Analysis of PPI price increases for MPPI, PLPPI and CCPPI

1. This appendix sets out our analysis on whether the level of consumer substitution between PPI products is sufficient to constrain the behaviour of the distributors in setting prices. We used data on sales and prices from the 12 largest distributors of PPI to estimate directly the impact of increasing PPI prices on the sales of an individual PPI product.

2. We estimated the impact of PPI prices on demand for PLPPI, MPPI and CCPPI. For PLPPI and MPPI we estimated the total level of consumer substitution in response to a PPI price increase, which included *(a)* those who substituted PPI products only, *(b)* those who substituted PPI/credit bundles and *(c)* those who substituted away from PPI altogether. We did not look at the relative importance of these three behaviours, but added together they represent the total constraint on the ability of PPI distributors to set prices and they also help us determine whether consumer substitution was enough to provide evidence of a wider market definition. For credit cards, we looked at whether individual consumers reduced their insured balances or cancelled their CCPPI.

3. We conducted econometric analyses of the data, using a number of different approaches, to estimate directly the degree of consumer substitution following an increase in the price of PPI by an individual distributor. We used data on prices and sales of credit and PPI to estimate directly the size of the reduction in sales for individual products following an increase in PPI or credit prices. We considered a number of methodologies in our analysis of the data.

4. With such econometric analysis it is possible that certain results could be generated by factors other than those we were trying to estimate, such as the quality of the data or events that we did not have data on, such as changes in marketing. These difficulties meant that the conclusions from this econometric analysis should be supported by other evidence.

5. We used the following estimates to inform our consideration of the relevant market for PPI. We used the SSNIP test and looked at whether a 5 per cent price rise above competitive levels would be profitable for an individual product. If so, this was evidence that there was market power and was consistent with a product-level definition of the market. If a 5 per cent price rise would not be profitable, then this suggested that the relevant market is wider than individual products. However, we were only able to look for evidence at current prices, which might be higher than competitive levels and so further increases may not be profitable for this reason (see paragraph 3.11).

6. We conducted two different analyses. First, for MPPI and PLPPI and we used data on a range of credit and PPI products over a period of five years and estimated the average impact of PPI changes over that period. Second, for credit cards, we had data on individual customers of a particular CCPPI distributor, [✂], and we used that data to estimate the impact of a single PPI price change.

7. From these analyses we found:

   (a) For MPPI: evidence that there was a sufficient degree of substitution for an MPPI price rise from current prices to be unprofitable and to suggest that current prices were constrained by substitution. This implied either a wider market definition or that prices were far enough above their competitive levels that further price increases were constrained. However, we were concerned about

the lack of observed MPPI price changes, which we consider make our results unstable and weakens the reliability of the evidence.

(b) *For PLPPI:* in all our econometric approaches we found that PLPPI sales were fairly unresponsive to changes in PLPPI prices. We did find some estimates that PLPPI sales were more responsive, but these cases were still consistent with high profit margins. This means there was little evidence that the level of consumer substitution was large enough to constrain PLPPI prices to competitive levels or to support a wider market definition.

(c) *For CCPPI:* we found no significant fall in average insured balances at the time of a CCPPI price increase. This might suggest that the price increase had no impact on balances, but this was not necessarily the case. It may be because another event at the same time that we were not able to control for led to [✂] CCPPI customers increasing balances and offsetting the impact of the price change; for instance, an increase in benefits for CCPPI customers or a change in marketing or selling approaches. We could not, therefore, conclude that there was no impact of the price increase, only that we found no evidence that there was a negative impact on demand from the price increase.

8. We consider below each of these analyses in turn, explaining the methodologies and results for PLPPI and MPPI , and then for CCPPI.[1]

9. The important relationships that we estimated were measured as elasticities. In our analysis, an elasticity gives the response in sales to a 1 per cent change in prices. For instance, the key relationship we estimated was the elasticity of PPI sales with respect to PPI prices. A value of –1.4 would mean that a 1 per cent increase in PPI prices reduces sales by 1.4 per cent. In particular, we were interested in whether the

[1]For more technical detail, see Appendix 3.3.

elasticity was above or below a threshold which would indicate whether a price rise would be profitable.

Analysis of MPPI and PLPPI

Methodology and data

Quality of data and number of PPI price changes

10. We were given monthly data on PPI and credit sales and prices by the 12 largest distributors of PPI for the period 2002 to 2006. This covered a range of products, some with very large sales volumes and some with relatively small, and each with different characteristics. We had data on all the combinations of credit products and PPI products available for which sales were above a minimum threshold. We then divided these into individual credit products and individual PPI products.

11. It was not possible to estimate a meaningful relationship between sales and prices for each individual product, as there were too many unobserved influences on sales volumes, which we could not explain using our data, and which would lead to biased elasticity estimates. However, we were able to estimate the average elasticities and relationships across all products.

12. Collecting consistent data from a large number of different distributors and checking that it was correctly reported was a difficult process, as these are complex financial products and there was no standardized process for recording data. We cannot be sure that errors in the data did not influence our results. However, we estimated across all the products so that the impact of these errors would offset each other. Table 1 shows the number of potential data points we had, including the number we lost due to missing information.

TABLE 1 **Number of observations in our data**

	Mortgages		*Personal loans*	
	Loan products	*PPI products*	*Loan products*	*PPI products*
Number of products	49	28	68	92
Potential number of monthly observations	2,940	1,680	4,080	5,520
Data misreported	60	180		
Potential observations with no sales	374	89	1,238	1,871
Potential observations with missing credit price data	13	0	244	103
Data with no APR variation			530	984
Potential observations with missing PPI price data	12	12	361	611
Observations used in preferred estimations	2,037	1,279	1,707	1,951

Source: CC, based on data provided by the 12 largest distributors of PPI.

13. To estimate accurately the elasticities with respect to PPI prices we need to observe a sufficient number of changes in these prices in the dataset. If there were only a small number of price changes, then it would be harder to identify whether changes in sales were a result of a PPI price change or some other event.[2] For many products we observed that there were no PPI price changes at all throughout the relevant five-year period (2002 to 2006). Table 2 shows the number of PPI price changes, and the number of credit products affected.

TABLE 2 **Number of PPI price changes observed in the sample**

	Number of products	*Number of products that change PPI price*	*Total number of PPI price changes*
Mortgage products	49	18	25
MPPI products	28	12	15
Personal loan products	68	41	113
PLPPI products	92	72	279

Source: CC, based on data provided by the 12 largest distributors of PPI.

Note: Some PPI prices may effectively change due to changes in APR. Such changes are not included in this table.

[2]It is not always clear what can be considered a 'large' number in econometric analysis. A standard rule of good practice is that 30 such observations in the data allow sufficient variation to provide a reasonably accurate estimate. However, this depends on these observations having well-behaved statistical properties, which is not always the case.

Variables used in our analysis

14. In our analysis we used the following variables:[3]

(a) *Quantity of PPI sales:* We used the total value of loan advances that were insured with each individual PPI product. The number of PPI policies issued could also be considered as a measure of quantity; however, this did not reflect the size of the policy.

(b) *Quantity of credit sales:* We used the total value of loan advances for each loan product in a particular month. We could also have looked at the number of loans sold in a particular month; however, profit and demand for loans was more closely related to the *amount* borrowed and so we considered loan advances a more representative measure of credit demand.

(c) *Price of credit:* This was measured by the 'typical' APR of the loan. For any particular loan, some customers may not be paying the typical APR, but a different rate to reflect their risk characteristics or, in the case of mortgages, an initial rate for a fixed period. However, we considered APR to be an appropriate measure of credit price. When looking at the demand for PPI, which might be available across different loan products, we took a weighted average of the APR used across these different loans, where the weights were constant over time and reflected the volume of PPI sales. For mortgages there might be a variety of interest rates available, and we tested our results using some alternatives, such as the initial interest rate for which we had data.

(d) *Price of PPI:* The price of PPI can be quoted in different ways. For MPPI, a cost per £100 of repayment was used, and for PLPPI, a percentage of the loan. We took whichever value was used as our price variable. Where more than one PPI product was offered with a unique loan product we used a weighted average of

[3]See Appendix 3.3 for further detail.

the price across the different PPI products, where the weights were constant over time and reflected the volume of PPI sales.

(e) *Advertising:* This variable was created using data from Nielsen[4] on advertising expenditure. This data matched only imperfectly to individual products as defined in the dataset, and so the advertising variable gives the monthly spending on loans advertising for each distributor.

Econometric methodology

15. We used a number of different approaches in trying to estimate each particular elasticity of interest. We attempted to draw conclusions where the results from different approaches were consistent, and highlighted the important issues to consider where they were not.

16. We estimated the relationships between prices, sales and our other variables using all the available data on credit and PPI products across the 60 months in the sample. We did not estimate these relationships for individual brand-specific products, and indeed we expected differences between products, for instance where they were targeted at different consumer groups. We estimated the average relationship across all brand-specific products in the sample, and over time. Whereas it might be difficult to estimate this relationship for one individual product, because we did not observe all the events and changes that were affecting its sales, we could effectively assume that these unobserved effects offset each other between the different products and so produce a reliable estimate of the average relationship.[5]

17. Some of the sales variation in our dataset was due to sustained differences in levels of sales between different products, which might be due to brand strength, or from

[4]Data on advertising expenditure of major financial firms provided by Nielsen.
[5]We needed to assume that the differences between products were normally distributed, so that most were around the average and that some products had more responsive relationships and some less so.

offering a niche product appealing to a small customer base. Such variation occurs independently of PPI prices, and so we were only interested in controlling for it in our estimates, not explaining it. We therefore used an econometric procedure which did not require us to explain this sustained product variation, but did require us to explain variation in sales over time.[6]

18. When explaining this variation over time, we were aware that much of it may have been caused by macroeconomic and other influences that apply across all products, such as expectations about future consumption or publicity about the PPI industry. Again, such sales variation occurs independently of PPI prices; however, if it was not controlled for, our model might spuriously connect it to changes in PPI price. Since it was not necessary to explain these common effects in detail, we controlled for them by simply estimating and removing changes in the mean across all products each month, without using any economic variables to try and explain them.[7]

19. In our preferred model, then, we have not explained any sustained variation between products, nor any industry-wide variation over time. This meant that the only variation that we analysed in our preferred estimate of the relationship between sales and prices was where a particular product varied differently over time to the industry in general. We then used product-level credit and PPI prices to explain this variation, as well as advertising data where it was available. In our view, this approach gave us reasonable estimators of the true underlying relationship between prices and sales. Further detail is given in Appendix 3.3.

20. Whilst we were interested in the impact prices have on sales, using current prices might have been inappropriate as these were 'endogenously determined'; that is,

[6]We used the 'within groups' estimator which we explain in more detail in Appendix 3.3.
[7]We used individual 'dummy' variables for each month. These allowed us to estimate how sales in a particular month differed from average across all products.

prices might actually be partially determined by demand, and that would bias our results. This was a statistical problem to which there were a number of solutions which involved using an alternative to prices in equations. We were only able to use a weak solution, as we did not have the data available for a stronger approach.[8] It is possible that we did not solve the original problem, and that we might have introduced further bias into the estimates. We show estimates using both the original prices and the alternatives, and have specified when we have done this in our results. See Appendix 3.3 for more detail.

Importance of different observations

21. In estimating these relationships, we expected some observations to vary a great deal from what was predicted by our equations. This might be because of some unobserved event, for instance a particularly effective advertising campaign or some error in the data. These observations might exert a particularly strong influence and increase the uncertainty that surrounds our final estimates. We considered it best practice to reduce the impact of these observations and used a 'robust regression' procedure to do this, which is explained in more detail in Appendix 3.3.

22. In our sample, some products had very large shares of total sales, and some were very small in comparison. In a standard econometric analysis each observation is treated as being as important as the next. However, this might not have been appropriate in this analysis where the impact of prices on the larger products was more important as they represented more customers and more sales. We looked at dealing with this issue in a number of ways:

    (a) We examined the impact of individual observations on our estimates. In particular, whether small products had a large influence on our results.

[8]We used prices in past periods to predict current prices, and then used these predictions as 'instrumental variables', rather than actual current prices in our estimations. Ideally, we would have used other non-price variables to predict prices, for instance information on costs, rather than past prices.

(b) We weighted each product by its volume of sales such that large products had more influence on the estimate than small products.

(c) We estimated elasticities based on total sales of each provider, rather than of each product. Whereas some products had very small sales, the distribution of sales between providers was more even.

We report which approach we used in our results.

23. There is no right answer when choosing which of these approaches is most appropriate; and indeed if sales were 'well behaved', then the results of each should have been similar.[9] However, where there were differences in results, we attempted to explain why these occurred, and why we might prefer one approach over another.

Penetration rates

24. We were interested in the impact of prices on sales of PPI and credit and so we could use either *(a)* actual sales of credit and PPI or *(b)* actual sales of credit and the penetration rate of PPI (that is the proportion of loans that were insured), as follows:

(a) We wanted to estimate the relationship between actual sales and prices and so this was most appropriate. However, if we found that large changes in PPI sales were driven by changes in the volume of credit sales which we could not explain, this might bias our result.

(b) By using the penetration rate, we would remove any bias which might be caused by unexplained changes in loan sales. However, this estimate is itself subject to downward bias and so could have produced a lower estimate than the true elasticity.[10]

We estimated elasticities using both of these approaches.

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[9]Although we would expect a lower elasticity by grouping products by provider, as this ignores those customers that switch between a provider's own products following a price change.

[10]This bias is described in Appendix.3.3, paragraph 26.

Complementary demand for credit

25. We also used estimates of the degree to which PPI prices impact on credit sales in order to calculate a lower bound of the elasticity of PPI sales with respect to PPI prices. This was the value that we were most interested in.[11] This was an indirect approach, but we used it as an alternative methodology for PLPPI, although not for MPPI, as we explain in paragraph 29.[12]

Variation over time

26. With a limited number of products, and data on sales over time, it could have been more appropriate to examine the data by looking at how it behaved over time. For instance, the impact of prices might not be felt for several periods, or sales in past periods might have told us something about sales in current periods. Our main approach outlined above did not consider these possibilities; this could have led to some bias in our results. However, without more information on what might cause variation in loan sales over time, such as marketing, we did not expect to be able to produce satisfactory results in this way. We attempted such an approach using data on one distributor at a time, using total PPI and credit sales. This approach using a 'vector error correction model' (VECM) is described in more detail in Appendix 3.3.

Results of analysis of MPPI and PLPPI[13]

Critical values

27. We were interested in whether an increase in PPI price from its competitive level would lead to higher or lower profits for an individual product, and we estimated the relevant elasticities linking prices to sales. To aid understanding of these estimates,

[11]We estimated how many credit customers substitute to another credit product following a PPI price rise. This number of credit customers was also an estimate of the number of PPI customers who substituted to an alternative PPI product—customers will not respond to a PPI price rise by substituting their credit product without also substituting the PPI product. If we had a number of those who substituted a PPI product following a PPI price rise, we could calculate the elasticity of PPI sales with respect to PPI prices. This is explained in more detail Appendix 3.3.
[12]For more detail see Appendix 3.3, paragraphs 27 and 28.

[13]More detail of our results is given in Appendix 3.3.

we calculated some critical values to compare with them. These critical values are the elasticities that would be consistent with a PPI price increase of 5 per cent from current levels having a zero-impact on profits, because the fall in PPI sales was just enough to offset the increased revenue from higher prices. We could also consider what the corresponding elasticity of credit is. We used information and data on the profit margin and the penetration rate of PPI. Table 3 shows these critical values.

TABLE 3 **Elasticities consistent with a zero-impact on profits from a 5 per cent PPI price rise**

	Mortgages	*Personal loans*
Profit margin on PPI (%)	50	50
Penetration rate of PPI (%)	10	35
Elasticity of PPI sales with respect to PPI prices for zero-impact on profit (no loss in credit)	–1.8	–1.8
Complementary elasticity of credit sales with respect to PPI price if all shoppers also cancel credit purchase*	–0.6	–0.2

Source: CC analysis.

*This is not strictly the profit-neutral elasticity. We simply assumed that all those substituting the PPI product also substituted the credit product following a PPI price rise. Using our assumptions of penetration rates we could calculate the elasticity corresponding to this assumption. It is therefore an upper bound of the critical value, as first, we would not see every customer who substitutes their PPI purchase also substitute their credit; some will instead purchase a stand-alone product or just go without PPI. Secondly, if this many customers substituted their credit, then this will reduce the profitability of the price rise further, and so both this and the own-price elasticity will be smaller.

28. An estimate of an elasticity higher than these values would mean that a PPI price rise would not be profitable given this level of profit margin and penetration rate. The critical value for the main elasticity of PPI sales with respect to PPI prices was –1.8. If, when we estimated this elasticity, we found it was lower (closer to zero), then it could imply that there was individual product market power; however, it may still be the case that profit lost from falling sales of credit could reduce the ability to raise prices. If the estimate of this elasticity was higher (further from zero) than this value, it would imply that a price rise from current levels would not be profitable. This would have to be combined with other evidence to determine whether it implied that a wider market definition was needed or whether the cellophane fallacy applies (as discussed in paragraphs 5 and 31) and prices are already above competitive levels such that further increases would not be profitable.

29. The critical elasticities of credit sales with respect to PPI prices were quite low, as shown in Table 3, even at the upper bounds reported, particularly for mortgages at –0.2. We therefore only attempted to estimate this elasticity for personal loans. For mortgages, where there was a much lower penetration rate and where the price of MPPI was only a small fraction of the credit price, we believed that the cross-price elasticity would be very close to zero, and that our econometric methodology was not accurate enough to estimate this level of detail.

30. These critical values are dependent upon the values used for the profit margin and penetration rates for PPI. They should therefore be viewed as a guide to the impact on profitability of a price increase. An alternative way we considered our results was to calculate the profit margins that were consistent with a 5 per cent price increase having a zero impact on profits. For instance, an elasticity estimate of –2.5 is consistent with a profit margin of 35 per cent if the firm is charging its profit-maximizing price. More detail on these calculations can be found in Appendix 3.3.

31. Finally, when assessing the profitability of an increase in prices from current levels, we had to take care with our interpretation, as the results of any analysis might be distorted by the cellophane fallacy. In general, consumers' responsiveness to a 5 per cent change in price will increase the higher the starting price relative to the competitive level. In other words, when relative prices are high, consumers are more likely to substitute to another product (either by switching to stand-alone PPI or to another combination of credit and PPI). Therefore, if prices were already in excess of competitive levels, any analysis of the responsiveness of demand to changes in prices at current levels may overstate the responsiveness of demand that would apply at a 'competitive' price level.

MPPI

32. We attempted a number of approaches, and our results vary between them for MPPI. We started with the most basic approach and then tried alternative approaches. We concluded for MPPI that the key elasticity of MPPI prices was at least as high as the critical value of –1.8, although this was weakened by the necessity of weighting or selecting our observations.

33. Using our most basic approach meant that we included all our data and weighted all observations equally. We found that the results from this approach were very sensitive to the inclusion of one particular unemployment MPPI product. The results are shown in Table 4.

34. The table gives the elasticity of MPPI sales with respect to MPPI prices, which was our key value, and the elasticity with respect to credit prices. We did not have a view on what the magnitude of the credit price elasticity should be, although we did expect it to be negative.

TABLE 4 **Elasticity estimates for MPPI using basic methodology**

Equation number	*Methodology description*	*Elasticity of PPI sales with respect to:* *PPI prices*	*Credit prices*
1	Basic methodology with all data weighted equally	*	-1
2	As above with one unemployment MPPI product excluded and using 'robust regression'†	-1.6	-1.4

Source: CC, based on data provided by nine large distributors of MPPI.

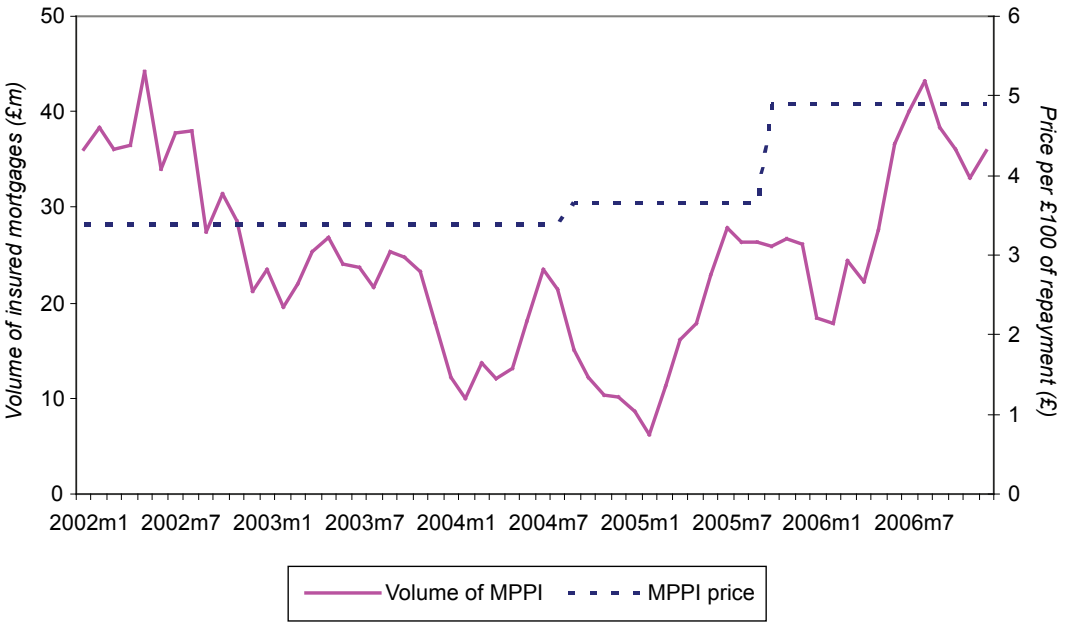
*This estimate was not significantly different from zero.
†See paragraph 21 for discussion of robust regression.

35. The results of using our most basic methodology, in equation 1, suggested that MPPI prices had no effect on MPPI sales. However, when we excluded the one unemployment MPPI product in equation 2 we found that the estimate of –1.6 was close to the critical value of –1.8. Figure 1 shows sales and prices for this product.

We found that the volume of MPPI sales increased after the MPPI price increased. This was driven by a large increase in credit sales in this period. As we had only 15 MPPI price changes in our sample, this one observation could have had a big impact on our results. It seemed sensible to exclude this product if it caused the results to be highly skewed, and it only covered 1.5 per cent of the total sales in our sample.

FIGURE 1

Sales and MPPI price for the unemployment MPPI product



Source: CC based on data provided by a main party.

Importance of different observations

36. While we might not wish to exclude observations, where we had some large products and some very small products, we might wish to weight each product in our estimations to reflect their importance in terms of sales of MPPI. Alternatively, we could have grouped all the products, large and small, sold by each distributor whose market shares could then be more evenly balanced. We calculated elasticities using these approaches to weighting data. The results are shown in Table 5.

TABLE 5 **Elasticity estimates for MPPI using different weighting approaches**

Equation number	*Methodology description*	*Elasticity of PPI sales with respect to:* *PPI prices*	*Credit prices*
3	Data weighted by relative volumes of PPI sales. All data included	–1.9	–1.5
4	Using total sales by each provider rather than individual products, using robust regression	–2.0	–1.1

Source: CC, based on data provided by nine large distributors of MPPI.

37. The results were similar to those we obtained when we excluded the one unemployment MPPI product. The elasticities were –1.9 and –2.0, which were close to our critical value of –1.8, and indicated that a further price rise would not be profitable.

38. As discussed in paragraph 20, there may be problems associated with using current prices. We therefore used MPPI and credit prices from earlier months as our 'instrumental variable'.[14] We repeated equations 3 and 4 using this approach to give us equations 5 and 6. The results are shown in Table 6.

TABLE 6 **Elasticity estimates for MPPI using instrumental variables and different weighting approaches**

Equation number	*Methodology description*	*Elasticity of PPI sales with respect to:* *PPI prices*	*Credit prices*
5	Equation 3 using prices 5 periods ago as an instrumental variable	–1.9	–3.8
6	Equation 4 using prices 5 periods ago as an instrumental variable	–1.6	–2.6

Source: CC, based on data provided by nine large distributors of MPPI.

39. The impact of using past prices was substantially to increase our estimate of the credit price elasticity. However, we were interested in the MPPI price elasticity, which

[14]We used prices with a lag of five months. For instance, we explained sales in July using prices from February. More detail is given in Appendix 3.3.

we found was similar to that in equations 3 and 4. This may have suggested that the 'endogeneity' problem described in paragraph 20 was not large for MPPI prices, or it may mean that we were not able to solve it using this approach.[15]

Using MPPI penetration rates rather than sales

40. One alternative to using MPPI sales as the dependent variable that we considered was to use the penetration rate of MPPI. This removed the problems caused by unexplained fluctuations in loan sales driving MPPI sales, which had the potential to bias our estimates. It was comparable with the direct elasticities with respect to sales we had estimated; however, it implicitly assumes there was no change in credit sales and so was biased downwards.[16] We repeated equations 1 and 5 using penetration rates as the dependent variable. The results are shown in Table 7.

TABLE 7 **Elasticity estimates for MPPI using penetration rates**

Equation number	*Methodology description*	*Elasticity of MPPI penetration rate with respect to:* *PPI prices*	*Credit prices*
7	Basic methodology with all data weighted equally, using penetration rates	–2.7	–2.2
8	Data weighted by relative volumes of PPI sales using prices 5 periods ago as an instrumental variable. All data included. Using penetration rates.	–7.0	–1.2
9	As equation 8 with two largest mortgages from one provider excluded	–2.6	*

Source: CC, based on data provided by nine large distributors of MPPI.

*This estimate was not significantly different from zero.

41. We found that using penetration rates produced higher estimates of the MPPI price elasticity. We also found that two loan products from one provider, which accounted for 21 per cent of the sample, had a large impact on the results. These highlighted the instability in our results, but even with these products excluded we found an

[15]As we described in paragraph 20, a preferred approach would have allowed us to use non-price variables to predict current prices, rather than lagged prices.
[16]This bias is described in Appendix 3.3, paragraph 26.

estimate of the elasticity higher than our critical value of –1.8. We expected the credit price elasticity to be low, as in equation 9, as credit prices should not have a major impact on penetration rates.

42. Finally, we attempted to look at the time-series properties of the sales of each individual distributor, over the 60-month sample, as described in paragraph 26. However, this did not produce coherent results[17] and without more data we were unable to explore this in more detail.

Conclusions for MPPI

43. In conclusion for MPPI, we found estimates for the elasticity of MPPI sales with respect to MPPI prices in the region of –1.6 to –1.9, or higher. This suggested that MPPI prices were around the level at which there was no impact on profit from further price increases—that is to say, prices were already at the profit-maximizing level. This might lead us to conclude either that a wider market definition was appropriate, or that prices were already above competitive levels and so further evidence was required. However, we found that we needed to weight or select observations to derive sensible results, as our results were unstable. This instability was caused by the small number of price changes in our dataset.

PLPPI

44. We attempted several approaches for PLPPI; however, we found that in nearly all of our specifications PLPPI sales were not very responsive to PLPPI prices. We started with the most basic approach and then tried alternative approaches. We had more data and observed more changes in PLPPI prices than we did with MPPI. Therefore,

[17]See Appendix 3.3 for more detail.

our results were less prone to instability and influenced by smaller observations. However, this did not mean that other sources of bias would not affect our results.

45. Using our most basic approach meant that we included all our data and weighed all observations equally, as shown in equation 10. We used the 'robust regression' approach (described in paragraph 21) in equation 11. This gave less weight to those observations that had more unexplained variation. Data from one distributor was incomplete in that it reported all APRs as being constant over six years; this was obviously incorrect and so we excluded these in equation 12 and 13. The results are shown in Table 8.

TABLE 8 **Elasticity estimates for PLPPI using our basic approach and excluding one distributor's data**

Equation number	*Methodology description*	*Elasticity of PLPPI sales with respect to:*	
		PLPPI prices	*Credit prices*
10	Basic methodology with all data weighted equally	*	–1.0
11	Robust regression with all data weighted equally†	–0.4	–0.5
12	As above with one distributor's products excluded	–0.7	–0.5
13	Equation 12 with prices from 5 months in the past	–1.2	–0.7

Source: CC, based on data provided by the 12 largest distributors of PPI.

*This was not significantly different from zero.
†See paragraph 21 for discussion of robust regression.

46. We found that the elasticity of PLPPI sales with respect to PLPPI prices was low compared with the critical value of –1.8, even in equation 13, which gave the highest value. This suggested that individual product suppliers had considerable market power.

Importance of different observations

47. When we looked at MPPI we were concerned that individual small products might have too high a weight in our estimations and so used different approaches to try and balance the importance of a product in terms of total sales with its influence on the

estimation (equations 5 and 6). We did not find such unstable results with PLPPI; however, for consistency we used similar approaches. We weighted our observations by PLPPI sales, so larger products were given more weight in equations 14 and 15, and we used sales grouped by distributor in equation 16. The results are shown in Table 9. We found that the results were similar to the unweighted results in Table 8 and showed that PLPPI sales seemed fairly unresponsive to changes in PLPPI price.

TABLE 9 **Elasticity estimates for PLPPI using different weighting approaches**

Equation number	*Methodology description*	*Elasticity of PLPPI sales with respect to:* *PLPPI prices*	*Credit prices*
14	As equation 10 with data weighted by relative volumes of PPI sales. All data included.	*	–0.7
15	As equation 14 with one distributor's products excluded. Data weighted by PPI sales and using a form of robust regression.	–0.4	–0.2
16	Using robust regression, as equation 11, with sales grouped by distributor	*	–0.4

Source: CC, based on data provided by the 12 largest distributors of PPI.

*This was not significantly different from zero.

Using PLPPI penetration rates rather than sales

48. As with MPPI, we also used the PLPPI penetration rate, rather than sales, as a dependent variable. This can strip out the variation in PLPPI sales that may be caused by unexplained fluctuations in loan sales. We repeated these approaches (equations 7 and 8) for PLPPI. The results are shown in Table 10.

TABLE 10 **Elasticity estimates for PLPPI using penetration rates**

Equation number	*Methodology description*	*Elasticity of PLPPI penetration with respect to:* *PLPPI prices*	*Credit prices*
17	Basic methodology with all data weighted equally, using penetration rates	–1.0	*
18	Data weighted by relative volumes of PLPPI sales using prices 5 periods ago as an instrumental variable. Using penetration rates. One distributor's data removed.	–1.2	–0.2

Source: CC, based on data provided by the 12 largest distributors of PPI.

*This was not significantly different from zero.

49. These results gave us higher estimates of the PLPPI price elasticity. However, they were still lower than the critical value of –1.8. The low values of credit price elasticity were expected as we would anticipate that changes in the credit price would change the volume of loans and therefore have an impact on PLPPI sales; but not have a large effect on PLPPI penetration.

Complementary demand for credit

50. We used estimates of the elasticity of credit sales to imply the elasticity of PLPPI sales, as we explained in paragraph 25; and we used the methodologies in equations 10 to 16 to estimate the impact of prices on credit sales. The results are shown in Table 11. As we explained in paragraph 25, we used these estimates of the impact on credit sales to calculate a corresponding elasticity of PLPPI sales.[18] This was because we expected the number of customers who substitute away from credit to be about the same as the number who would substitute away from PLPPI, although this ignores those who substitute away from PLPPI without substituting credit. These implied elasticities are shown in the right-hand column of Table 11.

[18]For more detail see Appendix.3.3, paragraphs 27 and 28.

TABLE 11 **Elasticity estimates for personal loans and implied estimates for PLPPI**

Equation number	*Compare with*	*Methodology description*	*Elasticity of credit sales with respect to:* *PLPPI prices*	*Credit prices*	*Implied elasticity of PLPPI sales with respect to: PLPPI prices**
19	10	Basic methodology with all data weighted equally	–0.7	–0.7	–2.0
20	11	As equation 19 but using robust regression procedure†	–0.4	–0.9	–1.1
21	12	As above with one distributor's products excluded	‡	–0.7	‡
22	13	Equation 21 with prices from 5 months in the past	–1	–1.3	–2.9
23	14	As equation 20 with data weighted by relative volumes of PPI sales. All data included	–0.6	–0.7	–1.7
24	15	As equation 23 with one distributor's products excluded and using a form of robust regression	–0.4	–0.6	–1.1
25	16	Using robust regression, as equation 20, with sales grouped by distributor	–0.2	–0.5	–0.6

Source: CC, based on data provided by the 12 largest distributors of PPI.

*These assume a PLPPI penetration rate of 35 per cent.
†See paragraph 21 for discussion of robust regression.
‡Not significantly different from zero.

51. We found a much wider range for the key elasticity using this approach, from zero to –2.9, some of which therefore exceed the critical value of –1.8. However, even in this case, an elasticity of –2.9 implies a profit margin of 30 per cent. We also found that the estimates highlighted some inconsistencies in our results; they were each (except equation 21) higher than the respective estimates looking directly at PLPPI sales (equations 10 to 16), which suggested the presence of some bias in our results.

52. The weight placed upon these results depended on whether the inconsistencies were general to the methodology and data that we used (in which case they apply to our earlier results), or were specific to this attempt to model personal loan sales. In modelling the impact of PLPPI prices on credit sales, when we had too few other explanatory variables, it may be that we were attributing fluctuations in credit sales to PLPPI prices which were biasing the estimates upwards. We therefore preferred to rely on our direct estimates where we stripped out these effects using penetration rates (equations 17 and 18).

Variation over time

53. Finally, we attempted to look at the time-series properties of the sales of each individual provider, over the 60-month sample, as described in paragraph 26. For these estimates we looked at one distributor at a time, with all the loan and PLPPI sales for each product grouped together. This allowed us better to explain time variation, but at a cost of not being able to use the unexplained variation across different products to identify the impact of PLPPI prices from other influences. We found unsatisfactory results from this approach; for instance, we obtained incorrectly signed estimates.[19]

Conclusions for PLPPI

54. In conclusion, for PLPPI we did not find much evidence of any impact of PLPPI prices on PLPPI sales, with elasticities not approaching our critical value of –1.8 for a 5 per cent price rise to be profit neutral. This suggested that there was substantial market power for individual products. The exception to this conclusion was where we modelled credit sales and tried to imply an elasticity of PLPPI sales from this. Even in this case our estimates implied a profit margin of at least 30 per cent. However, we considered our direct estimates of PLPPI sales to be more reliable as a measure of the impact of PLPPI prices

Analysis of CCPPI

55. A large distributor [✂] is a major distributor of CCPPI. It provided us with data on 100,000 credit card customers, of which around 20 per cent had CCPPI, from January 2005 to August 2007. During that period [✂] the distributor increased CCPPI prices [✂] for most customers and in [✂] for its [✂] product A customers.

[19]See Appendix 3.3 for more detail.

The price rise was around 10 per cent, and at the same time there was an increase in benefit levels.[20]

56. We looked at the credit card history of these customers. In particular, we looked for evidence that when [✂] the distributor changed its CCPPI price [✂] there was a significant impact on insured balances. Our analysis of this dataset follows that conducted by [✂] on behalf of the distributor [✂], which suggested that CCPPI prices had a significant impact on customer behaviour.

57. The challenge of our analysis was to identify the impact, if any, of the CCPPI price change, separated from any other factor which might have influenced customer behaviour. As there was [✂] price change over the period from [✂] to [✂], it was very difficult to rule out the possibility that some factor other than the price rise and change in terms and conditions also occurred at the same time. We used two strategies to identify the impact of the CCPPI price change and separate it from any other factor:

(a) [✂] the distributor increased the price of CCPPI in [✂] for most of its customers, but in [✂] for its [✂] product A customers. If the price change had impacted on CCPPI customers, we would expect that non-product A [✂] customers would have responded before product A [✂] customers. We tested to see if there was any difference between these two groups in the period after the first price change and before the product A [✂] price change.

(b) We did not expect the behaviour of uninsured customers to change following the CCPPI price change. We therefore tested to see if there was any difference in the behaviour of uninsured and insured customers before and after the price change.

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[20] [✂]

58. Even with these two strategies we were unable to reach a definite conclusion. Other factors, such as the increase in benefits at the same time as the price change, or a change in marketing strategy, might have occurred such that it was not possible to split out these different influences on customer decisions, which might work in opposite directions. If we found no significant impact of the price change, this might be because prices had no impact or because the fall in demand due to higher prices was offset exactly by some other factor that increased demand. Although we could not identify the correct conclusion in this case, we would be left with no evidence that the price rise had an impact on customers.

59. In this section, we review the analysis of the data produced by [✂], and then set out our own data and methodology. We then report our results.

Review of [✂] methodology

60. [✂] conducted a comprehensive analysis of this dataset on behalf of the distributor [✂], and reached the following conclusions:[21]

> With the cost of PPI being highly transparent and varying with the amount of credit demanded by the customer, there is no reason not to expect the cost of PPI to have an impact on the demand for credit, i.e. on who to borrow from, and how much to borrow.
>
> We have used data on a sample of Distributor customers in order to examine the impact of PPI charges—together with other variables—on
>
> - the decision whether to take up, or to cancel PPI;
> - the decision whether to cancel the underlying credit card; and
> - the decision how much to borrow.

[21]See 'Submission from a large distributor—competitive constraints in the provision of credit card PPI', paragraphs 56 to 58 on the CC website.

> We find that in relation to all of these decisions, the impact of PPI charges is as one would expect. Higher PPI charges reduce the likelihood of taking out PPI, increase the probability of cancelling PPI, and increase the probability of cancelling the underlying credit card. Moreover, higher PPI costs reduce the amount of borrowing. Thus, there are clear constraints on the pricing of PPI, not only in terms of the impact of such pricing decisions on PPI penetration, but also in terms of the effect that PPI pricing has on the demand for the primary credit product.

61. We made some suggestions for additional analysis in response to some concerns with this work, and [✂] provided further analysis. This follow-up analysis agreed with the conclusions from the initial work.[22] However, we still had some concerns about this analysis.

62. With only one price change in the dataset, the original [✂] analysis was effectively only a comparison of before and after the price change and it was not possible to say if the impacts it reported were due to the price change, or to other factors. In its further analysis, it used a number of techniques to explore this issue further. However, the new work still did not clearly show the impact of the price change separate from other factors. In particular, [✂] did not use the control groups that we describe in paragraph 58 in the same manner as we did.[23] We thought that our approach was a more effective way of observing the impact of price changes on the demand for CCPPI and credit.

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[22] 'Competitive constraints in the provision of credit card PPI: further analysis, April 2008' on the CC website.
[23] 'Competitive constraints in the provision of credit card PPI: further analysis, April 2008' on the CC website.

Methodology

Data

63. There were 100,000 customers included in the sample with a good range of information on each over 32 months. For our analysis we used just four months of data, two before and two after the CCPPI price increase in [✂]. We looked at the impact of the price change on card balances, which were both insured and uninsured.

Econometric methodology

Control and treated groups

64. We wanted to know if the CCPPI price change had any impact on demand for CCPPI from [✂] the distributor's customers. We therefore could have tested for the difference in balances before and after the CCPPI price change. However, there was no way of telling the cause of these changes and therefore it would have been difficult to draw any meaningful conclusion.

65. The approach we used to solve this problem was to adopt a 'control' group which we believed to be similar in all respects to those CCPPI customers 'treated' to the price change, except that it was not itself affected by the change. This way, if there was any change in the behaviour of the 'treated' group of CCPPI customers, which was not matched by the behaviour of the 'control' group, we could attribute this to the impact of the CCPPI price change. We used two different control/treatment groups:

(a) [✂] Product A customers were our control group and non-product A [✂] customers were the treatment group. In this case the treatment was an increase in prices, two months prior to the control group.

(b) Non-CCPPI customers were our control group and CCPPI customers the treatment group.

66. We acknowledged that this was an imperfect solution as it required the control and treatment groups to be identical, except for their exposure to the price change, which we knew was not the case. We attempted to account for some of the possible differences, such as income, and used two separate control group strategies to test for any impact of the price change.

67. We then conducted a difference-in-difference analysis. This analysis looked at the difference in balances between the control and treatment groups over the two time periods. If the price increase had an impact, we would have found a change in the difference between the two groups before and after the price increase. If there was no change in the difference between the control and treated groups, this would tell us that the CCPPI price change did not have an impact on customer behaviour. More detail of this approach can be found in Appendix 3.3.

Distribution of balances

68. Many customers had a zero balance, which meant that the distribution of our observed balances was distorted. The distribution of balances can be seen in Figure 2. With such a distorted distribution, it would not have been appropriate simply to estimate the expected balance of each customer. Instead we used a model which allows for zero or unobserved balances.[24] We used both the 'Heckman' estimator and the 'Tobit' estimator to calculate our results. More detail of these approaches is given in Appendix 3.3.[25]

[24]Some customers actually hold cash on their card, that is they have a negative balance; such balances will therefore be treated as if they were zero in this analysis.
[25]The 'Heckman' estimator is a model of self-selection, appropriate if customers' decisions of how much debt to hold is separate from their decision to use [✂] the distributor's credit card rather than an alternative credit card or personal loan provider. This means whether we observe their balances depends on them 'self-selecting' [✂] the distributor and therefore joining our sample. The 'Tobit' estimator is a model of a censored distribution, which is appropriate if customers' balances represent their current decision about savings and debt levels. However, it is not practical to hold savings on credit cards and so we only observe these customers when they choose to be in debt; the other customers' savings decisions are therefore censored from our sample.

FIGURE 2

Distribution of credit card balances in [✂]

[✂]

Source: CC, based on data provided by the distributor [✂].

Results of analysis of CCPPI[26]

69. We used five different tests to identify any significant impact of the CCPPI price change. Each of these is described below. For each of the tests we estimated the difference in balances before and after the price change, and between our control and treatment groups using the 'Heckman' and 'Tobit' estimators. We have illustrated these tests using aggregate balances—see Figures 3 and 4. By way of example, we have shown some estimates for Test A in Table 12. The full results of all of our estimates are given in Appendix 3.3.

Test A

70. The distributor [✂] increased the price of CCPPI for all but product A [✂] customers in [✂]. The price was increased for product A [✂] customers in [✂]. We looked at credit card balances of PPI customers in the four months [✂] to [✂]. We estimated the difference in balances before and after the CCPPI price increase and the difference between product A [✂] customers (the control group facing no price change) and the others (treated group facing price change).

Test B

71. This was similar to Test A above, except this time we included all customers, not just CCPPI customers, and looked at whether customers had CCPPI and, if so, the value of their insured balance. This allowed us to consider the impact of cancellations of CCPPI—a potential response to the price change which was not included in Test A.

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[26]More detail of our results is given in Appendix 3.3.

Test C

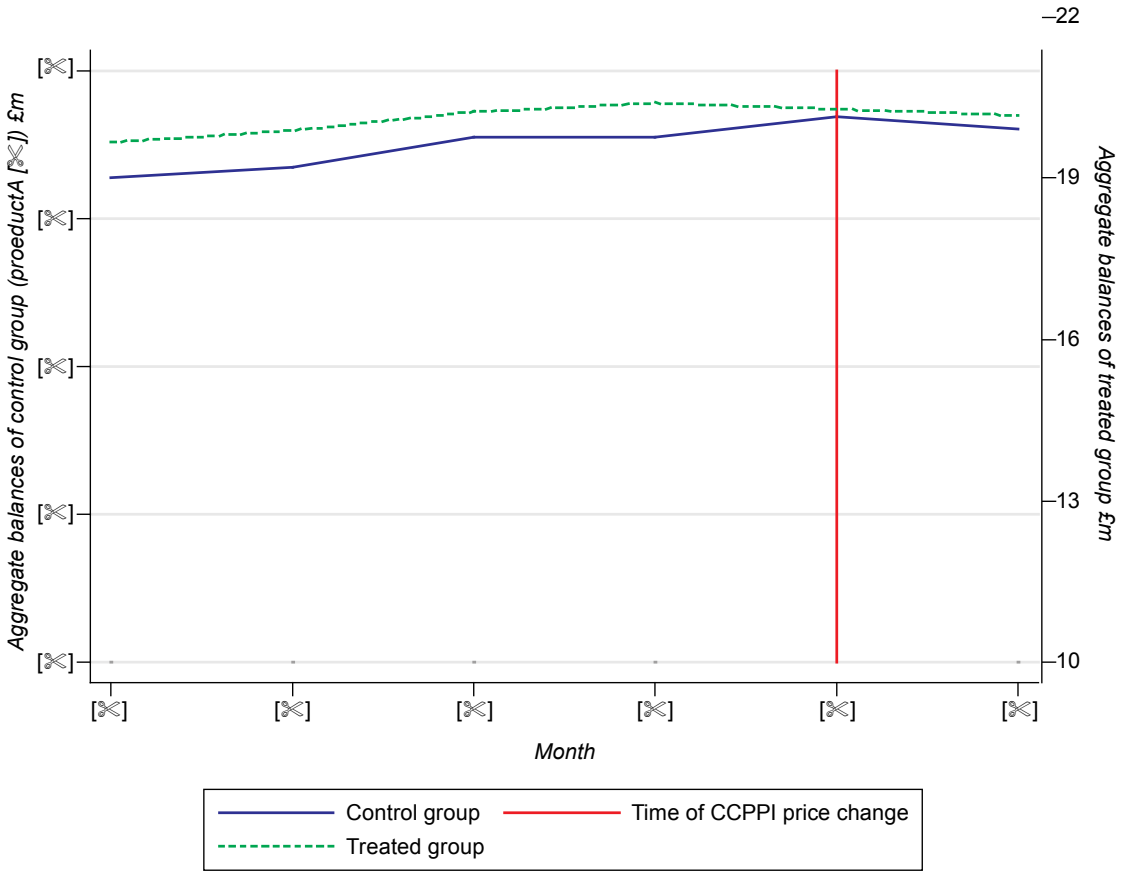
72. This was a repeat of Test A and Test B, except we considered different time periods before and after the price change. Customers were informed about the price change around two months before it took place, therefore if customers changed their behaviour we would expect to start to observe this in [✂], prior to the price change. We therefore used data from earlier months, [✂], as our 'before' period so as to pick up those customers who may have changed their behaviour in advance of the actual price change.

Results of Tests A to C

73. An illustration of these three tests can be seen in Figure 3, which shows the aggregate insured balances of the control (product A [✂]) and treated (non-product A [✂]) groups. We found that there was a decline in aggregate balances for the treated group, which begins the month prior to the price change. We found that aggregate insured product A [✂] balances also being to decline from [✂] (product A [✂] customers faced a price change in [✂]). It was not possible to say whether this decline was due to the PPI price change or not, as we do not know what would have happened in the absence of the change. However, we tested for any significant difference between the control and treated groups which would tell us if the price change had an impact.

FIGURE 3

Aggregate insured balances for product A [✂] and other customers



Source: CC, based on data provided by the distributor [✂].

74. Table 12 shows the results of Test A as an example of our econometric estimates. We found that the product A [✂] control group increased their balances on average by £5 between the periods [✂] and [✂], to [✂] and [✂], whilst the non-product-A [✂] customers who actually faced the CCPPI price change reduced average balances by £5. This difference of £10 between the groups was our difference-in-difference. However, it was very small compared with average balances (which were more than £1,000), and indeed we found that this was not significantly different from zero—that was there was no significant difference between product A [✂] customers and the treated group.

TABLE 12 **The results of Test A—with no additional explanatory variables**

	Expected size of balance
Product A [✂] 'control' customers before price change	>£1,000
Non-product A [✂] 'treated' customers before price change	>£1,000
Difference in balances of product A [✂] 'control' customers after price change	+£5
Difference in balances of non-product A [✂] 'treated' customers after price change	–£5
Difference-in-difference between control and treated groups	–£10

Source: CC, based on data provided by the distributor [✂].

Note: The difference-in-difference estimates here were not significantly different from zero. We used the Tobit estimates found in Appendix 3.3, Table D1, column I. These estimates do not include any explanatory variables. However, the results were not dependent on this restriction.

75. For tests A, B and C we found no difference between the product A [✂] control group and the other customers 'treated' by the price change.

Test D

76. We also tested for difference before and after the price change using a different control group in Tests D and E. If the price change had an impact we would expect to see a difference in the behaviour of CCPPI customers compared with non-CCPPI uninsured customers. In this test, we used uninsured customers as our 'control' group and compared their behaviour with those with CCPPI, who were our treatment group, before ([✂] and [✂]) and after ([✂] and [✂]) the price change. We defined our treatment group as those who had PPI in all four months and did not allow customers to 'switch' between groups. This meant that these estimates excluded those who took up or cancelled PPI during these months, and so we will have missed some impact of the price change. We also excluded product A [✂] customers from this test, as they experienced a price change at a different time.

Test E

77. This was similar to Test D, except that we considered the 'before' period as being [✂] and [✂] (ie the two months previous to the 'before' period in Test D), and the

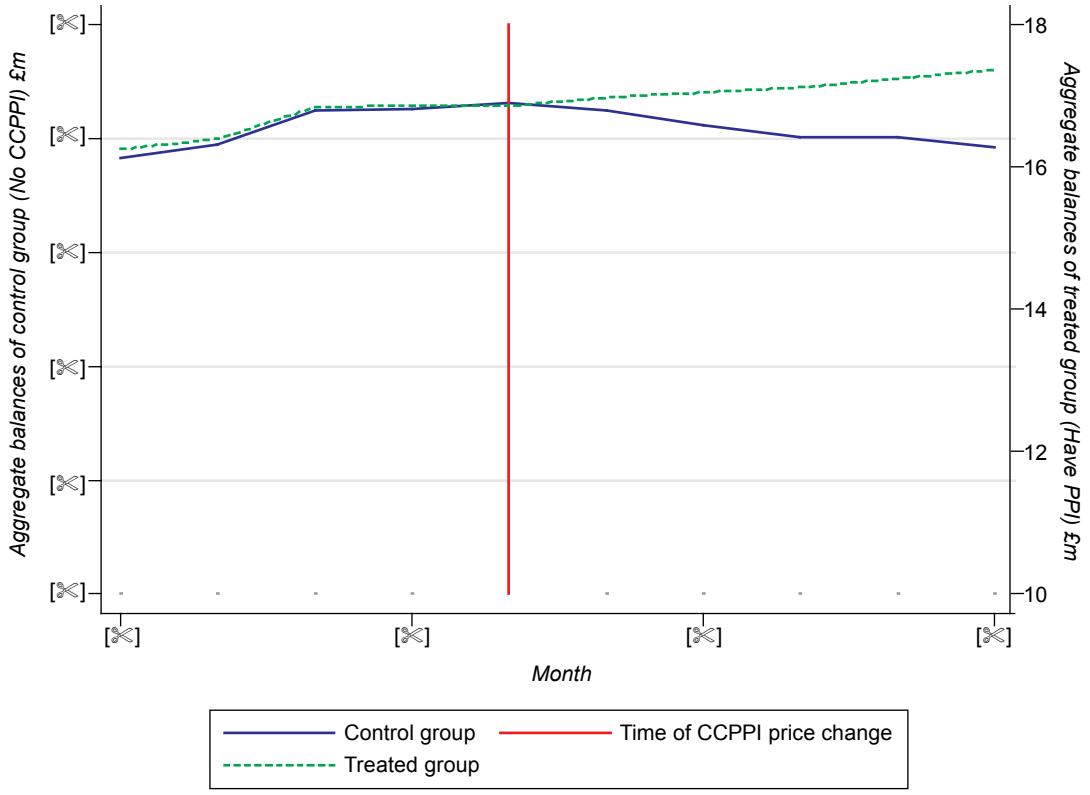
'after' period as being [✂] and [✂] (ie the two months following the 'after' period in Test D). As the change in behaviour might be a gradual process, by separating the before and after periods we could capture more of this behaviour, if it took place.

Results of Tests D and E

78. An illustration of Tests D and E can be seen in Figure 4, which shows the aggregate balances for the control group (no PPI) and the treated group (PPI consumers). We found that the balances of the treated group grew after the price change, whilst the balances of the control group were falling.

FIGURE 4

Aggregate balances for customers with and without CCPPI



Source: CC, based on data provided by the distributor [✂].

79. In both Tests D and E we found a significant increase in balances for the treated CCPPI customers. This may have been because of the increase in benefits that occurred at the same time as the price change or some other factor such as

marketing changes. The impact of CCPPI customers cancelling their insurance was also not taken into account here, except for in Test B. However, from these results we found no evidence of any negative impact on balances from the price change.

80. For CCPPI, we looked for an impact of the price change by comparing groups of customers exposed to a single CCPPI price change, with others who were not. We did not find any significant impact of the price change.