Two Asymmetric and Conflicting Learning Effects of Calorie Posting on Overeating: Laboratory Snack Choice Experiment

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Abstract

We develop a new framework to analyze the effect of calorie posting on overconsumption of calories in a fixed-price context (e.g., fixed-price buffets). The framework demonstrates that a desire to get `a good deal' (transaction utility) and loss aversion can induce asymmetry between two conflicting learning effects of calorie posing: a calorie-decreasing effect of learning that one was underestimating calorie contents (LUE effect) and a calorie-increasing effect of learning that one was overestimating calorie contents (LOE effect). Our laboratory snack choice experiments confirm that the LUE effect dominates the LOE effect under the context of overconsumption, which is consistent with transaction utility theory rather than loss aversion. The findings demonstrate the potential of calorie posting to mitigate overeating.

JEL Codes: D81, D91, I12

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1. Introduction

Providing calorie information in general, and calorie posting and labeling in particular, is one of the key policy tools used worldwide to promote healthier food choices and mitigate growing obesity epidemic. However, it is still controversial whether and how providing calorie information has any beneficial effect on calorie consumption. Some studies argue that it has only insignificant effects or even calorie-increasing effects (e.g., Downs et al. 2009; Nelson and McCluskey 2010; Giesen et al. 2011; Loewenstein 2011; Girz et al. 2012). These findings cast doubt on the effectiveness of improving consumers' knowledge about calories (i.e., learning effect), which is a key justification from economic theory for the efficacy of providing calorie information.

There are three mechanisms that can make the learning effect insignificant. First, people may never check the information. Second, even if people's knowledge is improved by checking the information, it may not be enough to change their behaviors. Third, there may be two types of learning effects which counteract each other. That is, people may decrease their calorie consumption by learning that one was underestimating calorie contents (learning-underestimation [LUE] effect), whereas they may increase their calorie consumption by learning that one was overestimating calorie contents (the learning-overestimation [LOE] effect). Thus, without distinguishing the two types, the net effect of the LUE and the LOE effects can be insignificant or even positive. To our best knowledge, there has been little systematic analysis on distinguishing the mechanisms, particularly for the third one.[1] This article attempts to fill this gap

[1] Bollinger et al. (2011) present the empirical evidence that consumers actually overestimate the calories in beverages, but they could not estimate the LUE and LOE effects explicitly due to data limitation.

by conducting snack choice experiments which provide an explicit measure of learning from calorie posting.

Moreover, this article develops a new conceptual framework that illustrates asymmetry between the LUE and the LOE effects in a fixed-price context, where the asymmetry enables us to empirically investigate the mechanism underlying the effect of calorie posting on overeating in the context. More specifically, the framework indicates that the LUE effect will dominate the LOE effect (i.e., a net calorie-decreasing effect) in a fixed-price context if risk-averse consumers have a desire to get `a good deal' as modeled using transaction utility in Just and Wansink (2011). In contrast, the LOE effect will dominate the LUE effect (i.e., a net calorie-increasing effect) in a fixed-price context if consumers are loss averse. Because of the growing number of both obese people and fixed-price restaurants in developed countries, it is of keen interest to clarify whether calorie posting can mitigate or accelerate overeating in a fixed-price context.

In empirically investigating this issue, a main difficulty is to measure a change in consumers' knowledge about calories between before and after calorie posting (i.e., learning from calorie posting) and consumers' risk preferences, which is particularly true in field experiments or surveys. To overcome the difficulty, this article employs laboratory snack choice experiments where the treatment is posting calorie information on a menu. There are two slightly different designs (study 1 and study 2) that provide two distinct measures of learning from calorie posting, where the two measures compensate each other. Three risk preference parameters in prospect theory (i.e., risk aversion, non-linear probability weight, and loss aversion) are measured by using the series of paired lotteries designed by Tanaka et al (2010). Moreover, to induce overconsumption in a fixed-price context, participants are asked to select snacks with a fixed budget, where the budget is set high enough to purchase more than a normal consumption level.

Using the measures of learning, we first decompose the effect of calorie posting on calorie consumption into two parts: a saliency effect and a learning effect. Then, we further decompose the learning effect into the LUE effect and the LOE effect. We also investigate how the decomposed effects of calorie posting are associated with three risk preference parameters in prospect theory.

In our experiments conducted with 463 university students in Hong Kong, we find that participants are actually loss averse and purchasing more snacks than they normally consume i.e., overconsumption. The results confirm that there exist two conflicting learning effects, the LUE and the LOE effects, and that the LUE effect is dominant over the LOE effect under the context of overconsumption. Also, we find no significant association between a loss aversion parameter and the learning effects while a risk aversion parameter is significantly negatively associated with the LUE effect. These findings are consistent with transaction utility theory rather than loss aversion, and suggest the potential of calorie posting to mitigate overeating behaviors in a fixed-price context.

This article contributes to the existing literatures in three important ways. First, it adds to the debate about the mechanism underlying the effect of calorie posting. In particular, it is novel in its framework that illustrates asymmetry in the two conflicting leaning effects by extending a loss aversion model and the transaction utility model proposed by Just and Wansink (2011). Second, we show that learning from calorie posting has a net calorie-decreasing effect in a fixed price context. Previous studies find that calorie posting can be beneficial mostly at fast food restaurants (e.g., Burton et al. 2006; Bassett et al., 2008; Wisdom et al. 2010; Bollinger et al.

2011; Ellison et al. 2011). Our results complement these studies by providing an additional case where calorie posting can be beneficial. Finally, our findings can be related to a literature examining how risk preferences are associated with health-related behaviors such as smoking, drinking, and being obese (e.g., Anderson and Mellor 2008; Dave and Saffer 2008). Our results complement these studies by showing the associations between risk preferences and the response to calorie posting.

The rest of the article is organized as follows. The second section presents our conceptual models to illustrate how calorie posting can affect calorie consumption in a fixed-price context. The third section describes our experimental designs. The fourth section presents our estimating equations. The fifth section describes the data and presents our estimation results. The last section offers concluding remarks.

2. Conceptual Framework

To illustrate how the learning from calorie posting influences people's calorie consumption in a fixed price context, we present three different models: a basic model, a model with transaction utility, and a model with loss aversion. Our basic model, which is often used to predict the effect of calorie posting in the existing literature, shows that the LUE effect may cause to reduce people's calorie consumption, while the LOE effect may cause to increase people's calorie consumption. However, it indicates no systematic difference in the magnitude between the two learning effects in a fixed price context. Thus, on average, the effectiveness of calorie posting depends on the initial distribution of people's expectations about calorie contents.

Our model with transaction utility indicates that the LUE effect will dominate the LOE effect if risk-averse consumers are over-consuming calories in a fixed price context. Thus, on average, calorie posting should reduce calorie consumption (or at worst no effect) regardless of the initial distribution of people's expectations about calorie contents. In contrast, if consumers are loss averse, our model with loss aversion indicates that the LOE effect will dominate the LUE effect in a fixed price context. Thus, on average, calorie posting should increase calorie consumption (or at best no effect) regardless of the initial distribution of people's expectations about calorie contents. In the following subsections, we present more details for each of the three models.

A Basic Model

We start from a simplest model as follows: $\max_q U^c(q|\theta)$, where q is the calorie consumption, θ is the amount that maximizes hedonic consumption utility $U^c(.|.)$ where it is continuously differentiable, $U_q^c(\theta|\theta) = 0$, and $U_{qq}^c(.|\theta) < 0$. People are assumed to maximize their utility by consuming θ. However, people often do not know exactly how much calories they are consuming. If people underestimate the calorie contents of food items, their actual calorie consumption q^{UE} will be larger than the optimal level (i.e., $\theta < q^{UE}$). Similarly, if people overestimate the calorie contents of food items, their actual calorie consumption q^{OE} will be smaller than the optimal level (i.e., $q^{OE} < \theta$).

Calorie posting can affect the calorie consumption q by informing people that they are underestimating or overestimating the calorie contents. That is, people may decrease calorie consumption from q^{UE} to θ if they learn that they were underestimating the calorie contents (i.e., the LUE effect); and people may increase calorie consumption from q^{OE} to θ if they learn that they were overestimating the calorie contents (i.e., the LOE effect). This is particularly true in a fixed-price context because there is no monetary cost for changing calorie consumption. Thus, the effect of calorie posting on one's calorie consumption depends on how one initially predicted calorie contents. In other words, the average effect of calorie posting in a certain group depends on the initial distribution of people's predications about calorie contents within the group.

A Model with Transaction Utility

We now incorporate Transaction Utility Theory into our basic model in a fixed price context i.e., consumers are assumed both to desire to get a "good deal" (transaction utility) and to increase their hedonic consumption utility ($U^c(q|\theta)$). Based on the model proposed in Just and Wansink (2011), we construct the model for analyzing the effect of calorie posting as follows.

$$\max_q U^t(q|c) + U^c(q|\theta) \tag{1}$$

where c is the subjective price per calorie, and $U^t(.|.)$ is transaction utility of consuming q given the price per calorie c. $U^t(.|.)$ is assumed continuously differentiable and $U_q^t > 0$, $U_{qq}^t < 0$, $U_c^t < 0$, and $U_{qc}^t > 0$. $U_{qc}^t > 0$ indicates that the marginal transaction utility of consumption U_q^t increases with price per calorie. That is, transaction utility and hedonic consumption utility are assumed compensatory. Thus, one who purchases poor quality snack at a low price per calorie may be similarly well off as if one had purchased a similar quantity of high quality snacks at a high price per calorie.

The first order conditions (FOC) solving (1) can be written as $U_q^t(q^*|c^*) + U_q^c(q^*|\theta) = 0$ where c^* is the true price per calorie. By monotonicity of U^t, $U_q^t(q^*|c^*) > 0$ and thus $U_q^c(q^*|\theta) < 0$. Therefore, consumers will over-consume calories in order to increase transaction utility. Here, we assume that people know the true price per calorie c^*. In the reality, however, people often do not know exactly how much calories they are consuming and thus do not know the true price per calorie i.e., $c \neq c^*$.

The subjective price per calorie among people who are underestimating the calorie contents (c^{UE}) is higher than c^*. In contrast, the subjective price per calorie among people who are overestimating the calorie contents (c^{OE}) is lower than c^*. The FOCs solving (1) under these prices per calorie can be written as $U_q^t(q^{UE}|c^{UE}) + U_q^c(q^{UE}|\theta) = 0$ and $U_q^t(q^{OE}|c^{OE}) + U_q^c(q^{OE}|\theta) = 0$. By monotonicity of U^t, $\theta < q^{OE} < q^* < q^{UE}$. To illustrate these relationships numerically, Table 1 presents an example in which people purchase snacks up until their optimal level q^* (= 200 kcal) based on their predicted calorie contents in a fixed price context.

Calorie posting can influence the calorie consumption q by changing the subjective price per calorie c. More specifically, if people learn that they were overestimating the calorie contents, the subjective price per calorie will increase from c^{OE} to c^*. In contrast, if people learn that they were underestimating the calorie contents, the subjective price per calorie will decrease from c^{UE} to c^*. Totally differentiating the FOC with respect to c and q, the effect of a change in c on q can be written as $\frac{dq}{dc} = \frac{U_{qc}^t(q^*|c)}{U_{qq}^t(q^*|c)+U_{qq}^c(q^*|\theta)}$. Thus, the effect is positive ($\frac{dq}{dc} > 0$) if $U_{qc}^t > 0$. That is, learning overestimation ($dc = c^* - c^{OE} > 0$) leads to an increase in q. In contrast, learning underestimation ($dc = c^* - c^{UE} < 0$) leads to a decrease in q. Thus, the predicted direction of changes in calorie consumption is the same to our basic model.

A key difference from our basic model is the utility effect of adjusting calorie consumption q. The total utility effect of increasing consumption from q^{OE} to q^* by learning that the true price per calorie is c^* (> c^{OE}) can be decomposed as follows:

$$U(q^*|c^*) - U(q^{OE}|c^{OE}) = [U^t(q^*|c^*) + U^c(q^*|\theta)] - [U^t(q^{OE}|c^{OE}) + U^c(q^{OE}|\theta)] \quad (2)$$

$$= [U^c(q^*|\theta) - U^c(q^{OE}|\theta)] + [U^t(q^*|c^{OE}) - U^t(q^{OE}|c^{OE})]$$

$$+[U^t(q^*|c^*) - U^t(q^*|c^{OE})].$$

Because $\theta < q^{OE} < q^{*}$ and $c^{OE} < c^{*}$, the first term in (2) is a consumption utility loss by deviating further from θ (i.e., $[U^{c}(q^{*}|\theta) - U^{c}(q^{OE}|\theta)] < 0$), the second term is a transaction utility gain from consuming more (i.e., $[U^{t}(q^{*}|c^{OE}) - U^{t}(q^{OE}|c^{OE})] > 0$), and the third term is a transaction utility loss due to an increase in a price per calorie (i.e., $[U^{t}(q^{*}|c^{*}) - U^{t}(q^{*}|c^{OE})] < 0$). Moreover, we can show that the magnitude of the first term is larger than that of the second term i.e., $|U^{t}(q^{*}|c^{OE}) - U^{t}(q^{OE}|c^{OE})| < |U^{c}(q^{*}|\theta) - U^{c}(q^{OE}|\theta)|$ (see Appendix 1 for proof). Thus, the total utility effect is negative i.e., $U(q^{*}|c^{*}) - U(q^{OE}|c^{OE}) < 0$. In other words, although people feel better about a deal with more calories, the good feeling is exceeded by a bad feeling by knowing a higher price per calorie and by deviating further from the non-overconsumption level.

Similarly, we can decompose the total utility effect of decreasing consumption from q^{UE} to q^{*} by learning that the true price per calorie is c^{*} ($< c^{UE}$) as follows:

$$U(q^{*}|c^{*}) - U(q^{UE}|c^{UE}) = [U^{c}(q^{*}|\theta) - U^{c}(q^{UE}|\theta)] + [U^{t}(q^{*}|c^{*}) - U^{t}(q^{UE}|c^{*})] \quad (3)$$
$$+[U^{t}(q^{UE}|c^{*}) - U^{t}(q^{UE}|c^{UE})].$$

Because $\theta < q^{*} < q^{UE}$ and $c^{*} < c^{UE}$, the first term in (3) is a consumption utility gain by getting closer to θ (i.e., $[U^{c}(q^{*}|\theta) - U^{c}(q^{UE}|\theta)] > 0$), the second term is a transaction utility loss from consuming less (i.e., $[U^{t}(q^{*}|c^{*}) - U^{t}(q^{UE}|c^{*})] < 0$), and the third term is a transaction utility gain due to a decrease in a price per calorie (i.e., $[U^{t}(q^{UE}|c^{*}) - U^{t}(q^{UE}|c^{UE})] > 0$). Moreover, following a similar steps in Appendix 1, we can show that the magnitude of the first term is larger than that of the second term i.e., $|U^{t}(q^{*}|c^{*}) - U^{t}(q^{UE}|c^{*})| < |U^{c}(q^{*}|\theta) - U^{c}(q^{UE}|\theta)|$. Thus, the total utility effect is positive i.e., $U(q^{*}|c^{*}) - U(q^{UE}|c^{UE}) > 0$. In other words, although people feel worse about a deal with fewer calories, the bad feeling is exceeded by a good feeling by knowing a lower price per calorie and by getting closer to the non-overconsumption level.

Thus, if people learn that they were overestimating calorie contents, people should not (or may at least hesitate to) adjust their consumption level because they are worse off by consuming q^* under c^* compared to their reference utility level with q^{OE} and c^{OE}. In contrast, if people learn that they were underestimating calorie contents, people should be willing to adjust their consumption level because they are better off by consuming q^* under c^*compared to their reference utility level with q^{UE} and c^{UE}. Thus, the LUE effect should dominate the LOE effect. Hereafter this prediction is referred to as the transaction utility hypothesis.

A Model with Loss Aversion

If consumers are loss avers, the relationship between the LUE and the LOE effects can be opposite from the transaction utility hypothesis, i.e., the LOE effect may dominate the LUE effect. To illustrate this possibility, we employ a simple consumption model from Koszegi and Rabin (2006). Consumer's utility is defined as $U(k|r) = m(k) + n(k|r)$ where $m(k)$ is consumption utility, $n(k|r)$ is gain-loss utility, k is a consumption outcome and r is a reference point. Suppose that there are two dimensions, with $m(k) = k_1 + k_2$ where $k_1, k_2 \in R$. Also, $n(k|r) = \mu(k_1 - r_1) + \mu(k_2 - r_2)$ where $\mu(x) = \eta x$ for $x > 0$ (i.e., gains) and $\mu(x) = \eta\lambda x$ for $x \leq 0$ (i.e., losses). In $\mu(x)$, $\eta > 0$ is the weight that the consumer attaches to gain-loss utility, and $\lambda > 1$ is a loss aversion parameter. In our model, the two dimensions are calorie consumption (q) and price per calorie (c), (k_1, k_2) is an outcome under the true price per calorie, and (r_1, r_2) is an outcomes under a subjective price per calorie (i.e., expectation-based reference points). Note that there is uncertainty in price per calorie because people may not know the exact calorie contents until they learn the calorie contents from calorie posting.

When people learn that they were overestimating calorie contents i.e., $(q^{OE}, -c^{OE})$ is a reference point, the utility from adjusting consumption from the reference point to $(q^*, -c^*)$ is $q^* - c^* + \eta(q^* - q^{OE}) - \eta\lambda(c^* - c^{OE})$ where $(q^* - q^{OE})$ is a gain in calorie consumption because $q^{OE} < q^*$, and $-(c^* - c^{OE})$ is a loss in price per calorie because $c^{OE} < c^*$. The utility from not adjusting is $q^{OE} - c^{OE}$. Thus, consumers will adjust their consumption level if and only if $q^* - c^* + \eta(q^* - q^{OE}) - \eta\lambda(c^* - c^{OE}) > q^{OE} - c^{OE}$. Solving this inequality, we obtain

$$c^* - c^{OE} < \frac{(1+\eta)}{(1+\eta\lambda)}(q^* - q^{OE}) \quad (4)$$

Similarly, when people learn that they were underestimating calorie contents i.e., $(q^{UE}, -c^{UE})$ is a reference point, the utility from adjusting consumption from the reference point to $(q^*, -c^*)$ is $q^* - c^* - \eta\lambda(q^{UE} - q^*) + \eta(c^{UE} - c^*)$ where $-(q^{UE} - q^*)$ is a loss in calorie consumption because $q^* < q^{UE}$, and $(c^{UE} - c^*)$ is a gain in price per calorie because $c^* < c^{UE}$. The utility from not adjusting is $q^{UE} - c^{UE}$. Thus, consumers will adjust their consumption level if and only if $q^* - c^* - \eta\lambda(q^{UE} - q^*) + \eta(c^{UE} - c^*) > q^{UE} - c^{UE}$. Solving this inequality, we obtain

$$c^{UE} - c^* > \frac{(1+\eta\lambda)}{(1+\eta)}(q^{UE} - q^*) \quad (5)$$

Note that, if people underestimate or overestimate calorie contents in the same magnitude i.e., $(q^* - q^{OE}) = (q^{UE} - q^*)$, $0 < \frac{(1+\eta)}{(1+\eta\lambda)}(q^* - q^{OE}) < \frac{(1+\eta\lambda)}{(1+\eta)}(q^{UE} - q^*)$ for loss averse consumers (i.e., $\lambda > 1$) because $(1 + \eta\lambda) > (1 + \eta)$. Thus, compared to inequality (4), inequality (5) requires a larger error in *c* and thus may be less likely to be satisfied.

Moreover, once we fix a total price and food quality, there will be no utility gain from a change in price per calorie *c*. Thus, the left-hand side of (4) and (5) will be zero under a fixed price context. Then, because $0 < \frac{(1+\eta)}{(1+\eta\lambda)}(q^* - q^{OE}) < \frac{(1+\eta\lambda)}{(1+\eta)}(q^{UE} - q^*)$, inequality (4) is always satisfied while inequality (5) is never satisfied. Therefore, if consumers are loss averse, they will always increase their calorie consumption by learning that they were overestimating calorie contents. In contrast, they will not decrease their calorie consumption by learning that they were underestimating calorie contents. Thus, the LOE effect will dominate the LUE effect. Hereafter this prediction is referred to as the loss aversion hypothesis.

In summary, these conceptual predictions allow us to test which mechanism dominantly explains the effect of calorie posting on calorie consumption in a fixed price context. First, if the LUE effect dominates the LOE effect, it will support the transaction utility hypothesis. Second, if the LOE effect dominates the LUE effect, it will support the loss aversion hypothesis. Third, if both the learning effects are equally either significant or insignificant, implication will depend on whether the LOE effect is significantly associated with a loss aversion parameter. If it is, the loss aversion hypothesis may be supported. If not, equally significant effects may be consistent with our basic model, and equally insignificant effects may simply indicate no significant learning effects.

3. Experimental Design

To test our hypotheses, it was necessary to obtain the measures of people's calorie knowledge before and after they observe calorie posting, and their loss aversion at the individual level. These requirements left us laboratory experiments as the only feasible method. Thus, we had to choose food items which are distributable at a laboratory room, whose consumption volume can be measured, whose serving amount per unit is small enough to capture overconsumption, and whose calorie contents can be reasonably controlled. To meet these criteria, we chose packaged snacks and conducted laboratory snack choice experiments.

Food Choice Experiment

To generate `overconsumption of calories', we offered a fixed budget (HK$30) to choose up to 6 packs of snacks (HK$5/pack) from a menu for one-day consumption, where the menu listed only general descriptions of four types of snacks (i.e., potato chips, chocolate cookies, raisins, and vegetable crackers). Because unspent budget would not be returned to a participant, there was no monetary incentive to save the budget. Theoretically there would be 210 different combinations to select snacks. This provides enough variation in calorie consumption to conduct a regression analysis. To examine whether they were really over-consuming, our post-experiment survey asked about their snacking habits and how soon they would finish eating all the purchased snacks.

The treatment in our experiment was to post calorie contents for each of the menu items. About a half of our sample received the menu with calorie posting (the treatment group), while the other half received the menu without calorie posting (the control group). We also used four different orders of listing the items so that all the items showed up at all positions on the menu with an equal probability, which enabled us to examine the so-called order effect. In total, the menu had eight different versions (with or without calorie posting × four different listings), and they were randomly distributed to the participants. The participants placed their orders by writing down on the menu how many packs of each of the items they would like to have. An example of the menu is presented in Panel A in Figure 1.

Before distributing the menu, participants were instructed to complete the following two tasks for each of the menu items: (a) a liking-rating task and (b) a familiarity-rating task. These tasks were designed following those of Bushong et al. (2010). In both tasks, each item was followed by the general description and the high-resolution picture of the item (see Panel B in Figure 1). The picture showed the amount of one package for each item (about 35g). To minimize the effects of brand names and the package appearance, the original packages were not shown. In task (a), the participant answered the question “How much would you like to eat this item after the experiment?” on a scale of -7 (not at all) to 7 (very much), where 0 denotes indifference. In task (b), the participant answered the question “How familiar are you with this item” on a scale of 1 (not much) to 3 (very much). These tasks also increased the familiarity of the participants with the menu items before placing their orders.

Strategies to Measure `Learning’ from Calorie Posting

We constructed two measures of learning by measuring participants’ calorie knowledge before and after calorie posting. To measure the knowledge after calorie posting, our post-experiment survey asked participants “How many kilocalories (kcal) do you think your entire selected snacks (for HK$30 or less) contain? If you are unsure, please make your best guess”. In contrast, it was more difficult to measure the knowledge before calorie posting. This is because asking participants about calories before they observe calorie posting could increase their attention to calories (i.e., a saliency effect) and may contaminate the effect of calorie posting. Thus, we employ two different strategies to measure participants’ calorie knowledge before calorie posting.

First, in study 1, we straightforwardly asked participants to predict calorie contents for each of the menu items before distributing the menu (i.e., just after a familiarity-rating task). More specifically, we asked: “How many kilocalories (kcal) do you think one pack of this snack item contains?”, and “how confident are you about your guess?” on a scale of 1 (not at all) to 7 (very confident). The second question was asked to distinguish between well-informed people and people who provide reasonable guesses by chance. Here, we assumed that only saliency effect would be influenced by asking about calories before calorie posting, and thus learning effects would not be influenced. However, increasing peoples’ attention to calories might lead people to check calorie posting more carefully, which can cause an upward bias in the estimate of the learning effect.

Thus, in study 2, we asked nothing about calories before distributing a menu. Instead, our post-experiment survey asked participants to predict `their recommended total daily calorie intake'. More specifically, we asked "About how many kilocalories (kcal) do you think a medical doctor or nutritionist would recommend you to eat for your daily diet? If you are unsure, please make your best guess". Here, we assumed that calorie posting could improve only knowledge about snack calories and had no significant effect on knowledge about recommended total daily calorie intake.[2] Thus, participants' knowledge about their own recommended total daily calorie intake can be a proxy for their calorie knowledge before calorie posting. In other words, we conjecture that a participant is more likely to provide a reasonable prediction about snack calories if the participant has a reasonable prediction about one's recommended total daily calorie intake; and a participant was more likely to over-predict (under-predict) snack calories if the participant over-predicts (under-predicts) one's recommended total daily calorie intake. This possibility was empirically tested using data from Study 1 because we asked this question in study 1 as well.

To define learning statuses, we first define calorie-knowledge statuses (underestimate, reasonable estimate, and overestimate) using the above measures of calorie-knowledge. The definitions of calorie knowledge statuses are summarized in Table 2, and more details are presented in Appendix 2. Based on a change in the calorie-knowledge status between before and after calorie posting, we define three learning statuses: learn underestimation (underestimate → reasonable), learn overestimation (overestimate → reasonable), and no learning (all other

[2] This assumption is supported by Elbel (2011) and our experimental data.

changes). We then construct three learning indicators: learning indicator, LUE indicator and LOE indicator (see Table 2). The ex-post calorie-knowledge status is always defined using `one's ex-post prediction about the total snack calories'. The ex-ante calorie-knowledge status is defined in two different ways. First, it is defined using ` one's ex-ante prediction about snack calories', which provides the so-called direct learning measure. Second, it is defined using `one's ex-post prediction about recommended total daily calorie intake', which provides the so-called indirect learning measure.

Experiment to Measure Risk Preference Parameters

To measure three risk preference parameters in prospect theory (σ, λ and α), we employ three series of paired lotteries designed by Tanaka et al. (2010).[3] σ represents the curvature of individual's value function: the individual is risk averse if $\sigma > 0$, risk neutral if $\sigma = 0$, and risk loving if $\sigma < 0$. λ represents a loss aversion parameter in cumulative prospect theory: higher λ indicates that an individual is more loss averse. α is the nonlinear probability weight parameter: if $\alpha < 1$, an individual overweights low probabilities of large gains and losses and underweights high probabilities. The utility function can be reduced to the standard expected utility function if $\lambda = \alpha = 1$.

Post-Experiment Survey

In the post-experiment survey, as we mentioned above, we asked (i) prediction about the total calories of one's ordered snacks, (ii) prediction about one's recommended total daily calorie intake, (iii) general snacking habits on a scale of 1 (once a moth or less) to 5 (everyday), and (iv) how long one thinks it will take to finish eating all the ordered snacks on a scale of 1 (today) to 5

[3] I converted Vietnamese dong (VND) in the Tanaka et al. (2010) into HK$ by dividing the VND amounts by 1,000.

(within a month or longer)". In addition to these questions, we also asked the following questions: (v) how hungry one currently is on a scale of 1 (not at all) to 7 (very much); (vi) whether one is currently dieting; (vii) one's weight, height, and ideal weight; (viii) one's pocket money spent during the last 30 days, and (ix) basic background information (age, sex and marital status).

Procedures

We used university's UG student mailing list, which covers all undergraduate students in our university, to recruit participants from a wide range of departments. In total, 120 students (62 males and 58 females) participated in Study 1, and 343 students (172 males and 171 females) participated in Study 2. No participants were overlapped between Studies 1 and 2.We had two sessions of about 60 students for Study 1, and seven sessions of about 50 students for Study 2. Sessions were conducted between 11:30 am and 12:30 pm for study 1, and between 11:00 am and 3:30 pm for study 2. All participants received HK$100 as compensation upon completion of the experiment.

We advertised our experiment as an experiment to measure risk preferences in order to prevent participants from checking calorie information in advance. At the beginning of each session, participants were informed for the first time that there was a snack choice experiment in addition to the advertised experiment. Participants were also told that we would hold a lucky draw to select two participants after they complete the experiment. One of the selected participants would actually play a lottery selected randomly from the experiment for measuring risk preferences. The earning in the lottery depends on the participant's answer in the selected lottery. If the participant wins some money in the lottery, the money will be the participant's to take home; and if the participant loses some money in the lottery, the loss will be subtracted from the participant's compensation (the loss never be larger than the compensation). The other selected participant will get the snacks ordered in the snack choice experiment.

Whole procedures are presented below, which took about 60 minutes in total. In all steps, participants were not allowed to consult anyone else about their decisions.

Step 1. Measure Risk Preference Parameters [advertised as a main task]

Step 2. Snack Choice Experiment [not advertised]

Step 2-1. liking-rating and familiarity-rating tasks

Study 1 asks participants to predict the calorie contents of each item.

Study 2 asks nothing about calories.

Step 2-2. Distribute a menu and instruct to place an order.

Step 3. Post-Experiment Survey

Step 4. Conduct lucky draws [select one for money and one for snacks]

4. Estimation Method

A dependent variable in our analysis is the total calories of ordered snacks in the snack choice experiment (hereafter referred to as `total snack calories'). We first estimate the total effect of calorie posting by specifying the following equation.

$$tkcal = \alpha_0 + \alpha_1 cinfo + \alpha_X' \boldsymbol{X} + \varepsilon_1, \tag{6}$$

where *tkcal* is the total snack calories (kcal), *cinfo* is the indicator of calorie posing, $\boldsymbol{X}$ is a vector of control variables, and ε is the remaining error. Then, α_1 represents the total effect of calorie posting i.e., the difference between the control and the treatment group.

Second, we decompose the total effect into the learning effect and the saliency effect by specifying the following equation.

$$tkcal = \beta_0 + \beta_1 learn + \beta_2 control + \beta_X' \boldsymbol{X} + \varepsilon_2, \quad (7)$$

where $learn$ is the learning indicator defined in Table 2, and *control* is the indicator of the control group (1 = without labeling; 0 = otherwise). The base group is the treatment group with no learning (i.e., only saliency effect). Then, β_1 can be interpreted as the learning effect because it represents the difference between the base group and the learning group, where the learning group is affected by both saliency and learning effects. β_2 measures the difference between the base group and the control group. Thus, $-\beta_2$ can be interpreted as the saliency effect.

Third, we decompose the learning effect into the learning-underestimation effect and the learning-overestimation effect by specifying the following equation.

$$tkcal = \gamma_0 + \gamma_1 LUE + \gamma_2 LOE + \gamma_3 control + \gamma_X' \boldsymbol{X} + \varepsilon_5, \quad (8)$$

where LUE is the indicator of learning underestimation, and LOE is the indicator of learning overestimation (see Table 2). Then, γ_1 represents the learning-underestimation effect, and γ_2 represents the learning-overestimation effect. Thus, our key interests are the signs of γ_1 and γ_2 and a difference in magnitude between γ_1 and γ_2.

Lastly, to examine the associations between the effects of calorie posting and risk preference parameters, we will interact the risk preference parameters with each of *cinfo*, *learn*, *control*, *LUE*, and *LOE* in equations (6) - (8). We are particularly interested in the coefficients on the interaction terms with a loss aversion parameter λ.

In the vector of control variables ***X***, we include the following factors as predetermined factors: three risk preference parameters, female dummy, BMI (kg/m^2), obesity dummy, snack preferences, the degree of hungriness, and dieting dummy. A female dummy and current body size (BMI and obesity) are controlled because the factors determine one's required or desired calorie intake. One's snack preferences are included because people are more likely to choose what they like better. Similarly, the degree of hungriness and a dieting dummy are included because hungrier people may select higher-calorie snacks, and people on diet may select lower-calorie snacks.

5. Results

We first show that our conceptual and experimental assumptions are supported by our experimental data. Second, we present our main results from estimating equations (6) – (8). Lastly, we conduct robustness checks in terms of four aspects: sensitivity to the definition of calorie knowledge status, the effect of asking ex-ante calorie questions, the effect of initial calorie knowledge, and the effect of menu listing orders.

Empirical Supports for Our Conceptual and Experimental Assumptions

First, we check randomization balance in our experiments. Table 3 summarizes pre-determined characteristics for the control and the treatment groups. It presents means and tests differences in means between the two groups. In study 1, we find no significant difference between the two groups. In study 2, snack preferences and loss aversion are happen to be significantly different i.e., the control group on average likes potato chips and chocolate cookies more and is less loss averse. In our main results, we include these factors into a set of control variables to control for the differences. Table 3 also shows that people are loss averse because λ is significantly larger than 1 (ranges from 2.42 to 3.13). In addition, it shows that people actually underestimate or overestimate the calorie contents. In our sample, the recommended total daily calorie intake or snack calorie contents were initially underestimated by 50-62% of people, overestimated by 14-31% of people, and reasonably predicted by 10-27% of people.

We next assess two key assumptions for our indirect learning measure. First, we examine whether snack calories were predicted better by people who know one's recommended total daily calorie intake compared to those who do not know it. Using data from Study 1, Figure 2-A shows the distribution of errors in predicted total snack calories for the group with knowing one's recommended total daily calorie intake and the group without knowing it. The distributions are significantly different (two-sample Kolmogorov-Smirnov test: p-value = 0.04), and the errors are significantly smaller for the group with knowing it i.e., the distribution concentrates more around zero. Second, we examine the influence of calorie posting on the knowledge about recommended total daily calorie intake. Using all sample, Figure 2-B shows the distribution of predicted recommended total daily calorie intake for the control and the treatment groups. While the predictions are slightly better in the treatment group than the control group, the difference is insignificant (two-sample Kolmogorov-Smirnov test: p-value = 0.36). These results support the validity of the assumptions for our indirect learning measure.

To examine whether people really learn about snack calories from calorie posting, Figure 3 presents a change in the distribution of errors in predicted total snack calories for the control and the treatment groups. It shows that the distribution of the treatment group significantly shifts toward zero after calorie posting, while we find no significant change in the distribution of the control group. This indicates that calorie posting significantly improves people's knowledge about snack calories within the treatment group. Table 4 focuses on the treatment group and summarizes our direct and indirect learning indicators. It shows that there are actually two types of learning. In our treatment group, 23.3-29.7% of people improve their knowledge about snack calories, where 18.3-21.6% of them learn that they were underestimating the calorie contents and

5.0-8.2% of them learn that they were overestimating the calorie contents. 71.9-76.7% of people showed no improvement in their knowledge about snack calories even after calorie posting.

Table 5 summarizes snack order outcomes in our snack choice experiments for the control and the treatment groups in each study. The mean total snack calories range from 1119 kcal to 1201 kcal across the groups, and they are not statistically significantly different. While a majority of participants ordered 6 packs of snacks (82-92%), some participants ordered fewer than 6 packs (about 8% in study 1 and about 15% in study 2). The table also shows that chocolate cookies are the most popular item followed by potato chips, which is consistent with initial snack preferences in Table 3. It is also worth noting that the treatment group ordered noticeably more packs of raisins (relatively lower-calorie item) than the control group in both studies. In study 1, the treatment group also ordered fewer packs of chocolate cookies and potato chips (relatively higher-calorie items) than the control group. Although all these differences in the number of packs are not statistically significant, the observations may imply that calorie-decreasing effect may come from substituting chocolate cookies (or potato chips) with raisins.

Lastly, we examine whether our experiments really induced overconsumption of calories. For this purpose, we compare the snack consumption level in the experiments to the level in normal days. To measure the consumption level in the experiments, we divide the number of packs ordered in the experiment (*# ordered packs*) by the reported number of days to finish eating all the ordered snacks (*# days to finish*) i.e., $ec = \frac{\#\ ordered\ packs}{\#\ days\ to\ finish}$ in packs/day. To measure the consumption level in normal days, we use data on how frequently one has snacks (*# days of frequency*): everyday (1 day), several times a week (2 days), once a week (7 days), once two weeks (14 days), and once a month or less (30 days). We consider three hypothetical consumption levels (*# hypoth packs*): (i) 1 pack for each time, (ii) 2 packs for each time, and (iii)

3 packs for each time. Then, we compute $nc = \frac{\#\, hypoth\ packs}{\#\, days\ of\ frequency}$ in packs/day. We define `over-consumption' as $ec > nc$. We find that the proportion of over-consuming participants is 84.2% for case (i), 61.7% for case (ii), and 55.8% for case (iii).[4] Thus, even in case (iii), more than half of our subjects consume more than they normally do. This may support our assumption of overconsumption.

Main Results

We employ OLS to estimate the equations (6) – (8) and the models with interaction terms with risk preference parameters. The results are summarized in Tables 6 and 7. All reported standard errors are clustered by session. In addition to the results for study 1 (column 1) and study 2 (column 2), we also present the results for total sample from both studies using the indirect learning measure (column 3). In the total sample case, we added the indicator of asking ex-ante calorie questions into a set of control variables.

Table 6 shows that the total effect of calorie posting is significantly negative in study 1, significantly positive in study 2, and positive and insignificant in the total sample. We conjecture that the difference between studies 1 and 2 may be due to asking ex-ante calorie questions which may absorb the saliency effect of calorie posting. More details on the effect of asking ex-ante calorie questions will be examined in our robustness checks.

Decomposing the total effect into the learning and the saliency effects, we find a negative learning effect in all three cases. The magnitude is similar and ranges from -69.1 kcal to -84.7 kcal (5.8% to 7.1% decline from the control-group mean). Although the effect is insignificant in Study 1, this may be due to its relatively small sample size compared to other cases.

[4] Because these data are available only in study 1, we present the proportions only for study 1. We expect the same patterns would be observed for study 2.

Decomposing the learning effect into the LUE and the LOE effects, we find a significantly negative LUE effect in all three cases. The magnitude of the LUE effect is similar and ranges from -103.8 kcal to -125.0 kcal (8.7% to 10.4% decline from the control-group mean). In contrast, the LOE effect is positive in all three cases. The magnitude ranges from 40.5 kcal to 62.7 kcal (3.4% to 5.3% increase from the control-group mean), although the effect is statistically significant only in the total sample case.

In Table 7, we investigate the associations between risk preference parameters and the decomposed effects of calorie posting. We find that the total effect of calorie posting is significantly negatively associated with risk aversion and loss aversion (columns 2 and 3). The negative association with risk aversion is mostly attributable to the negative association with the LUE effect. That is, the magnitude of the LUE effect is larger for a more risk-averse person. For example, if a risk aversion parameter is one standard deviation higher (SD = 0.31), the magnitude of the LUE effect is 132 kcal larger i.e., -132 kcal (column 3). In contrast, the negative association with loss aversion is mostly attributable to the negative association with the saliency effect. That is, the saliency effect is smaller for a more loss-averse person. These results in Tables 6 and 7 support our transaction utility hypothesis while provide no support for our loss aversion hypothesis.

Robustness Checks

We first check the sensitivity of our results to the definition of the direct learning measure. When we constructed the direct learning measure, we had to set the range of acceptable errors to define reasonable calorie knowledge. However, the choice of the acceptable error range (i.e., within $\pm$100 kcal) had little scientific justification, whereas the indirect learning measure was based on the FAO/ WHO /UNU guidelines (see Appendix 2 for more details). We examine three other acceptable error ranges: errors within $\pm$150 kcal, $\pm$200 kcal, and $\pm$250 kcal.[5] We estimate equations (7) and (8) using the direct learning indicator based on the different error ranges. Table 8 presents the results. Although we find a negative LUE effect and a positive LOE effect in all three cases, the LUE effect is statistically significant only when we use the range of $\pm$150 kcal. The table also shows that, increasing the acceptable error ranges, the magnitude of the LUE effect decreases substantially from -121.8 kcal to -40.8 kcal while that of the LOE effect increases slightly from 37.5 kcal to 52.4 kcal. This explains why the overall learning effect becomes smaller as the acceptable error range increases.

To understand the findings in Table 8, it is important to note that increasing the acceptable error range affects the learning measure in two ways: (1) it increases the number of people who make a reasonable ex-post prediction, and (2) it decreases the number of people who underestimate or overestimate calorie contents before calorie posting. Thus, increasing the error range does not necessarily increase the number of people who learn from calorie posting. In our sample, the number increased only from 17 to 24 people by increasing the range from $\pm$100 kcal to $\pm$250 kcal. Worse still, the two effects may results in replacing people who learn the best from calorie posting (e.g., errors decrease from 200kcal to 10kcal) with people who learn worse from calorie posting (e.g., errors decrease from 300kcal to 190kcal). Thus, given the small change in the number of people who learn from calorie posting across the different error ranges, our priority now shifts to capturing better learners by using a narrower error range. Therefore, we decided to use the range of $\pm$100 kcal in our main results.

[5] For example, there are about 100kcal in 1 medium banana (7” to 7-7/8” long), about 150kcal in 2 boiled eggs (65g), about 200kcal in Chicken McNuggets (4 pieces), and about 250kcal in 1 McDonald hamburger.

Second, we examine how asking calorie questions before calorie posting (ex-ante calorie questions) affects the effects of calorie posting by combining data from both studies 1 and 2. The indicator of asking ex-ante calorie questions is interacted with the learning indicators and the control group indicator in equations (6)-(8). Panel A in Table 9 presents the results. The table shows that the total effect of calorie posting becomes positive once we control for the effect of the ex-ante calorie questions. It also shows that asking the ex-ante calorie questions significantly decreases the saliency effect (from -114.0 to -112.7 kcal), while it has no significant effect on the learning, the LUE and the LOE effects. These findings support the validity of our direct learning measure.

Third, we examine how the effects of calorie posting can be different between people who reasonably know one's recommended total daily calorie intake (so-called daily calorie needs) and people who do not know it. We first examine the difference in the saliency effect by focusing on the study 2 sample in which we observed a positive saliency effect. We construct the saliency indicator (1 = no learning within the treatment group, 0 = otherwise) and the indicator of knowing one's daily calorie needs (cknow), and include an interaction term between the indicators. Panel B in Table 9 presents the results (column 1). Note that cknow cannot be interacted with the LUE and the LOE indicators because the indirect learning indicators always take value 0 if cknow is 1 (i.e., no learning for well-informed people by definition). We find that the saliency effect is significantly smaller among people who reasonably know one's daily calorie needs compared to people who do not know them (79.8 kcal smaller). Moreover, by employing the direct learning measure and the study 1 sample, we add interaction terms between cknow and the LUE and the LOE indicators (clumn 2). The negative coefficient estimates on the interaction terms imply that the LUE effect may be strengthened and the LOE effect may be weakened by knowing one's daily calorie needs, although all the coefficients are statistically insignificant. These results at least show that the LUE effect would not be significantly weakened by knowing one's daily calorie needs.

Lastly, we examine the effect of listing orders on total snack calories. We include dummy variables for each of the four different listing orders (i.e., three dummy variables) into equations (6) – (8). Alternatively, we also include the dummy variable of listing high-calorie snacks (potato chips and chocolate cookies) on the top into the equations. In all cases, we find that the coefficients on the dummy variables are statistically insignificant (p-values range from 0.64 to 0.97), where the results are suppressed for simplification. This is probably because the liking-rating and familiarity-rating tasks made participants got familiar with all the items before they saw a menu.

6. Conclusions

Following a sharp rise in the obesity prevalence, calorie posting has been attracting increasingly more attention as one of key anti-obesity policies. However, it is still controversial whether calorie posting is effective at reducing calorie consumption. As a potential case in which calorie posting can be beneficial, this article focuses on the case when people are over-consuming calories in a fixed-price context (e.g., fixed-price restaurants). To our best knowledge, this is the first attempt to clarify the mechanism underlying the effect of calorie posting on calorie consumption in a fixed-price context.

Our findings suggest that calorie posting can mitigate overeating in a fixed-price context. By decomposing the effect of calorie posting on calorie consumption into three effects (the saliency, the LUE and the LOE effects), along with a conceptual framework incorporating transaction utility and loss aversion, our experimental results show that the net effect of the LUE and the LOE effects is negative and thus decreases the degree of overconsumption of calories. We also find that calorie posting may be more effective to a more risk-averse person because the magnitude of the LUE effect (a calorie-decreasing effect) tends to be larger for a more risk-averse person. Although loss aversion is not significantly associated with the learning effects, it is significantly negatively associated with the calorie-increasing effect of saliency. Thus, calorie posting may be more effective to a more loss-averse person because the magnitude of the calorie-increasing effect tends to be smaller for a more loss-averse person.

Although the learning effect significantly reduces calorie consumption, the total average effect of calorie posting on calorie consumption is insignificant or positive due to the positive saliency effect. The good news, though, is that the positive saliency effect is significantly smaller among people who approximately know one's daily calorie needs compared to those who do not know them, while the magnitude of the LUE effect is larger (at least no smaller) among the former than the latter. Moreover, in our sample, BMI is 1.3 kg/m^2 higher among people who underestimate calorie contents than those who overestimate calorie contents. Thus, calorie posting is more likely to reduce calorie consumption among heavier people through the LUE effect. These findings leave a chance for calorie posting to be more effective by combining it with information about one's daily calorie needs. Further analysis on mitigating a positive saliency effect will be essential for future research to make calorie posting more effective.

From a policy perspective, our findings will be related to the potential of calorie posting at all-you-can-eat restaurants. While recent calorie posting regulations aim at fast food chain restaurants, all-you-can-eat restaurants can be another target to mitigate overeating. It may be possible to display calories per 100g or per serving for each item at such restaurants. Also, the calorie-decreasing effect of calorie posting may be enhanced by posting information about total daily calorie needs for a representative male and female. More generally, information campaigns about daily calorie needs may complement the beneficial effect of calorie posting regulations.

In interpreting our results, it is important to note that we only examine the effect of calorie posting on one particular type of food, snacks. Although snack consumption patterns may be different from other types of foods such as grains and vegetables, snacks still share key characteristics with unhealthy fast foods such as cheap calories, high in fat and sugar, low in fiber, and high in palatability. Considering that such fast foods are key targets for calorie posting regulations, our results may still provide useful information for policy makers. It is also worth noting that our experimental set up is different from other types of providing calorie information such as different designs of calorie posting, and calorie labeling on packaged food items. For example, while we use numeric labels, symbolic traffic light labels may be more effective at reducing calorie consumption (e.g., Ellison et al. 2011). Also, calorie labeling on a packaged food may be less likely to be checked compared to calorie posting on a menu. The efficacy of such types of providing calorie information is beyond the scope of this article and our results should not be extrapolated as evidence of the efficacy of providing calorie information in general.

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Appendix 1: Proof for $|U^t(q^*|c^{OE}) - U^t(q^{OE}|c^{OE})| < |U^c(q^*|\theta) - U^c(q^{OE}|\theta)|$ in eq (2)

First, we can show that the following relationship will hold.

$$|U^t(q^*|c^{OE}) - U^t(q^{OE}|c^{OE})| < \left|U_q^t(q^{OE}|c^{OE}) \cdot (q^* - q^{OE})\right| . \quad \text{(A1)}$$

The left hand side is the actual difference in $U^t(q|c^{OE})$ between q^* and q^{OE}. The right hand side is a linear prediction about a change in $U^t(q|c^{OE})$ when q increases from q^{OE} to q^*, where it is evaluated at q^{OE}. Because $U^t(q|c^{OE})$ is diminishingly increasing from q^{OE} to q^* (i.e., $U_q^t > 0$ and $U_{qq}^t < 0$), the actual change on the left hand side should be smaller than the linear prediction on the right hand side. This relationship is illustrated in Figure A1.

Similarly, we can show that the following relationship will also hold.

$$|U^c(q^*|\theta) - U^c(q^{OE}|\theta)| > \left|U_q^c(q^{OE}|\theta) \cdot (q^* - q^{OE})\right| . \quad \text{(A2)}$$

The left hand side is the actual difference in $U^c(q|\theta)$ between q^* and q^{OE}. The right hand side is a linear prediction about a change in $U^c(q|\theta)$ when q increases from q^{OE} to q^*, where it is evaluated at q^{OE}. Because $U^c(q|\theta)$ is increasingly decreasing from q^{OE} to q^* (i.e., $U_q^c < 0$ and $U_{qq}^c < 0$), the actual change on the left hand side should be larger than the linear prediction on the right hand side. This relationship is illustrated in Figure A1.

[Figure A1 here]

From the FOC solving equation (1) under c^{OE}, $\left|U_q^t(q^{OE}|c^{OE})\right| = \left|U_q^c(q^{OE}|\theta)\right|$. Thus, the linear predictions in (A1) and (A2) are equal in their magnitude i.e., $\left|U_q^t(q^{OE}|c^{OE}) \cdot (q^* - q^{OE})\right| = \left|U_q^c(q^{OE}|\theta) \cdot (q^* - q^{OE})\right|$. Therefore,

$$|U^t(q^*|c^{OE}) - U^t(q^{OE}|c^{OE})| < |U^c(q^*|\theta) - U^c(q^{OE}|\theta)|. \quad \blacksquare$$

Appendix 2: Measure for Calorie Knowledge Status

To define learning, statuses, we start from defining three calorie knowledge statuses: underestimate, reasonable estimate, and overestimate. More specifically, we set the allowable range of errors in one's prediction about (1) recommended total daily calorie intake (an indirect measure) and (2) total calories of ordered snacks (a direct measure).

For the indirect measure, we set the allowable error range using Basal Metabolic Rate (BMR). Weijs et al. (2008) compared a number of different ways to compute BMR and found that the FAO/ WHO /UNU equations with weight and height (FAO/ WHO /UNU 1985) have smallest errors. Thus, we used the equations to compute BMR for each participant. Because our subjects are aged 18-27 years old, the equations are 15.4*weight(kg)-27*height(m)+717 for men, and 13.3*wight(kg)+334*height(m)+35 for women. To define a reasonable estimate of one's recommended total daily calorie intake, we use BMR*1.4 (sedentary lifestyle) as the lower bound, and BMR*1.99 (active lifestyle) as the upper bound. Then, one has reasonable calorie knowledge if one's prediction about recommended total daily calorie intake is between the lower and the upper bounds. Accordingly, one is assumed to underestimate calorie contents if one's prediction is lower than the lower bound, and one is assumed to overestimate calorie contents if one's prediction is higher than the upper bound.

For the direct measure, we decided the allowable error ranges based on following simulations. If one predicts calorie contents at 10 kcal intervals, even closest predictions may have errors ranging from 0 kcal to 48 kcal (= (208-200)*6) in magnitude. If one predicts calorie contents at 50 kcal intervals, even closest predictions may have errors ranging from 48 kcal to 132 kcal (= (172-150)*6) in magnitude. If one predicts calorie contents at 100 kcal intervals, even closest predictions may have errors ranging from 48 kcal to 240 kcal (= |(160-200)*6|) in magnitude. Thus, we examined the error ranges $\pm$100, $\pm$150, $\pm$200 and $\pm$250. We found that the range of $\pm$50 is too strict to have a enough number of people with reasonable calorie knowledge. We use the range $\pm$100 for our main results, and use other error ranges in our robustness checks. Then, one has reasonable calorie knowledge if `a difference between one's prediction and the true calorie contents of one's ordered snacks' (the so-called error in predicted total snack calories) is less than or equal to 100 kcal in magnitude. Accordingly, one is assumed to underestimate calorie contents if one's error in predicted total snack calories is smaller than -100 kcal, and one is assumed to overestimate calorie contents if one's error in predicted total snack calories is larger than 100 kcal.

Table 1: An Example for Our Model with Transaction Utility

	When people underestimate calorie contents	True Information	When people overestimate calorie contents
Fixed Price	$5	$5	$5
- Predicted calories contents of a snack per pack	50 kcal	100 kcal	200 kcal
- Subjective price per calorie	c^{UE} = $0.10/kcal	c^{*} = $0.05/kcal	c^{OE} = $0.025/kcal
Suppose q^{*} = 200 kcal [i.e., people want to take 200 kcal in total]			
- # of packs to purchase based on predicted calorie contents	4 packs (= 200/50)	2 packs (= 200/100)	1 pack (= 200/200)
- Actual calorie consumption	q^{UE} = 400 kcal	q^{*} = 200 kcal	q^{OE} = 100 kcal

Table 2: Definition of Calorie Knowledge Status and Learning Indicators

Definitions of Calorie Knowledge Status			
	Underestimate (UE)	Reasonable Estimate	Overestimate (OE)
Indirect Measure	pdkcal < 1.40*BMR	1.40*BMR ≤ pdkcal ≤ 1.99*BMR	1.99*BMR < pdkcal
Direct Measure	pskcal < tskcal - 100	tskcal - 100 ≤ pskcal ≤ tkcal + 100	tskcal + 100 < pskcal

Change in Calorie Knowledge Status		Learning Status	Learning Indicator	LUE Indicator	LOE Indicator
Before Posting	After Posting				
Any Status	UE or OE	No learning	0	0	0
Reasonable	Reasonable	No learning	0	0	0
UE	Reasonable	Learn UE	1	1	0
OE	Reasonable	Learn OE	1	0	1

Note:

(1) pdkcal = predicted one's recommended total daily calorie intake (kcal), pskcal = predicted total calorie contents of ordered snacks (kcal), tskcal = true total calorie contents of ordered snacks (kcal).

(2) Basal Metabolic Rate (BMR) is computed using the FAO/WHO/UNU equations with weight and height. See Appendix 2 for more details.

Table 3: Pre-determined Characteristics of the Control and Treatment Groups

	Study 1 [n =120]				Study 2 [n = 343]			
	Control [n = 61]	Treatment [n = 59]	Diff	*(SE)*	Control [n =172]	Treatment [n =171]	Diff	*(SE)*
Age in years	20.85	20.51	0.34	*(0.29)*	20.91	20.89	0.02	(0.15)
Female dummy	0.44	0.53	-0.08	*(0.09)*	0.48	0.52	-0.04	(0.05)
BMI (kg/m2)	21.29	21.01	0.29	*(0.53)*	20.68	20.38	0.31	(0.29)
Overweight dummy (BMI≥24)	0.10	0.12	-0.02	*(0.06)*	0.08	0.06	0.02	(0.03)
Ideal weight - Actual weight (kg)	-2.84	-2.80	-0.05	*(1.17)*	-1.50	-1.41	-0.09	(0.68)
Hungry dummy	0.56	0.61	-0.05	*(0.09)*	0.45	0.43	0.02	(0.05)
Diet dummy	0.08	0.08	0.00	*(0.05)*	0.10	0.11	-0.01	(0.03)
Snack Preferences: Proportion of people who chose positive preference								
Chocolate Cookies	0.85	0.83	0.02	*(0.07)*	0.90	0.83	0.06	(0.04)**
Potato Chips	0.49	0.54	-0.05	*(0.09)*	0.63	0.53	0.10	(0.05)**
Raisins	0.51	0.51	0.00	*(0.09)*	0.49	0.44	0.05	(0.05)
Vegetable Crackers	0.48	0.54	-0.07	*(0.09)*	0.42	0.37	0.05	(0.05)
Risk Preference Parameters								
Risk aversion (σ)	0.30	0.34	-0.04	*(0.06)*	0.27	0.30	-0.02	(0.03)
Non-linear prob weight (α)	0.71	0.74	-0.02	*(0.05)*	0.71	0.70	0.02	(0.03)
Loss aversion (λ)	2.99	2.96	0.03	*(0.52)*	2.42	3.13	-0.71	(0.32)**
Initial Calorie Knowledge before Calorie Posting								
Recommended total daily calorie intake								
Reasonable Estimate	0.21	0.27	-0.06	*(0.08)*	0.24	0.27	-0.03	(0.05)
Underestimate	0.62	0.59	0.03	*(0.09)*	0.54	0.50	0.04	(0.05)
Overestimate	0.16	0.14	0.03	*(0.07)*	0.22	0.22	-0.01	(0.04)
Calorie contents of selected snacks								
Reasonable Estimate	0.15	0.10	0.05	*(0.06)*	-	-	-	-
Underestimate	0.54	0.59	-0.05	*(0.09)*	-	-	-	-
Overestimate	0.31	0.31	0.01	*(0.09)*	-	-	-	-

Table 4: Learning from Calorie Posting within the Treatment Group

	Study 1 [n=59]	Study 2 [n=171]	All sample [n=230]
Indirect Learning Measure			
Learn	23.3%	29.7%	28.1%
Learn Underestimation	18.3%	21.6%	20.8%
Learn Overestimation	5.0%	8.1%	7.3%
Saliency (no learning)	76.7%	70.3%	71.9%
Direct Learning Measure			
Learn	28.3%	-	-
Learn Underestimation	20.0%	-	-
Learn Overestimation	8.3%	-	-
Saliency (no learning)	71.7%	-	-

Table 5: Snack Order Outcomes in Food Choice Experiments

Study 1 [n=120]	Control [n=61]		Treatment [n=59]	
	Mean	*(SE)*	Mean	*(SE)*
Total snack calories (kcal)	1201.25	*(172.63)*	1151.56	*(187.19)*
# of ordered packs				
Chocolate Cookies	2.92	*(1.51)*	2.68	*(1.50)*
Potato Chips	1.77	*(1.45)*	1.31	*(1.15)*
Raisins	0.62	*(0.92)*	1.22	*(1.51)*
Vegetable Crackers	0.51	*(0.77)*	0.58	*(0.81)*
Total # of ordered packs	Freq	% share	Freq	% share
0	0	0.00	0	0.00
1	0	0.00	0	0.00
2	0	0.00	2	3.39
3	2	3.28	1	1.69
4	2	3.28	0	0.00
5	1	1.64	2	3.39
6	56	91.8	54	91.53
Study 2 [n=343]	Control [n=172]		Treatment [n=171]	
	Mean	*(SE)*	Mean	*(SE)*
Total snack calories (kcal)	1119.41	*(278.11)*	1152.23	*(237.84)*
# of ordered packs				
Chocolate Cookies	2.56	*(1.62)*	2.55	*(1.54)*
Potato Chips	1.66	*(1.50)*	1.70	*(1.50)*
Raisins	0.75	*(1.21)*	0.96	*(1.37)*
Vegetable Crackers	0.49	*(0.88)*	0.45	*(0.88)*
Total # of ordered packs	Freq	% share	Freq	% share
0	1	0.58	1	0.58
1	5	2.91	2	1.17
2	6	3.49	4	2.34
3	6	3.49	4	2.34
4	6	3.49	5	2.92
5	7	4.07	4	2.34
6	141	81.98	151	88.30

Note: Freq = Frequency

Table 6: Effects of Calorie Posting on Total Snack Calories

Dependent Variable = Total calories of ordered snacks (kcal)						
	(1) Study 1 [n=120]		(2) Study 2 [n=343]		(3) Total Sample [n=463]	
Learning Measure	Direct		Indirect		Indirect	
	Coef	*(SE)*	Coef	*(SE)*	Coef	*(SE)*
Calorie posting	-51.58	*(29.42)**	50.66	*(26.45)**	24.16	*(20.88)*
R-squared	*0.30*		*0.10*		*0.11*	
Saliency	-29.30	*(29.70)*	75.56	*(26.72)****	43.16	*(20.88)***
Learn	-73.72	*(58.43)*	-84.74	*(46.43)**	-69.10	*(40.02)**
R-squared	*0.31*		*0.11*		*0.12*	
Saliency	-29.03	*(29.88)*	76.86	*(26.78)****	43.87	*(20.92)***
LUE	-119.95	*(72.83)**	-124.97	*(57.13)***	-103.84	*(47.40)***
LOE	45.05	*(45.70)*	40.50	*(37.80)*	62.67	*(33.92)**
R-squared	*0.33*		*0.12*		*0.13*	

Note: All regressions include the full set of control variables in equations (6)-(8). ***, ** and * indicate statistical significance at 1% level, 5% level and 10% level, respectively.

Table 7: Interactions between Risk Preference Parameters and the Effects of Calorie Posting

Dependent Variable = Total calories of ordered snacks (kcal)						
	(1)		(2)		(3)	
	Study 1 [n=120]		Study 2 [n=343]		Total Sample [n=463]	
Learning Measure	Direct		Indirect		Indirect	
	Coef	*(SE)*	Coef	*(SE)*	Coef	*(SE)*
Calorie Posting* σ	-49.68	*(93.4)*	-257.06	*(115.7)***	-201.28	*(86.4)***
Calorie Posting * α	67.13	*(175.1)*	-63.89	*(116.6)*	-55.37	*(96.1)*
Calorie Posting * λ	-8.30	*(11.6)*	-14.05	*(7.6)**	-11.11	*(6.1)**
R-squared	*0.31*		*0.12*		*0.13*	
Saliency	20.32	*(176.1)*	210.55	*(121.5)**	166.81	*(98.4)**
Saliency* σ	13.27	*(118.1)*	-147.87	*(102.5)*	-117.25	*(78.0)*
Saliency* α	-4.79	*(173.5)*	-76.05	*(135.1)*	-78.09	*(107.3)*
Saliency* λ	-16.58	*(11.4)*	-14.94	*(7.3)***	-12.17	*(5.9)***
learn	-494.80	*(289.9)**	41.62	*(155.7)*	-37.83	*(142.3)*
learn* σ	-269.33	*(163.5)**	-406.69	*(182.1)***	-346.60	*(155.4)***
learn* α	481.49	*(309.9)*	-37.36	*(169.7)*	49.91	*(153.2)*
learn* λ	35.77	*(21.4)**	2.58	*(22.6)*	5.35	*(18.9)*
R-squared	*0.39*		*0.16*		*0.16*	
Saliency	13.71	*(178.1)*	211.88	*(121.5)**	167.32	*(98.7)**
Saliency* σ	9.60	*(119.4)*	-144.34	*(102.7)*	-117.05	*(78.0)*
Saliency* α	5.20	*(175.7)*	-81.74	*(134.9)*	-80.30	*(107.5)*
Saliency* λ	-16.45	*(11.5)*	-14.05	*(7.3)**	-11.60	*(6.0)**
LUE	-534.85	*(307.5)**	-11.15	*(180.1)*	-119.31	*(168.1)*
LUE* σ	-393.97	*(170.8)***	-522.32	*(210.5)***	-426.46	*(176.1)***
LUE* α	470.72	*(333.9)*	123.63	*(201.9)*	200.72	*(183.7)*
LUE* λ	49.56	*(25.1)***	-30.91	*(26.9)*	-13.53	*(24.1)*
LOE	-18.68	*(304.2)*	93.04	*(125.6)*	89.38	*(109.5)*
LOE* σ	173.29	*(274.2)*	-72.79	*(122.2)*	-59.02	*(106.7)*
LOE* α	-89.45	*(350.0)*	-74.83	*(143.3)*	-54.47	*(124.3)*
LOE* λ	41.79	*(49.6)*	4.09	*(7.1)*	5.18	*(6.4)*
R-squared	*0.43*		*0.19*		*0.19*	

Note: σ = risk aversion parameter, α = nonlinear probability weight parameter, and λ = loss aversion parameter. LUE = learning-underestimation, and LOE = learning-overestimation. All regressions include the full set of control variables in equations (6)-(8). ***, ** and * indicate statistical significance at 1% level, 5% level and 10% level, respectively.

Table 8: Sensitivity to Different Definitions of Reasonable Calorie Knowledge in the Direct Learning Measure

Dependent Variable = Total calories of ordered snacks (kcal)						
Acceptable Error Range =	±150 kcal		±200 kcal		±250 kcal	
	Coef	*(SE)*	Coef	*(SE)*	Coef	*(SE)*
Saliency	-28.74	*(29.54)*	-40.83	*(30.58)*	-48.03	*(32.01)*
Learn	-76.39	*(57.29)*	-27.65	*(52.06)*	-8.33	*(52.86)*
R-squared	*0.31*		0.30		0.30	
Saliency	-27.89	*(29.69)*	-39.49	*(30.59)*	-46.34	*(32.10)*
LUE	-121.77	*(72.56)**	-69.96	*(69.11)*	-40.76	*(66.71)*
LOE	37.48	*(44.83)*	45.96	*(40.60)*	52.41	*(43.68)*
R-squared	*0.33*		0.32		0.31	
Observation #	120		120		120	

Note: LUE = learning-underestimation, and LOE = learning-overestimation. All regressions include the full set of control variables in equations (6)-(8). ***, ** and * indicate statistical significance at 1% level, 5% level and 10% level, respectively.

Table 9: Effects of Ex-ante Calorie Question and Initial Calorie Knowledge on the Effects of Calorie Posting

Dependent Variable = Total calories of ordered snacks (kcal)				
	(1)		(2)	
	Coef	*(SE)*	Coef	*(SE)*
A. Asking ex-ante calorie questions (CQ)				
Ex-ante calorie questions (CQ)	100.99	*(26.84)****		
Calorie posting (CP)	50.66	*(26.50)**		
CP*CQ	-100.56	*(39.73)***		
R-squared	*0.12*			
Ex-ante calorie questions (CQ)	-11.64	*(30.03)*	-12.04	*(30.06)*
Saliency	74.11	*(26.61)****	75.18	*(26.68)****
Saliency*CQ	-112.67	*(40.63)****	-114.01	*(40.70)****
Learn	-79.52	*(46.39)**	-	
Learn*CQ	28.46	*(78.64)*	-	
LUE	-		-120.00	*(57.35)***
LUE*CQ	-		56.00	*(88.72)*
LOE	-		46.86	*(35.92)*
LOE*CQ	-		57.59	*(61.87)*
R-squared	*0.13*		*0.14*	
Observations	463		463	
B. Knowing one's recommended total daily calorie intake (cknow)				
Saliency	106.86	*(26.57)****	-19.62	*(26.81)*
Saliency*cknow	-79.83	*(40.44)***	-41.08	*(79.48)*
LUE	-125.27	*(57.13)***	-71.13	*(78.88)*
LUE*cknow	-		-194.72	*(121.34)*
LOE	41.41	*(37.98)*	41.90	*(44.39)*
LOE*cknow	-		-6.65	*(65.05)*
R-squared	*0.12*		*0.36*	
Observations	343		120	

Note: LUE = learning-underestimation, and LOE = learning-overestimation. All regressions include the full set of control variables in equations (6)-(8). ***, ** and * indicate statistical significance at 1% level, 5% level and 10% level, respectively.

A. A Menu for the Treatment Group

Please fill out the following order form.

Snacks	**Package Size**	**Calorie /pack (kcal [千卡])**	**Price /pack (HK$)**	**Quantity (packs)**	**Subtotal (HK$)**
Raisins	About 35g	160 kcal	HK$5		
Chocolates Cookies	About 35g	208 kcal	HK$5		
Vegetable Crackers	About 35g	172 kcal	HK$5		
Potato Chips	About 35g	230 kcal	HK$5		

Total (HK$)

The total must be less than or equal to HK$30.

B. Snack Pictures

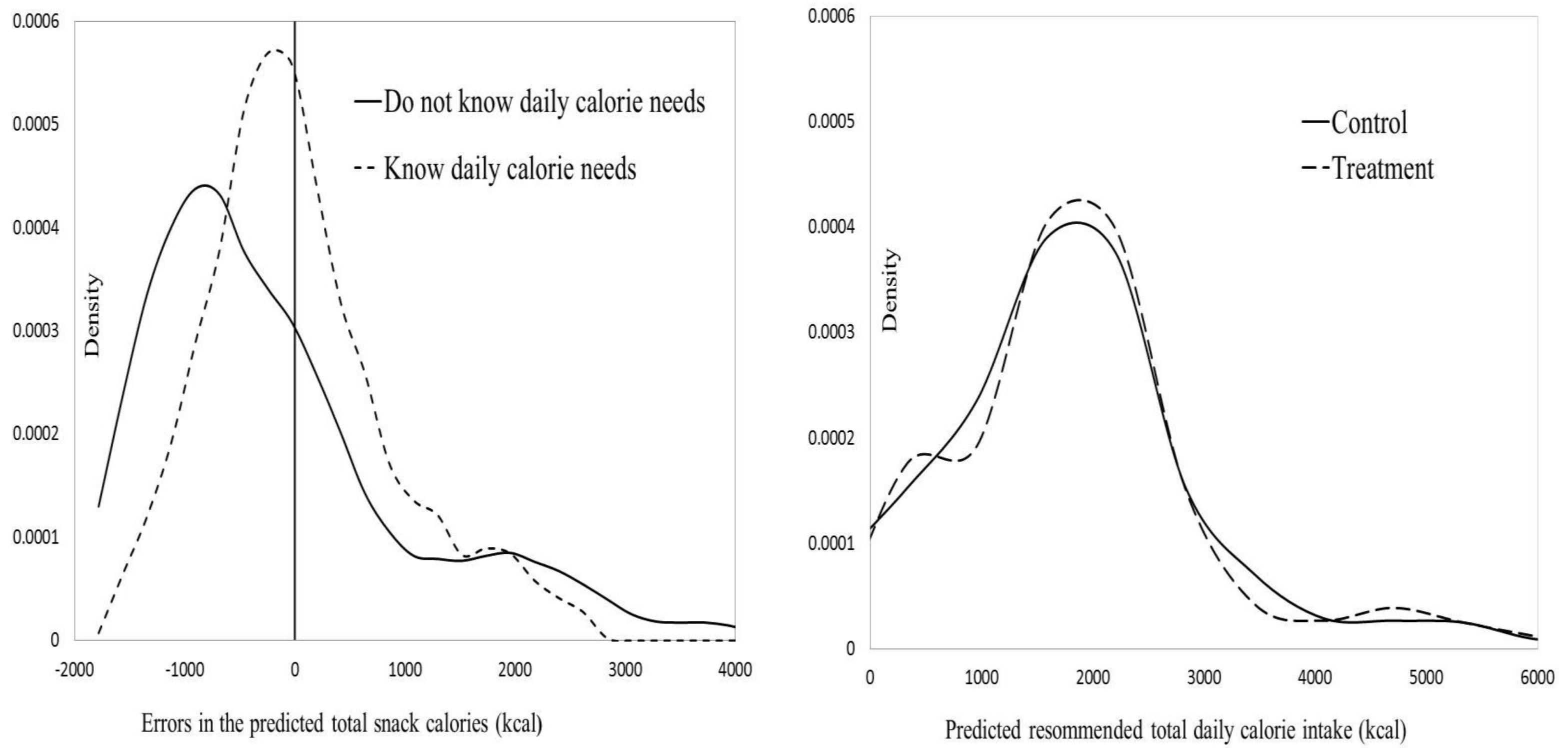
Potato Chips

Chocolate Cookies

Raisins

Vegetable Crackers

Figure 1: Examples of a Menu and Snack Pictures in Snack Choice Experiments



A. Ex-ante distribution of errors in predicted total snack calories

B. Ex-post distribution of predicted recommended total daily calorie intake

Figure 2: Assessing Two Key Assumptions for the Indirect Learning Measure

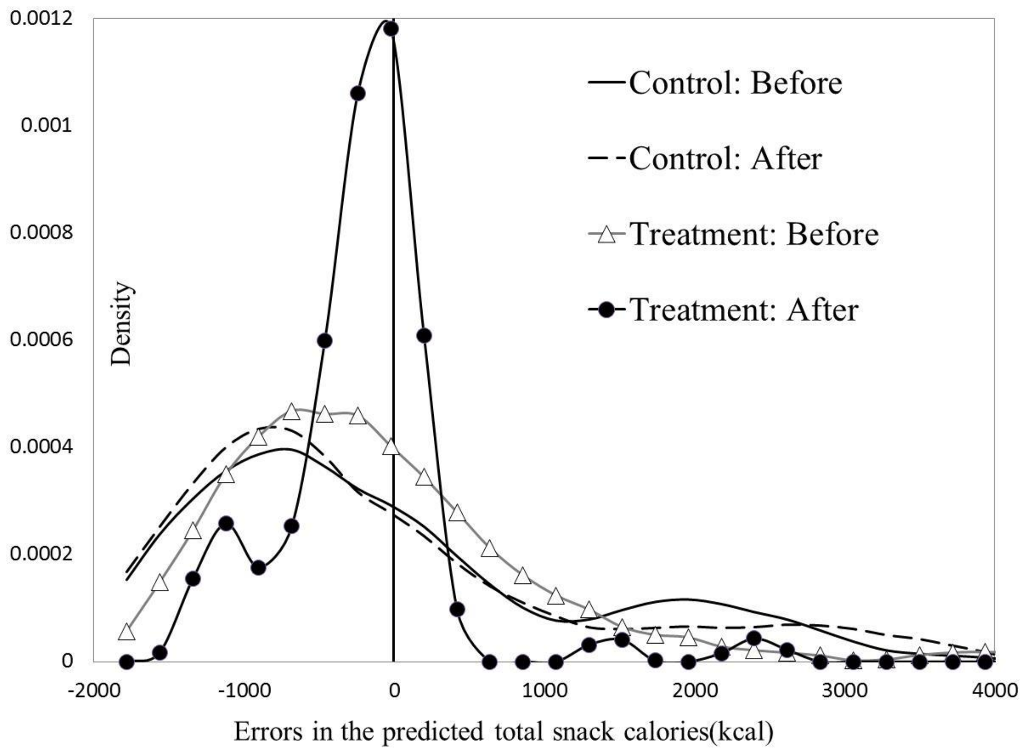


Figure 3: Effect of Calorie Posting on the Distribution of Errors in Predicted Total Snack Calories

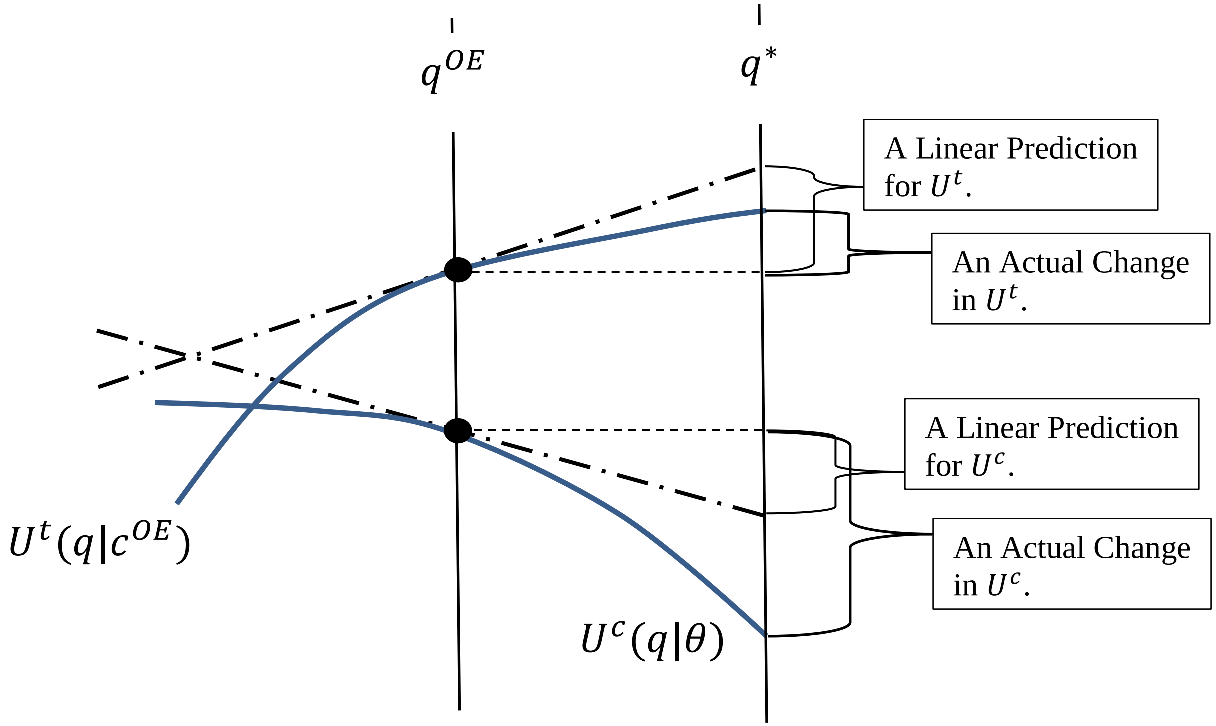


Figure A1: Illustrating the Proof for Equation (2)