the regressions at the treatment insurer-year level. We argue that while for a large number of the treatment-level regressions within the IPA the coefficients are not statistically significant, we still have good reasons to belief that our regression model is explaining the majority of the variation in the data.

Coefficient estimates in the treatment-level regressions

2. As part of our analysis we present our recalculated R-squared statistics for the treatment-level regressions in our IPA methodology and show that, generally, our model explains the majority of the variation in episode prices. However, the R-squared statistic is only a descriptive figure that summarises the extent to which a regression model explains the variation in the dependent variable (episode prices in our case).

3. We have also reviewed the regression results to confirm that the explanatory variables that relate to patient characteristics – age, gender and length of stay – produce reasonable estimates of the relationship between the patient characteristics and episode prices or 'coefficients'. We have examined both the value of the coefficients which capture the relationship between each explanatory variable and the episode prices, and whether these estimated coefficients were statistically significant. For example, in our regressions the coefficient on length of stay is our estimate of the relationship between the length of stay for patients who have had a specific treatment and the episode price charged for that treatment. A positive coefficient indicates that an additional night as an inpatient is associated with a higher episode price being charged to the insurer.

4. Looking in detail at the results from these approximately 700 treatment-level regressions, we have found that for length of stay we generally estimate positive and statistically significant coefficients, as we would expect.[1] However, many of the treatment-level regressions reported age and gender effects that were not statistically significant. While this is not wholly unexpected – for some treatments we would not expect age or gender to drive cost differences[2] – we are using these patient characteristics to control for differences in patient complexity, so we would generally expect them to play a

[1] Note that for day-case treatments we would not expect to find a statistically significant effect (or any effect at all).
[2] For example, whether a cataract patient is a man or woman may not affect the level of costs involved.

role in explaining price differences for treatments. As such, we considered whether we had adequately modelled the relationship between these patient characteristics and the episode prices.

5. Having considered the issue, we set out a number of reasons why our methodology is still a robust way to model this relationships:[3]

   (a) First, even if the coefficients on age and gender are not statistically significant, these are still our best estimates of the relationship between these variables and episode prices.

   (b) Second, if these patient characteristics were poor predictors of episode prices then they would potentially have zero (or near-zero) coefficient estimates and therefore would not affect the estimated prices that form the price indices in any case. We have checked this point and found that excluding these coefficients from the regressions does not substantially affect our estimated price differences. This indicates that where these coefficients are statistically insignificant they are not introducing significant biases or distortions into our results.

Prediction error

6. On a related point [✂].[4,5]

7. As we discuss in Section 8, paragraphs 8.119, we have acknowledged a [✂] point on the share of treatment-level regressions that are statistically insignificant.[6] The overall results suggest that we nevertheless explain a large share of the variation in the data.

---

[3] This issue was raised by Nuffield in response to the Provisional Findings and dealt with in the Final Report at footnote 18 of Appendix 6.12.
[4] IPA WP DRR, paragraph 3.25.
[5] IPA WP DRR, paragraph 3.26.
[6] IPA Working Paper, paragraph 116.

Data-related issues

Data-related issues

1. The data set we have used for the IPA is based on invoice data received from Healthcode, an intermediary between hospital operators and PMIs.[1] The Healthcode data provides information on the hospital visits of insured patients. It includes details of the hospital visited, the treating consultant, the treatment received, and the prices invoiced by the hospital operators to the PMIs.[2] We have cleaned and consolidated the data to produce a cleaned data set for our analysis that covers the period 2007 to 2011. Each row in this data set is an 'episode', which we have defined as a single visit to a hospital by a patient.

2. In this appendix we deal with data-cleaning and other data issues. We address in detail points raised by KPMG in the CAT DRR and the IPA WP DRR. We provide our reasoning for the changes that we have made to the data set and explain our reasoning behind choices in relation to the data cleaning. In addition, we provide a description of the data-cleaning algorithm that we have used to remove duplicate line items from the data set, enabling us to use line-item information in our analysis.

Diagnosis code and the medical speciality of the treating consultant

3. The Healthcode data set includes variables on the diagnosis code for each patient episode, as well as the medical specialty of the treating consultant. In principle, including these variables in the regressions explaining episode prices could add explanatory power (in terms of how well our model explains the variation in prices), because, as KPMG has argued, these variables could play a role in explaining the costs that providers face in treating these patients. KPMG has argued that: 'large price variations within treatments are driven by patient medical need as related to complications and comorbidities. Some patients, for example, may require more or more costly diagnostic procedures, drugs or nursing care at different levels of intensity, and each of these factors would result in a higher episode charge'.[3]

[1] See Final Report, Appendix 6.12, paragraphs 9–13 and Annex A.
[2] We considered this data, on actual prices paid, to be a better basis for our analysis than the (paper or electronic) contractual agreements between hospital operators and PMIs. The latter were not easily available in a format that was comparable between hospital operators or PMIs, and are typically based on a detailed contract which may span several documents. We noted that PMIs also use the actual prices paid, rather than their contractual agreements, to compare the prices of hospital operators.
[3] KPMG (1 May 2015), 'A Submission on the Analysis of Insured Prices', paragraph 37.

4. We have given some consideration to using the diagnosis code variable and we have reconsidered its use in response to the points made by HCA's economic advisers, KPMG, in the CAT DRR.

5. The data provider, Healthcode, stated that: 'the quality of diagnosis coding in the sector is very poor', that the diagnosis codes 'cannot be used as an accurate barometer of patient's condition', and that, for the purposes of including diagnosis codes in our analysis, the 'data [on diagnosis code] is unreliable in this data set'. We therefore consider the diagnosis code variable not to be a reliable source of information in the econometric analysis conducted as part of the IPA.[4]

6. In relation to the consultant's medical specialty, the fact that our regressions in the IPA are already estimated for each treatment separately means that including this variable in our analysis separately would add little explanatory power. For example, when explaining the price of hip replacements adding a variable that indicates when an orthopaedic surgeon has been used is unlikely to add to the accuracy of our analysis if all such procedures are delivered by an orthopaedic surgeon.[5] In addition, adding a variable for the consultant's specialty would complicate the construction of the representative patient; it is not clear what the median medical speciality would be if more than one is relevant for a given treatment. Alternatively, we would have to calculate separate predicted prices for the same treatment when delivered by consultants with different specialties: this would reduce the size of our sample for each treatment further and decrease the accuracy of our results.

7. Healthcode's view is that the treating consultant's medical specialty 'does not provide information on the patient's medical condition'. This means that, for each treatment, there is unlikely to be any meaningful variation in the medical specialty variable that would add useful information in the regressions.

8. For the reasons stated above, we have not used the information on diagnosis code or the consultant's speciality in our treatment-level regressions as part of the IPA.

Multiple-CCSD episodes

9. In cleaning the data for the IPA we defined a treatment by its CCSD code. For example, the CCSD code for a common cataract procedure is C7122.[6]

---

[4] From an econometric perspective, measurement error leads to a bias in the estimated coefficient and would therefore lead to a bias in the average price indices.
[5] We note, however, [✄].
[6] C7122 relates to 'Phakoemulsification of cataract, with lens implant - unilateral (including topical or local anaesthetic)'.

However, the data set also includes episodes that are associated with multiple CCSD codes, where more than one treatment has been recorded for the same patient within the same episode. The IPA results presented in the Final Report did not include episodes with multiple CCSD codes.

10. On its webpage, Clinical Coding and Scheduling Development (the organisation that developed and maintains the CCSD system of classification) clarifies that when recording CCSD codes for a clinical procedure 'users should use a single CCSD code to describe the majority of common clinical interventions. This single code will usually fully describe the procedure from start to finish'.[7]

11. We queried with Healthcode whether multiple CCSD codes are comparable across hospital providers. Healthcode stated that multiple CCSD codes were sometimes used by hospital providers, in particular if a single CCSD code did not cover the whole procedure. This was, to a limited degree, accepted practice by PMIs.[8] However, the relationship between the number of CCSDs recorded for an episode and the price charged might not be straightforward, as the extent to which hospital operators were reimbursed fully for each individual CCSD recorded could vary depending on the specific contracts in place between the hospital operator and the insurer. For example, an insurer might pay in full for the main (most expensive) CCSD, but only partially cover the costs of the additional CCSDs.

12. Given the above, especially the risk that episodes with multiple CCSD codes might not be comparable between hospital providers, we have excluded episodes with multiple CCSD codes from our analysis.

13. Nevertheless, we have checked the sensitivity of our results to the inclusion of those episodes with multiple CCSD codes (see Table 1 below).

[7] See CCSD Single Codes webpage.
[8] Healthcode stated that there were limits to using multiple CCSDs, for example that an insurer might only pay 50% of a second CCSD on the invoice.

Table 1: Insurer-year results with multiple-CCSD episodes – % price differences

		5 episodes				*30 episodes*			
		CMA		*Pathology*		*CMA*		*Pathology*	
		Single	*Multiple*	*Single*	*Multiple*	*Single*	*Multiple*	*Single*	*Multiple*
		(A)	*(B)*	*(C)*	*(D)*	*(E)*	*(F)*	*(G)*	*(H)*
2007	AXA PPP	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2008	AXA PPP	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2009	AXA PPP	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	AXA PPP	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	AXA PPP	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	Aviva	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2007	Bupa	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2008	Bupa	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2009	Bupa	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	Bupa	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	Bupa	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2007	Bupa Int'l	[✂]	[✂]	[✂]	[✂]	[✂]			
2008	Bupa Int'l	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2009	Bupa Int'l	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	Bupa Int'l	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	Bupa Int'l	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2007	Cigna	[✂]	[✂]	[✂]	[✂]				
2008	Cigna	[✂]	[✂]	[✂]	[✂]				
2009	Cigna	[✂]	[✂]	[✂]	[✂]				
2010	Cigna	[✂]	[✂]	[✂]	[✂]				
2011	Cigna	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	Exeter	[✂]	[✂]	[✂]	[✂]				
2008	PruHealth	[✂]	[✂]	[✂]	[✂]				
2009	PruHealth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	PruHealth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	PruHealth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2007	SLH	[✂]	[✂]	[✂]	[✂]				
2008	SLH	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2009	SLH	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	SLH	[✂]	[✂]	[✂]	[✂]				
2011	SLH	[✂]	[✂]	[✂]	[✂]				
2009	Simplyhealth	[✂]	[✂]	[✂]	[✂]				
2010	Simplyhealth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	Simplyhealth	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	WPA	[✂]	[✂]	[✂]	[✂]				
2011	WPA	[✂]	[✂]	[✂]	[✂]				
Total		**[✂]**	**[✂]**	**[✂]**	**[✂]**	[✂]	[✂]	[✂]	[✂]

Source: CMA analysis.

Table 2: Annual results with multiple-CCSD episodes – % price differences

	5 episodes		*30 episodes*	
Year	*CMA*	*Pathology*	*CMA*	*Pathology*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	[✂]	[✂]	[✂]	[✂]

Source: CMA analysis.

14. The estimated overall price differences including multiple CCSDs range from [✂]% to [✂]%, for a 5- and 30-episode threshold respectively. For the insurer-year price differences, the estimated price differences are mostly in line with the results for single CCSDs only. We observe some changes in the insurer-year price indices, for example, for [✂] in 2008 the price difference

turns from [✂]% to [✂]%. We conclude that our estimated price differences between HCA and TLC are robust to the inclusion of multiple-CCSD episodes.

'Irrational' price predictions

15. In the CAT DRR, HCA's economic advisors (KPMG) identified a number of issues in relation to the 'irrational' price predictions produced by the treatment-level regressions that are used in constructing the price indices in the IPA. These issues are:

    (a) Zero price predictions occurred in four out of the 694 treatment-insurer-year prices that KPMG calculated. This resulted from a coding error, which we have now rectified.

    (b) Negative price predictions occurred in four out of 694 treatment-insurer-year prices. This was not an error, but rather a result of the regression methodology.

    (c) Out-of-sample price predictions occurred in two out of 694 treatment-insurer-year prices, where our representative patient for those particular treatments was not representative of both operators' patients' characteristics.

16. We agree with KPMG that the issue of 'irrational' price predictions should be addressed, however, we disagree with its approach. KPMG addresses this issue by excluding treatments with 'irrational' prices from the analysis on the basis that they produce irrational results for certain years. We do not agree that we should simply exclude treatments on the basis that they produce odd results. As we detail below, we do not encounter this issue when we increase the threshold of minimum number of patient episodes. As set out in Appendix C, this approach has the additional desirable effect that it increases the precision of the estimates in our regressions.

17. In the remainder of this section we deal with each of the 'irrational' price predictions in turn.

Negative price predictions

18. In the CAT DRR KPMG identified four treatment-insurer-year combinations for which negative prices are predicted.[9] Negative price predictions occur as a result of the methodology we have used. In particular, the estimator that we

---

[9] CAT DRR, p17, Table 2.

use in our treatment-level regressions in the IPA does not restrict the dependent variable (in this context the predicted price of a patient episode) to taking only positive values.[10] However, observed prices in this context, as opposed to the predicted prices that our methodology produces, are by their nature only ever positive. The fact that we are not restricting prices to be positive in our methodology is not a problem as such, in particular when prices are predicted using explanatory variables that are within the sample.[11] We therefore do not agree with KPMG that negative price predictions are an error.

19. In addition, when we calculate price differences on the basis of a 30-episode threshold, we do not observe negative prices. The reason is that with a larger number of patients available for the estimation, the estimates are more robust with respect to outlier observations.[12] For example, an outlier may include a patient for a specific treatment who stayed more than 50 days in one of the hospitals, whereas the average length of stay for that treatment is around 5 days. The effect of the outlier is to bias the estimates, and, therefore, to misrepresent the effect of length of stay on prices.

20. Notwithstanding our arguments that negative price predictions are a by-product of our methodology and the fact that they do not arise when we calculate prices based on a 30-episode threshold, we also checked our results based on KPMG's suggested methodology of excluding the treatments which give rise to negative predicted prices from our data. The results suggest that dropping those treatments does not affect the estimated price differences materially.[13]

Zero price predictions

21. In the CAT DRR, KPMG showed that for four out of 694 treatment-insurer-year prices the analysis predicted that one of the hospital operators would have charged a price of zero. We agree with KPMG that zero price predictions should be avoided. We therefore implemented an approach in the computer code for the price index calculation that resolves this issue.[14]

---

[10] We use an OLS estimator.
[11] In our case explanatory variables are the patient's age, gender and length of stay.
[12] An outlier is classified as a patient with a characteristic that is out of line with the other observations, eg a patient with an excessive number of pathology counts. For a general definition of an outlier see Moore and McCabe (1999).
[13] The notable exception is SLH in 2009. Excluding the corresponding CCSD reduces the price difference by [✂] percentage points.
[14] We use the Stata command '_rmcollright', which excludes collinear variables in the specified order.

22. Zero price predictions occur where Stata deals with collinear variables in the data set by randomly dropping one of them.[15] For example, in our data set we observe that for a small number of treatments a hospital is treating female patients only. If this corresponds with a treatment where the hospital operator is only treating day-case patients, ie patients that have a length of stay equal to zero nights, then both patient characteristics have the same values for all patients and so are perfectly correlated or 'collinear'. Therefore, the relationships between these variables and the episode price cannot be estimated. This can lead to problems when we use our regression results to predict the episode price.[16]

23. In order to calculate the average price per treatment, we use a representative patient, ie a patient with the median characteristics for patients of that specific treatment. The representative patient gives us specific values for the patient's characteristics, that is, age, gender and length of stay. Our regression results generate a 'constant' – in other words, it tells us what the price would be before adding the effects of patient characteristics.[17] However, for some regressions this 'constant' element is incorrectly removed from the regression, while another term assumes the role of the constant.[18] Our methodology then multiplies the patient's characteristic with this term, which is not missing, and so we get a zero price prediction. For example, if patient gender is constant within a treatment as in the above example, we would multiply the median gender – that is female – by the constant term, which results in a zero.

24. After implementing the solution to our computer code we do not observe any zero price predictions.

Out-of-sample price predictions

25. In the CAT DRR, KPMG showed that for two out of 694 treatment-insurer-year prices the IPA made 'out-of-sample' price predictions based on the characteristics of a representative patient, where one of the hospitals did not treat any patients with these characteristics.[19] We do not agree with KPMG that the out-of-sample price prediction is a mistake, but agree that it potentially raises an issue in relation to the precision of our predicted price

[15] In statistics and econometrics, two variables are described as being 'collinear' when they are a linear combination of each.
[16] If the variable that is dropped is the variable for the hospital operator, then we do not have this 'constant' available in the data.
[17] For example, the price of a hip replacement might be made up of a 'constant' of £500 plus £10 for every extra year of patient age, plus £1,000 for every additional night spent in hospital, plus £100 more if the patient is male rather than female.
[18] The reason for the omission of the constant term is collinearity.
[19] On one occasion the representative patient is female, while TLC did not treat any female patients. On the second occasion, the average length of stay of the representative patient is positive, while TLC did not treat any inpatients.

estimates. Specifically, the out-of-sample predictions are part of our methodology and are a result of the 'representative patient' assumption. To understand this, one could consider the following stylised example. If for a specific treatment, patients at one hospital tend to stay for one night and patients at the other hospital are always treated as day cases, then the median patient may be one who stays for zero nights or for one night, depending on which hospital operator treats more patients for that particular treatment. Therefore, using the median patient to calculate the price for the treatment would lead to an out-of-sample prediction for one or other of the hospital operators.

26. We have tested the sensitivity of our results to out-of-sample price predictions by using alternative definitions of the representative patient (see Appendix G for more detail). Taking again the example from the previous paragraph, using a representative patient based on the mean, rather than the median, characteristics of the relevant patients would give a mean length of stay somewhere between zero and one night. While not fully correcting for the difference between day-case and longer hospital stays, this alternative definition would mitigate the problem. Furthermore, based on a minimum threshold of 30 episodes per treatment, it does not appear that the issue of out-of-sample predictions arises. We present the results of this analysis – using alternative definitions of the representative patient – among the sensitivities robustness checks presented in Appendix G.

Errors identified prior to the Data Room

27. When preparing the CAT Data Room, we identified a number of minor errors in our cleaning and processing of the Healthcode data for the IPA. We corrected all but one of those, and put both the corrected and the uncorrected results (that is, as presented in the Final Report) in the CAT Data Room.

28. We uncovered three errors in our computer code prior to opening the CAT Data Room, which were:

(a) mistakenly pooling patients from King Edward VII's Hospital (KEVII) into the calculation of the representative patient for outside central London;

(b) mistakenly classifying patients with a missing insurer name as self-pay patients. This error only affected the comparison of insured prices to self-pay prices; and

(c) obtaining differences in the way line items were aggregated to episodes every time the computer code was processed.

29. The impact of the first two errors on the IPA results was negligible, and we noted that we were not able to solve the third issue prior to opening the data room, but explained that the data discrepancies caused by this issue were negligible as well. KPMG acknowledged and did not challenge our corrections of the errors described in paragraphs 28(a) and 28(b) above. This is acknowledged in paragraphs 27 to 29, and paragraph 31, of the CAT DRR.

30. In paragraph 32 of the CAT DRR, KPMG suggested a solution to the issue described in paragraph 28(c), above. We agree that this solution is appropriate, and have now implemented this in the processing of the Healthcode data.

Measurement of patient age

31. KPMG found that there was an error in our computer code which meant that patient's age – one of the control variables in the regression analysis – was calculated incorrectly (paragraph 34 of the CAT DRR, and paragraphs 12 to 16 in Annex 2 of the CAT DRR). KPMG explained that the CMA incorrectly subtracted the year of patient's birth from 2012 in order to calculate the patient's age, whereas it should have subtracted the year of birth from the date when the episode took place.[20] KPMG noted that this error affected both the regressions, where age was one of the three control variables, and the characterisation of the representative patient.

32. We agree that this was an error in the computer code. The code calculated each patient's age as of 2012, and not in the year that the patient was treated. This error meant that all patients' ages were overestimated by a constant amount of years for each year (eg by two years for the 2010 analysis). However, since our baseline analysis was conducted for each year separately, and since it is patients' age relative to each other that matters in the analysis, this error does not affect our analysis or results in any way.[21]

33. We have now corrected this error such that patient age is correctly calculated by subtracting the year of birth from the year in which the patient was discharged from the hospital for the particular episode.

[20] KPMG gave an example of a patient born in 1980 and treated in 2011: the CMA calculated the age of such patient to be 32, whereas it should have been 31.
[21] KPMG have acknowledged that this error gave rise to a mismeasurement of the age variable in a non-systematic way (CAT DRR, Annex 2, footnote 7).

Inclusion or exclusion of episodes at certain HCA hospitals

34. KPMG made two points in relation to the inclusion or exclusion of episodes at HCA's hospitals. First, it noted that the CMA failed to exclude non-central London HCA hospital episodes from the analysis. HCA operates, in partnership with the NHS, two hospitals outside of central London, and KPMG claimed that data related to these non-central London hospitals should be excluded from the IPA for central London (and it has done so in the analysis presented in its CAT DRR).[22]

35. We do not agree with the approach suggested by KPMG to exclude the non-central London HCA episodes from the analysis. We chose to include these hospitals in the comparison of HCA's and TLC's prices because hospital operators negotiate prices with insurers for their complete portfolio of hospitals (see the Final Report, paragraph 6.292). Footnote 237 in the Final Report (as well as footnote 13 in Appendix 6.12 of the Final Report) acknowledges that we have included HCA's units outside London in the analysis, and notes that 'these facilities accounted for less than 1% of the price data that we analysed and are therefore unlikely to have a material effect on our results'.

36. Second, KPMG submitted that, for a small number of episodes, the Healthcode data identified the operator as HCA but did not identify the specific hospital where the episode took place. KPMG has excluded these [✂] episodes[23] from the analysis it presented in the DRR.

37. We disagree with this approach as it unnecessarily removes useful information that can be reliably used in the analysis. We did not exclude these episodes from the data because the IPA compares prices charged by hospital operators, and as such the identity of the specific hospital where an episode took place is not important. As explained above, we deliberately included HCA's patient episodes in the central London analysis even if these took place in one of the hospitals HCA operates outside of London (this is, in any case, a small proportion of its overall business).

38. Thus, we remain of the view that the approach adopted in the Final Report is appropriate – ie we have included both the non-central London HCA hospital episodes and the unknown HCA hospital episodes in the insured price comparison between HCA and TLC for central London for the reasons explained above.

---

[22] KPMG also stated that including observations for these HCA hospitals slightly increases the common baskets of treatments between HCA and TLC for some insurers and in some years. See paragraph 38 of the DRR, and paragraphs 22 & 23 in Annex 2 of the CAT DRR.
[23] See the CAT DRR, Annex 2, footnote 18 to paragraph 24.

Duplicate line items

39. KPMG claimed that it found ‘duplicate line items’ in the Healthcode data and decided to exclude such line items (see the CAT DRR, Annex 2, paragraph 33). KPMG noted that: ‘the duplicate line items have the same invoice ID, Industry Standard Code ... and line item price. They only differed in the diagnosis code associated with them’.

40. We have queried this issue with Healthcode, which clarified that those line items with the same invoice ID, Industry Standard Code and line item price, but with a different diagnosis code were, in fact, likely to be duplicates. It explained that sometimes patients had more than one diagnosis code or CCSD recorded for the same treatment and so an extra line was added in the Healthcode data set to record this. Based on this, we accepted KPMG’s suggested change to the data set and excluded from our analysis those line items that appear to be duplicates within the same episode. We have not assessed the impact of this change, although, given KPMG’s results, we do not expect it to be material given that it only affect a small number of episodes.

Ancillary fees

41. KPMG stated that, contrary to what paragraph 12 of Appendix 6.12 in the Final Report suggested, the CMA had not removed ancillary fees from the data when calculating episode prices (CAT DRR, Annex 2, paragraphs 31 and 32). KPMG noted that it had already queried this error with the CMA, and the CMA had confirmed, in the course of the CAT appeal, that it did not remove such fees from episode prices. The CMA also noted that it ‘has reviewed the data and considers that only a negligible number of charges included in this data relate to ancillary items’.[24]

42. While inaccurately described in the Final Report, the fact that we have not removed ancillary fees from our episode prices is not an error, as such, and either approach could be taken. KPMG stated that it was not able, in the time provided, to exclude such charges from the data (of the CAT DRR, paragraph 44 and Annex 2, paragraph 32) and determine the materiality of this error. We have kept any ancillary fees in the data (ie we have followed the same approach as originally in the Final Report) on the basis that ancillary fees arise in a negligible number of charges and so are extremely unlikely to materially impact our results.

[24] CAT DRR, paragraph 43.

Consultant fees

43. For the IPA in the Final Report, we excluded consultant fees when calculating episode prices.[25] KPMG submitted that the CMA only excluded consultant fees where the industry standard code for a given line item was present within the 'Specialist and Practitioner fees' industry standard category. KPMG claimed that it had identified a number of other industry standard codes that related to consultant fees, and implied that these should have been excluded.[26] However, due to time constraints, KPMG was unable during its period of review to provide a list of these other industry standard codes and an explanation of how these categories could be consistently identified in the data.[27] KPMG stated in its CAT DRR that it had not excluded any such further codes in the course of its analysis.

44. We accept the possibility that the invoices in the Healthcode data may have included a small number of consultant fees that we did not identify. However, we did remove consultant charges to the extent that this was possible, and KPMG did not provide an explanation as to how any remaining charges could be identified. Further, based on KPMG's results, we do not anticipate that removing additional consultant fees would have a material impact on the price difference between the hospital operators.

45. In relation to consultant fees, KPMG also claimed that the CMA failed to exclude consultant fees correctly where there were multiple line items having both the same industry standard code belonging to the same invoice and the same price.[28] As set out below, we have looked into this issue and did not find any errors that required correction.

Removing duplicated line-item data

46. We found that in a non-negligible share of the data, the sum of all line-item charges for a given invoice did not add up to the invoice total, ie some line-item charges were duplicated within a given invoice. These duplicated line items occurred in approximately [✂]% of the overall episodes within the whole data set. Were we to use the information on the line-item count, we

---

[25] The CMA noted that 'for the majority of episodes, the Healthcode data does not include the consultant fee. In cases where the consultant fee is included (eg because a hospital operator bills on behalf of the consultant), we have subtracted this from the episode price.' (Final Report, Appendix 6.12, Annex A, footnote 2.) The CMA, therefore, excluded all consultant fees to the extent that these were clearly identified in the data.
[26] See the CAT DRR, paragraphs 35 & 36 and Annex 2, paragraphs 18 & 19.
[27] KPMG did describe one such example relating to the identification of additional radiologist fees, and it reported the total number of line items that may have been affected (see IPA WP DRR, Annex 2, paragraph 19 and Table A2-2)
[28] See the CAT DRR, paragraph 37 and Annex 2, paragraphs 20 & 21.

would introduce significant measurement error through double counting of line items.

47. In order to be able to use the line-item information in our IPA, we have developed a methodology to isolate the duplicated line items, and remove them from the data set. Each invoice lists the number of charge items, which correspond to the medical procedures, tests and so on (for example, pathology tests, X-ray or theatre time) performed on the patient during an episode.[29] If an identical charge item on the invoice is listed more than once, the invoice total may no longer correspond to the reported invoice total. If the invoice total does not correspond to the sum of all charges on the invoice, we found a duplicated line item. In order to extract the charge items information for analysis, we need to eliminate those duplicated charge items. Below we describe our approach to the removal of the duplicated line items in detail.

48. In a conversation with Healthcode we raised the issue of duplicated line items. It explained that the duplicated line items arose from the procedure Healthcode followed to extract the invoice data from its IT system and provide the requested information on all CCSD codes and diagnosis codes for each invoice. In addition, Healthcode acknowledged that multiple CCSDs were a problematic area of the data. We confirmed the correctness of our approach of removing duplicated line items with Healthcode.

49. We excluded line items according to the following criteria:

(a) We excluded exact duplicates across all variables, which accounted for about [✂]% of all the line items in the whole data set. For a given invoice, we identified charge items, which were identical to the corresponding charge item in another line of the same invoice. When deleting one of these two lines, the line item charges added up to the invoice total.

(b) We excluded duplicates that were exact duplicates of line items, once some variables were not considered. Those corresponded to about [✂]% of all the line items in the whole data set. We identified charge items in the data set that, for a given episode, were identical to the corresponding entry in another line of the same invoice, but for the value taken by the CCSD code, the diagnosis code or the service item code. Once these variables were not considered, deleting one of the entries resulted in line-item charges adding up to the invoice total.

[29] Note that this is not an exclusive list of procedures performed. As we have discussed above, due to contractual restrictions, invoices might not list separately the different procedures. For example, consider packages, which comprise several procedures performed on the patient.

50. After removing the duplicated line items identified in the above steps, we are left with [✂] episodes, ie less than [✂]% of the line-item data that is part of the IPA common basket, which is still affected by duplicated line items. We opted to keep those episodes in the data set because they still provided valuable information in the original price index approach.[30] To assess whether their inclusion had an effect on the results, we excluded them from the data, calculated the price index and found that this did not affected our results.

[30] Healthcode acknowledged that invoices at the episode level were verified and thus not affected by the issue of duplicates.

Statistical significance testing

1. To test the statistical significance of the price differences that we have estimated, we need to calculate the standard error of the price differences between the two hospital operators – for each insurer-year pair. While we can readily calculate the standard error at the treatment level, it is not straight-forward when we come to test the difference in the insurer-year price indices. We therefore employ a generally accepted statistical technique called a bootstrap, which allows us to calculate the standard error of the difference in the price indices. In this appendix we discuss our approach to statistical significance testing – the 'bootstrap' – and two statistical elements on the bootstrap specification

The bootstrap

2. Our IPA methodology begins by constructing a number of price indices in order to estimate the price differences between HCA and TLC for each insurer in each year. We are then interested in the statistical significance of these price differences. We therefore have to calculate the standard error of the price differences at the insurer-year level, as a high standard error would indicate that our price estimates are imprecise. While we can readily calculate the standard error at the treatment level, it is less straightforward when we come to test the statistical significance of the difference in the insurer-year-specific price indices.[1]

3. The idea behind the representative patient is to compare prices for the hospital operators, based on this 'typical' patient's characteristics, as if the representative patient were choosing between these hospital operators for a specific treatment. We use regression analysis to estimate the effect of the different patient's characteristics on the episode price per treatment. We then use the representative patient, for the specific treatment, to predict the price that this patient would face at HCA and TLC if faced with the choice of these two hospital operators. Because the representative patient has no variation in the patient characteristics we are unable to calculate the standard deviation of this estimated price directly.[2] We therefore employ a statistical technique

[1] Note that the same argument holds for the annual and overall price difference.
[2] Note that, by construction, the representative patient has constant patient characteristics – in our case, the median characteristics for patients within the relevant treatment, insurer and year. The variation in estimated prices is coming from the differences in patients' characteristics used in the regression analysis. If the representative patient also had variation in its characteristics it would not be possible to compare like for like and hence the price indices.

called a 'bootstrap', which allows us to calculate the standard deviation of the difference in the price indices.

4. The 'bootstrap' follows a simple logic: based on the original data set, we create a 'new' data set by randomly reshuffling the patient episodes. This new data set has the same number of patient episodes, however, some patient might not be recorded, while others might be recorded multiple times.[3] From this 'newly' generated data set, we recalculate the price difference, and repeat the reshuffling of the data set and the price calculation a large number of times.[4] Using this logic, we are able to use the repeatedly calculated price differences to establish a standard deviation of the price difference, which we subsequently use for statistical significance testing. While we do not go further into the statistical theory underlying the bootstrap methodology, we note that the bootstrap is a recognised and regularly used method for computing the standard deviation for this type of statistical significance testing.[5]

5. To generate the bootstrap we are able to use a built-in command in our statistical software package, Stata. The program contains an algorithm which automatically resamples the data, and carries out the specified statistical calculation. After repeatedly calculating the prices for HCA and TLC, Stata returns the price difference and the standard deviation of the price difference.

The error

6. In its Re-amended Notice of Appeal, HCA set out its view on the coding error in the bootstrap program and on its impact on the statistical significance testing:

> … a computer coding error had the consequence that the statistical significance tests for each [price] index comparison were performed in relation to the price for only one treatment in the common basket in the insurer-year pair in question rather than for the entire basket… That is, for each insurer-specific price index, the CMA took the estimated price variation of one treatment and interpreted it as the variability of the entire insurer-

---

[3] The resampling method is 'with replacement'. In other words, once we have recorded the patient's characteristics and the price for a specific episode, we put the episode back into the sample, so that it may be (randomly) drawn again and may be used more than once in generating the bootstrap sample. This is likely for treatments with small numbers of episodes in our data set.

[4] Note that our computer program repeats these steps 500 time at maximum. If the programme cannot replicate the underlying correlation in the data, the repetition is discarded and the programme moves to the next repetition.

[5] The bootstrap is an established statistical method to calculate the variance of an estimator, and thus its standard error. See, for example, Wooldridge, J M (2010), *Econometric Analysis of Cross Section and Panel Data*, section 12.8.2.

specific price index, which was in fact composed of multiple treatments differing in nature and price …[6]

7. This statement was supported by section 5.1 of the CAT DRR, where KPMG identified the error in the code in more detail. In particular, the DRR stated that: 'due to an error in the CMA's writing of its bootstrapping code, […], the CMA performed its bootstrapping analysis for each insurer-specific price index making use of the episodes associated with only one treatment'. Further, 'the CMA took the estimated price variation of one treatment and interpreted it as the variability of the entire insurer-specific price index, which was composed of multiple treatments …'

8. This led to an underestimation of the standard deviation of the price indices and thus an overstatement of the statistical significance of the insurer-year price index.

9. We agree that there is a coding error in the bootstrap program. As a result, our estimates of the statistical significance of the price differences were incorrect. We corrected the program, by including the 'nodrop' option as suggested by KPMG in its CAT DRR.

10. The nature of the error is the result of a peculiarity of Stata's bootstrap program. This program was used to calculate the statistical significance of the price differences. As mentioned above, the program repeatedly resamples the data and performs the calculation of the price index. To avoid statistical problems that can sometimes occur in this process, the bootstrap program drops all missing values from the data set.[7] If missing values are dropped, Stata relies on examining the most recent treatment. In our program we rely on more than one treatment and Stata only considers the most recent one, and does not consider any treatment that may have preceded it. Consequently, Stata deleted all of the data except for a single treatment (the last one in an alphabetical list) and ended up computing the statistical significance for only one treatment.

11. In addition, HCA stated that the error made in the bootstrap was compounded by erroneously multiplying the incorrectly estimated standard error with the weight of the single treatment in the basket. We agree with this point. This was a direct outcome of the way our code was written, but not a separate error. Therefore, when correcting the coding error in the calculation of the bootstrap, the aforementioned problem disappears.

---

[6] Re-amended Notice of Appeal, 17 October 2014, paragraph 115.
[7] We removed all missing values from the data set prior to running the bootstrapping algorithm.

The composition of the common basket in the bootstrap

12. In the results presented in the Final Report, the weights of the treatments were kept fixed, while the number of patients per treatment was allowed to be random during the bootstrap procedure. The aim was to reflect the fact that hospital operators do not know in advance how many patients for each treatment they will treat in a given year. However, we have reconsidered our approach to calculating the weights within each iteration of the bootstrap.

13. Our revised approach is to keep the number of observations per treatment, and hence the weight of the treatments, fixed. In particular, we restrict the re-sampling of the bootstrap to the treatment-hospital operator level.[8] In other words, in each iteration of the bootstrap, we allow the computer program to resample such that the number of patients for a given treatment and for a given hospital operator are constant in each iteration of the bootstrap, rather than being randomly drawn in each bootstrap iteration.

14. The reason for this approach is that it corresponds better with the economic context in this market, where, as set out in paragraph 6.4 (a), discussions between hospital operators and the insurers typically focus on the price of the overall bundle of a hospital operator's services (ie the associated revenue), with relatively little focus on the price of individual treatments. In particular, in this context, PMIs may not take into consideration how many patients are likely to be treated for each treatment. It is therefore reasonable to assume that a hospital would expect to treat the same number of patients each year. This thinking is reflected in the assumption that hospital operators and insurers assume fixed weights, ie the same number of patients, within a treatment.[9]

15. For its work in the CAT DRR, KPMG used a different approach to the composition of the common basket. While it also fixed the number of treatments in the basket, the number of observations and the weight each treatment receives varies with each iteration of the bootstrap. For the reason set out in the preceding paragraph, we do not pursue this approach.

16. Table 1 below summarises the differences in the three approaches outlined above: the CMA's original approach; KPMG's methodology used for the CAT DRR; and our current view.[10] We report the results of the statistical

---

[8] Note that for the annual and overall price difference we also restrict the bootstrap at the corresponding levels.
[9] This is also in line with the bootstrapping principle that the number of observations of the sampled distribution should be constant.
[10] Our current view is informed by the work undertaken for the IPA WP DRR.

significance tests based on the current approach, and a comparison to the previous approach, in Table 1 below.

Table 1: Summary of approaches to the 'bootstrapping' methodology

	Original approach in the FR	*KPMG DRR approach*	*Updated approach*
Treatments in basket	Fixed in bootstrap	Fixed in bootstrap	Fixed in bootstrap
Observations per treatment	Random in bootstrap	Random in bootstrap	Fixed in bootstrap
Weights of treatments	Fixed in bootstrap	Random in bootstrap	Fixed in bootstrap

Source: CMA analysis.

17. [✂][11,12] the bootstrapping approach is consistent with the economic model of bargaining between an insurance provider and a hospital provider.

The number of insurers considered

18. In the Final Report, we reported the results of statistical significance tests for 25 insurer-year-specific price differences. This approach was taken in order to focus the statistical significance testing on the larger insurers only. For the insurers that were not considered, we did not have observations for all years, with the exception of [✂].[13] This was a deliberate choice made when testing the statistical significance. For the sake of completeness we now report the results of the statistical significance testing for all insurer-years although, as pointed out above, a number of smaller insurers have patient volumes such that no treatment meets the 30-episode threshold and so these insurers are not included in these results.

[11] IPA WP DRR, p9, footnote 19.
[12] IPA WP DRR, p9, footnote 19.
[13] The omitted insurers were [✂] (2010, 2011), [✂] (2011) and [✂] (2009–2011), as well as [✂].

Results and robustness checks

1. In this appendix we present the detailed results on the main specification and the difference robustness checks presented in Section 8.

Results

2. In this section we present the results of the IPA main specifications. We will first present the results on the insurer-year level and then move to more aggregated levels, ie the annual price differences and the overall price difference. We present the results, for both 5- and 30-episode thresholds, for the IPA, both our specification (including patient age, gender and length of stay) and the IPA WP DRR specification, which includes an additional variable for the number of pathology charges in the relevant invoices. The statistical significance of the results are presented in the relevant tables below as well.

3. In columns A and B of Table 1 we present the results for the insurer-year price differences based on a 5-episode threshold. These results in column A (that is, excluding the count of pathology charges) suggest that there is a price difference between HCA and TLC of [✄]%, which is statistically significant for [✄] out of 36 insurer-years. When adding the number of pathology charges into the treatment-level regressions, the results suggest that the price differences for most insurer-years reduce considerably, with some insurer-year showing no price difference or even suggesting that TLC may be charging higher prices. [✄] is a notable exception: the price differences fall when the count of pathology charges is included in the IPA, but (with the exception of the 2007 results) the price differences remain substantial, compared with other insurers. Statistical significance testing suggests that [✄] out of 36 insurer-year price indices are statistically significant in column B.

4. In columns C and D of Table 1 we also present the results for the insurer-year price differences based on a 30-episode threshold. The results are consistent with the results for the 5-episode threshold (for the insurer-year price indices we can compare). While we find a positive price difference between HCA and TLC for the specification not including the pathology count, the price differences fall substantially for many insurers in many years with the inclusion of the pathology charge variable, with, again, some price results suggesting that HCA prices are no higher or even lower than TLCs for some insurers in some

years. Furthermore, we find that [✂] out of 23 insurer-year price differences are statistically significant.[1]

Table 1: Insurer-year price difference

					%
		5-episodes		*30-episodes*	
		CMA	*Pathology*	*CMA*	*Pathology*
		(A)	*(B)*	*(C)*	*(D)*
2007	AXA PPP	[✂]	[✂]	[✂]	[✂]
2008	AXA PPP	[✂]	[✂]	[✂]	[✂]
2009	AXA PPP	[✂]	[✂]	[✂]	[✂]
2010	AXA PPP	[✂]	[✂]	[✂]	[✂]
2011	AXA PPP	[✂]	[✂]	[✂]	[✂]
2011	Aviva	[✂]	[✂]	[✂]	[✂]
2007	Bupa	[✂]	[✂]	[✂]	[✂]
2008	Bupa	[✂]	[✂]	[✂]	[✂]
2009	Bupa	[✂]	[✂]	[✂]	[✂]
2010	Bupa	[✂]	[✂]	[✂]	[✂]
2011	Bupa	[✂]	[✂]	[✂]	[✂]
2007	Bupa Int'l	[✂]	[✂]		
2008	Bupa Int'l	[✂]	[✂]	[✂]	[✂]
2009	Bupa Int'l	[✂]	[✂]	[✂]	[✂]
2010	Bupa Int'l	[✂]	[✂]	[✂]	[✂]
2011	Bupa Int'l	[✂]	[✂]	[✂]	[✂]
2007	Cigna	[✂]	[✂]		
2008	Cigna	[✂]	[✂]		
2009	Cigna	[✂]	[✂]		
2010	Cigna	[✂]	[✂]		
2011	Cigna	[✂]	[✂]	[✂]	[✂]
2010	Exeter	[✂]	[✂]		
2008	PruHealth	[✂]	[✂]		
2009	PruHealth	[✂]	[✂]	[✂]	[✂]
2010	PruHealth	[✂]	[✂]	[✂]	[✂]
2011	PruHealth	[✂]	[✂]	[✂]	[✂]
2007	SLH	[✂]	[✂]		
2008	SLH	[✂]	[✂]	[✂]	[✂]
2009	SLH	[✂]	[✂]	[✂]	[✂]
2010	SLH	[✂]	[✂]		
2011	SLH	[✂]	[✂]		
2009	Simplyhealth	[✂]	[✂]		
2010	Simplyhealth	[✂]	[✂]	[✂]	[✂]
2011	Simplyhealth	[✂]	[✂]	[✂]	[✂]
2010	WPA	[✂]	[✂]		
2011	WPA	[✂]	[✂]		
Total		[✂]	[✂]	[✂]	[✂]
Positive and significant		[✂]	[✂]	[✂]	[✂]

Source: CMA analysis.

Small number of treatments account for much of the price difference

5. In this section we present the graph for the contribution of the price differences to the overall price difference. We have calculated the price differences by taking the average for a given treatment overall price differences on the insurer-year level. In the graph we present the order results of this. Figure 1 is based on the original specification with a minimum of 5 patient episodes.

[1] Note that for computational reasons we test the statistical significance of the percentage price difference for the aggregate price index.

Figure 1: Contribution of CCSDs to price difference (5 episodes)

[✂]

Source: CMA analysis.
Note: Price differences on the vertical axis are in percentages.

Alternative definitions of the 'representative patient'

6. To estimate the prices for a specific treatment for a specific insurer in a given year we use a 'representative patient' to ensure that we are making a like-for-like comparison between HCA and TLC. The underlying idea is to compare the price that an insurer would be charged for an identical, and typical, patient (in terms of the characteristics that we observe – age, gender and length of stay) for that specific treatment at each of HCA and TLC.

7. In order to understand whether our results are sensitive to the definition of the representative patient, we checked the robustness of our baseline results to different types of representative patients. In particular we used:

   (a) mean patient;

   (b) the 25th and 75th percentile patient characteristics, meaning that we used the patient characteristics below which 25 and 75% of the patients may be found; and

   (c) the median HCA and TLC patient to understand whether the price difference is affected by the distribution of the patient characteristics.

8. The first sensitivity check we have conducted is to define the representative patient as having the mean characteristics of the patients for each treatment in the data set. The advantage of this definition is that it may better reflect the distribution of patient characteristics in the data. The results of our comparison of using the median (our baseline approach that we use in the IPA) and the mean patient are presented in column A and C of Table 2 below, using the 5-episode and 30-episode threshold. The results suggest that the estimated annual price differences are in line with the baseline approach. We also check the results for the price differences at the insurer-year level. The results suggest an increase for some insurers and years and decrease for others. However, overall there are still substantial positive price differences between HCA and TLC, for most insurers, with [✂] being the main exception to this, as it is in the median-based IPA. Looking at the overall price difference, across insurers and years, HCA is [✂]% more expensive compared with TLC when we use a mean representative patient, compared with [✂]% using a median representative patient.

Table 2: Annual price differences for mean representative patient – % price differences

	5 episodes		*30 episodes*	
	(A)	*(B)*	*(C)*	*(D)*
Year	*CMA*	*Pathology*	*CMA*	*Pathology*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

9. In addition, we defined the representative patient as having the 25^{th} and 75^{th} percentile characteristics. The results for the annual and overall price difference are reported in Tables 3 and 4, below. While there is some variation in the results compared with the baseline median patient, the results suggest that we consistently estimated a positive price difference. We therefore conclude that the results are in line with our median representative patient.

10. The rationale behind using a representative patient defined as the median of either the HCA or the TLC patients, is motivated by the HCA's argument that its patient population may be different to TLC's to the extent that using a single representative patient is not an appropriate way to compare their prices. In particular we are aiming to understand whether a representative patient of HCA's median patient characteristics is more expensive to treat at HCA or at TLC. We also carry out the same thought experiment for a TLC patient. Suppose we find that the price difference between HCA and TLC for treating a TLC-specific patient is negative, while the price difference for treating an HCA-specific patient is negative as well. This pattern would suggest that each of HCA and TLC is relatively more efficient in treating its respective patients. Furthermore this pattern would suggest a selection of patients to the respective hospitals.

11. In Tables 5 and 6 we present the estimated annual and overall price differences for a 5- and 30-episode threshold. Our original approach, presented in columns A and C in the corresponding tables, suggests that there is a small change between the two specifications and relative to our main specification, using a median patient over both hospital operators' patient populations in the data. Including the pathology count (columns B and D) suggests there is a larger price difference for the HCA-specific patients compared with the TLC-specific patient. Our results suggest that we do not find evidence based on the above robustness check for the selection of patients to the respective hospitals.

Table 3: Annual price differences for 75th percentile patient – % price differences

	5 episodes		*30 episodes*	
	(A)	*(B)*	*(C)*	*(D)*
Year	*CMA*	*Pathology*	*CMA*	*Pathology*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

Table 4: Annual price differences for 25th percentile patient – % price differences

	5 episodes		*30 episodes*	
	(A)	*(B)*	*(C)*	*(D)*
Year	*CMA*	*Pathology*	*CMA*	*Pathology*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

Table 5: Annual price differences for median HCA patient – % price differences

	5 episodes		*30 episodes*	
	(A)	*(B)*	*(C)*	*(D)*
Year	*CMA*	*Pathology*	*CMA*	*Pathology*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

Table 6: Annual price differences for median TLC patient – % price differences

	5 episodes		*30 episodes*	
	(A)	*(B)*	*(C)*	*(D)*
Year	*CMA*	*Pathology*	*CMA*	*Pathology*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

Alternative charge items

12. In addition to the number of pathology tests, there are additional charge categories, such as theatre or X-ray, in the data that could, in principle, be

informative about the characteristics of the patient and the episode. Therefore, we also analysed whether any of these additional line-item charges had an impact on the overall price difference when these variables were included in the treatment-level regressions in the IPA. We present the outcomes of this analysis in Table 7 below. We begin by presenting the results of our own replication of the KPMG analysis which included the number of pathology tests in the CCSD-level regression in the IPA. The effect of including pathology in the price-index regressions is that the price difference between HCA and TLC reduces considerably to [✂]% (see Table 7).

13. We also included additional charge categories, which, as Table 7 shows, affect the price difference by increasing or decreasing it by [✂] percentage points. Specifically, the effects range from a reduction to [✂]% or an increase to [✂]% from the 'original' [✂]% (see Table 6). This work suggest that the pathology count is the variable that has the most impact on the price difference. That the pathology charges have the strongest effect on the average price difference can be explained by revenue derived from pathology charges representing a large share in the overall costs of the line items (see Table 2), while other charge categories occur less frequently.[2]

Table 7: IPA and alternative charge items (30 episodes)

	Path	*CT*	*X-ray*	*MRI*	*ECG*	*Theatre*	*Nursing*	*Prosthesis*
2007	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

Pathology outliers

14. We also looked at whether a small number of episodes with an unusually large number of pathology charges could be driving the results. The rule that we use to exclude an episode from the analysis is to do so if the pathology count is respectively above one, two or three times the standard deviation of the mean pathology count for a particular treatment.[3] Our analysis drops those observations that are more than two or three times the standard deviation.[4] We report the results in Table 8. The exclusion of 'outliers'

[2] Note that the next largest line item, theatre, represents [✂]% and [✂]% for HCA and TLC. The largest group of line items is insurer-specific package, which represents [✂]% and [✂]% for HCA and TLC.
[3] It is a common procedure used in econometric work to classify outliers by the distance from the mean value for that variable. Assessing outliers in terms of how many standard deviations they are from the mean is often used as an objective measure of the extent to which they are 'out of line' with data or unusual in this context.
[4] The lower the multiple of the standard deviation we drop, the more observations we drop and therefore we might lose more useful information.

increased the price difference by up to one percentage point for the 5-episode threshold, which is a slightly higher price differences than in the KPMG analysis. For the 30-episode threshold (Table 9), the price difference increases by up to [✂] percentage points.

Table 8: Pathology outliers, 5 episodes (in common basket)

Year	*CMA (all)*	*Pathology (all)*	*Pathology (3 standard deviations dropped)*	*Pathology (2 standard deviations dropped)*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

Table 9: Pathology outliers, 30 episodes (in common basket)

Year	*CMA (all)*	*Pathology (all)*	*Pathology (3 standard deviations dropped)*	*Pathology (2 standard deviations dropped)*
2007	[✂]	[✂]	[✂]	[✂]
2008	[✂]	[✂]	[✂]	[✂]
2009	[✂]	[✂]	[✂]	[✂]
2010	[✂]	[✂]	[✂]	[✂]
2011	[✂]	[✂]	[✂]	[✂]
Average	**[✂]**	**[✂]**	**[✂]**	**[✂]**

Source: CMA analysis.

The regression approach

15. In this section we provide more detail on the regression approach. Our approach is based on modelling the price of each episode as a function of the hospital where the treatment is provided (HCA or TLC), while controlling for the patient mix, using the patient characteristics and any other factors that are specific to the insurer, treatment or year. The aim of this approach is to assess the robustness of the price-index approach, in particular the robustness of the representative patient approach.

16. While in the regression approach we avoid having to make the same assumptions as we do in implementing the IPA and the bootstrapping approach – in relation to the representative patient, statistical distributions, independence of variables and so on – estimating a regression is based on a number of assumptions about the relationship between prices and patient characteristics, the relationship between prices and HCA's bargaining power, among others.

17. In addition, calculating the standard error from the regressions on the insurer-year-treatment level, and aggregating them up to the insurer-year level

presents a challenge. The reason is that treatment prices might be correlated, which has to be taken into account when calculating the standard error. Hence, we use a bootstrapping approach to calculate the standard error of the price difference between HCA and TLC. We then use the standard error to test the statistical significance of the price differences. However, the bootstrap approach relies on a number of assumptions. For example, the bootstrap approach implicitly relies on, and is sensitive to, the minimum episode threshold that is applied for a given treatment. For example, looking at the price difference [✂] 2009: using a threshold of 5 episodes, the price difference ([✂]%) is not statistically significant. Moving to a 30-episode threshold, the price difference ([✂]%) is statistically significant at the 99% confidence level.

18. Notwithstanding the limitations identified above with the bootstrapping approach, we consider that it produces robust results. However, it is important to understand to what degree the bootstrap might be affected by changes in the assumptions. A simple way to test the results of the bootstrap is to use the regression approach, which provides a test of the statistical significance of the coefficient estimates as part of the regression output.

19. In comparing the regression approach and the price-index approach used in the IPA, particularly relevant points include the following:

   (a) While the two approaches aim to answer the same questions, there are a number of differences:

      (i) Depending on the exact specification of the regression equation estimated, the effect of patient characteristics may be estimated in aggregate (across all treatments) rather than for each treatment and for each of HCA and TLC separately.

      (ii) In the regression approach we estimate the effect of being treated by HCA on episode prices directly while simultaneously controlling for patient characteristics and any treatment-, insurer- and year-specific effects, rather than constructing a series of price indices in order to do this.

20. While in the regression approach we avoid having to make the same assumptions as we do in implementing the IPA and the bootstrapping approach – in relation to the representative patient, statistical distributions, independence of variables and so on – estimating a regression is, of course, based on a number of assumptions about the relationship between prices and patient characteristics, the relationship between prices and HCA's bargaining power, among others.

21. We have used the same cleaned data set for the regression approach as we did for the IPA, although the regression approach uses more of the data. In the IPA we restricted the minimum number of patients treated at a hospital operator for a given treatment, insurer and year – using both 5- and 30-episode thresholds. We did this because we estimated regressions at the treatment-insurer-year-hospital-operator level, including three explanatory variables, and we therefore needed a sufficient number of episodes, ie at least 5 or 30, in order to be able to estimate the individual treatment-level regressions in the IPA approach. While we still consider patients within the common basket only, in the regression approach we are able to reduce the minimum episode threshold for each treatment to at least two episodes.[5] As a result of being able to include more treatments in our analysis, the number of observations for the regressions approach is about 91,000 compared with around 68,000 for the 5-episode IPA.[6]

22. The baseline regression equation we estimate is

$$\ln p_{tij} = \beta + \beta_1 HCA + \beta_2 X_t + \gamma_t + \gamma_i + \gamma_j + u_{tij},$$

where X is a matrix containing the patients' (logarithm of) age, length of stay and gender. The γ's are treatment (t), insurer (i) and year (j) fixed effects, respectively.[7] HCA denotes an HCA dummy, indicating whether a patient received the treatment at an HCA hospital.

23. In the regression approach we control for the patient mix by including treatment fixed effects (denoted by γ_t).[8] This approach follows Haas-Wilson and Garmon (2009). In addition we include patient characteristics in the regression. The former takes into account all factors that are constant within a treatment group. The latter controls for the severity of the individual patients.

24. Similar to the academic literature on healthcare we use the CCSD code to identify the treatment that a patient receives.[9] The aim of the CCSD codes is to provide a standardised way of recording medical procedure, ie treatments, to hospital operators and insurers.[10] The CCSD codes provide a fine grained

[5] Lower patient numbers per treatment means that we are not able to estimate the respective treatment fixed effect. Note that all treatments for which this is the case are subsumed in the constant.
[6] This also means that we are considering a larger share of the hospital operators' revenues.
[7] Note that some treatment fixed effects are dropped if there is an insufficient number of patients for that treatment.
[8] We use similar control variables in the treatment-level regressions that we estimate as part of the IPA as well.
[9] For details on the CCSD codes please see the CCSD website.
[10] A CCSD code does not provide any guidance on the price a hospital operator is able to charge for the medical procedure, which is determined by the insurer and hospital operator in their price negotiations. The CCSD code also does not provide any indication about costs of a specific medical procedure relative to another medical procedure. This is unlike the Diagnosis Related Group used in academic publication focusing on the US-

indication of complexity of the patient. For example, within the chapter of Chemotherapy (Chapter 18) the CCSD codes are subdivided into 0–7 days, 1–14 days, 1–21 days and 1–28 days. However, there could still be differences in patients' severity with a treatment group. We therefore control for additional patient characteristics, such as age, length of stay and gender.

25. The standard errors are clustered at the treatment level.[11] The reason for clustering at the treatment level is that the error term across patients might be correlated for patients receiving a particular treatment. The standard response in the academic literature is to adopt a clustering approach to estimating the standard error.[12] In addition we explore alternative clustering, for example at the treatment-hospital level. We are conservative in our choice of clustering, reporting clustering with the largest standard errors compared to other reasonable approaches.[13]

26. We also used two further sets of control variables:

(a) We took into account different effects of insurers on the price. Each insurer may possess a degree of bargaining power, which is likely to lead to different prices being charged for different insurers' patients.

(b) We took into account factors that vary across years but do not have different impacts on different insurers, treatments or providers, for example inflation in input costs.

27. We are mainly interested in the sign of the HCA-specific effect, β_1, and whether the coefficient is statistically different from zero. A positive coefficient suggests that HCA is charging a higher price relative to TLC. Based on the price-index approach we employ in the IPA, we would expect a positive price difference.

28. We present the results of the baseline regression approach, defined in paragraph 22, in Table 10 below. The results of the main specification are presented in column A. The coefficient on HCA suggests that HCA is on average [✄]% more expensive than TLC. Also, the price difference is statistically significant at the 99% level.

healthcare market. Because the relative weights are not available to us, we rely on a fixed-effects approach in controlling for the treatment.

[11] By clustering the standard errors, ie the standardised deviation from the mean, we take into account the correlation within a group, here, we cluster at the treatment level.

[12] In addition we explore alternative clustering, for example at the treatment-hospital level, for our baseline approach. We chose to report the clustering at the treatment level only, because the standard errors are the largest compared with other reasonable approaches.

[13] We do not explore clustering at the hospital operator level because of too few clusters. Additional clustering we explored was at the treatment-hospital-operator level and heteroscedasticity-robust standard errors.

Table 10: Regression approach

	(A)	(B)	(C)
	Baseline	*Day-case dummy*	*Treatment patient interaction*
HCA	[✂]	[✂]	[✂]
	[✂]	[✂]	[✂]
Male	[✂]	[✂]	
	[✂]	[✂]	
Age (log)	[✂]	[✂]	
	[✂]	[✂]	
Length of stay	[✂]	[✂]	
	[✂]	[✂]	
Day case		[✂]	
		[✂]	
R-squared (adjusted)	[✂]	[✂]	[✂]
Number of observations	[✂]	[✂]	[✂]

%

Source: CMA analysis.

29. With respect to the patients' characteristics, only the length of stay and the day-case dummy have effects on the episode price which are statistically significant.[14] For length of stay we would expect a positive effect on the price of the treatment. Our regression approach suggests that for each additional night a patient stays in hospital, on average, the price increases by [✂]%. The effect of a patient's gender indicates that male patients incur lower prices, while for patient age the effect is positive, but, as both effects are statistically insignificant we cannot conclude that these variables have explanatory power for the price differences in this specification of the regression.

30. In column B we also use a day-case dummy to understand whether controlling for the differential costs involved in treating day cases affects our estimate of the price difference between HCA and TLC. For day-case patients we would expect the treatment to have a lower price because a day-case patient does not have the added costs of needing overnight care. We find that, on average, hospital operators charge 50% less for a day-case patient.[15] Compared with the results presented in column A, the HCA effect increases. The results suggest that HCA charges a [✂]% higher price compared with TLC and that this difference is statistically significantly.

[14] Which indicates those episodes where the patient was treated as a day-case with no overnight stay.
[15] Again, the coefficient on 'day-case' is roughly equivalent to a percentage difference, but not exactly so, as in we need to exponentiate the estimated coefficient to calculate the percentage difference.

KPMG's comments

31. [✂][16,17]

Our response

32. [✂][18] estimating a regression where coefficients are allowed to vary for each treatment.[19] In our baseline regression, we deliberately chose a different (less flexible) approach because we wanted to produce a simpler estimate of the price difference between HCA and TLC without making assumptions around, for example, the representative patient. Furthermore, one concern that was raised in relation to the IPA analysis was that it covered relatively few treatments and patient numbers. When using the regression approach, where we did not have to estimate the effect of age, gender and length of stay separately for each treatment, each provider, each insurer and each year, we could then include more treatments (those with smaller patient volumes for some insurers) and so considerably increase the coverage of our analysis (by more than one-third in terms of number of episodes).

Regression specification

33. In this section we provide some detail on the regression specifications that we have estimated. Each of the regressions is estimated at the insurer-year level, because it allows more flexibility of the regression approach. This approach moves the regression approach closest to the IPA without sacrificing the advantages of the regression approach. As a result we focus on the price difference between HCA and TLC at the insurer-year level. In the regression equation we relate the price a patient insured with insurer i pays for receiving treatment t in year j to the patient's characteristics and a HCA dummy. Specifically, the baseline regression equation we estimate is:

$$\ln p_{tij} = \beta_{0\mathrm{tij}} + \beta_{1\mathrm{ij}} HCA + \beta_{2\mathrm{tij}} X_{tij} + u_{tij},$$

where X is a matrix containing the patient's age, length of stay and gender. We observe the estimated variables at the insurer-year level for each treatment. For example, the effect of a patient's age is allowed to be different for every treatment we observe for the insurer and the year in the common

[16] Also, strictly speaking its test suggests that the coefficients are not statistically equal. However, which set of coefficients is statistically preferable is not answered by the test.
[17] IPA WP DRR, paragraph 1.10.
[18] IPA working paper, paragraphs 20–23.
[19] IPA working paper, Table E1, Column E.

basket.[20] HCA denotes a HCA dummy, indicating whether a patient received the treatment at a HCA hospital.[21]

34. We are interested in the HCA-specific effect, β_{1ij}; its sign, magnitude and whether the coefficient is statistically different from zero. A positive coefficient suggests that HCA is charging a higher price relative to TLC. In particular we are interested in comparing the coefficients on the HCA dummy with and without the inclusion of the pathology count. We first present the results of our original analysis. We then provide the results when we include the pathology count. This step informs whether the price effect reduces in response to inclusion of the pathology count, similar to the effect in the IPA.[22]

35. In Table 11 we present the results on the regression approach. The results for our 'original' approach shown in column A suggest that price difference at the insurer-year level are positive. In column B we include the pathology count variable. This results in a clear reduction of the price difference for the majority of the insurer-year price difference (column C).[23] The exception, as in the price-index approach, is the price differences for [✂], where we observe a small decrease in the price differences. Overall, relative to the IPA, the price differences reduce by less with the inclusion of the pathology count variable.

36. Overall we conclude that the regression approach is consistent with the IPA results, specifically, that the inclusion of the pathology count variable reduces the price difference between HCA and TLC in the majority of the price differences estimated.

---

[20] Note that for the IPA we would interact each of the treatment-patient characteristics with a hospital dummy as well. We do not do this here otherwise we would have to rely on a representative patient.
[21] Note that we do not cluster the standard errors for the insurer-year regressions. The standard errors are robust standard errors.
[22] Note that the including the number of pathology charges into the regression approach has the same problems as described in the IPA as discussed in Section 8, paragraph 8.23 and following.
[23] Note that for [✂] 2011 we were not able to estimate the effect of the pathology count on the price difference because it is collinear with the HCA dummy.

Table 11: Regression results

Year	*Insurer*	*CMA (%)*	*Pathology (%)*	*Difference*
		(A)	*(B)*	*(C)*
2011	Aviva	[✂]	[✂]	[✂]
2007	AXA PPP	[✂]	[✂]	[✂]
2008	AXA PPP	[✂]	[✂]	[✂]
2009	AXA PPP	[✂]	[✂]	[✂]
2010	AXA PPP	[✂]	[✂]	[✂]
2011	AXA PPP	[✂]	[✂]	[✂]
2007	Bupa	[✂]	[✂]	[✂]
2008	Bupa	[✂]	[✂]	[✂]
2009	Bupa	[✂]	[✂]	[✂]
2010	Bupa	[✂]	[✂]	[✂]
2011	Bupa	[✂]	[✂]	[✂]
2007	Bupa Int'l	[✂]	[✂]	[✂]
2008	Bupa Int'l	[✂]	[✂]	[✂]
2009	Bupa Int'l	[✂]	[✂]	[✂]
2010	Bupa Int'l	[✂]	[✂]	[✂]
2011	Bupa Int'l	[✂]	[✂]	[✂]
2007	Cigna	[✂]	[✂]	[✂]
2008	Cigna	[✂]	[✂]	[✂]
2009	Cigna	[✂]	[✂]	[✂]
2010	Cigna	[✂]	[✂]	[✂]
2011	Cigna	[✂]	[✂]	[✂]
2011	Exeter	[✂]	[✂]	[✂]
2009	Exeter	[✂]	[✂]	[✂]
2008	PruHealth	[✂]	[✂]	[✂]
2009	PruHealth	[✂]	[✂]	[✂]
2010	PruHealth	[✂]	[✂]	[✂]
2011	PruHealth	[✂]	[✂]	[✂]
2009	Simplyhealth	[✂]	[✂]	[✂]
2010	Simplyhealth	[✂]	[✂]	[✂]
2011	Simplyhealth	[✂]	[✂]	[✂]
2007	SLH	[✂]	[✂]	[✂]
2008	SLH	[✂]	[✂]	[✂]
2009	SLH	[✂]	[✂]	[✂]
2010	SLH	[✂]	[✂]	[✂]
2011	SLH	[✂]	[✂]	[✂]
2010	WPA	[✂]	[✂]	[✂]
2011	WPA	[✂]	[✂]	[✂]

Source: CMA analysis.

Glossary

Act	The Enterprise Act 2002.
Admission	A patient will be admitted to hospital where their treatment requires admission to a hospital bed. This is a clinical decision and a patient admitted may be admitted either as a **day-case patient** or as an **inpatient**.
AEC	Adverse effect on competition as set out in section 134(2) of the **Act**.
Aviva	Aviva Health UK Limited, a principal subsidiary of Aviva plc, provider of insurance, savings and investment products.
AXA PPP	AXA PPP healthcare, a subsidiary of The AXA Group and provider of **PMI**.
BMI	BMI Healthcare Limited and any company in the group as appropriate, part of GHG, a private **hospital group** in the UK.
Bupa	The British United Provident Association Limited, a provider of **PMI** and a **private hospital operator**.
Catchment area	Geographical area from which a hospital draws its patients.
CC	Competition Commission.
CC3	*Guidelines for market investigations: Their role, procedures, assessment and remedies* (April 2013).
CCSD	The Clinical Coding & Schedule Development Group. A group consisting of representatives from five **PMI**s: **Aviva**, **AXA PPP**, **Bupa**, **PruHealth** and **Simplyhealth**, which establishes and maintains a common standard of procedure codes and narratives within the independent healthcare sector.
Central London	The NUTS 2 region of Inner London, which roughly coincides with the areas within the North and South Circular Roads. Inner London consists of Camden, City of London, Hackney, Hammersmith and Fulham, Haringey, Islington, Kensington and Chelsea, Lambeth, Lewisham, Newham, Southwark, Tower Hamlets, Wandsworth, and Westminster.

Clinician	A health professional such as a **GP**, **consultant**, other physician or nurse involved in the care of patients.
CMA	Competition and Markets Authority.
Consultant	A registered medical practitioner who holds, or has held, or is qualified to hold, an appointment as a consultant in the **NHS** in a specialty other than general practice or whose name is on the register of specialists kept by the **GMC**. A consultant may work exclusively for the **NHS** or in private practice or a combination of the two. Except where the context otherwise provides, consultant refers to a consultant in private practice whether or not they also work in the **NHS**.
Corporate PMI	**PMI** provided by an employer to its employees and in some cases dependants of the employee.
Cost of capital	The return that investors in a project expect to receive over the period of that investment. It is an opportunity cost and can be seen as the yield on capital employed in the next best alternative use.
Day-case patient	A patient admitted during the course of a day with the intention of receiving care without requiring the use of a hospital bed overnight. If the patient's treatment then results in an unexpected overnight stay they will be admitted as an **inpatient**.
Episode	An episode is defined as a single visit to a hospital by a patient. In the context of the **IPA**, it is defined as a single visit to a private hospital by an insured patient to receive treatment on a day-case or inpatient basis.
Final Report	The Final Report of the market investigation published on 2 April 2014.
GMC	General Medical Council, the independent regulator for doctors in the UK.
GP	General practitioner, a doctor who works in a local surgery or health centre, providing medical advice and treatment to patients registered on their list.
GP referral	A referral from a **GP** for specialist treatment.

Greater London	The combined area of **central London** and **outer London**, synonymous with **London**.
HCA	HCA International Limited and any company in the group as appropriate, a **private hospital operator**.
Healthcare provider	An organisation or person that provides preventive, curative, promotional, or rehabilitative healthcare services including a hospital, clinic, **GP**, **consultant** or other medical professional.
Healthcode	A provider of online practice management software and services to the **private healthcare** market. Healthcode processes medical bills for private hospitals and **PPU**s, acting as an intermediary between private hospitals and **PMI**s.
Hospital group	A **private hospital operator** that operates more than one hospital.
Hospital services	All services provided by a **private hospital** including **inpatient**, **day-case** and **outpatient** services. Where it is necessary in this report to distinguish between different types of hospital services this is made clear in the text.
HPA	Healthcare Purchasing Alliance, a joint venture between **Aviva** and **VitalityHealth** to procure healthcare services from **private healthcare providers** for both PMIs.
IPA	Insured price analysis is an analysis of prices charged by **private hospital operators** to **PMI**s, based on invoice data for **insured patient**s covering the period 2007 to 2011.
Independent hospital	A private hospital not belonging to a **Hospital Group**.
Inpatient	A patient admitted to hospital with the expectation that they will remain in hospital for at least one night.
Insured patient	A patient who will use **PMI** to pay (in whole or in part) for their medical care.
Insurer network	A list of private hospitals and other **private healthcare facilities** that are on a **PMI**'s approved list. Some **PMI**s create narrower networks for different types of policies.

KPMG	HCA's external economic advisers.
LOCI	A measure of weighted-average market share used by the **CC** to measure local concentration. Based on the 'Logit Competition Index', a measure of competition that has been used to analyse healthcare markets.
London	The combined area of **central London** and **outer London**, synonymous with **Greater London**.
Medical treatment	Except where the context otherwise provides, medical treatment includes medical, surgical and/or diagnostic/pathology treatments.
NHS	National Health Services in England, Scotland and Wales and the Health and Social Care Services in Northern Ireland.
NHS trust	A public benefit healthcare organisation created by Act of Parliament to treat **NHS** patients.
Nuffield	Nuffield Health and any company in the group as appropriate, a **private hospital operator**.
OFT	Office of Fair Trading.
OPCS coding ICD-10	An international standard for diagnostic coding.
Open referral	A referral from a **clinician** that does not name the **consultant** and/or **private healthcare facility** to whom/which the **patient** is being referred.
Outer London	The NUTS 2 region of Outer London, roughly the area between the North and South Circular Roads and the M25 ring road. Outer London consists of Barking and Dagenham, Barnet, Bexley, Brent, Bromley, Croydon, Ealing, Enfield, Greenwich, Harrow, Havering, Hillingdon, Hounslow, Kingston upon Thames, Merton, Redbridge, Richmond upon Thames, Sutton, and Waltham Forest.
Outpatient	A patient treated in a hospital, consulting room or clinic, who is not admitted.
PCA	Price-concentration analysis.

PHIN	Private Healthcare Information Network, a body whose membership is made up of **private hospital operator**s.
PMI/insurer	As the context provides, either a private medical insurer or private medical insurance. Private medical insurance is an insurance product under which an insurer agrees to cover the costs, in whole or in part, of acute medical care. Insurer in this report refers to a PMI.
PPU	Private patient unit, a facility within the **NHS** providing medical care to private patients. Such units may be separate units dedicated to private patients or facilities within the main **NHS** site that are made available to private patients either on a dedicated or non-dedicated basis.
Private healthcare facility	Any facility providing medical treatments on an **inpatient**, **day-case** and/or **outpatient** basis, which charges fees for its services including a **PPU**.
Private healthcare provider	A **healthcare provider** that charges fees for its services.
Private hospital	A facility which provides **inpatient hospital services** that charges fees for its services including a **PPU**. Except where the context provides otherwise, in this report hospital refers to a **private hospital**.
Private hospital operator	A person that operates a **private hospital** including, where relevant, an **NHS trust** in relation to a **PPU**.
Privately-funded healthcare services/ private healthcare	Services provided to patients via **private facilities/clinics** including **PPU**s through the services of consultants, medical and clinical professionals who work within such facilities.
Private patient	A patient who is charged for private medical services either as a **self-pay patient** or as an **insured patient**.
PruHealth	Prudential Health Services Limited, Prudential Health Insurance Limited and any company in the group as appropriate, now known as **VitalityHealth**, providers of **PMI**.
Ramsay	Ramsay Health Care UK Operations Limited and any company in the group as appropriate, a **private hospital operator**.

Relevant customer benefit	A benefit as defined by section 134(8) of the **Act**.
Remedies Notice	The notice of possible remedies published on the same date as publication of this provisional findings report.
Self-pay patient	A patient who pays for their private medical care themselves.
Simplyhealth	Simplyhealth and any company in the group as appropriate, a **PMI** provider.
Specialties	The **GMC** divides areas of medical care into 65 specialties.
Spire	Spire Healthcare Limited and any company in the group as appropriate, a **private hospital operator**.
TLC	The London Clinic, a **private hospital operator**.
ToH	Theory of harm.
VitalityHealth	Vitality Health Limited, Vitality Health Insurance Limited, and any company in the group as appropriate, formerly known as **PruHealth**, a **PMI** provider.