

A dual-process approach to exploring the role of delay discounting in obesity

Price, Menna; Higgs, Suzanne; Maw, James; Lee, Michelle

DOI:

[10.1016/j.physbeh.2016.02.020](https://doi.org/10.1016/j.physbeh.2016.02.020)

License:

Creative Commons: Attribution-NonCommercial-NoDerivs (CC BY-NC-ND)

Document Version

Peer reviewed version

Citation for published version (Harvard):

Price, M, Higgs, S, Maw, J & Lee, M 2016, 'A dual-process approach to exploring the role of delay discounting in obesity', *Physiology and Behavior*. <https://doi.org/10.1016/j.physbeh.2016.02.020>

[Link to publication on Research at Birmingham portal](#)

Publisher Rights Statement:

Validated Feb 2016

General rights

Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

- Users may freely distribute the URL that is used to identify this publication.
- Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
- User may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?)
- Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

Take down policy

While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact UBIRA@lists.bham.ac.uk providing details and we will remove access to the work immediately and investigate.

1 A dual-process approach to exploring the role of delay discounting in obesity

2 Menna Price^{1*}, Suzanne Higgs², James Maw³, Michelle Lee¹

3 ¹ Department of Psychology, College of Human and Health Sciences, Swansea University,
4 Singleton Park, Swansea, UK.

5 ² School of Psychology, University of Birmingham, Edgbaston, Birmingham, UK.

6 ³Department of Economics, College of Business and Economics, Swansea University, Bay
7 Campus, Swansea, UK

8 Running title: Dual-parameter model for obesity related delay discounting

9 *Correspondence: Menna Price: email: m.j.price@swansea.ac.uk; Department of Psychology,
10 College of Human and Health Sciences, Swansea University, Singleton Park, Swansea, UK
11 (Tel: +44 (0) 1792 515279).

12

13

14

15

16

17

18

19

20 Abstract

21 Delay discounting of financial rewards has been related to overeating and obesity.
22 Neuropsychological evidence supports a dual-system account of both discounting and
23 overeating behaviour where the degree of impulsive decision making is determined by the
24 relative strength of reward desire and executive control. A dual-parameter model of
25 discounting behaviour is consistent with this theory.

26 In this study, the fit of the commonly used one-parameter model was compared to a new
27 dual-parameter model for the first time in a sample of adults with wide ranging BMI. Delay
28 discounting data from 79 males and females (Males=26) across a wide age (M=28.44 years
29 (SD=8.81)) and BMI range (M=25.42 (SD=5.16)) was analysed. A dual-parameter model
30 (saturating-hyperbolic; Doya, 2008) was applied to the data and compared on model fit
31 indices to the single-parameter model.

32 Discounting was significantly greater in the overweight/obese participants using both models,
33 however, the two parameter model showed a superior fit to data ($p < .0001$). The two
34 parameters were shown to be related yet distinct measures consistent with a dual-system
35 account of inter-temporal choice behaviour.

36 The dual-parameter model showed superior fit to data and the two parameters were shown to
37 be related yet distinct indices sensitive to differences between weight groups. Findings are
38 discussed in terms of the impulsive reward and executive control systems that contribute to
39 unhealthy food choice and within the context of obesity related research.

40 Keywords: Obesity, delay discounting, dual-process, two-parameter, model

41

42 1. Introduction

43 The ability to delay gratification may be crucial for exerting self-control in a tempting food
44 environment. The conflict between the delayed rewards of good health and weight
45 maintenance versus the immediate reward of tasty foods is a dilemma well captured by the
46 delay discounting task [1]. Typically, participants are presented with a choice between a
47 small reward available immediately, or a larger reward available after a delay. Several trials
48 are presented over a number of delay periods and an indifference point (IP) is calculated as
49 the value at which the participant is indifferent to the reward being received now or after a
50 delay. The lower the IP values, the less an individual is willing to wait for the reward,
51 indicating a reduced ability to delay gratification. Discounting of the future on both money
52 and food-based tasks has been related to over eating and obesity, albeit inconsistently [2-15].
53 A commonly used model of discounting outcomes in obesity research is the single parameter
54 (*k*) hyperbolic model [16] which is fitted to data using the formula:

$$V = \frac{A}{1 + kD}$$

55 Where: V is the Indifference Point (IP), A is the Larger Later Reward (LLR), D is the delay
56 (days) and *k* is the free parameter for estimating steepness of temporal discounting.

57 As delays increase the IPs typically decrease as respondents are willing to accept less money
58 immediately instead of waiting for the delayed reward. This decline is however time-
59 inconsistent, being steeper when the delays are proximal (one day versus one week) and
60 shallower when delays are more distal (six months versus nine months). This enhanced
61 sensitivity to differences between shorter compared to longer delays may be reflecting a
62 reduced ability to imagine distal time periods with the same clarity as the near future. For
63 example, the greater the temporal distance to the time period being imagined, the less detail

64 or ‘pre-experiencing’ of that event that is reported [17]. The ability to imagine the future
65 varies between individuals and is considered to be an important component of executive
66 functioning related to activity in the prefrontal cortex [18].

67 Most reports of delay discounting applied to obesity have cited Mazur’s original paper to
68 justify using the single parameter hyperbolic model [16], in which the model provided the
69 best fit to data. However, Mazur examined discounting behaviour in rats, over very short
70 delays (usually seconds or minutes), and the question arises of whether it is a suitable model
71 for describing human discounting behaviour over longer delay periods.

72 A number of psychological theories support a dual-process account of the ability to inhibit
73 impulsive responses in favour of long-term gain [19]. Koffarnus and colleagues [20]
74 reviewed delay discounting research in different impulsive populations, exploring the
75 plausibility of a ‘Competing Neurobehavioural Decision Systems’ (CNDS) explanation of
76 inter-temporal choice. The authors suggest that behaviours related to a reduced ability to
77 delay rewards (including drug use, gambling and over eating) may be the result of a common
78 underlying trait predisposing a person to choose immediate rewards over long term benefits.
79 They discuss evidence favouring a role for two neural systems in trans-disease choice
80 behaviour: an executive decision system correlating with lateral pre-frontal cortex (PFC)
81 activation; and an impulsive system correlating with limbic reward activity. The CNDS
82 model predicts that individual differences in one or both of these systems, determines choice
83 behaviour. For example, it has been reported that that obese women gained more weight over
84 the subsequent year if they showed reduced activation in brain areas associated with
85 executive function when completing difficult discounting trials, compared to easy trials [21].
86 This supports the idea that sub-optimal functioning of executive areas leads to reduced self-
87 control and overeating behaviour. However, it has been found that a ‘dual-hit’ of reduced
88 executive control *and* increased desire for food cues reflected in nucleus accumbens (NAcc)

89 reactivity, determined a vulnerability to over eating and higher BMI [22]. Hence, outcome
90 behaviour in the delay discounting task may relate to activity in the reward system *and* the
91 executive system. In support of this idea, Lopez et al [23] reported that NAcc activity in
92 response to food cues predicted subsequent food desire and consumption over a week long
93 period, but this was moderated by inferior frontal gyrus activity in a self-control task. Reward
94 sensitive individuals displaying greater activity in this frontal region at baseline were more
95 able to resist strong food temptations than those who showed lower activity. This evidence
96 supports a dual-process approach to overeating and obesity [24]. Consistent with this,
97 neuroscientific evidence indicates that discounting is sensitive to two separate considerations
98 – time delay and reward magnitude, corresponding to PFC and Ventral Striatum (in particular
99 NAcc) activity respectively [25-27]. Thus the one parameter hyperbolic model may not be as
100 appropriate as a dual-parameter model, which is more in line with obesity related empirical
101 research evidence and neuropsychological theory.

102 In behavioural economics and addiction research, two-parameter models have been applied to
103 discounting data and compared favourably to single parameter models [28-30]. For example,
104 McKercher and colleagues [28] showed that in a general undergraduate student sample, two
105 hyperboloid models fitted with an additional power function showed superior fit to
106 discounting data compared to one parameter exponential and hyperbolic models. However, as
107 both two-parameter models showed equally good fit to data, the authors advise that model
108 selection should be based on theoretical, rather than just empirical reasons in any given
109 population. A two-parameter model which has two parameters that distinguish between
110 immediately available and delayed rewards is the $\beta\delta$ model [31]. However, Kable and
111 Glimcher [32] have suggested that it is more likely that there is a single system underpinning
112 desire for reward as soon as possible rather than a separate system for immediate versus
113 delayed reward.

114 Therefore a novel two-parameter model that is consistent with evidence and theory is put
115 forward. The saturating-hyperbolic model [33] is based on the premise that everyday decision
116 making is difficult because decisions can result in rewards of different amounts at different
117 timings. Within a delay discounting paradigm, the choice outcome behaviour is therefore
118 dependent upon both temporal discounting and reward utility. This model has two free
119 outcome parameters, k and Q , proposed to represent these processes respectively and is
120 calculated using the equation:

$$V = A * \left(\frac{A}{A + Q} \right) * \left(\frac{1}{1 + kd} \right)$$

121 Where: V = Indifference Point (IP); A = Larger later reward; k = hyperbolic temporal
122 discounting parameter; d = delay (days); Q = reward utility parameter.

123 The k parameter reflects the extent to which an individual discounts rewards over time. This
124 is identical to the single parameter hyperbolic function k and represents the relative steepness
125 of discounting at proximal versus distal delays. It is theorised to represent the ability to
126 imagine the future which relies on activity in executive decision systems [18]. The Q
127 parameter is called the reward utility function. This is typically a nonlinear function with a
128 sigmoid shape with a threshold and saturation point [33, 34]. It is hypothesised to represent
129 impulsive needs and desires, with variation in Q values indicating variation in nonlinear
130 valuation [33]. A larger Q value indicates a shallow reward utility curve and signals that the
131 reward is less appealing, whereas a smaller Q value indicates a steep reward curve and
132 signals that the reward is more appealing. When combined with the hyperbolic function k , the
133 Q parameter reflects the overall utility of the reward after a delay. If the reward is desired as
134 soon as possible then the Q value will be large, indicating that any delay very rapidly
135 devalues the reward. Therefore, the curve becomes saturated by enhanced proximal reward
136 utility and the value of Q describes the extent of this saturation. In descriptive terms this is

137 seen as a 'flattening' of the discounting curve where there is an immediate drop in where the
138 curve starts on the y-axis. The larger the Q value, the larger the 'drop' and therefore the
139 greater the emphasis on receiving the reward immediately.

140 To sum up, Q is theorised as a related yet distinct process to k , where the k parameter is a
141 measure of 'temporal discounting' and is theorised to represent the ability to imagine the
142 future and the Q parameter is a measure of reward utility, theorised to represent the impulsive
143 need and desire for reward. When combined into a single model, the Q value represents the
144 utility of the rewards as a function of delay, with higher values representing an emphasis on
145 receiving that reward as soon as possible. Therefore, Q affects the overall valuation of the
146 delayed reward being examined, contrasting with the single parameter model which only
147 considers the steepness of discounting across indifference points. The saturating-hyperbolic
148 model was selected because 1) it is directly comparable with the commonly used (nested)
149 one parameter hyperbolic model, and 2) it is consistent with dual-process theories and
150 neuropsychological evidence emphasising the importance of separate executive and reward
151 functions in determining delay discounting in obesity research [21-23].

152 Although there have been numerous studies of delay discounting in obesity research, the
153 relative fit of a dual-parameter model in an adult sample with wide ranging BMI is yet to be
154 tested. The aim of the current study was to apply the commonly used one-parameter
155 hyperbolic and the theory consistent, two-parameter saturating-hyperbolic model to
156 discounting data from a sample of males and females with a wide BMI and age range. We
157 predicted that the two-parameter model would show superior fit to data, and that Q and k
158 would be related but independent constructs. In addition, the parameters were compared
159 across weight groups to assess if they were sensitive to differences in discounting behaviour
160 between lean and overweight/obese participants. We also included self-report measures of
161 hedonic response to palatable food (Power of Food Scale [35]), disinhibited and restrained

162 eating (Dutch Eating Behaviour Questionnaire [36]), and perceived control over food intake
163 (Yale Food Addiction Scale [37]) to describe the population in terms of eating behaviour
164 dimensions.

165 2. Method

166 2.1 Participants:

167 One hundred and one participants were recruited from the student and staff population at
168 Swansea University and from professional/administration staff working for the local authority
169 via email and poster advertisement. A pre-screening questionnaire was administered to ensure
170 an equal distribution of lean and overweight/obese participants. Delay discounting and self-
171 report data were collected from each participant. After applying Johnson and Bickel's [38]
172 algorithm for identifying non-systematic delay discounting responders, and the removal of
173 one outlier (with an area under the curve greater than 2.5 standard deviations from the mean),
174 data from seventy nine participants was included for analysis (for sample characteristics, see
175 Table 1).

176 Written consent was obtained from all participants and consent and all study procedures were
177 granted departmental ethical approval by the Swansea University, Department of Psychology
178 Research Ethics Committee.

179

180

181

182

183

184 Table 1: Sample characteristics for the Lean and Overweight/obese groups.

Demographic Characteristics	Lean (BMI 18-24.9): Mean (Range (SD))	Overweight/Obese (BMI 25+): Mean (Range (SD))
N	41	38
Age (years)	26.76 (19-46(7.9))	30.11 (18-51(9.5))
Males (N)	9	16
Females (N)	32	22
BMI	21.6 (18.3-24.8(1.9))	29.6 (25.4-43.6(4.4))
PFS	2.86 (1.3-4.3(.9))	2.54 (1.3-4(.8))
YFAS	1.49 (0-4(1.1))	1.89(0-6(1.5))
DEBQext	3.25 (1.8-4.4(.66))	2.93 (1.7-3.9(.56))
DEBQem	2.65 (1-4.2(.76))	2.35 (1-4.8(.89))
DEBQrest	1.51 (1-2(.51))	1.5(1-2(.51))

185 BMI (Body Mass Index); PFS (Power of Food Scale); YFAS (Yale Food Addiction Scale);
 186 DEBQ (Dutch Eating Behaviour Questionnaire) ext (External eating), em (Emotional eating),
 187 rest (Restrained eating).

188

189

190 2.1 Procedure:

191 Participants were invited to attend a study ostensibly investigating ‘mood and decision
 192 making’. Each participant completed the delay discounting task, followed by the Power of
 193 Food Scale [35], Dutch Eating Behaviour Questionnaire [36] and Yale Food addiction Scale
 194 [37]. Height and weight was recorded by the researcher using the SECA laboratory scales in
 195 order to calculate body mass index (BMI) using the standard formula (kg/m^2). Participants
 196 were then debriefed, thanked and assigned course credit if they were students or £5 if they
 197 were members of the community.

198 2.2 Measures

199 2.2.1 Delay discounting task: A computer-based monetary delay discounting task with nine
 200 delays ranging from one day to one year. The larger, later amount was constant at £100 and
 201 the smaller, sooner amount varied using a random adjusting procedure, until the indifference
 202 point (IP) was calculated (the point at which the participant became indifferent to receiving
 203 the reward now or later). The IP for each delay was plotted as an indicator of the subjective

204 value of that reward at the given delay. The lower the value, the less willing a participant is to
205 wait for the reward. The plotted IPs can then be used to calculate a given outcome measure
206 for discounting behaviour. A detailed description of the task can be found in McHugh and
207 Wood's original paper [1].

208 2.2.2 Power of food scale (PFS): The PFS (Short version) is a 15 item questionnaire
209 measuring participants' appetite at three levels: when food is available, present and tasted.
210 The scale has been shown to predict food craving [39] and intake [40] in previous studies and
211 is included here as a general measure of appetite for palatable foods readily available in the
212 environment. Cronbach's alpha for the original scale was reported as 0.91 [35]. For group
213 means see Table 1.

214 2.2.3 Dutch Eating Behaviour Questionnaire (DEBQ): The DEBQ is a commonly used self-
215 report measure with three sub-scales. The external eating and emotional eating sub-scales
216 measure readiness to eat in response to external and emotional cues (disinhibited eating) and
217 the dietary restraint sub-scale measures the extent to which a person restricts their food intake
218 in order maintain/lose weight. The scale is commonly used and was included to allow cross-
219 comparison of sample characteristics with related research. Cronbach's alpha for the original
220 scales were reported as between 0.8-0.95 [36]. For group means see Table 1.

221 2.2.4 Yale Food Addiction Scale (YFAS): The YFAS is a 25 item self-report measure of
222 'food addiction'. It attempts to identify those who have truly lost control over their eating
223 behaviour. Participants receive a continuous score relative to the number of addiction criteria
224 that have been met (for example, use continues despite knowledge of adverse consequences)
225 with a maximum score of seven. The scale was included here as recent research has shown it
226 to be a direct predictor of BMI [41], and a mediator between general impulsivity and BMI

227 [42]. Good internal reliability for the original scale was reported as Kuber-Richardson
228 $\alpha=0.86$ [37]. For group means see Table 1.

229 3. Analysis:

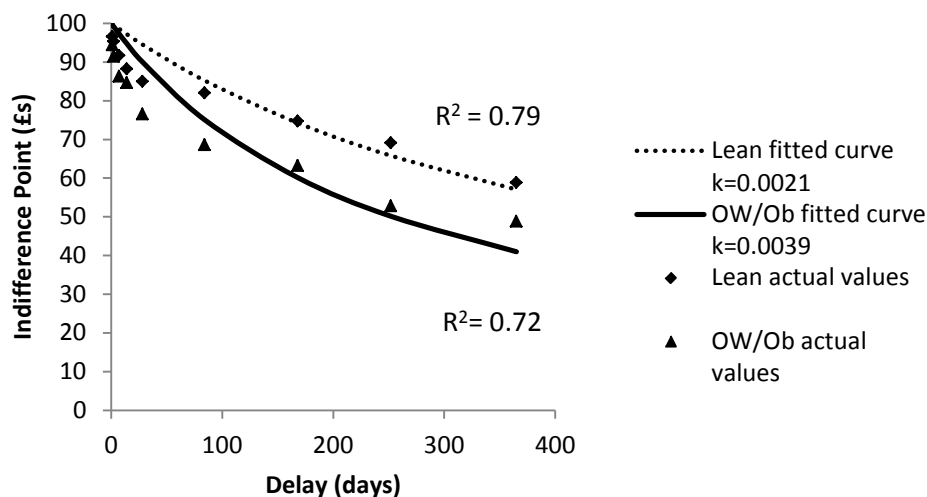
230 The one-parameter hyperbolic model was applied to the data using a least squares procedure
231 on Gnuplot open source software [43], to estimate a k value for each participant. The
232 saturating-hyperbolic model was applied to the delay discounting data using both Excel
233 solver and Gnuplot software. Both fit the two parameters simultaneously and produced
234 identical values. As a result the Q and k values were considered to be reliable.

235 The R^2 value for both models was calculated for descriptive purposes. Although often
236 reported, the use of R^2 as a unit of comparison is more appropriate for linear regression
237 models and has been argued to have little meaning for non-linear models [38]. As a result, the
238 Sum of Squared Residuals (SSR) for both models were calculated and used for comparison
239 analysis. The SSR is equivalent to a chi-square (χ^2) measure of model fit, and reflects the
240 total deviation of the response values from the fit to the response values. As with χ^2 , goodness
241 of fit is indicated by lower values reflecting a smaller random error component. Given that a
242 two-parameter model will always be expected to have a superior fit to a single parameter
243 model, a comparison method accounting for this difference is necessary. The two indices that
244 account for the number of parameters in each model and employed here were: Reduced SSR
245 (RSSR) and Root Mean Square (RMS) of RSSR. RSSR is calculated by dividing the SSR by
246 the number of degrees of freedom in the model, and the RMS (RSSR) is simply the square
247 root of this. The degrees of freedom were calculated by subtracting the number of parameters
248 from the number of data points (in this case there were nine data points, one for each delay
249 period). In each case lower values indicate a better fit. A significantly better fit can be
250 determined using a χ^2 difference test, as the models are nested.

251 Bivariate correlations were used to test if the parameters represented related or distinct
 252 processes. All analyses were conducted using IBM SPSS 20.0 software. All effect sizes were
 253 calculated post hoc using G* Power3 software [44].

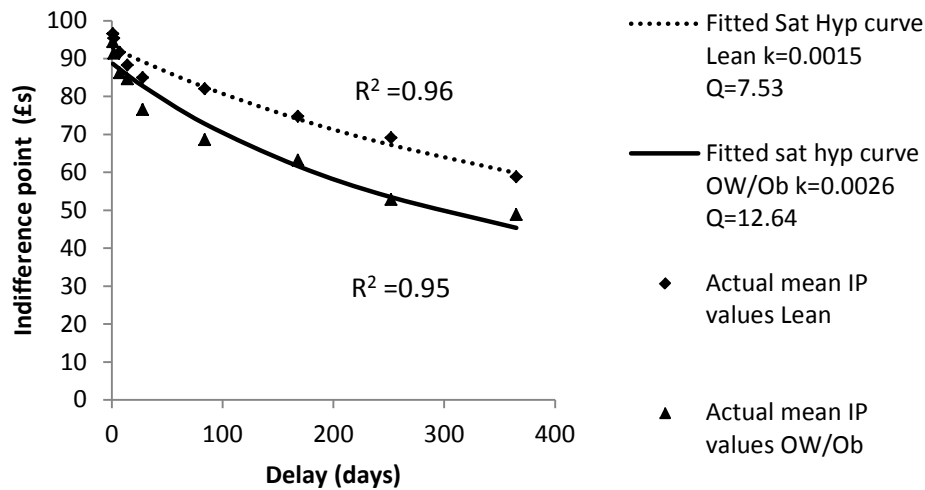
254 4. Results:

255 The single parameter (k), and two-parameter (Q and k ($satk$)) curves were fit to data from
 256 each participant and to the mean indifference points for the lean and overweight/obese groups
 257 for descriptive purposes (see Figures 1 & 2 respectively). The saturating-hyperbolic shows a
 258 visually superior fit to data (especially at the shorter delay periods) and has a markedly
 259 improved R^2 value for both weight groups. However, for a valid comparison, the SSR, RSSR
 260 and RMS (RSSR) were calculated for both models for each participant. Table 2 shows the
 261 mean fit indices for each model, along with the χ^2 difference test results. The SSR, RSSR and
 262 RMS (RSSR) values are smaller for the saturating-hyperbolic model, and the difference test
 263 is significant, indicating a statistically superior fit to data.



264

265 Figure 1: Graph to show the k values and one-parameter hyperbolic curves fitted to mean
 266 indifference points for lean and overweight/obese (Ow/Ob) participants (N=79).



267

268 Figure 2: Graph to show the Q and satk values and saturating-hyperbolic curves fitted to the

269 mean indifference points for lean and overweight/obese (OW/Ob) participants (N=79).

270 Table 2: Mean (SD) values, for goodness of fit indices for the one-parameter hyperbolic

271 model and the saturating-hyperbolic model.

Model/ Fit index	One parameter hyperbolic	Saturating- hyperbolic	X ² Difference test (Df difference=1)
SSR	879.40 (1020.11)	528.24 (642.44)	351.16*
RSSR	109.93 (127.51)	75.46 (96.78)	
RMS (RSSR)	8.96 (5.48)	7.27 (4.77)	

272 SSR (Sum of Squared Residuals); RSSR (Reduced Sum of Square Residuals); RMS (RSSR)

273 (Root Mean Square (RSSR)); Df (degrees of freedom); *p<0.0001. (p=0.35).

274 In order to explore the relationship between the two parameters Q and satk, from the

275 saturating-hyperbolic model, and the original k value from the one parameter model, they

276 were entered into a bivariate correlation matrix (see Table 3). Results confirm that the k

277 parameter in both models showed a near perfect correlation (r=.97). The Q parameter

278 however, shows only a moderate correlation (r=.22) and so it is likely to represent a related

279 yet distinct function.

280 Table 3: Spearman's correlation coefficients for the model parameters

	1	2	3
1. Q			
2. <i>satk</i>	0.22*		
3. <i>k</i>	0.41**	0.97**	

281 Q (Saturating-hyperbolic model); *satk* (Saturating-hyperbolic model); *k* (one-parameter
 282 hyperbolic model) * $p < 0.05$ ** $p < 0.01$

283 The *k*, Q and *satk* values were also compared across weight groups. The one parameter *k*
 284 values were significantly positively skewed ($z_{skewness} > 1.96$; $p < .05$) and so analysis was
 285 performed on log transformed data. ANOVA showed that the $\log k$ values were significantly
 286 higher for the overweight/obese group compared to the lean group ($F(1,77) = 8.016$; $p = .006$;
 287 $f = 0.51$). Demographic variables age and gender were compared across weight groups and
 288 although there were no significant differences ($p > .05$) there was a trend for the
 289 overweight/obese group to be older and include more males ($p < .10$). Therefore, the
 290 comparison was also run using ANCOVA, controlling for age and gender, however the
 291 outcomes did not change significantly. The overweight/obese group still showed significantly
 292 higher discounting rates than the lean group ($F(1,75) = 7.09$; $p = .009$).

293 As a result of the significantly skewed nature of the *satk* and Q values, and the fact that log
 294 transformation did not correct this, non-parametric tests were applied to the data. The Mann-
 295 Whitney U test of independent samples showed that the overweight/obese sample ($N = 38$) had
 296 significantly ($t = 2.25$; $p = .025$; $d = 0.8$) higher *satk* values ($M = 0.0042$; $SD = 0.004$) than the lean
 297 sample ($N = 41$; $M = 0.0032$; $SD = 0.004$), as found with the original one parameter model. This
 298 is interpreted as particularly robust as the populations do not represent top and bottom
 299 quartiles, but a separation of those with a BMI below 25 and those with a BMI of 25 and
 300 above. There was also a significant difference between the weight groups for Q values

301 (t=2.23; p=.026; d=0.8), where the overweight/obese group showed significantly greater Q
302 values (M=12.8; SD=16.7) than the lean group (M=5.4; SD=6.1). For consistency, the raw *k*
303 values from the single parameter model were also compared using the Mann-Whitney U test,
304 and were once again significant (t=2.82, p=.005, d=.9), with the overweight/obese group
305 displaying higher *k* values (M=.01; SD=.02) than the lean group (M=.005; SD=.01).

306

307 5. Discussion

308 Delay discounting has been related to obesity and has typically been modelled using a single
309 hyperbolic parameter (*k*) representing the relative steepness of temporal discounting.

310 However, neuropsychological research supports a dual-process account of discounting
311 behaviour. The saturating-hyperbolic model has two parameters, *satk* and Q, which are
312 related but distinct indices proposed to represent temporal discounting and reward utility
313 respectively. The model was therefore deemed consistent with the neuropsychological
314 evidence and theory. The model was applied to discounting data from a sample with a wide
315 range of BMIs and compared to the original single-parameter hyperbolic model. The new
316 model showed a superior 'goodness of fit' to current discounting data and has therefore been
317 shown to be a more accurate model of discounting behaviour in the current population.

318 The almost perfect correlation between the one parameter *k* value and the *satk* value indicates
319 that both parameters are measuring the same process and are therefore directly comparable.

320 The more modest correlations between *k* and Q indicate that Q is measuring a related but
321 distinct process to *k*. The parameters from both models were shown to be significantly higher
322 in overweight/obese versus lean participants. This supports previous findings using the single
323 parameter model, that delay discounting is an important component of obesity
324 [3,4,6,7,8,10,11], but shows for the first time that the saturating-hyperbolic model is not only

325 a better fit to data but maintains sensitivity to these differences. It is therefore a valid model
326 for future use in obesity research. Indeed, very recently, Franck and colleagues [45] published
327 a paper indicating that different models of discounting may best describe different
328 populations and provide a tool for allowing different models to be compared. The saturating-
329 hyperbolic model was not included in Franck and colleagues' [45] paper and would make a
330 useful addition if applied to obesity research.

331 The CNDS model of delay discounting maintains that poor choices like over eating are the
332 result of a high impulsive reward system, low executive system functioning or a combination
333 of both. In the current sample, the overweight/obese group had significantly higher $satk$ and
334 Q parameter values on the discounting task and it is theorised that the parameters may
335 represent functioning of the executive and impulsive reward systems respectively. This is
336 consistent with findings that it is the 'dual hit' of (food) reward desire and poor executive
337 control that leads to over eating [22]. The saturating-hyperbolic model proposes that the two
338 parameters represent temporal discounting ($satk$) and reward utility (Q) which is consistent
339 with neuropsychological research showing that delay discounting involves two related yet
340 distinct processes [26]. The use of the saturating-hyperbolic model to measure these
341 processes separately using the discounting task would be of great advantage in more precisely
342 elucidating the factors that contribute to overeating. However, it would be informative to
343 investigate the specific nature of the underlying processes by testing convergent validity of
344 $satk$ and Q with neural responsivity in pre-frontal and reward areas and with measures of
345 executive function and reward utility.

346 Carr et al. [50] coined the term 'reinforcement pathology' to describe the extent to which
347 food is a reinforcer but also the degree of impulse control a person has. A strong motivation
348 for food, measured using the Relative Reinforcement Value (RRV) of food task, has been
349 shown to predict BMI and intake particularly in those who discount the future more steeply

350 [12, 51]. This suggests that food responsiveness is an important contributor to overeating in
351 those with poor impulse control [49]. Research has also shown the discounting of food to be
352 steeper in overweight/obese groups [13, 47] and so it would now be useful to apply the
353 saturating-hyperbolic to food-related discounting behaviour. Findings from such research
354 would allow us to begin to assess the relative influence of a general, trans-disease tendency to
355 discount the future and a food specific tendency to discount the future in relation to
356 overeating and obesity.

357 A few limitations are notable. Firstly, socio-economic indicators (income, IQ and education)
358 were not recorded, but have previously been shown to be related to discounting behaviour [4,
359 53]. However, the majority of participants were recruited from the university student and
360 staff population or local authority professional employees. Significant socio-economic-status
361 (SES) differences between the weight groups were deemed unlikely. Future studies would
362 benefit from a valid measure of SES in this context and from extending the sample to include
363 a wider SES range (especially given the association between SES and obesity). Secondly, the
364 sample was quite small for cross-sectional research however the predicted effects for Q and k
365 emerged nonetheless, suggesting a robust finding. Future studies may benefit from a larger,
366 more representative cohort. Lastly, the (sat) k parameter has been theorised to be
367 representative of the ability to imagine the future and that this is an important aspect of
368 executive control. But the fact that pigeons demonstrate hyperbolic discounting behaviour
369 [57] and that dopaminergic activation of the reward circuitry also decreases in hyperbolic
370 proportion to reward delay length in rhesus monkeys [59], suggests that other mechanisms
371 may be responsible for discounting behaviour. However, human evidence showing that
372 episodic future thinking (EFT) reduces k values [58], supports the idea that the ability to
373 imagine the future might be one factor that underlies k , in humans at least.

374 As discounting is mutable under certain circumstances [54], it is a viable target for weight
375 loss intervention research. Application of the two-parameter model could expand our
376 understanding of exactly how an intervention exerts its influence. Recently, it was found that
377 EFT reduces both discounting behaviour and food intake in lean and obese individuals [55,
378 56], presumably through enhancing the valence of future time periods and making
379 discounting of the future less likely. Application of the saturating-hyperbolic to such data
380 would further inform us of whether EFT is enhancing executive consideration of the future
381 (satk), reducing immediate reward utility (Q) or both? Application of this model in future
382 research may enhance our understanding of which system underlies over eating in different
383 individuals and contribute towards behavioural interventions that can be targeted effectively.

384 Acknowledgements

385 The authors thank Neil Carter for assisting with computing the model fit. Financial support
386 was provided by Swansea University Bridging the Gaps, funded by EPSRC.

387 References

- 388 1. McHugh, L. & Wood, R.L. (2008). Using a temporal discounting paradigm to measure
389 decision-making and impulsivity following traumatic brain injury: A pilot study. *Brain*
390 *Injury*, 22(9): 715-721.
- 391 2. Nederkoorn, C., Smulders, F.T.Y., Havermans, R.C., Roefs, A. & Jansen, A. (2006).
392 Impulsivity in obese women. *Appetite*, 47: 253-256.
- 393 3. Weller, R.E., Cook, E.W., Avsar, K.B. & Cox, J.E. (2008). Obese women show greater
394 delay discounting than healthy-weight women. *Appetite*, 51: 563-569.

- 395 4. Davis, C., Patte, K., Curtis, C. & Reid, C. (2010). Immediate pleasures and future
396 consequences: A neuropsychological study of binge-eating and obesity. *Appetite*, 54: 208-
397 213.
- 398 5. Manwaring, J.L., Green, L., Myerson, J., Strube, M.J. & Wilfley, D.E. (2011). Discounting
399 of various types of rewards by women with and without binge-eating disorder: Evidence for
400 general rather than specific differences. *The Psychological Record*, 61: 561-582.
- 401 6. Appelhans, B.M., Woolfe, K., Pagoto, S.L., Schneider, K., Whited, M.C. & Leiberhan, R.
402 (2011). Inhibiting food reward: Delay discounting, food reward sensitivity, and palatable
403 food intake in overweight and obese women. *Obesity*, 57: 1-8.
- 404 7. Best, J.R., Stein, R.L., Welch, R.R., Perri, M.G., Epstein, L.H., Theim, K.R., Gredysa,
405 D.M. Saelens, B.E., Schechtman, K.B. & Wilfley, D.E. (2012). Behavioral economic
406 predictors of overweight children's weight loss. *Journal of Consulting and Clinical*
407 *Psychology*, 80(6): 1086-1096.
- 408 8. Fields, S.A., Sabet, M. & Reynolds, B. (2013). Dimensions of impulsive behaviour in
409 obese, overweight, and healthy weight adolescents. *Appetite*, 70: 60-66.
- 410 9. Vainik, U., Dagher, A., Dube, L. & Fellows, L.K. (2013). Neurobehavioural correlates of
411 body mass index and eating behaviours in adults: A systematic review. *Neuroscience and*
412 *Biobehavioral Reviews*, 37: 279-299.
- 413 10. Bickel, W.K., Wilson, A.G., Franck, C.T., Mueller, E.T., Jarmolowicz, D.P., Koffarnus,
414 M.N. & Fede, S.J. (2014). Using Crowdsourcing to Compare Temporal, Social Temporal,
415 and Probability Discounting Among Obese and Non-obese Individuals. *Appetite*, 75: 82-89.

- 416 11. Jarmolowicz, D.P., Cherry, J.B., Reed, D.D., Bruce, J.M., Crespi, J.M., Lusk, J.L.,
417 & Bruce, A.S. (2014). Robust relation between temporal discounting rates and body mass.
418 *Appetite*, 78, 63-67.
- 419 12. Epstein, L.H., Jankowiak, N., Fletcher, K.D., Carr, K.A., Nederkoorn, C., Raynor, H.A.
420 and Finkelstein, E. (2014). Women who are motivated to eat and discount the future are more
421 obese. *Obesity*, 22 (6), 1394-1399.
- 422 13. Schiff, S., Amodio, P., Testa, G., Nardi, M., Montagnese, S., Caregaro, L., ... & Sellitto,
423 M. (2015). Impulsivity toward food reward is related to BMI: Evidence from intertemporal
424 choice in obese and normal-weight individuals. *Brain and cognition*.
- 425 14. Ely, A. V., Howard, J., & Lowe, M. R. (2015). Delayed discounting and hedonic hunger
426 in the prediction of lab-based eating behavior. *Eating behaviors*, 19, 72-75.
- 427 15. Lawyer, S. R., Boomhower, S. R., & Rasmussen, E. B. (2015). Differential associations
428 between obesity and behavioral measures of impulsivity. *Appetite*, 95, 375-382.
- 429 16. Mazur, J.E., Stellar, J.R. & Waraczynski, M. (1987). Self-control choice with electrical
430 stimulation of the brain as a reinforcer. *Behavioural Processes*, 15: 143-153.
- 431 17. D'Argembeau, A. and van der Linden, M (2004). Phenomenal characteristics associated
432 with projecting oneself back into the past and forward into the future: Influence of valence
433 and temporal distance. *Consciousness and Cognition*, 13, 844-858.
- 434
- 435 18. Bickel, W.K., Miller, M.L., Yi, R., Kowal, B.P., Lindquist, D.M., Pitcock, J.A. (2007).
436 Behavioural and neuroeconomics of drug addiction: Competing neural systems and temporal
437 discounting processes. *Drug and Alcohol Dependence*, 90S, S85-S91.
- 438

- 439 19. Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist
440 drugs: A neurocognitive perspective. *Nature Neuroscience*, 8: 1458-1463.
- 441 20. Koffarnus, M.N., Jarmolowicz, D.P., Mueller, E.T., & Bickel, W.K. (2013). Changing
442 delay discounting in the light of the competing neurobehavioral decision systems theory: A
443 review. *Journal of the Experimental analysis of Behavior*, 99: 32-57.
- 444 21. Kishinevsky, F.I., Cox, J.E., Murdaugh, D.L., Stoekel, L.E., Cook, E.W. & Weller, R.E.
445 (2012). fMRI reactivity on a delay discounting task predicts weight gain in obese women.
446 *Appetite*, 58: 582-592.
- 447 22. Lawrence, N.S., Hinton, E.C., Parkinson, J.A. & Lawrence, A.D. (2012). Nucleus
448 accumbens response to food cues predicts subsequent snack consumption in women and
449 increased body mass index in those with reduced self-control. *NeuroImage*, 63: 415-422.
- 450 23. Lopez, R.B., Hofmann, W., Wagner, D.D., Kelley, W.M., Heatherton, T.F. (2014).
451 Neural predictors of giving in to temptation in real life. *Psychological Science*, published
452 online 30 April 2014: DOI: 10.1177/0956797614531492.
- 453 24. Appelhans, B. M. (2009). Neurobehavioral Inhibition of Reward-driven Feeding:
454 Implications for Dieting and Obesity. *Obesity*, 17(4), 640-647.
- 455 25. McClure, S.M., Laibson, D.I., Lowenstein, G. & Cohen, J.D. (2004). Separate neural
456 systems value immediate and delayed monetary rewards. *Science*, 306: 503-507.
- 457 26. Ballard, K & Knutson, B. (2009). Dissociable neural representations of future reward
458 magnitude and delay during temporal discounting. *NeuroImage*, 45: 143-150.

- 459 27. Stripada, C.S., Gonzalez, R., Phan, K.L. & Liberzon, I. (2011). The Neural Correlates of
460 Intertemporal Decision-Making: Contributions of Subjective Value, Stimulus Type, and Trait
461 Impulsivity. *Human Brain Mapping*, 32: 1637-1648.
- 462 28. McKercher, T.L., Green, L., Myerson, J., Pickford, S.T., Hill, J.C. & Stout, S.C. (2009). A
463 comparison of four models of delay discounting in humans. *Behavioral Processes*, 81: 256-
464 259.
- 465 29. Yi, R., Landes, R.D. & Bickel, W.K. (2009). Novel Models of Intertemporal Valuation:
466 Past and Future Outcomes. *J Neurosci Psychol Econ*. 2(2): 102.
- 467 30. Peters, J., Miedl, S.F. & Büchel, C. (2012). Formal Comparison of Dual-parameter
468 Temporal Discounting Models in Controls and Pathological Gamblers. *PLoS One*, 7(11):
469 e47225.
- 470 31. Phelps, E.S. and Polack, R.A. (1968). On second-best National Saving and Game-
471 Equilibrium Growth. *The Review of Economic Studies*, 35, 2 , 185-199.
- 472 32. Kable, J.W. & Glimcher, P.W. (2010). An “As Soon As Possible” Effect in Human
473 Intertemporal Decision Making: Behavioural Evidence and Neural Mechanisms. *Journal of*
474 *Neurophysiology*, 103, 2513-2531.
- 475 33. Doya, K. (2008). Modulators of decision making. *Nature Neuroscience*, 11(4): 410-416.
- 476 34. Iglesias, A., del Castillo, M.D., Serrano, J.I. and Oliva, J (2010a). A psychologically and
477 neurophysiologically plausible model for emulating human behaviour in decision making
478 tasks. In *Proceedings of the brain inspired cognitive systems- BICS*.
- 479

- 480 35. Lowe, M.R., Butryn, M.L., Didie, E.R., Annunziato, R.A., Thomas, J.G., Crerand, C.E. et
481 al (2009). The Power of Food Scale. A new measure of the psychological influence of the
482 food environment. *Appetite*, 53: 114-118.
- 483 36. van Strein, T., Frijter, J.E.R., Bergers, G.P.A., & Defares, P.B. (1986). The Dutch Eating
484 Behavior Questionnaire (DEBQ) for assessment of restrained, emotional, and external eating
485 behavior. *Eating Disorders*, 5(2): 295-315.
- 486 37. Gearhardt, A.N., Corbin, W.R. & Brownell, K.D. (2009). Preliminary validation of the
487 Yale Food Addiction Scale. *Appetite*, 52: 430-436.
- 488 38. Johnson, M.W. & Bickel, W.K. (2008). An algorithm for identifying non-systematic
489 delay-discounting data. *Exp Clin Psychopharmacol*, 16(3): 264-274.
- 490 39. Forman, E.M., Hoffman, K.L., McGrath, K.B., Herbert, J.D., Brandsma, L.L., & Lowe,
491 M.R. (2007). A comparison of acceptance- and control-based strategies for coping with food
492 cravings: an analog study. *Behav Res Ther*, 45: 2372–2386.
- 493 40. Levitsky, D.N. & Shen, X (2010). Food power scale predicts dessert eating, but not meal
494 eating or portion size effect. *Appetite*, 51: 350-412.
- 495 41. Pedram, P., Wadden, D., Amini, P., Gulliver, W., Randell, E., Cahill, F., Vasdev, S.,
496 Goodridge, A., Carter, J.C., Zhai, G., Ji, Y. & Sun, G. (2013). Food Addiction: Its prevalence
497 and significant association with obesity in the general population. *PLoS ONE* 8(9): e74832.
498 doi:10.1371.
- 499 42. Murphy, C.M., Stojek, M.K. & Mackillop, J. (2014). Interrelationships among impulsive
500 personality traits, food addiction, and Body Mass Index. *Appetite*, 73: 45-50.
- 501 43. Gnuplot: Version 4.4 Open source software. Available at <http://www.gnuplot.info/>

- 502 44. Faul, F., Erdfelder, E., Lang, A-G. & Buchner, A. (2007). G*Power 3: A flexible
503 statistical power analysis program for the social, behavioural and biomedical sciences.
504 *Behavior Research Methods*, 39(2): 175-191.
- 505 45. Franck, C. T., Koffarnus, M. N., House, L. L., & Bickel, W. K. (2015). Accurate
506 characterization of delay discounting: A multiple model approach using approximate
507 bayesian model selection and a unified discounting measure. *Journal of the experimental*
508 *analysis of behavior*, 103(1), 218-233.
- 509 46. Ouwens, M.A., van Strein, T. & van der Staak, C.P.F. (2003). Tendency toward
510 overeating and restraint as predictors of food consumption. *Appetite*, 40: 291-298.
- 511 47. Burton, P., Smit, H.J. & Lightowler, H.J. (2007). The influence of restrained and external
512 eating patterns on overeating. *Appetite*, 49: 191-197.
- 513 48. Snoek, H.M., Engels, R.C.M.E., van Strien, T. & Otten, R. (2013). Emotional, external
514 and restrained eating behaviour and BMI trajectories in adolescence. *Appetite*, 67: 81-87.
- 515 49. Price, M., Higgs, S. & Lee, M. (2015). Self-reported eating traits: Underlying components
516 of food responsiveness and dietary restriction are positively related to BMI. *Appetite*, 95,
517 203-210.
- 518 50. Carr, K.A., Daniel, T.O., Lin, H. and Epstein, L.H. (2011). Reinforcement Pathology and
519 Obesity. *Current Drug Abuse Reviews*, 4 (3), 190-196.
- 520 51. Rollins, B.Y., Dearing, K.K. and Epstein, L.H. (2010). Delay discounting moderates the
521 effect of food reinforcement on energy intake among non-obese women. *Appetite*, 55, 420-
522 425.

- 523 52. Rasmussen, E.B., Lawyer, S.R., and Reilly, W. (2010). Percent body fat is related to
524 delay and probability discounting for food in humans. *Behavioural Processes*, 83, 23-30.
- 525 53. de Wit, H., Florry, J.D., Acheson, A., McCloskey, M., Manuck, S.B. (2007). IQ and
526 nonplanning impulsivity are independently associated with delay discounting in middle-aged
527 adults. *Personality and Individual Differences*, 42, 111-121.
- 528 54. Loewenstein, G. (1996). Out of control: visceral influences on behaviour. *Organ Behav*
529 *Human Decision Processes*, 65: 272-292.
- 530 55. Daniel, T.O., Stanton, C.M. & Epstein, L.H. (2013). The future is now, Comparing the
531 effect of episodic future thinking in lean and obese individuals. *Appetite*. 71: 120-125.
- 532 56. Dassen, F. C., Jansen, A., Nederkoorn, C., & Houben, K. (2016). Focus on the future:
533 Episodic future thinking reduces discount rate and snacking. *Appetite*, 96, 327-332.
- 534 57. Green, L., Fisher, E.B.Jr., Perlow, S., & Sherman, L. (1981). Preference reversal and self-
535 control: Choice as a function of reward amount and delay. *Behaviour Analysis Letters*, 1, 43-
536 51.
- 537 58. Peters, J., & Büchel, C. (2010). Episodic future thinking reduces reward delay
538 discounting through an enhancement of prefrontal-mediotemporal interactions. *Neuron*,
539 66(1), 138-148.
- 540 59. Kobayashi, S., & Schultz, W. (2008). Influence of reward delays on responses of
541 dopamine neurons. *The Journal of Neuroscience*, 28(31), 7837-7846.

542

543