The effect of personalised weight feedback on weight loss and health behaviours: Evidence from a regression discontinuity design

Abstract: Using a regression-discontinuity approach on a UK longitudinal dataset, this research analyses whether personalised weight feedback resulted in individuals losing weight over a period of between 2 and 7 years. The analysis presented here finds that being told one was 'overweight' had, on average, no effect on subsequent weight loss, however being told one was 'very overweight' resulted in individuals losing, on average, approximately 1% of their bodyweight. The effect of feedback was found to be strongly moderated by household income, with those in higher income households accounting for seemingly all of the estimated effect due, in part, to increased physical activity. These findings suggest that the provision of weight feedback may be a cost effective way to reduce obesity in adults. They do however also highlight that the differential response to the provision of health information may be a driver of health inequalities and that the provision of feedback may bias longitudinal health studies.

Keywords: feedback, health information, obesity, regression discontinuity

1 Introduction

The proportion of adults who are obese is increasing in most developed countries and this is contributing to the increased prevalence of chronic health conditions such as heart disease, diabetes and cancer (Must et al, 1999; Cawley, 2015). The economic costs of obesity include the costs to health services to treat and manage these conditions (Wang et al, 2011), as well as the adverse labour market outcomes experienced by obese adults (Averett, 2014). Economic analysis of the causes of obesity typically focuses on time inconsistent preferences and imperfect information in food purchase and consumption, which gives rise to policy responses around economic incentives and food labelling regulation, approaches that have a mixed record of effectiveness (Cawley, 2015).

A relatively unexplored cause of obesity is that of individuals who are imperfectly informed with regards to their own weight status. Aggregate measures of what is considered a ‘healthy’ weight have shifted upwards over time and declining proportions of people who are overweight are correctly recognising themselves as being so (Johnson et al, 2008; Johnson et al, 2014). This ‘weight misperception’ may be important in explaining why overweight individuals do not take action to lose weight (Duncan et al, 2011) as those who perceive themselves as overweight make less weight gain and lose more weight over time (Lynch et al, 2009; Inoue et al, 2010). Correcting weight misperceptions through personalised weight feedback therefore has been identified as a possible method by which public policy can encourage weight loss behaviour (Duncan et al., 2011; Yaemsiri et al 2011; Johnson et al, 2008; Gregory et al, 2008).

While a number of studies report that personalised health feedback is associated with self-reported *intention to change* (Godino, 2013; Prina and Royer, 2014; Yaemsiri et al, 2011) there is a lack of evidence that it results in *actual behaviour change* and improved health outcomes (McClure, 2002; Jepson et al, 2010). A related area of research concerns the effects of technology that records and analyses individuals' health, diet and exercise (e.g. wearables, apps). The evidence as to the weight loss effects of these technologies is mixed (e.g. Jakicic et al, 2016) and there is a need to understand better how the feedback provided can better induce behaviour change and weight loss (Pagoto et al, 2013).

This study provides evidence that personalised weight feedback can result in weight loss in adults through instigating behaviour change, and thus supports the idea that tackling weight misperception as a cause of excess weight may be a cost-effective policy tool in reducing adult obesity. The evidence presented here is an analysis of the effect of receiving weight feedback that was provided as part of the UK Biobank data collection (see www.ukbiobank.ac.uk for further details of the UK Biobank). This feedback was determined by participants' body mass index ("BMI"; calculated as an individual's weight in kilograms divided by their height in metres squared). UK Biobank participants also received health feedback on their body fat percentage, waist circumference and blood pressure; however, this study focuses in on the effect of the BMI feedback on weight change at follow up. This is because BMI is the most widely used measure of healthy weight and the weight feedback associated with it tends to be easily understood by the general public (Stevens et al, 2008; Hall, 2006; Lorimer et al, 2011).

As the weight feedback provided was based on fixed predetermined thresholds, the sharp regression discontinuity ("RD") design method is implemented to estimate the causal effects of feedback. The results suggest that receiving feedback that one was 'overweight' had, on average, no effect on subsequent weight loss, however receiving feedback that one was 'very overweight' resulted in modest weight loss. This effect was concentrated amongst high-income individuals, a finding consistent with the Grossman (1972) health capital framework that predicts that higher income groups are more likely to act on personal health information (Zhao et al, 2013). It also concurs with studies that link the affordability of healthy food and exercise opportunities to weight loss effort (e.g. Johnston and Lordan, 2014). A series of robustness checks are employed that provide assurance of the results. This study has ethics approval via the institutional ethics procedures *[Details omitted for double-blind reviewing]*. Details of the ethical approval for the UK Biobank data collection are available at http://www.ukbiobank.ac.uk/ethics/.

2 Method

2.1 UK Biobank dataset and feedback rules

The UK Biobank dataset (Sudlow et al, 2015) contains data on health and personal characteristics of 502,632 individuals collected during 2006-2010 (the 'baseline assessment'). The recruitment of the baseline sample was done via an invitation letter to individuals aged 40-69 registered with a National Health Service (NHS) General Practitioner who lived within a 'reasonable' travelling distance of one of the 22 UK Biobank assessment centres, with the sample further stratified by age, gender and postcode level social deprivation to obtain a representative sample. Follow up health data on 20,345 of these individuals (the 'repeat assessment') was collected between 2012 and 2013. The repeat assessment recruitment consisted of inviting all those baseline participants who lived within a 30-mile radius of the UK Biobank Co-ordinating Centre, Stockport, UK. Of the 103,514 invited, 20,345 individuals attended the repeat assessment.

At the baseline assessment, participants completed a touchscreen survey, face-to-face interview and a series of physical measurements at their initial visit. At the end of the visit, participants were provided with a printout of selected measurements and feedback associated with these measurements. Participants did not have their results discussed with them by anyone at the UK Biobank assessment centre and did not have any other contact regarding the feedback subsequent to the visit. The weight feedback rules for participants' BMI are shown in Table 1.

[Table 1. UK Biobank weight feedback rules]

The analysis sample in this study is restricted to healthy adults, i.e. those without a long-standing illness, disability or infirmity. This left 13,727 cases in the analysis sample. Descriptive statistics for the analysis sample are shown in Table 2.

[Table 2. Descriptive statistics]

2.2 Empirical Strategy

The causal effect of weight feedback on weight loss and other health outcomes is identified by exploiting the sharp change in treatment status that occurs over the "Overweight" and "Very Overweight" feedback thresholds (BMI=25 and BMI=30 respectively) as detailed in Table1. Estimates of the treatment effect of weight feedback are obtained through implementing the non-parametric 'sharp' RD method of estimating local linear regressions with a triangular kernel using a small window of data (i.e. the bandwidth, 'h') around the treatment threshold cut-offs. Broadly, this approach is applied in this study by estimating the following (See Imbens and Lemieux, 2008 for a full exposition of the non-parametric RD method):

For observations *below* the treatment cut-off 'c' (i.e. c-*h* <$BMI\_baseline_i$ < c)

$$Outcome_i = \alpha_0 + \beta_0(BMI\_baseline_i - c) + \gamma_0(Controls_i) + \epsilon_i \tag{1}$$

i= 1, 2, ….. N^-

For observations at or *above* the treatment cut-off , 'c' (i.e. c ≤ $BMI\_baseline_i$ < c + *h*)

$$Outcome_i = \alpha_1 + \beta_1(BMI\_baseline_i - c) + \gamma_1(Controls_i) + \epsilon_i \tag{2}$$

i= 1, 2, ….. N^+

Where $Outcome_i$ is an outcome measure for individual *i*, *BMI_baseline* is the BMI measurement at baseline (the 'running variable' in RD parlance) and *Controls* are a set of control variables. The treatment effect is estimated as the difference between the intercepts in these two regressions, $\hat{\tau} = \hat{\alpha}_1 - \hat{\alpha}_0$, as this corresponds to the difference in predicted values of the outcome variable for treated and non-treated cases either side of the cut-off at the cut off boundary. The Stata program *rdrobust* (Calonico et al, 2017) is used to produce bias-corrected point estimates with accompanying robust standard errors. The bandwidths for each local linear regression are selected using the optimal data-driven method as per Calonico et al (2014).

3 Results

3.1 Graphical analysis

Figures 1a and 1b show the scatterplots of the baseline BMI against the percentage change in bodyweight between the baseline and repeat assessment. Those who were initially at lower BMI levels experienced a gain in weight, whereas those with higher levels of BMI lost weight – this is consistent with other studies of weight change of older adults over time (Stenholm et al, 2015). There is little evidence of a discontinuity at the BMI=25 cut-off in Figure 1a , however Figure 1b indicates that weight loss is noticeably greater for individuals to the right of the BMI=30 cut-off and suggests a causal effect of the 'very overweight' feedback on weight loss.

Figure 1a- Percentage change in body weight by baseline BMI: BMI=25 cut-off

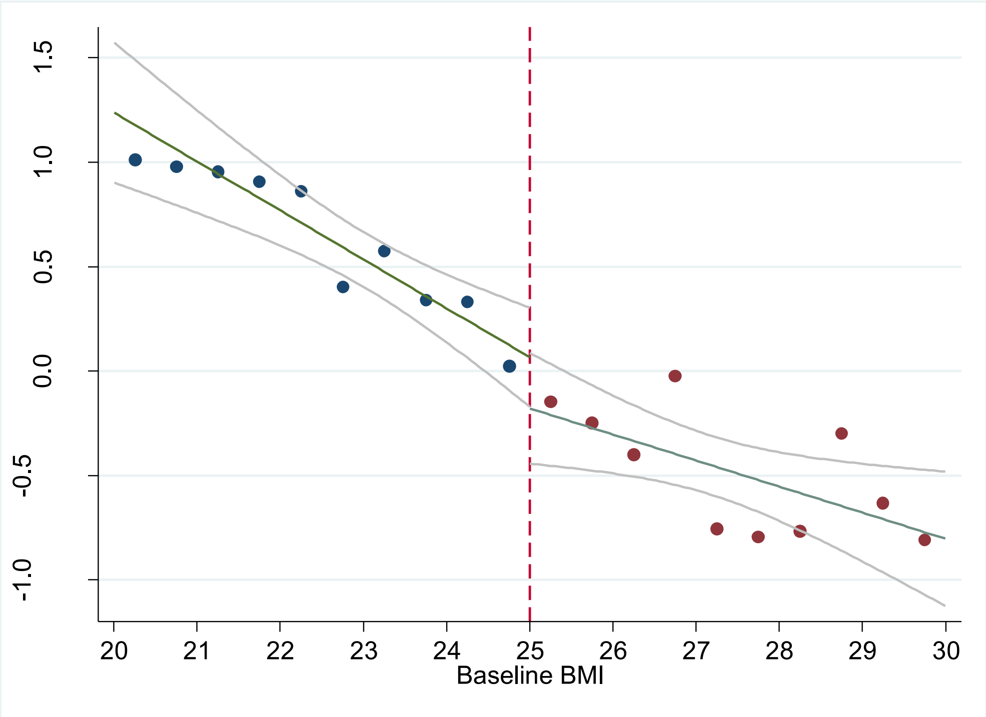
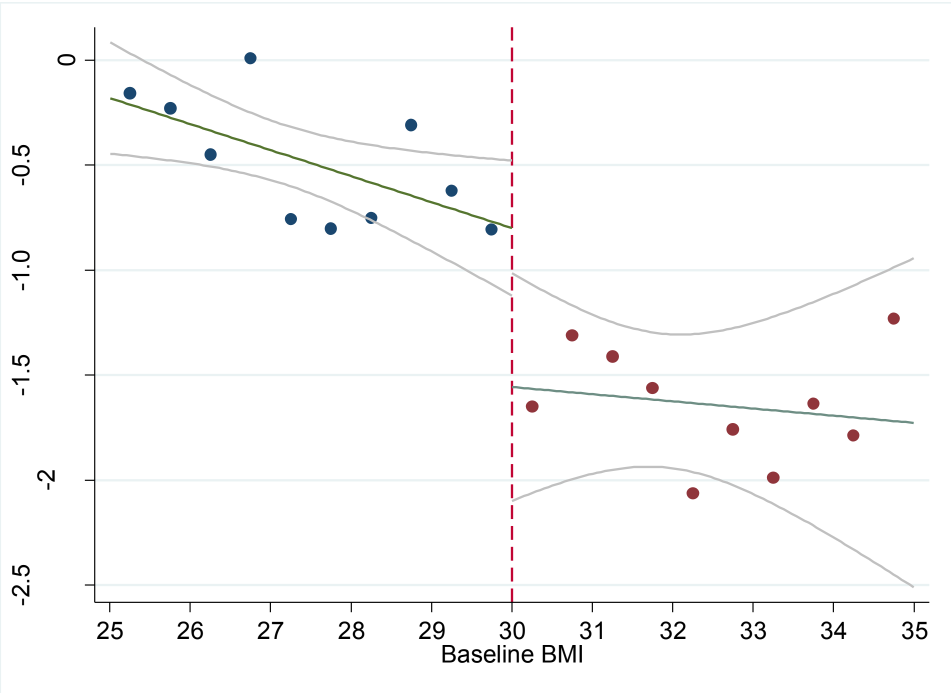


Figure 1b - Percentage change in body weight by baseline BMI: BMI=30 cut-off



Notes: Figures 1a and 1b plot the percentage change in bodyweight between baseline and repeat assessments against baseline BMI using binned means for each 0.5 BMI unit. The lines indicate a linear fit with corresponding 95% confidence intervals.

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3.2 Estimated effects of feedback

Table 3 presents the local linear regression estimates of the effect of weight feedback on percentage change in bodyweight. Reassuringly for the RD identification strategy employed, the point estimates vary little with the inclusion of controls, but the precision is increased. The estimated effects of the “Overweight” feedback for individuals at the BMI=25 cut-off are negatively signed though are very imprecisely estimated. For those at the BMI=30 cut-off, those receiving feedback that they were ‘Very Overweight’ lost, on average, just over 1% of their bodyweight compared to those that were told they were “Overweight”.

[Table 3. Local linear regression estimates of the effects of weight feedback]

3.3 Robustness checks

Analysis by the UK Biobank found that those who responded to the follow up invitation had different baseline characteristics to those who were invited but did not respond. Responders tended to be older, healthier and live closer to the assessment centre (UK Biobank, 2014). While differential response to follow up by baseline characteristics does not necessarily bias the RD estimates, it does present the possibility that participants may have a differential response to follow up according to feedback received. If this is the case then the estimated effects of feedback on weight loss might simply be explained by selection bias at the treatment threshold.

To investigate this threat to the validity of the results, a series of robustness checks are implemented to test whether the probability of response to follow up and/or the composition of the follow up sample is affected by adverse weight feedback. First, attendance at the repeat assessment is modelled as an outcome in an RD model using data on all those *invited* to attend the repeat assessment; second, the continuity of the density around the cut offs is tested using the test proposed by Cattaneo et al (2017). The results from these tests are shown in Table 4 and density plots of participants attending the repeat assessment by baseline BMI are shown in Figure 2. Taken together these results suggest that there is little evidence that the feedback received influenced the probability of attendance at the repeat assessment. Further checks establish whether the composition of the sample displays a discontinuity at the feedback thresholds. These checks are implemented as a series of RD models estimated on the repeat assessment participants using outcomes that should be continuous over the thresholds if there is no selection bias present: baseline anthropometric measures (Table A1), baseline control variables (Table A2), baseline health behaviours (Table A3, and, outcomes at follow up that should not vary as a result of weight loss (Table A4).

These checks reveal no evidence of discontinuities over the thresholds in these variables and in combination with the density tests indicate that the results in Table 3 are not affected by differential response to follow up according to weight feedback received. Standard RD robustness checks of placebo discontinuities (Table A5), and; sensitivity to bandwidth variation (Table A6) also provide further assurance as to the validity of the results.

[Table 4. Robustness checks for discontinuities in repeat assessment response]

Figure 2a. Kernel density plot of repeat assessment participants by baseline BMI

(BMI=25 cut-off)

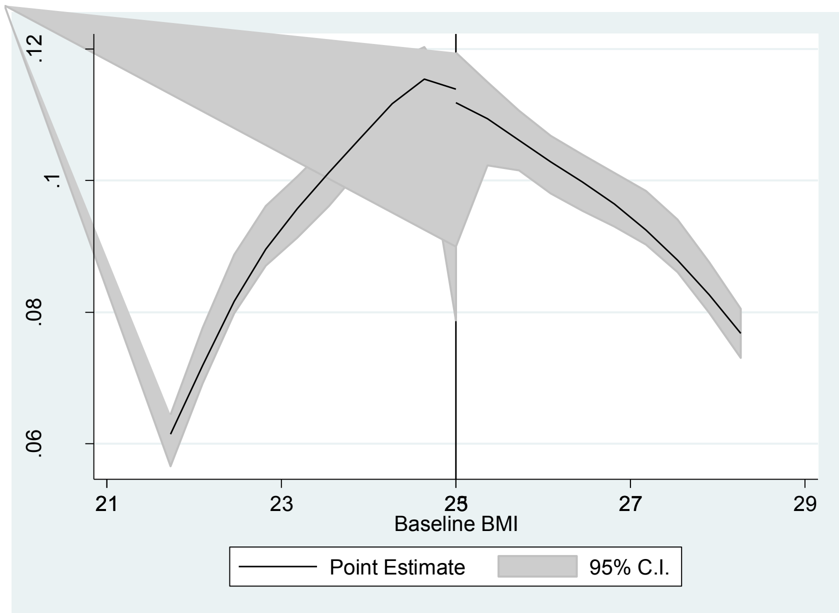
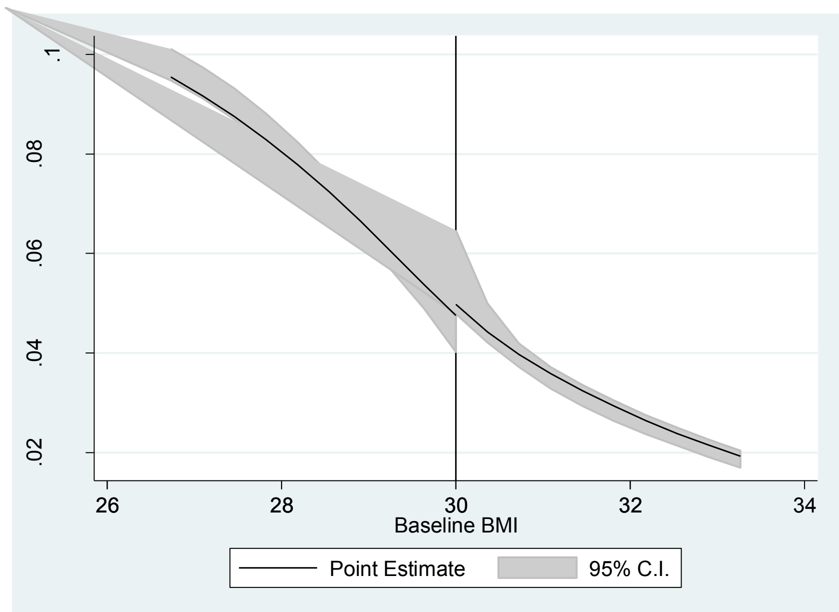


Figure 2b. Kernel density plot of repeat assessment participants by baseline BMI

(BMI=30 cut-off)



3.4 Sub group analyses

As mentioned in the introduction, theory predicts that higher income individuals are more likely to respond to personalised health information and are better able to access weight loss technologies such as healthy food and exercise opportunities. Table 5 presents the analysis of the effect of weight feedback split by household income grouping. The effects of 'Overweight' feedback are mostly small and insignificant across the sub-samples. The subsample analysis of the effects of the 'Very Overweight' feedback however strongly suggests that the effect of this feedback is moderated by household income, with the effect of this feedback only discernible for those living in households with higher incomes. For the high income group, the estimates suggest that the 'Very Overweight' feedback caused, on average, a reduction in bodyweight of approximately 3%, in comparison to those receiving the 'Overweight' feedback. The Cattaneo et al (2017) density tests for each subsample provide further evidence that the results are not affected by differential attendance at the repeat assessment due to the feedback received.

3.5 Mechanisms

To test whether the effects of the 'Very Overweight' feedback identified previously can be related to behaviour change, RD estimates of the effect of this feedback on intentional weight loss and self-reported physical activity variables are provided in Table 6. Most of these estimates for the full analysis sample are positively signed; however, none are statistically significant. Estimating the same models on the sub-sample of individuals in the highest household income category, clearly finds that 'Very Overweight' feedback is associated with increases in physical activity and intentional weight loss, which corresponds with the findings in Table 5 that weight feedback had the greatest effect on the high-income sub-group.

[Table 5. Heterogeneity in the effects of feedback by household income (Dependent Variable: percentage change in bodyweight)]

[Table 6. Effects of 'Very Overweight' feedback: mechanisms]

4 Discussion

The evidence presented in this article suggests that personalised weight feedback alone, with no further health interventions, can result in modest long-term weight loss. This is in contrast to other studies that have found that even when public health messages are understood they are not acted upon (King et al, 2013). The efficacy of the feedback in this case is possibly due to the personalised nature of the feedback, which would concur with the findings of a systematic review of health behaviour change that found that individualised public health interventions were more effective than mass media campaigns (Jepson et al, 2010). A distinct pattern of heterogeneity is found; those who reside in high income households are most responsive to feedback both in terms of weight loss and in terms of increased physical activity, a finding consistent with Zhao et al (2013) who find similar heterogeneity in response to blood pressure feedback.

While the estimated effects appear small, it should be borne in mind that interventions that have only a small reduction on the average BMI can make a 'significant impact on the burden of chronic disease' at the population level (Kearns et al, 2014). Furthermore these results identify effects on weight loss over a period of between 2 and 7 years, this is in contrast to the poor record of weight loss incentives in effecting long term behaviour change (Royer et al, 2015).

This study also contributes to the understanding of whether the provision of feedback in longitudinal health studies affects the subsequent behaviours of participants. This is an area for which there is extremely limited knowledge (Lorimer et al, 2011), yet has important implications for both the reliability of longitudinal health data and the ethics of whether to provide participant feedback (Jeffery et al, 2005).

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Tables

Table 1. UK Biobank weight feedback rules

Baseline BMI measure	**Weight Feedback**
BMI<18.5	Underweight
18.5≤ BMI<25	Good
25≤ BMI<30	Overweight
BMI≥ 30	Very Overweight

Table 2. Descriptive statistics

Variable	Mean	S.D.	Min.	Max.
Baseline Covariates				
Age	56.6	7.54	40	70
Male	0.471	0.499	0	1
Height (cm)	169.3	9.12	144	200
Years between baseline and repeat assessments	4.35	1.01	2	7
Neighbourhood Deprivation (Townsend Index)	-2.17	2.58	-6.23	8.31
High Income Household	0.295	0.456	0	1
Health Measures at baseline				
Weight (kg)	75.9	14.6	41.6	152.8
BMI	26.4	4.12	16.4	50.1
Health Behaviours at baseline				
Losing weight	0.135	0.342	0	1
Walking for pleasure in last 4 weeks	0.774	0.418	0	1
Exercises (e.g. swimming, cycling, etc.) in last 4 weeks	0.563	0.496	0	1
Strenuous Sports in last 4 weeks	0.138	0.345	0	1
Change in weight between baseline and repeat assessment				
Percentage of bodyweight	-0.278%	5.65%	-31.6%	+37.1%
Kg	-0.306	4.51	-32.3	+28.1
BMI	+0.0661	1.601	-11.7	+10.4

Table 3. Local linear regression estimates of the effects of weight feedback

		Feedback			
		A: "Overweight"		**B: "Very Overweight"**	
	Running Variable:	BMI-25		BMI-30	
		w/o controls	*with controls*	*w/o controls*	*with controls*
Outcome Variable					
Change in bodyweight (%)	Coeff. (S.E)	-0.226 (0.291)	-0.267 (0.303)	-0.919*(0.488)	-1.011** (0.486)
	Bandwidth	2.971	2.712	3.272	3.268
	N^-/N^+	4082/4066	3766/3733	3348/1425	3342/1421

Notes: Robust bias corrected (Calonico et al, 2014) p values: *=p<0.1; **=p<0.05; ***=p<0.01; N^- and N^+ denote the number of cases within the bandwidth below and above the threshold respectively. Local linear regressions include controls for sex, age at baseline, standing height at baseline, neighbourhood deprivation index, time between baseline and repeat assessment (years).

Table 4. Robustness checks for discontinuities in repeat assessment response

		Feedback	
		A: "Overweight"	**B: "Very Overweight"**
	Running Variable:	BMI-25	BMI-30
Outcome= Attended Repeat Assessment	Coefficient (S.E)	0.003 (0.014)	0.010 (0.129)
(Sample: invitees to repeat assessment)	Bandwidth	1.722	3.062
	N^-/N^+	11,292/12,102	16,269/8,006
CJM Density test†	Test Statistic	0.748	1.112
	p-value	0.454	0.266

Notes: Robust bias corrected (Calonico et al, 2014) p values: *=p<0.1; **=p<0.05; ***=p<0.01; Local linear regressions include controls for sex, age at baseline, standing height at baseline, neighbourhood deprivation index. † the density test as described in Cattaneo et al (2017), where the null hypothesis is that there is no discontinuity in the density of cases at the cut-offs.

Table 5. Heterogeneity in the effects of feedback by household income (Dependent Variable: percentage change in bodyweight)

		Feedback	
		A: "Overweight"	**B: "Very Overweight"**
	Running Variable:	BMI-25	BMI-30
Sub-sample			
Household Income:			
High Income	Coefficient (S.E)	-0.281(0.642)	-3.383*** (1.145)
	Bandwidth	2.218	2.794
	N^-/N^+	855/794	754/328
	CJM p-value†	0.783	0.622
Middle Income	Coefficient (S.E)	-0.010 (0.406)	0.446(0.663)
	Bandwidth	2.918	2.908
	N^-/N^+	1949/2059	1425/670
	CJM p-value	0.0926*	0.449
Low Income	Coefficient (S.E)	-0.307 (1.008)	-1.561 (1.342)
	Bandwidth	1.726	3.656
	N^-/N^+	304/285	461/198
	CJM p-value	0.208	0.791

Notes: As per table 3; † The CJM p-value refers to the p-value from the density test as described in Cattaneo et al (2017), where the null hypothesis is that there is no discontinuity in the density of cases at the cut-offs. The sub-samples by income are determined by the income groups presented to participants in the touchscreen survey and are defined in this study as: high income = annual household income before tax> £51,999; middle income= annual household income before tax between £18,000 and £51,999; low income = annual household income before tax < £18,000.

Table 6. Effects of 'Very Overweight' feedback: mechanisms

	Sample: Running Variable:	Full Analysis Sample BMI-30	High Income Households BMI-30
Outcome Variable (at repeat assessment):			
Lost weight in past year (self-reported)	Coefficient (S.E)	0.053* (0.032)	0.133** (0.065)
	Bandwidth	3.696	3.904
	N^-/N^+	3836/1479	1101/390
Walking for pleasure in last 4 weeks	Coefficient (S.E)	-0.006 (0.034)	0.213** (0.088)
	Bandwidth	3.515	1.892
	N^-/N^+	3691/1480	448/246
Exercises (e.g. swimming, cycling, etc.) in last 4 weeks	Coefficient (S.E)	0.028 (0.034)	0.065 (0.068)
	Bandwidth	4.222	4.47
	N^-/N^+	4675/1635	1336/421
Strenuous sports in last 4 weeks	Coefficient (S.E)	0.025 (0.024)	0.099* (0.053)
	Bandwidth	3.096	3.744
	N^-/N^+	3124/1374	1063/392

Notes: As per table 3

Appendix

Table A1 – Robustness Check: Tests for discontinuities in baseline anthropometric measures

		Feedback	
		A: "Overweight"	**B: "Very Overweight"**
	Running Variable:	BMI-25	BMI-30
Outcomes= Baseline health			
Waist Circumference	Coefficient (S.E)	-0.047 (0.303)	-0.568 (0.363)
	Bandwidth	2.627	4.508
	N^-/N^+	3669/3644	5112/1686
Fat Percentage	Coefficient (S.E)	0.334 (0.228)	-0.041 (0.228)
	Bandwidth	1.902	3.089
	N^-/N^+	2754/2671	3080/1353
Systolic Blood Pressure	Coefficient (S.E)	0.409 (1.047)	-1.111 (1.228)
	Bandwidth	2.489	4.136
	N^-/N^+	3259/3199	4217/1513
Diastolic Blood Pressure	Coefficient (S.E)	-0.080 (0.545)	-0.991 (0.731)
	Bandwidth	2.915	3.805
	N^-/N^+	3701/3674	3781/1451

Notes: As per table 3

Table A2 – Robustness Check: Tests for discontinuities in baseline variables

		Feedback	
		A: "Overweight"	**B: "Very Overweight"**
	Running Variable:	BMI-25	BMI-30
Outcomes			
Age at baseline	Coefficient (S.E)	0.041 (0.485)	0.760 (0.577)
	Bandwidth	2.064	3.167
	N^-/N^+	3002/2902	3210/1394
Gender (0=female; 1=male)	Coefficient (S.E)	0.015 (0.024)	0.003 (0.027)
	Bandwidth	1.764	3.07
	N^-/N^+	2607/ 2521	3094/ 1370
Time between baseline and repeat assessments	Coefficient (S.E)	-0.077 (0.064)	0.105 (0.077)
	Bandwidth	2.189	3.586
	N^-/N^+	3146/3063	3791/1497
Index of neighbourhood deprivation	Coefficient (S.E)	0.292* (0.164)	0.180 (0.191)
	Bandwidth	2.042	4.145
	N^-/N^+	2970/2879	4557/1623
Height	Coefficient (S.E)	0.227 (0.395)	0.312 (0.417)
	Bandwidth	1.967	4.172
	N^-/N^+	2887/2781	4594/1628

Notes: As per table 3, though leaving out the corresponding dependent variable of the controls for each model.

Table A3 – Robustness Check: Tests for discontinuities in baseline health behaviours

		Feedback	
		A: "Overweight"	**B: "Very Overweight"**
Outcomes	Running Variable:	BMI-25	BMI-30
Already losing weight at baseline	Coefficient (S.E)	0.025 (0.021)	-0.004 (0.025)
	Bandwidth	2.271	3.734
	N^{-}/N^{+}	3213/ 3143	3937/ 1507
Walking for pleasure in last 4 weeks	Coefficient (S.E)	0.007 (0.025)	-0.016 (0.035)
	Bandwidth	2.219	3.233
	N^{-}/N^{+}	3104/3057	3225/1377
Exercises (e.g. swimming, cycling, etc) in last 4 weeks	Coefficient (S.E)	-0.049 (0.030)	0.027 (0.038)
	Bandwidth	2.398	3.399
	N^{-}/N^{+}	3324/3277	3455/1423
Strenuous sports in last 4 weeks	Coefficient (S.E)	-0.017 (0.023)	0.028 (0.022)
	Bandwidth	2.404	3.886
	N^{-}/N^{+}	3333/3289	4095/1530

Notes: As per table 3.

Table A4 – Robustness Check: Tests for discontinuities in unrelated outcomes at follow up

		Feedback	
		A: "Overweight"	**B: "Very Overweight"**
Outcomes	Running Variable:	BMI-25	BMI-30
Serious illness/injury in last 2 years	Coefficient (S.E)	0.0138 (0.017)	0.031 (0.021)
	Bandwidth	1.918	3.217
	N^{-}/N^{+}	2803/2706	3269/1399
Taking prescription medications†	Coefficient (S.E)	0.019 (0.031)	0.003 (0.040)
	Bandwidth	2.190	3.058
	N^{-}/N^{+}	3145/3059	3071/1367
Death of a close relative or partner in last 2 years	Coefficient (S.E)	-0.019 (0.024)	-0.008 (0.032)
	Bandwidth	2.546	2.921
	N^{-}/N^{+}	3574/3526	2889/1318
Marital separation/divorce in last 2 years	Coefficient (S.E)	-0.002 (0.008)	0.017 (0.011)
	Bandwidth	2.318	3.634
	N^{-}/N^{+}	3288/3239	3839/1498
Financial difficulties in last 2 years	Coefficient (S.E)	-0.0002 (0.014)	-0.001 (0.019)
	Bandwidth	1.952	3.034
	N^{-}/N^{+}	2865/2747	3037/1356
Distance (metres) travelled to assessment centre	Coefficient (S.E)	-43.771 (1421.2)	312.6 (1260.3)
	Bandwidth	1.961	3.021
	N^{-}/N^{+}	2876/2765	3023/1356

Notes: As per table 3; †Medications other than for blood pressure, cholesterol, diabetes and exogenous hormones.

Table A5 – Robustness Check: Placebo cut-offs (Dependent Variable: percentage change in bodyweight)

Cut-off= median of 'Very Overweight' (BMI=32.219)	Coefficient (S.E)	-0.264 (1.784)
	Bandwidth	0.822
	N^-/N^+	321/259
Cut-off= median of 'Overweight' (BMI=27.110)	Coefficient (S.E)	-0.504 (0.759)
	Bandwidth	0.542
	N^-/N^+	724/698
Cut-off= median of 'Good' (BMI=23.200)	Coefficient (S.E)	-0.236 (0.573)
	Bandwidth	0.673
	N^-/N^+	853/939

Notes: As per table 3

Table A6. Robustness Check: Bandwidth variation (Dependent Variable: percentage change in bodyweight)

		Feedback	
		A: "Overweight"	B: "Very Overweight"
	Running Variable:	BMI-25	BMI-30
0.5 x Optimal Bandwidth	Coefficient (S.E)	-0.813 (0.566)	-0.682 (0.858)
	Bandwidth	1.356	1.634
	N^-/N^+	2047/1966	1346/875
1.5 x Optimal Bandwidth	Coefficient (S.E)	-0.278 (0.309)	-0.977** (0.496)
	Bandwidth	4.068	4.902
	N^-/N^+	4845/5125	5675/1752
2 x Optimal Bandwidth	Coefficient (S.E)	-0.174 (0.271)	-0.939** (0.434)
	Bandwidth	5.524	6.536
	N^-/N^+	5395/6109	8113/1965

Notes: As per table 3