Efficacy of Price Interventions for Mitigating Childhood Obesity by Promoting Healthy Food Choices: An fMRI Study in Parents with Low Socioeconomic Status

by

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Abstract

Childhood obesity has been a rising problem among rural and low income populations. Childhood obesity increases the risk of various diseases later in life. Government has tried several price interventions such as lowering tax and giving subsidies to encourage parents to shop more healthy food for their family. The efficacy of such fiscal policies is currently being debated. In this thesis, functional magnetic resonance imaging (fMRI) is employed as a tool to understand the mechanistic underpinnings of neural processes while parents from lower socioeconomic status choose between healthy foods with lower than normal taxes or subsidy, compared with unhealthy foods without price interventions. First, we show that healthy food items elicit least reward response in the brain and unhealthy food items elicit maximal reward response. Further, by offering lower tax or subsidy on healthy food items, the reward response in the brain for such items were significantly enhanced. Second, we demonstrate that subsidy is more effective than lower tax in encouraging consumers to purchase healthy food items, driven in part, by higher reward-related response in the brain for subsidy in comparison to lower tax. Finally, we propose that it is possible to titrate the amount of subsidy or tax reductions on healthy food items so that they consistently become more preferable than unhealthy foods. This could then inform fiscal policy employed by Governments in this regard.

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Chapter 1: Introduction

With the developing and updating technologies in science and medical field, people revealed many secrets of our body and can explain lots of things that are related. However, human brain has always been a mysterious organ because of its complex structure and components. Various ways had been attempted in history to analyze our brain since there are so many brain-related topics such as emotion, cognition, etc. People are always showing great interest in how the brain handles such these complicated tasks that even today we still couldn't model. Thanks to various non-invasive imaging modalities such as MRI (Magnetic Resonance Imaging) and fMRI (Functional Magnetic Resonance Imaging), we can decipher some things about our brain today.

1.1 MRI

Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique. It has been widely used clinically to study body organs. MRI employed magnetic field and radio wave pulses to generate pictures of organs and structures inside our body. Hydrogen nuclei are the most common components in our body tissues since water makes up most of our body. And these abundant hydrogen nuclei in our body are continuously spinning around an arbitrary axis according to the physical rules. As a result, the movement of these hydrogen nuclei produces a magnetic field around themselves. Because their motion is randomly under no outside field influence, the net strength of the magnetic field produced by them is zero. However, when applying an outside magnetic field, these hydrogen nuclei will begin align themselves to the direction of the outside magnetic field, which in return will generate a non-zero net magnetic field of themselves. MRI makes use of nuclear magnetic resonance (NMR): If we give a pulse to the hydrogen whose frequency equals the resonance frequency of the hydrogen nuclei, the proton will absorb the energy from the pulse and jump from lower energy level to higher energy level, which results in the change of its previous motion and generate an addition new magnetic field; Then if we turn off the pulse, the proton will release the energy and go back to its original track (energy level). The energy released by the hydrogen proton is the signal we can detect and record. The signal frequency contains the spatial information. By applying inverse Fourier transformation, the spatial information can be recovered so that the image can be constructed as well [1]. Usually the MRI scanner has a set of electromagnetic coils, gradient coils and radio frequency coils. Electromagnetic coils are used to provide static magnetic field. Gradient coils make each point of space has a different magnetic strength, so the spinning speed of the hydrogen nuclei at that point is different, which gives us the spatial information. The RF coils will generate RF pulse that has ha specific resonance frequency (also known as Larmour frequency). Unlike other radial ways, MRI can provide us with high 3D spatial image with no harm. Hence, the safety and extraordinary performance of MRI has made it one of most promising diagnostic imaging techniques nowadays.

Figure 1.1 MRI scanner

1.2 Functional MRI

Functional magnetic resonance imaging is a neuroimaging technique using MRI scanner to investigate the neuronal changes in brain function over time [2]. Our brain serves as the information-processing center, which process all the signals and make decisions. Mapping the brain network has been a heated topic in neuroimaging ever since the emergence of MRI technology. Brain can be seen as made up of different regions. Generally, people assume that different brain regions perform different brain functions. A neuronal activity is usually conducted by several regions of the brain, i.e. by a brain network consist of several regions. Under the concept of functional MRI, ROIs (Regions of Interest) are defined as nodes within the network. The connections of these nodes are estimated using various approaches. The most common adopted method is to get the correlation of these node pairs. The correlation is used to estimate how close a pair of nodes is related to each other. Functional connectivity and effective connectivity are the two main categories used to estimating the intervention between brain regions [3]. Functional connectivity is defined as "temporal correlations between spatially remote neurophysiology events" while people define effective connectivity as "the influence one neuronal system exerts over another" [4]. Of course just estimating whether a connection between node pairs exist or not is relatively simple, but as the effective connectivity can provide much more information underlying the neuronal process, it also gains lots of interest. fMRI is based on the Cerebral Blood Flow (CBF) principle [5]. Whenever a neuronal activity occurs in a certain parts of the brain, the metabolic demand will lead to an increase in blood flow to that region according the knowledge of biology. This rapid blood delivery to the neuronal region is named as Hemodynamic Response (HDR) [6]. The metabolic process caused by neuronal activity within the brain will consume oxygen, and the oxygen is transferred in the blood by hemoglobin. Hemoglobin has a physical property that it will become diamagnetic if carrying oxygen (oxygenated hemoglobin) and it will become paramagnetic if without oxygen (deoxygenated hemoglobin). As a result, the blood flooding towards active neuronal region is more diamagnetic than the other parts, which can be detected by MRI. By employing this property of hemoglobin, we can get an indirect measurement of the neuronal activity within our brain, and it is general named as blood oxygenation level dependent (BOLD) fMRI [7]. The advantage of fMRI is the high spatial resolution as well as safety inherited from MRI technology. However, since fMRI is an indirect method, there is always a latency (usually 1 to 2 seconds) between actual triggering and the hemodynamic response, so fMRI has a poor temporal resolution. Despite this drawback, fMRI has been largely used and become a dominant and essential tool in research and clinical applications.

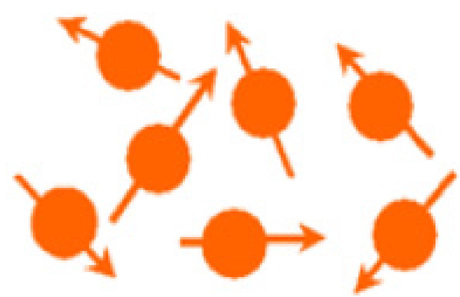

Figure 1.2 Protons randomly aligned in the absence of external magnetic field thus not producing any magnetic field [8]

1.3 fMRI data preprocessing

The data got directly from the scanner is raw and needs several preprocessing steps before we use to analyze. According to the data acquisition process and property of MRI scanner, the MRI image slices of a single voxel at different time points will be together. However, this does not match our analysis habit. Of greater interest are the MRI image slices of different voxels at the same time point to do the contrast. Hence the first conventional step is the slice timing, i.e., divide the slices of one voxel separately, and put slices of same time point together. In this process we are under the assumption that the voxel's intensity value is smooth and derivable, so the whole plot of the value intensity can be restored as a continuous curve by calculating methods.

The second preprocessing step is head motion correction. This is because of the influence of subject's head movement on the signal. As discussed above, a continuous time curve is represented to describe a voxel's intensity. Hence the time course of a time point may represent that of some other voxel due to the head motion during scan. To address this effect, a rigid-body transform is applied to the volume by shifting and rotating the whole volume data to account for motion influence [9]. Similar to the principle of Least squares, we compare the transformed volume to the volume at the first time point statistically. A cost function (such as correlation) is employed to measure how these two match, and eventually the transformation that has the least cost is chosen [10]. One fact that needs attention is that the transformation is not necessarily the globally optimal solution in practice. Due to variety of head movement, it is neither practical nor worthy to compare all possible transformations.

The third step is distortion correction. This is because of the field non-uniformities of the scanner. Tow mainly methods are adopted to make corrections. One way is to use shimming coils, which is a direct way and can make up the difference from the origin [11]. The other method is to acquire two images with different echo times and recreate the field map of interest. Several statistical algorithms are taken to correct the distortion (such as Markov random fields and expectation maximization algorithms [12]). Generally, functional images with fMRI and a structural image with MRI are both acquired, and the structural is of higher resolution compared to the fMRI images. Whenever marking the focused regions in fMRI images, we can align it with the structure image.

Next step is temporal filtering, aiming at removing the uninterested frequencies from the signal. A voxel's time course is a sum of the various frequency signals. With the help of Fourier transformation, we can get the power spectrum of the signal, which is a plot with periods of the signals on the x-axis and amplitudes on the y-axis. Filters of all kinds (High-pass, band-pass, low-pass) can be applied to the spectrum based on our particular choice. Then the filtered time course for the voxel can be restored by inverse Fourier transformation.

The last step is smoothing. It is to average the intensities of the nearby voxels to produce a smooth spatial intensity map across the ROIs [13]. This process is usually done by conducting convolution with Gaussian filter. The weights assigned to the neighboring voxels are measured by the distance to the voxel. If the true spatial extent of activation matches the width of the Gaussian filter, the SNR can be improved. Otherwise the SNR can be enlarged and thus the signal will be reduced.

1.4 Motivations and Organization

Functional MRI as non-invasive technique has very powerful use in helping us understand human behaviors, especially sometimes human may have difficulty explaining their own behaviors. Hence, with the help of fMRI technology, we have to chance to see what is really happening during the neuro activity, so that we can better understand the human behaviors. So far, there has been a lot studies in economic field on how the government can take price interventions to help to eliminate childhood obesity, and lots of useful conclusions have been proposed by researchers. However, there are no direct and objective scientific evidence to support these conclusions.

The goal of this thesis is to apply fMRI technology to infer brain function and analyze people's brain activities during making shopping decision under different price promotions. By doing this, we can picture the reason of their shopping preference. In chapter 2, the background of our project will be introduced first as well as the corresponding related previous researches. Then the experiment task design and data acquisition process are explained in detail. Finally, the result and discussion part of the project is presented. Chapter 3 presents a conclusion of the whole work in the thesis.

Chapter 2: Efficacy of Price Interventions for Mitigating Childhood Obesity by Promoting Healthy Food Choices: An fMRI Study in Parents with Low Socioeconomic Status

2.1 Introduction

Obesity is currently a growing problem in both developing and developed nations all over the world. According to the data provided by U.S. Department of Health and Human Service, approximately 3000 deaths are caused by obesity in United States alone. Obesity increases the risk of heart disease, high blood pressure, diabetes, cancer, sleep apnea, arthritis, pregnancy complications and many other disorders [14]. Also, the fact that a higher body-mass index (BMI) in developmental years increases the risk for all the above diseases when compared with obesity developed in adulthood only makes the situation even worse for children [15][16]. Childhood obesity is of particular concern nowadays, and especially a rising one among rural and low-income populations. People from lower income and socioeconomic status usually have limited access to knowledge and education, thus the potential harmful effects of unhealthy food are probably not clear to them. Also, since children rely on their parents for food, parents' choices of the food supply for the whole family directly affect childhood obesity level.

Taking Alabama as an example, it is currently facing an obesity epidemic. The rural population within this state is particularly vulnerable because of poverty and lack of access to healthy food. According to the Centers for Disease Control and Prevention's survey "Alabama Behavior Risk Factor Surveillance System (BRFSS)"[17], 14 of Alabama's counties have over 40% adult obesity rates. Also, in the year of 2013, Alabama Youth Risk Behavior Survey depicted that children in Alabama are at particular risk[18]. It is reported that 17% of children in Alabama are obese whereas the national average is only 13.1%. Geographical study of obesity using BRFSS data shows that the Black Belt of Alabama, including 16 counties, have highest burden of obesity (as shown in Fig 2.1). These counties are also economically backward. The population of these areas has less access to education and healthy food.

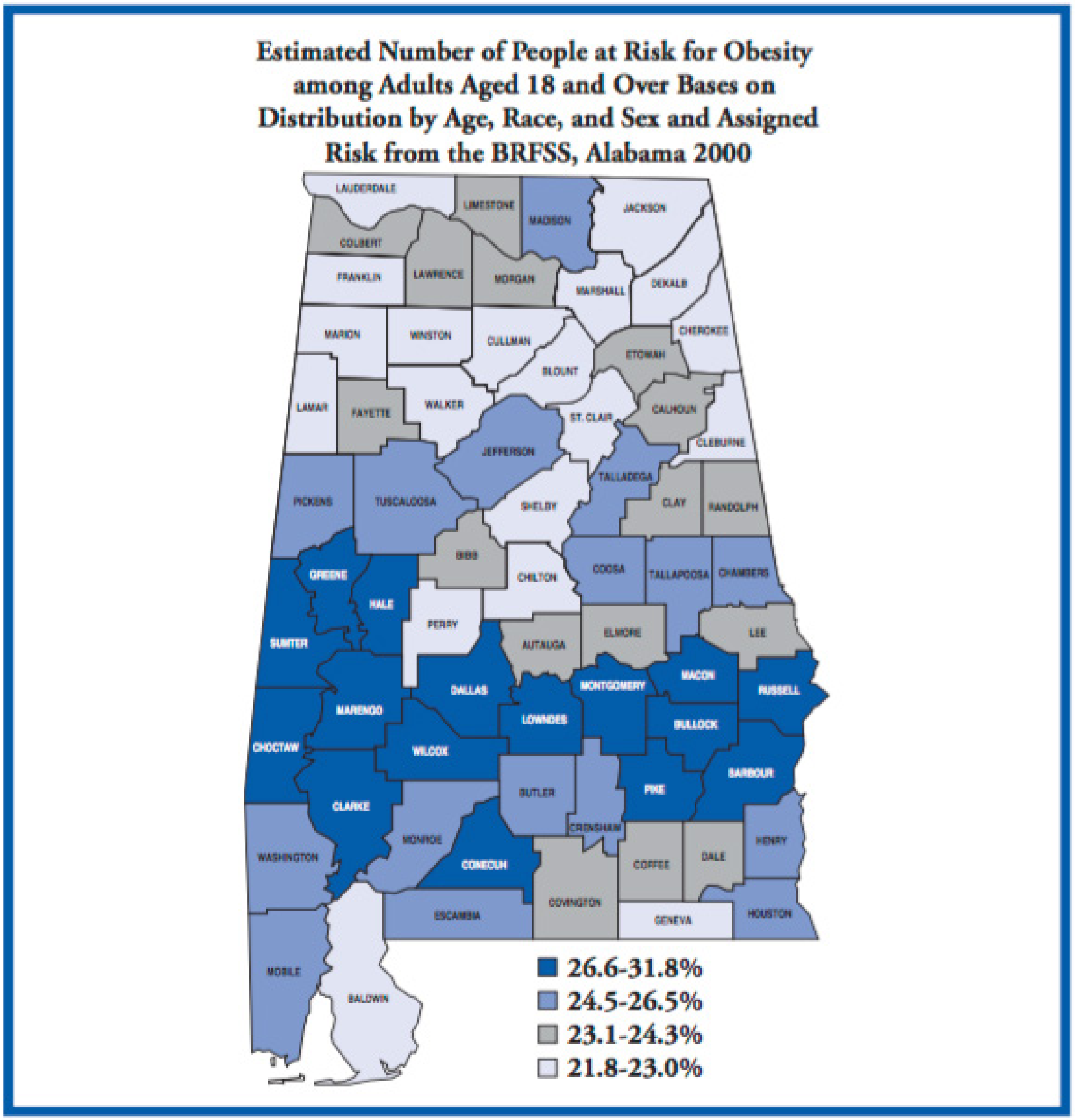

Figure 2.1 Estimated number of people at risk for obesity in Alabama [19]

Several fiscal policies have been employed by the government to encourage people to purchase more healthy food over unhealthy food [20][21][22][23][24]. Among various such fiscal policies, lowering the tax and giving subsidy on the healthy food are most frequently adopted ones [25][26][27][28]. These actions are anticipated to influence parents' choices on the family food supply and encourage them to shop more healthy food in order to alleviate childhood obesity. Many behavioral economists have investigated whether these governmental price interventions related to healthy food offerings are effective or not. Maniadaskis et al studied the influence of higher taxes on unhealthy foods, however, the results are not straight forward due to complex consumer behavior and underlying substitution effects [29]. For example, when higher taxes are levied on unhealthy food items such as candy and soda, people purchase less of these items but substitute their purchase with other higher calorie food. This results in the same amount of calories as before or even more for their total purchases. Also, several previous behavioral studies showed that unless the tax on unhealthy food items is abnormally and unrealistically high, their effect on mitigating obesity was small [25][30][31][32][33][34]. Higher taxes on unhealthy food items has also attracted some moral concerns because it will result in low-income and vulnerable populations spending more money on a basic necessity such as food. Therefore, lowering taxes on healthy food items has been proposed as an alternative.

Previous researchers found that when tax is lowered on healthy food items, parents were more likely to purchase more healthy food for their family in order to save money [35]. But if they were required to spend the saved money in the store, they would use this money to buy unhealthy food items as well [36]. As a result, if consumers cannot have full control of this saved money and can only use it under certain circumstances, the desired effect of promoting healthy food purchase at the expense of unhealthy food items might not be obtained. As depicted in the literature, consumers will be more price sensitive as their income goes down [37][38][39]. We can expect that individuals with lower socioeconomic status will be more receptive to fiscal incentives than individuals with higher socioeconomic status since median incomes in the former case are generally lower than in the latter case.

An alternative fiscal tool to lower taxes is subsidy. In the former case, the rate of taxation will be lower for healthy food items compared to unhealthy food items. Whereas in a subsidy a certain amount of money is refunded to consumers only for the healthy food items they buy. While the amount of money the government spends on lower tax or subsidy may be the same, it is noteworthy that these two price interventions are framed differently. While lower taxes are framed as a discount on healthy food purchases, subsidy is framed as “cash back” on healthy food choices. Consequently, even though the net amount of money saved may be the same, the framing affects choice behavior. There are also studies showing that subsidies are not as helpful as expected in encouraging the purchase of healthy food. Though people would purchase more healthy food when subsidized, they spent the saved money on buying additional less healthy alternatives [20]. However, behavioral studies often do not provide mechanistic insight and hence we need to look at underlying biology for understanding which fiscal tools work and why they work.

Functional magnetic resonance imaging (fMRI) is a non-invasive way of quantitatively measuring brain activity in awake humans. It provides vastly superior spatial resolution as compared to previous modalities such as electroencephalography (EEG), which coupled with its high sensitivity, has enabled researchers to probe human brain function and develop mechanistic models of behavior [40]. Previous studies employed fMRI technology to identify brain regions which activate in response to food-related stimuli. These studies are useful as they showed how obese people might process food-related information differently [41][42][43][44]. However, no studies have investigated the effects of subsidies and lower taxes on parents' neural response together with their choice of food purchase. Hence, neural mechanisms underlying the efficacy of public policy interventions using fiscal tools (taxes and subsidies) remains completely unexplored. Therefore, the aim of this work is to compare the effectiveness of lowered taxes and higher subsidies on healthy foods in promoting healthy food consumption among lower income populations.

Specifically, we test the following hypotheses in this work. First, we hypothesize that healthy food items will elicit least reward response and unhealthy food items will lead to highest reward response. Further, by offering lower tax or subsidy on healthy food items, the reward response in the brain for such items will be significantly enhanced. Second, we hypothesize that subsidy will be more effective than lower tax in encouraging consumers to purchase healthy food items, driven in part, by higher reward-related response in the brain for subsidy in comparison to lower tax.

2.2 Methods

2.2.1 Participants

We were primarily interested in the effect of price interventions on purchase choices made by parents with low-income and socioeconomic status. Therefore, we recruited subjects from low-income families within the so-called black belt of Alabama (Macon County and Lee County). Potential subjects were first pre-screened via phone to check whether they qualified for the study or not. The pre-screening criteria were as follows. The subjects who would take part in this study were required to be responsible for one or more 2-18 year-old children in the family, and their whole family household income was required to be under the limit that we set. Also, we screened subjects for MR-compatibility which included an exhaustive questionnaire documenting among other things whether the subject (i) had any medical condition that prevented him/her from finishing an MRI scan before, (ii) had been injured by a metabolic object or a foreign body before, (iii) had been implanted by a medical device within their body before, (iv) had any tattoo /permanent makeup that contains metal or body-piercing jewelry that cannot be removed. Subjects who self-reported to be claustrophobic were excluded. In total 19 subjects (13 females and 6 males, ages 37.7 ± 10.5) participated in the study. All experimental methods and procedures were approved by the Auburn University Institutional Review Board (IRB) and the experiments were performed in conformance with expected international ethical standards. After the fMRI scan the subjects were financially compensated for their participation.

2.2.2 Stimuli

Since we were interested in investigating the effect of two different price interventions, three types of fMRI stimuli were designed (subsidy, low tax, control). For control condition, subject were required to pay regular tax (10%) on purchased food items and received no subsidy. For the subsidy condition, subjects had to pay regular tax (10%) on purchased healthy food items, but received 9% cashback. For the low tax condition, subjects payed reduced tax (1%) on purchased healthy food items and received no subsidy. Each fMRI stimulus image was made up of the picture of a food item along with its price tag. The brand of the food was covered to avoid possible influence of brand preference on subjects' shopping decisions. Three different colors representing two different price interventions (subsidy and low tax) as well as the control condition were assigned to the price tags. Blue represented the subsidy condition, green represented low tax condition (example in Fig. 2.2) and yellow represented control condition, i.e. no subsidy and regular tax. Subjects were given detailed instructions regarding the color codes before their experiment. They also performed a practice run outside the scanner just to make sure that they understood all aspects of the price tag.

(a) (b) (c)

Figure 2.2 (a). An example of price tag under control condition. (b). An example of price tag under subsidy condition. (c). An example of price tag under low tax condition. These price tags include the unit price of the food item and its corresponding fiscal intervention.

The fMRI stimuli involved images of 36 different food items (18 healthy food and 18 unhealthy food). Foods items were classified as healthy or unhealthy based on the following criteria: (1) Standards required by Alabama schools for cafeteria foods with regards to fat content, sodium, calories, etc. [45], (2) The healthy snack calculator (https://foodplanner.healthiergeneration.org), and (3) The USDA guideline for healthy food [46]. These were selected to represent commonly found healthy and unhealthy food items in a typical grocery store. For each healthy food item, three different images were used to create stimuli corresponding to subsidy, low tax and control conditions (example in Fig 2.3). However, unhealthy food items were not associated with subsidy or low tax. Therefore, for unhealthy food items, three different images were used separately to produce three fMRI stimulus images whose price tags remained the same under the control condition. In total there were 108 fMRI stimuli (54 belonged to unhealthy category and 54 belonged to healthy category).

(a)

(b)

(c)

Figure 2.3 (a). An example of fMRI stimulus image under control condition. (b). An example of fMRI stimulus image under subsidy condition. (c). An example of fMRI stimulus image under low tax condition. These three fMRI stimulus images refer to the healthy food banana.

2.2.3 Task Design

The fMRI experimental session consisted of presentation of the 108 stimulus images (in random order) for 10s duration, followed by a variable inter-trial interval (ITI; range 7s-13s; mean 10s), which was a dark blank image containing a small white fixation cross at the center. The purpose of inserting the variable ITI was to jitter the onset of stimuli and conditions so that it improves the estimation of the hemodynamic response function (HRF) [47]. During the 10 s that the stimulus images were available to view, subjects indicated their decision to either buy or not buy the product using two different buttons on a standard, 4-button, MR-compatible button box (Current Design, Philadelphia, PA). When deciding to buy the presented food, subject pressed "1", otherwise they pressed "2" for deciding not to buy the item.

In each experimental session, the total of 108 stimuli were randomly divided evenly into three runs for each subject using E-prime software. Each run consisted of 36 images. "Optseq" software was employed to determine the ideal sequence of variable ITIs and trials in this experiment design [48][49]. The sequence generated by Optseq maximized the variance of the predicted fMRI response and minimized the overlap of HRFs.

2.2.4 Experimental Procedure

Upon their arrival and before the scan, the participants were again screened for MR-compatibility in-person and were requested to provide informed consent if they agreed to participate in the study. They were also informed that participation in the study was completely voluntary and they were free to quit the experiment at any point during the experiment without giving a reason. Additionally, they were notified that their personal information would be kept confidential in accordance with HIPPA (Health Insurance Portability and Accountability Act of 1996) regulations. The subjects were then given a more detailed introduction about the experiment and procedures by a research assistant. To ensure comprehension of the task requirements, all subjects completed a practice run prior to scanning using a laptop outside the scan room. The practice run was identical to a real run implemented during scanning but had only five stimuli which were not used during data acquisition. Following the practice run, the subjects were asked to insert their head inside a 32-channel head coil (from Nova Medical) and made comfortable. A mirror was placed atop the coil so that the subjects could view visual stimuli being projected onto a screen at the other end of the bore using an MR-compatible projection system (from Avotec). Soft sponge was placed inside the coil in order to secure the head so as to minimize head motion. They were also given a squeeze ball which could be squeezed to stop the scan anytime if they wanted to exit. They were then asked to test the MR-compatible button box to make sure it functioned well. The subject was also given time to adjust himself/herself to the projector screen, as well as the scanning environment before the actual scan. The stimulus display via the projector was controlled using E-prime software on a PC connected to the scanner console so that stimulus presentation and data acquisition could be triggered and temporally synchronized.

2.2.5 Data Acquisition

MRI Data was acquired on a 3 Tesla MAGNETOM scanner (Siemens Healthcare, Erlangen, Germany) using 32-channel Nova Medical head coil at Auburn University MRI Research Center in Auburn, AL, USA. Functional brain imaging data were acquired using an echo-planner imaging sequence (EPI) [50] with repetition time (TR) = 1000ms, echo time (TE) = 30ms, field of view (FOV) = 24cm, in-plane resolution = 3x3 mm^2, slice thickness = 5mm with whole brain coverage. Also, a high-resolution 3D MPRAGE (magnetization-prepared rapid gradient echo) sequence was used to collect T1-weighted structural data for anatomical localization [51].

2.3 Data Analysis

2.3.1 Preprocessing

Brain imaging data were analyzed using statistical parametric mapping (SPM) software (http://www.fil.ion.ucl.ac.uk/spm/) in MATLAB environment. Several standard image processing steps were performed as follows: motion correction was done to detect and correct for head movements, normalization was preformed to transform MRI images from native subject space into Montreal Neurological Institute (MNI) standard brain template space using nonlinear warping; spatial smoothing was conducted to improve image quality; and finally temporal bandpass filtering was performed to remove low frequency drift and high frequency noise.

2.3.2 Statistical Analysis

A general linear model (GLM) was applied to the pre-processed BOLD fMRI data in order to find brain regions activated by conditions of interest. A GLM can be described as the equation below,

$$Y = XB + \mathrm{U},$$

Where Y is the observed fMRI time series, X is a design matrix consisting of explanatory variables, B is a matrix containing parameters that are to be estimated and U is a matrix containing the model error. X consisted of time courses expected due to each condition as well as time and dispersion derivative function allowing for variations in subject-subject and voxel-voxel response[52]. The expected time courses were modeled with a boxcar function convolved with the canonical hemodynamic response function (HRF). The boxcar function assumed a value of 1 at times when the subjects saw images corresponding to the condition of interest and a value of zero during other times. Specifically, the conditions of interest were: bought unhealthy food (BUH), bought healthy food control (BHC), bought healthy food low tax (BHT), bought healthy food subsidy (BHS), not bought unhealthy food (NUH), not bought healthy food control (NHC), not bought healthy food low tax (NHT), not bought food subsidy (NHS). The coefficients of the linear model B were then computed as beta-values. Linear contrasts were defined on the columns of the design matrixes, in order to statistically compare the fMRI response to different conditions in every voxel across the brain using t-tests. The voxels which were significantly different between the conditions being compared were displayed as functional activation maps overlaid on the MNI T1-wrighted brain template.

For each individual subject, BHS, BHC and BUH were first compared to find regions significantly different between the conditions. Next, BHT, BHC and BUH were compared to find regions significantly different between the conditions. Finally, BHS and BHT were directly compared. Once t-maps were obtained for these three different contrasts from individual subjects, a second GLM model was fit in order to obtain group level maps for these contrasts.

2.4 Results

2.4.1 In-scanner Behavior Data

The percentage of products bought under each category is shown in Fig 2.4. We found that the percentage of products were significantly ($p<0.05$) higher when these products were associated with price interventions.

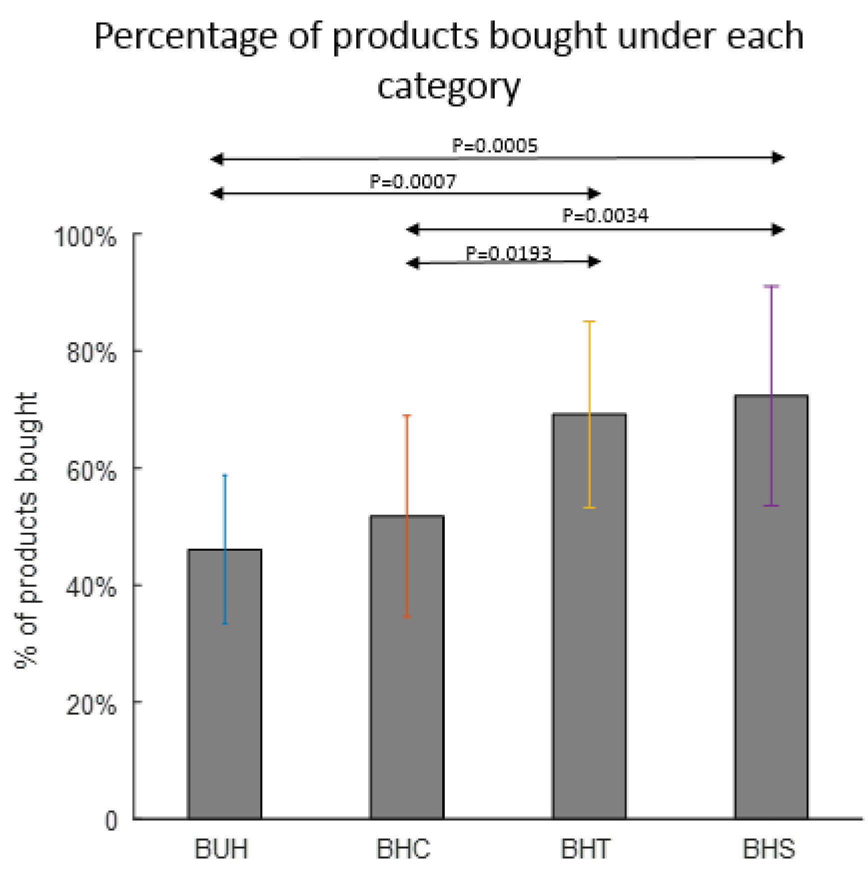

Figure 2.4 The percentage of products bought under each category across subjects. Since the number of products on offer under each category was different, the percentage was calculated by

comparing the number of products belong to a particular category that were bought compared to the number of products on offer in that category. The percentage of products bought were significantly higher ($p<0.05$, as indicated) when they were associated with lower tax or subsidy (BHT and BHS) compared to control conditions (BUH and BHC).

2.4.2 fMRI Activations

We found that reward-related regions such as ventral striatum, substantia nigra and orbitofrontal cortex (Fig 2.5 for subsidy and Fig 2.6 for low tax) as well as executive control regions such as the dorsolateral prefrontal cortex (Fig. 2.10 for subsidy and Fig. 2.11 for low tax) showed significant differences between price incentives (subsidy or low tax) and control conditions. Specifically, the regions of the reward network showed a pattern of increasing response from BHC to BHS/BHT to BUC conditions as shown in Figs 2.7, 2.8 and 2.9. On the other hand, the activated executive control region of dorsolateral prefrontal cortex (DLPFC) or Brodmann area 9 showed the opposite pattern of decreasing response from BHC to BHS/HT to BUC conditions as shown in Fig 2.12. Also, a direct comparison of the responses under BHS and BHT conditions showed that the ventral striatum (Fig. 2.13) showed greater reward-related activity for subsidy compared to lower tax on healthy items (Fig. 2.14).

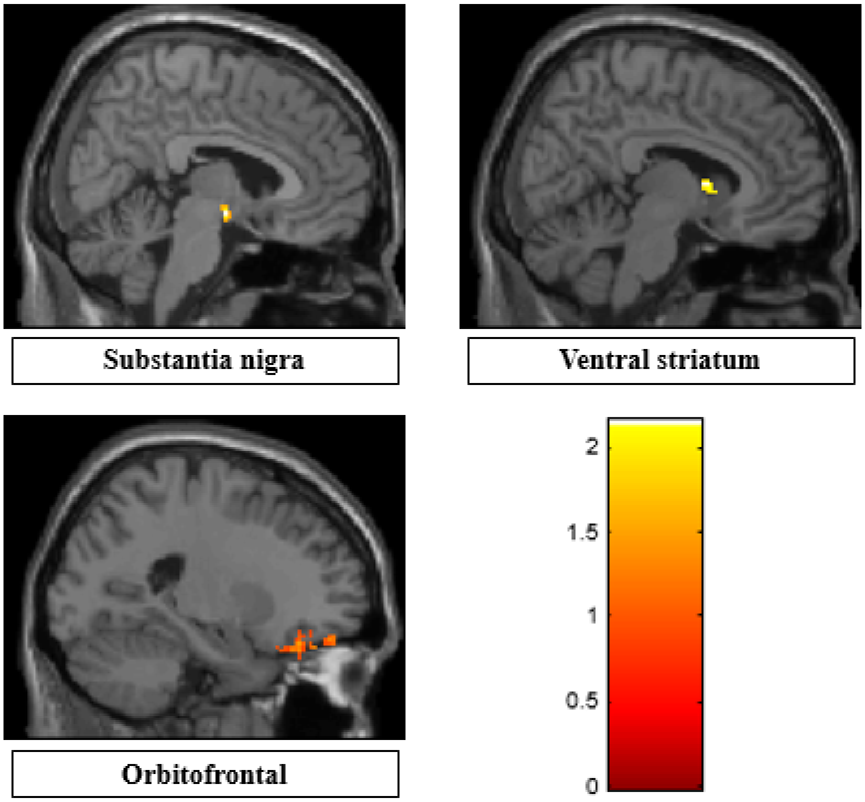

Figure 2.5 Three brain regions (Substantia nigra, Ventral striatum, Orbitofrontal) which showed significant ($p<0.05$) differences between BHC, BHS and BUC conditions, with highest response to BUC and lowest to BHC.

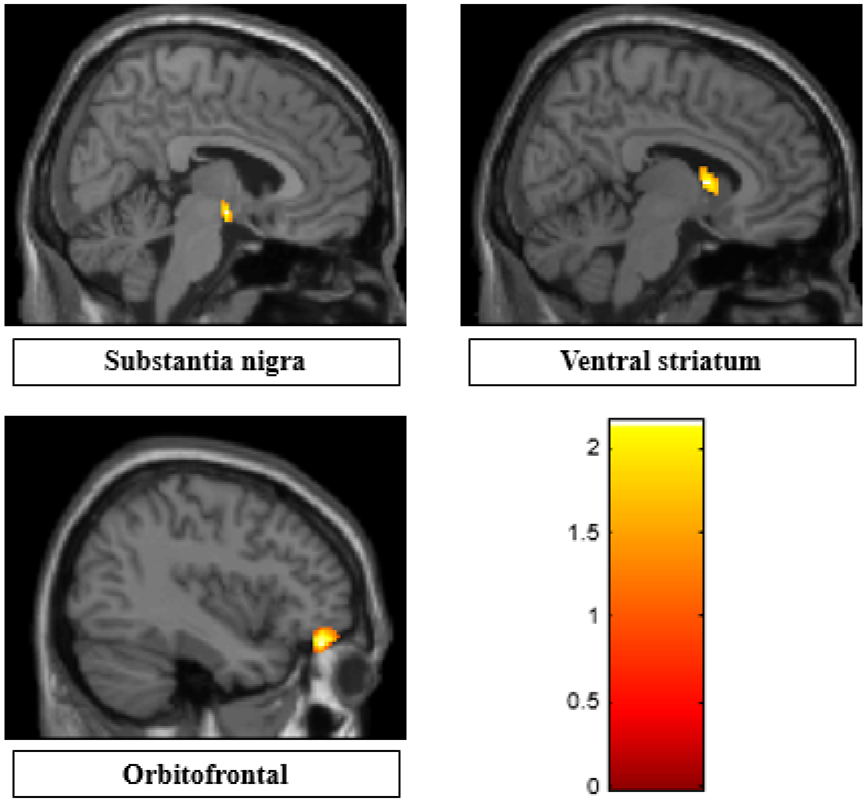

Figure 2.6 Three brain regions (Substantia nigra, Ventral striatum, Orbitofrontal) which showed significant ($p<0.05$) differences between BHC, BHT and BUC conditions, with highest response to BUC and lowest to BHC.

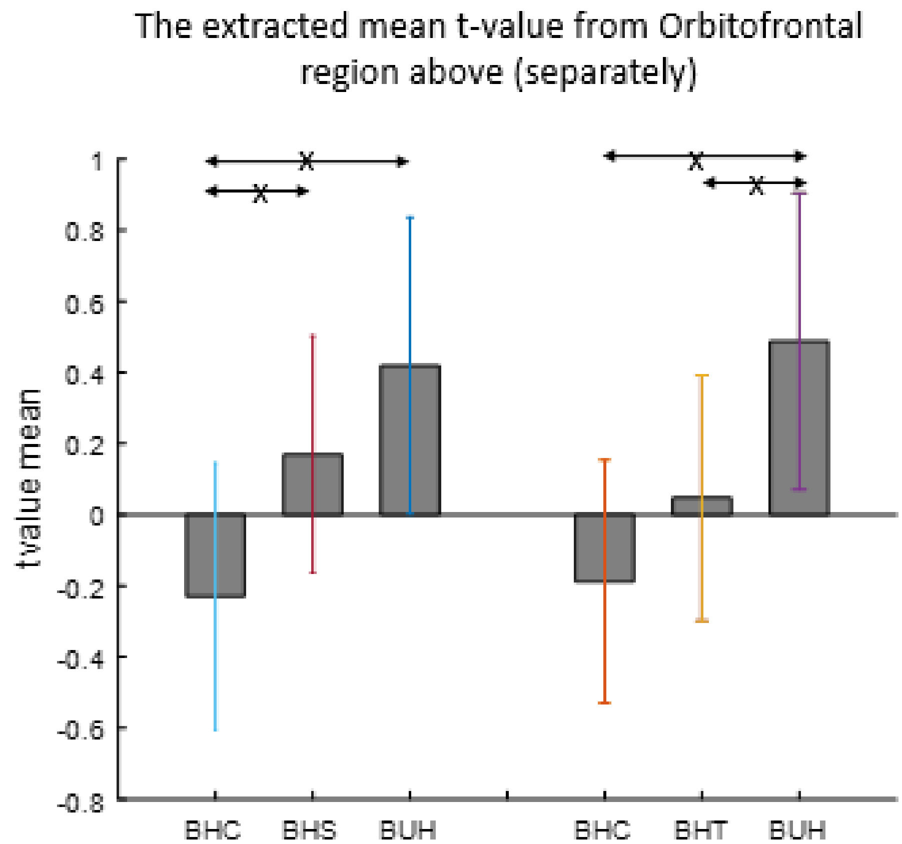

Figure 2.7 The mean t-values extracted from activated voxels in the orbitofrontal region shown in Figs 2.5 and 2.6. Bar plots on the left correspond to activated voxels in Fig 2.5 while those on the right correspond to activated voxels in Fig 2.6. The "x" in the figure indicates that the t-value of two conditions were significantly different with p-value less than 0.05. p-values for the comparisons shown on the left: BHC-BHS p-value=0.0487, BHC-BUH p-value=0.005. p-values for the comparisons shown on the right: BHT-BUH p-value=0.02, BHC-BUH p-value=0.002 .

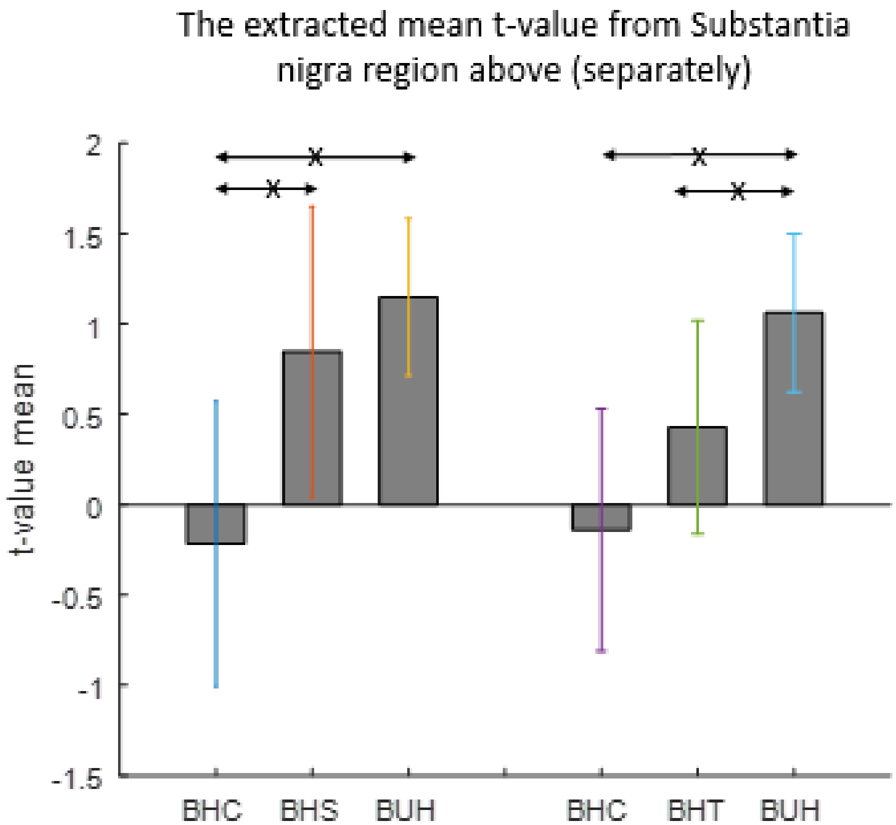

Figure 2.8 The mean t-values extracted from activated voxels in the substantia nigra region shown in Figs 2.5 and 2.6. Bar plots on the left correspond to activated voxels in Fig 2.5 while those on the right correspond to activated voxels in Fig 2.6. The "x" in the figure indicates that the t-value of two conditions were significantly different with p-value less than 0.05. p-values for the comparisons shown on the left: BHC-BHS p-value=0.05, BHC-BUH p-value=0.003. p-values for the comparisons shown on the right: BHT-BUH p-value=0.023, BHC-BUH p-value=0.003.

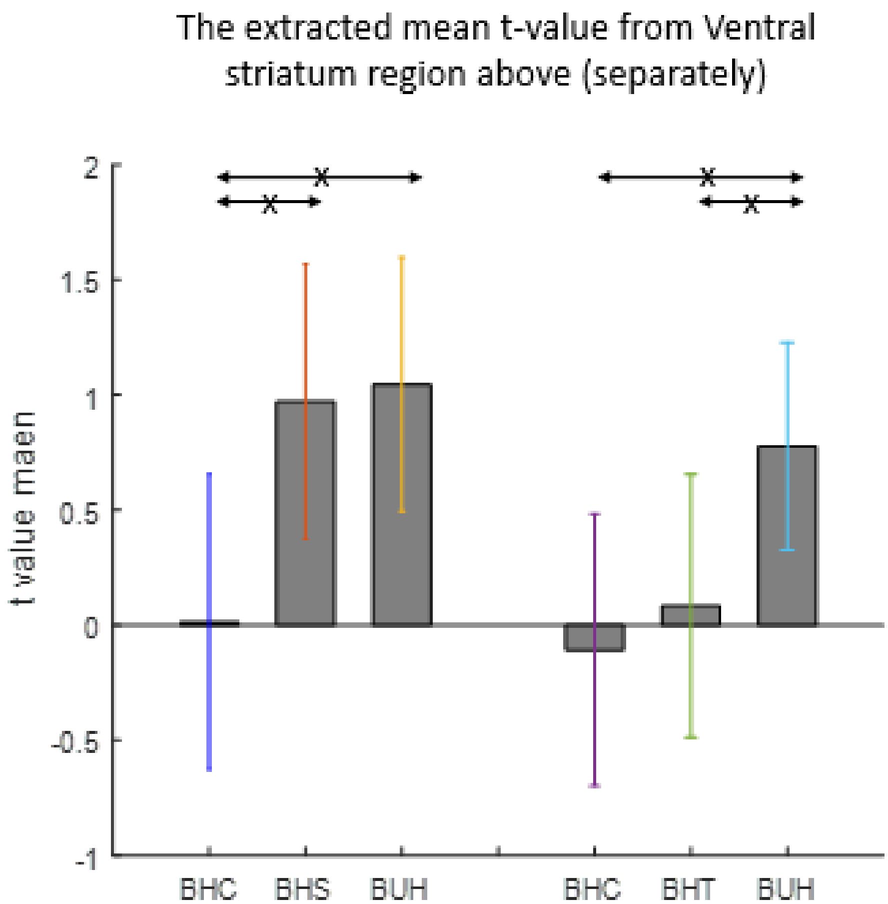

Figure 2.9 The mean t-values extracted from activated voxels in the ventral striatum region shown in Figs 2.5 and 2.6. Bar plots on the left correspond to activated voxels in Fig 2.5 while those on the right correspond to activated voxels in Fig 2.6. The "x" in the figure indicates that the t-value of two conditions were significantly different with p-value less than 0.05. p-values for the comparisons shown on the left: BHC-BHS p-value=0.0148, BHC-BUH p-value=0.0186. p-values for the comparisons shown on the left:: BHT-BUH p-value=0.032, BHC-BUH p-value=0.029.

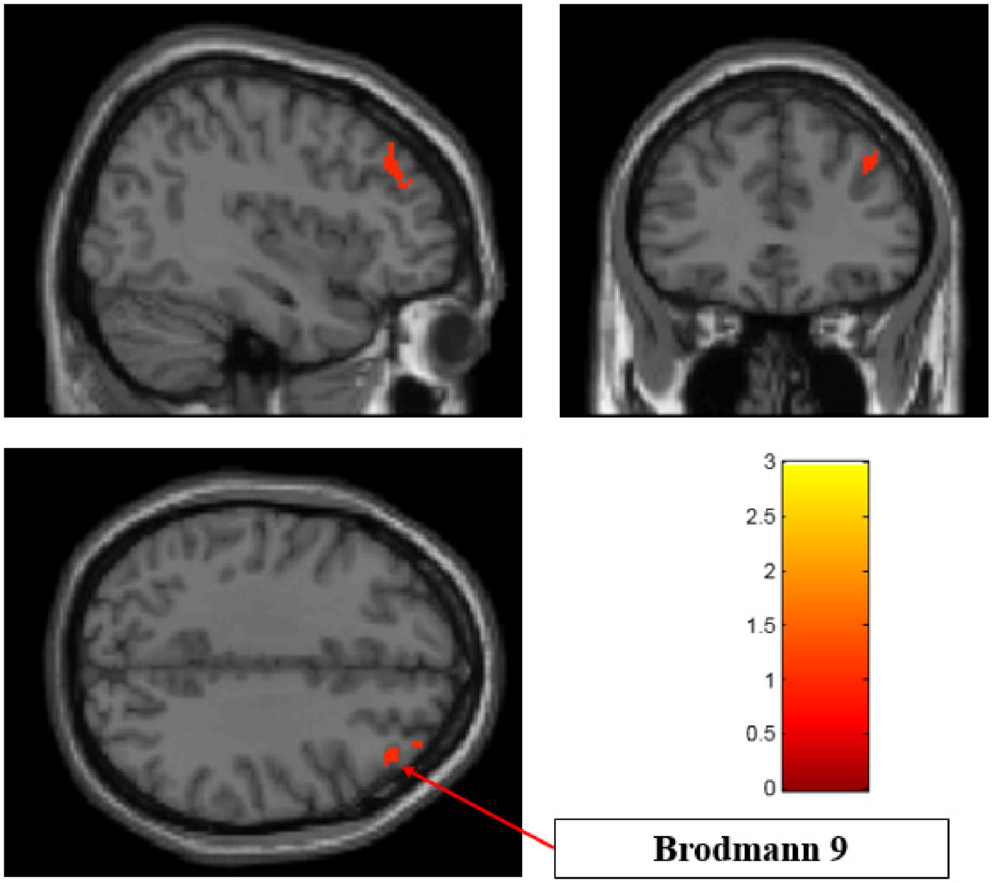

Figure 2.10 The brain region (dorsolateral prefrontal cortex or Brodmann area 9) which showed significant ($p<0.05$) differences between BHC, BHS and BUC conditions, with highest response to BHC and lowest to BUC.

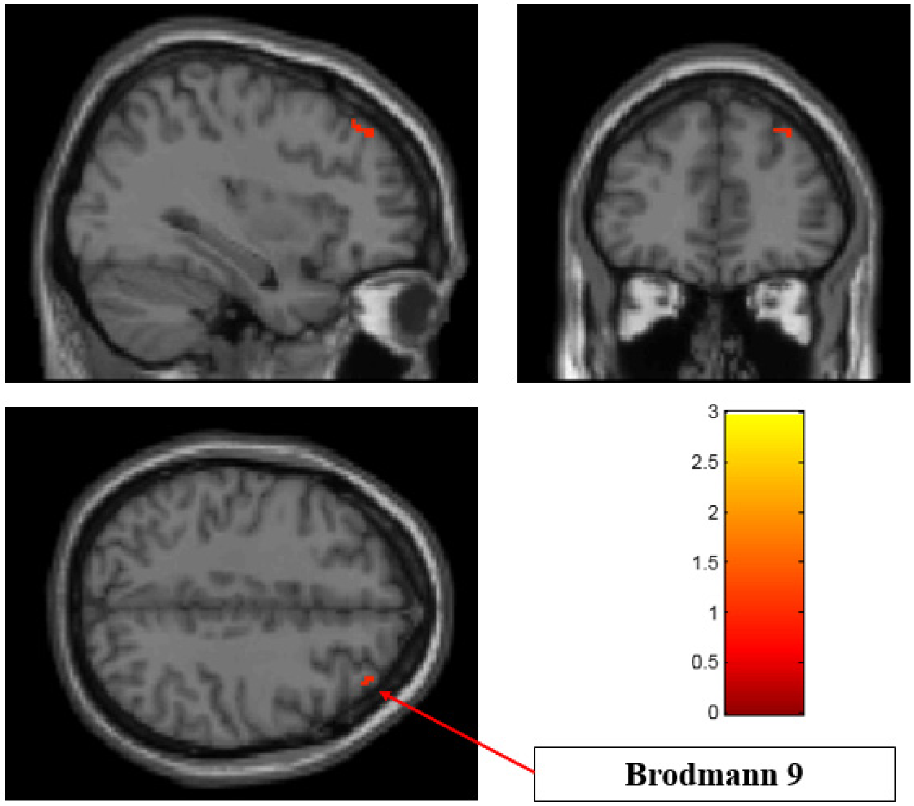

Figure 2.11 The brain region (dorsolateral prefrontal cortex or Brodmann area 9) which showed significant ($p<0.05$) differences between BHC, BHT and BUC conditions, with highest response to BHC and lowest to BUC.

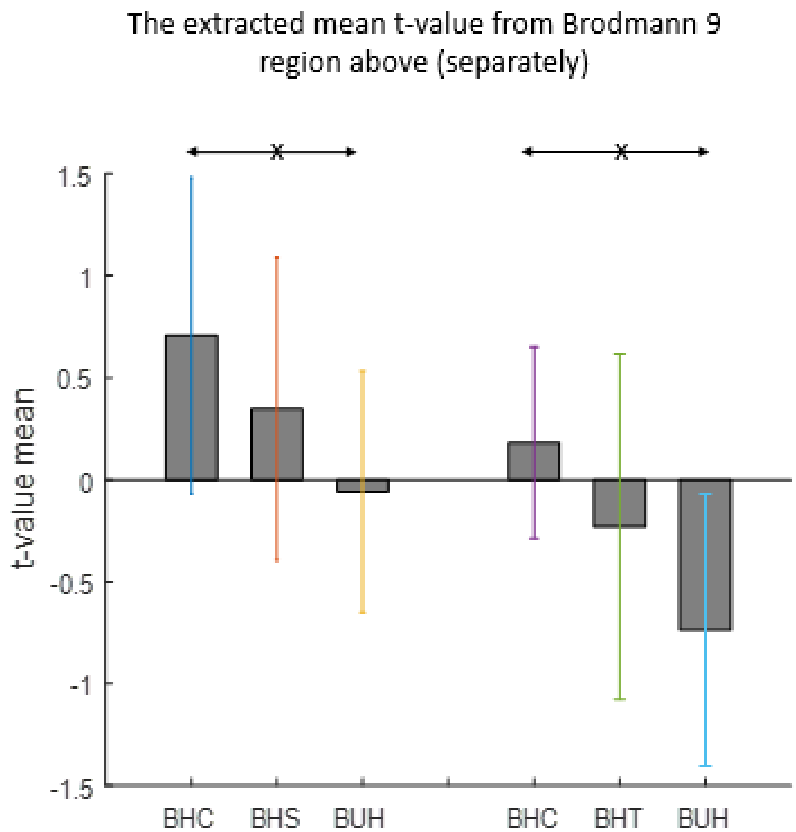

Figure 2.12 The mean t-values extracted from activated voxels in dorsolateral prefrontal cortex (DLPFC) or Brodmann area 9 shown in Figs 2.10 and 2.11. Bar plots on the left correspond to activated voxels in Fig 2.10 while those on the right correspond to activated voxels in Fig 2.11. The "x" in the figure indicates that the t-value of two conditions were significantly different with p-value less than 0.05. (left: BHC-BUH p-value=0.042, right: BHC-BUH p-value=0.0158).

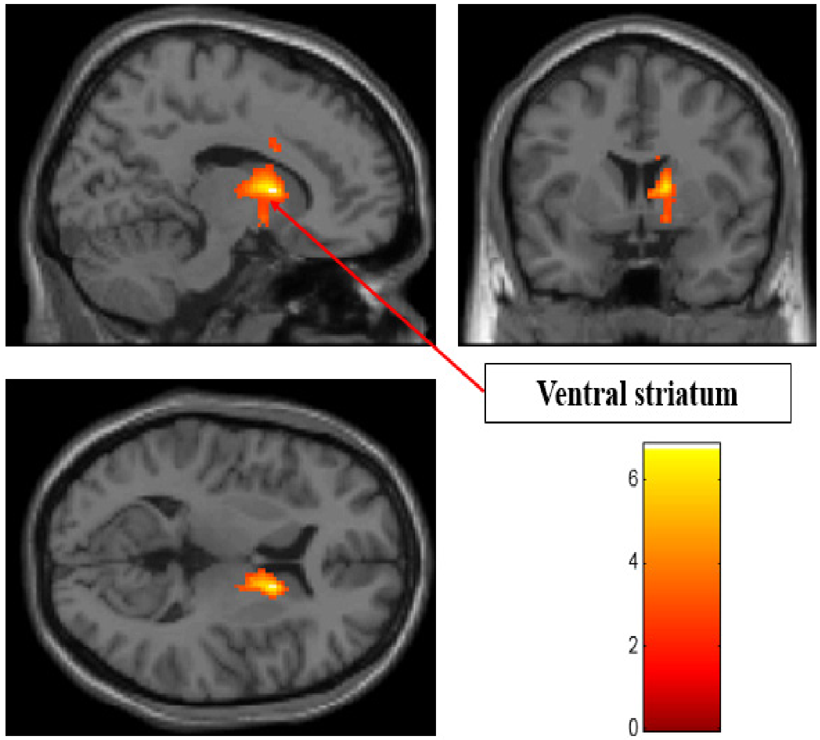

Figure 2.13. The Ventral striatum showed significant ($p<0.05$) differences between BHS and BHT condition.

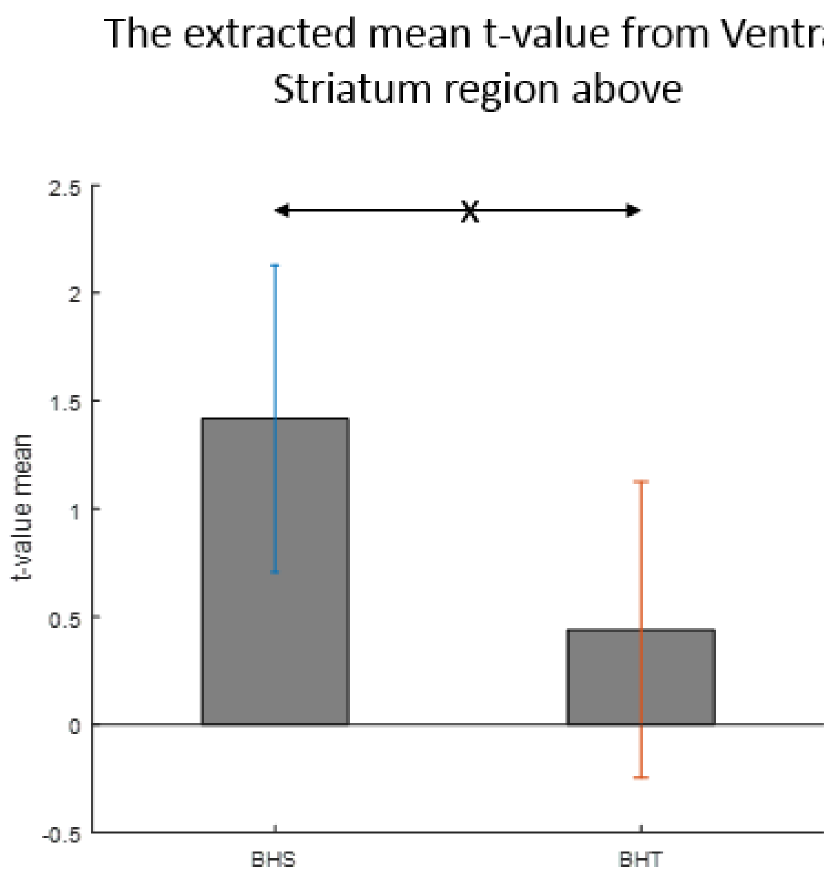

Figure 2.14 The mean t-values extracted from activated voxels in Ventral striatum shown in Fig 2.13. The “x” in the figure indicates that the t-value of two conditions were significantly different with p-value less than 0.05 (p-value=0.0002).

2.5 Discussion

Our results demonstrate that the Orbitofrontal, Ventral striatum and Substantia nigra regions were found to have maximal response to BUC condition, followed by BHS (and BHT) and minimal response to BHC condition. In previous reports, all these three regions had been studied and usually defined as regions part of the “reward” network in the brain [53]. Specifically, in food and obesity related research, these regions are thought to encode the calorific reward value in the brain. For example, a study on neural correlates of restrained eaters’ high susceptibility to food cues showed that the Orbitofrontal region was activated by high-energy food cues [54]. Also Orbitofrontal region was found to have a greater response to high-calorie food versus low-calorie food in a study on emotional eating [55]. Another study investigating the alterations in brain response to food stimuli in overweight and obese individuals, reported that obesity is associated with greater food-evoked responsivity in the ventral striatum [56]. As for the substantia nigra region, previous studies have shown it to be activated with the choice of high energy-density foods [57]. All these previous studies shed light on how these regions encode “reward value” in the brain and corroborates our findings.

Unhealthy food usually contain higher calories per dollar spent and is usually perceived to taste better than healthy food. Hence, people tend to choose unhealthy food over healthy food. This is consistent with our results showing that brain regions which encode calorific reward value also showed highest response to unhealthy foods compared to healthy foods in the absence of price interventions. This is reasonable because all creatures have a preference for food that contains more energy for survival and hence is a preference that is naturally selected during the evolutionary process. In this context, the role of price interventions (subsidy or lower tax) is to offset the low reward signal for healthy foods due to their lower calorific value, by enhancing perceived reward value for healthy products by associating it with a monetary reward. Many previous studies have shown that the three regions – ventral striatum, substantia nigra and orbitofrontal cortex – which were activated in our task also encode monetary reward value. For example, ventral striatum was showed to be modulated by the magnitude of monetary reward [58]. Another study showed that both substantial nigra and orbitofrontal cortex had a stronger activation when provided with monetary reward than verbal reward [59]. Our results indicate that the subsidy or lower tax on healthy products does exactly that, by enhancing the reward value encoded by these regions for healthy food items. We provided a low tax promotion of 1% tax (compared to 10% tax on unhealthy foods) on selected healthy food and subsidy of 9% cashback on selected healthy items (compared to no cash back or subsidy on unhealthy foods). Therefore, one could envision a scenario where in the amount of tax break or subsidy can be titrated to determine the level at which the perceived reward value of healthy food items on low tax or subsidy equals or exceeds that of unhealthy food items. This could potentially provide policy prescriptions for the government which are based on sound scientific evidence.

It is noteworthy that the above discussion centers around BOLD responses to healthy and unhealthy food items, all of which were purchased by the subjects. In our analysis, we did not consider or compare responses during viewing items which were not purchased. Therefore, naturally the question arises as to why healthy food items with and without price interventions were bought in spite of lower reward value compared to unhealthy food items. The answer to this question lies in the pattern of responses we found in the dorsolateral prefrontal cortex (DLPFC), specifically in Brodmann area (BA) 9. The responses to BHC, BHS/BHT and BUC in BA 9 followed a pattern exactly opposite to that observed in reward related regions, i.e. it showed maximal response to BHC, followed by BHS/BHT and least response to BUC. BA 9 is an executive control region which exercises top-down cognitive control on decision making [60][61]. Of specific interest is the role of this region in overriding automatic responses generated by bottom-up processes [62]. In our context, this would be to override the bottom-up input from reward-related regions on the calorific reward value of unhealthy foods, and instead opt for healthy foods with lower tax or subsidy. Therefore, our results indicate that in order to buy healthy food items without price interventions, BA 9 had to exert maximum cognitive control due to its lowest calorific reward value. In contrast, unhealthy food items already had high calorific reward value and hence needed little cognitive control in order to make a purchase decision. The enhancement of reward value of healthy food items after price interventions reduced the amount of cognitive control required by subjects to buy them. This is critical in populations with low socioeconomic status because it has been shown that poverty impacts the brain [63] and its development [64] and potentially top-down cognitive control mechanisms [65]. Therefore, reducing the amount of cognitive control needed by individuals in such populations for making healthy food choices for themselves and their children is an objective that can be met by titrating the magnitude of price intervention needed.

One important question is which of the two price interventions – subsidy or lower tax – is better at achieving those objectives. In our experimental design, for buying same amount of a particular healthy food, subjects paid the same net amount money under two price intervention conditions. However, people reacted differently to these two promotions even if there were no difference in the amount of money saved. As discussed in the introduction earlier, many studies in the field of behavioral economics have investigated this aspect [20][35][36] since subsidy and tax breaks are framed differently and that might influence choice behavior. Based on this prior literature, we hypothesized that subsidy might be more effective than lower taxes in urging consumers to buy healthy food products. Our in-scanner behavioral results indicate that, in terms of the percentage of items bought, these two interventions did not differ significantly (with p-value = 0.648). However, the fMRI responses were significantly greater in the ventral striatum for the subsidy condition compared to the lower tax condition. This provides support for our hypothesis.

Some limitations of this study are noteworthy. First, we did not offer different levels of lowered taxes or subsidy in order to investigate neural correlates which parametrically modulate with the amount of these price interventions. However, we did suggest earlier that these levels could be titrated in order to arrive at optimal values in order to inform public policy. Second, we did not put a control group of subjects not from low-income populations. By doing this, we could further certify the conclusions of this study. Third, the sample size of the experiment was not that large given the exploratory nature of the study. Future studies with larger samples may be required to confirm the conclusions drawn from this study.

Chapter 3: Conclusion

In this thesis, fMRI technology was employed to study the efficacy of tow price interventions (low tax and subsidy) in mitigating childhood obesity. We found brain regions within "reward" network (Orbitofrontal, Ventral striatum and Substantia nigra regions) showed difference in activation to different kinds of food category, with the highest response to unhealthy food and least to healthy food. By adding the price intervention of healthy food, the reward response became higher in these three regions. More specific, subsidy triggered a stronger reward response than low tax. Also, we found that brain region in charge of cognitive decision Brodmann 9 showed difference in activation to different kinds of food category, which provided us more information on how the two price interventions work. All these results could give insights to government to make future price interventions to help alleviate the situation of childhood obesity, especially for the rural and low-income populations.

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