A(NOTHER) PIECE OF CAKE?

Why dieting is so difficult for some and not for others: Using time-discounting to rationalize immediate pleasure over future health.

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Master thesis submitted to

Department of Applied Economics,

Erasmus School of Economics, Erasmus University Rotterdam (EUR)

in partial fulfillment of the requirements for the degree of

Master of Economics and Business – Behavioral Economics.

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Utrecht, August 2015

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ERASMUS UNIVERSITEIT ROTTERDAM

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ABSTRACT

The recent rise in obesity rates in the Netherlands could be explained by a combination of technological innovation and time preferences. The decrease in food prices and the decline in the time costs of food preparation together with the preference of immediate utility over delayed utility might explain the recent obesity epidemic. In this paper, the possible relationship between obesity and time preferences for the Dutch population is examined. Two different samples (N=2138 and N=1236) using different measures of time preferences are used to determine whether BMI is related to time discounting. The results are ambiguous; the two samples show opposite outcomes for the OLS and logit regression, but the significant results do show that discounting more heavily indeed leads to a higher BMI. I can cautiously conclude that this is the first study with an all Dutch sample to demonstrate some sort of relationship between time preferences and obesity. However, alternative ways to measure impulsive behavior might be more efficient.

In this paper use is made of data of the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands).

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1. Introduction

Almost half of the Dutch population is overweight; since 1981 the number of individuals with an unhealthy weight increased to 48%. The amount of people with obesity even doubled to a distressing 12% (CBS, 2014). The consequences are immense, for obese individuals themselves as well as society as a whole. Obesity is linked with a higher prevalence of all kinds of medical conditions, including arthritis, asthma, chronic diabetes, cancer, severe cardiovascular risks (Bray, 2004) and significant psychological and psychiatric problems (Strauss, 2000). Accordingly, the Dutch government spends yearly more than 2,5 billion euros to obesity-related healthcare (RIVM, 2012).

Since 2006, fighting obesity is one of the main objectives of the Dutch government. In its prevention policy at that time it formulated the following goals: ‘The percentage of overweight adults should not increase any further; and the percentage of overweight youth has to decrease’ (VWS, 2006). In order to reach these goals, it focused on prevention and promotion of a healthy lifestyle by stimulating sports and healthy diets (for example Nationaal Actieplan Sport en Bewegen; Richtlijnen Goede Voeding; Ik-Kies-Bewust-logo) and collaborated with schools using education programs as Gezonde School and Lekker Fit! (Nationaal Kompas Volksgezondheid, 2015). Also are to mention Handreiking Gezonde Gemeente, a health promotion and prevention plan for local governments, and Convenant Gezond Gewicht, a collaboration of 26 independent parties to fight obesity among youth. Despite all these and numerous more efforts, overweight and obesity among children and adults is still increasing. Studies on the effect of educational programs similar to abovementioned show little to no improvement (Hebden, Chey & Lman-Farinelli*,* 2012*;* Sbruzzi et al., 2013). We might thus conclude that current governmental policies to fight this problem are failing. How is it possible that, in spite of national, local and individual efforts, this problem keeps on growing?

Generally understood, obesity is the result of a combination of excessive calorie consumption and physical inactivity. Studies show that calories expended (physical activity) has not changed much since the eighties, while worldwide caloric consumption has increased significantly leading to a global obesity epidemic (Cutler, Glaeser & Shapiro, 2003). But then, why has there been such an increase in daily caloric intake? Following the line of reasoning of Cutler et al. (2003) and Lakdawalla & Philipson (2009), I propose an explanation based on the Grossman Model of Health Capital, arguing that technological innovation together with individual time preferences could have caused this rise in caloric intake. More specific, the decrease in food prices as well as a decline in the time costs of food preparation (due to timesaving devices and convenience foods), together with the preference of immediate utility over delayed utility could explain the rising obesity rates over the last years.

Various researchers have studied the topic of obesity and time preference in recent years, but their studies show ambiguous results. Some evidence supports a positive relationship between time preferences and obesity (Smith, Bogin, & Bishai, 2005); others found evidence for women but not for men (Davis, Patte, Curtis & Reid, 2010; Weller, Cook, Avsar & Cox, 2008) or only for men but not for women (Borghans & Golsteyn, 2006; Zhang & Rashad, 2008); or found no association at all (Epstein et al., 2003; Nederkoorn, Havermans, Roefs, Smulders & Jansen, 2006; Yeomans, Leitch, & Mobini, 2008). These equivocal results can be caused by differences in sample sizes, measures for time preferences and including different confounding factors.

Most studies have been done with samples from the United States and the United Kingdom. In perspective of the Dutch policy, it would be interesting to see what the results would be with an all Dutch sample. So far studies using an all Dutch sample focused on the relationship between impulsivity and childhood obesity. Scholten, Schrijvers, Nederkroon, Kremers & Rodenburg (2014) used a sample containing 1377 Dutch children (mean age of 10 years), but found no conclusive evidence. Whereas Van den Berg et al. (2011) – using a sample of 346 Dutch children, 6-13 years – did find evidence that impulsivity is significantly related to BMI through overeating. When looking more specifically into time discounting of adults, Nederkroon et al. (2006) used a Dutch sample containing 50 individuals, but did not include the confounding factors income and intelligence. Therefore, the intent is to study the possible relationship between time preferences and obesity, including the confounding factors income and education, using a larger Dutch sample. Accordingly, this study aims to display insights into one of the possible causes of obesity, namely time discounting preferences of obese and non-obese individuals. However, it is possible that obesity is just the result of utility maximization of rational individuals. But even if this is true, the society has to pay for the consequential costs of this phenomenon and therefore political intervention is justified. Therefore, this study is relevant for formulating and adjusting consumer policy aimed at fighting obesity. Measures aimed at impulsive behavior or commitment mechanisms might be more successful.

The outline of this paper is organized as follows. Section 2 defines the research question and hypothesis. In Section 3 the theoretical framework is presented, discussing the Grossman Model of Health Capital, technological innovation, time preferences and some conflicting but very interesting factors. The methodology will be discussed in Section 4, which will be followed by the results in Section 5. Finally, Section 6 contains a discussion of the findings.

2. Research Question & Hypothesis

Differences in time preference between obese and healthy-weight individuals could explain the increasing rise in obesity. Therefore, the research question of this study will be:

> To what extent display overweight individuals and individuals with a healthy weight different rates of time-discounting, controlling for the confounding factors education and income?

There is empirical evidence that demonstrates a relationship between time preferences and obesity (e.g. Smith et al., 2005; Weller et al., 2008; Zhang & Rashad, 2008). It is very likely that overweight and obese individuals discount time at a different rate than people with a healthy weight: the utility gain from consuming food at this moment outweighs the future utility loss of its health consequences. Hence, it is possible that overweight individuals, consciously or unconsciously, care less about the potential future health-loss consequences of their behavior.

The study of Nederkroon et al. (2006) did not include the confounding factors education and income. I argue that these factors should be taken into account when studying time preferences. In general, there is a close correlation between education and income; individuals with a higher education level are more likely to have a higher income. Both of these factors have an influence on an individual’s time preferences as well as their body mass index (BMI). BMI is calculated by dividing an individual's weight (kg) by his or her length-squared (m) – $\frac{\text{weight (kg)}}{\text{length (m)}^2}$. This study considers a BMI of roughly 18,5-25 as healthy, 25-30 as overweight and 30 or above is classified as obese (WHO, 1995).

To highlight the importance of including the confounding factors education and income, their influence on time preferences as well as BMI will be discussed in more detail.

Time preferences | There is empirical evidence that preference for immediate rewards is related to intelligence (De Wit, Flory, Acheson, McCloskey, & Manuck, 2007), so this factor should be taken into account when studying the impulsive behavior leading to obesity. De Wit et al. (2007) show that education is positively related to IQ and negatively to impulsive behavior. This indicates that individuals with a higher level of education will show less impulsive behavior than people with a lower education level. Also Reimers, Maylor, Stewart & Chater (2009) show that the choice of sooner over later is related to lower education levels.

Income is also an important factor in time discounting. Studies show a significant relationship between these two factors: adults with a lower income discount more heavily than adults with a higher income (De Wit et al., 2007; Reimers et al., 2009). Similarly, Green, Myerson, Lichtman, Rosen & Fry (1996) found that participants with a higher income discount less than lower-income individuals.

Body Mass Index | There is a strong association between education and health behaviors; both cognitive as well as non-cognitive skills contribute heavily to this (Conti & Hansman, 2013). According to the productive and allocative efficiency, better educated people 'make more efficient use of existing knowledge' and they 'choose more efficient inputs into health investment' (Koç & Kippersluis, 2015). This might partly be due to cognitive abilities – higher educated respondents are better able to process and implement health information. But findings show that, even after fully controlling for health information across education groups, higher educated individuals care more about the health consequences of food than the lower educated (Cutler & Lleras-Muney, 2010; Kenkel, 1991; Meara, 2001).

Next to health knowledge, health valuation and affordability of health also come into play. Lakdawalla & Philipson (2009) show that income has an inverted U-shaped relationship with BMI. They show that a higher income increases the demand for food consumption (volume, quantity), but at high levels of income a further increase in income lowers weight due to an increase in the demand for an ideal body weight. Furthermore, low income respondents are more likely to buy energy dense foods (refined grains, added sugars and fats), considering that these products are more affordable than healthy foods (Drewnowski & Specter, 2004). Therefore, income and education influence BMI in multiple ways: first through the ability of processing and implementing health knowledge, secondly through the change in body weight preferences, and thirdly through the affordability of healthy foods/lifestyles.

Therefore the following hypothesis will be tested:

H_0: There is no difference between time discounting rates of overweight/obese individuals and individuals with a healthy weight, when controlling for education and income.

H_1: Overweight and obese individuals show a higher rate of time discounting than individuals with a healthy weight, when controlling for education and income.

3. Literature Review

3.1 The Grossman Model of Health Capital

Various recent studies have tried to explain the rise in obesity. Many of which are (whether or not implicitly) based on the Human Capital Model of the Demand for Health by Michael Grossman (Grossman, 1972). This discounted utility model shows how individuals make health-related decisions in a way that the marginal benefits from health investments (living longer and healthier) equal the marginal costs of these investments (time forgone and money spend). 'Demand for health' implies health stock – i.e. level. Individuals have an initial stock of health which can be increased by health investments (exercise, diet, medical care) and depreciates with age, while the costs of health investments increase with age. During their lifecycle, individuals constantly make trade-offs between health investments and health costs.

An implication of the model is that an individual's level of education influences the efficiency of his/her health investments, which implies that education is positively related to health. Therefore, economists have generally supported the view that providing consumers with nutrition information is a good instrument of fighting obesity (Scharff, 2009). Over the last years, the level of general and nutrition-specific education in the Netherlands has gone up (CBS, 2015). Following the Grossman model, this should indicate that the demand for good health should have gone up as well and health issues such as obesity should have decreased. This has not happened. Despite increased access to nutrition specific information, numerous educational programs and campaigns, obesity rates keep rising.

A first reason for the recent rise in obesity could be technological change. Studies show that the reduction in food prices due to technological innovation and mass production (Lakdawalla & Philipson, 2009; Lakdawalla, Philipson & Bhattacharya, 2005) together with a decline in the time costs of food preparation – due to timesaving devices and ready-made meals (Cutler et al., 2003) – has lowered the costs of current food consumption. In the Grossman model, cost reductions of this kind are likely to 'increase the net benefits from current food consumption relative to future health benefits, thereby increasing the optimal level of obesity' (Scharff, 2009, p.6-7).

Another possible explanation are time preferences: the preference for immediate utility over delayed utility, 'rather sooner than later' (Frederick, Loewenstein & O'Donoghue, 2002). An individual with a relatively high rate of time preference will have a relatively low demand for future health capital (Fuchs, 1986; Scharff, 2009), since the present counts heavier than the future. This will influence this individual's optimal health-consumption tradeoffs in the Grossman model. The urge of wanting something rather now than later can be seen as a form or rational impatience or irrational self-control issues. Section 3.3 will deliberate more on this.

To be able to explain the recent rise in obesity rates, technological change or time preferences by itself cannot clarify the matter – as will be discussed in more detail in Sections 3.2 and 3.3. Taking technological change as sole explanation would be too short-sighted. Data shows all individuals are affected by industrial development, but not all of these individuals have severe weight gain and therefore become overweight – e.g. more than half of the Dutch population still has a healthy weight. Therefore other factors should also come into play. With regard to time preferences, Borghans & Golsteyn (2005) show that, even though individual's BMI changed over a timeframe of 10 years, their time discount rates did not differ in that time. So whereas BMI and time discounting are related, time discounting in itself does not explain the recent rise in obesity rates either. In standard economics, technological change implies that lower food prices and a decline in time costs of food preparation would make people better off. But if people have difficulty controlling their eating behavior, as in 'discounting heavily', this may aggravate the obesity problem. Therefore, a combination of technological change together with time preferences might be a suitable explanation for the rise in obesity rates in recent years.

This paper uses time preferences as indicator for impatience, even though this indicator might be too simplistic (Section 3.3 will deliberate more on this). When thinking of alternative ways to model this behavior one could think of the models of temptation and commitment of Gul & Pesendorfer (2001) and Benhabib & Bisin (2005) discussing dynamic self-control preferences, the model of time-inconsistency by Strotz (1956) and dynamically inconsistent preferences by Laibson (1997), decision making triggered by environmental cues (Bernheim & Rangel, 2004) and the dual-self models of Thaler & Shefrin (1981) and Fudenberg & Levine (2004). Some of these alternatives will be further discussed in Section 3.3.

3.2 Technological innovation

During the last century, technological innovation and mass production caused a significant reduction in food prices, about 0.2 percentage point annually since 1950 (Lakdawalla & Philipson, 2009). Lower food prices together with an increase in income (due to economic progress) will lead to weight gain, which is not a bad thing in itself. Lakdawalla et al. (2005) show that lower food prices correlate with significant better nutrition, improved health and well-being in the United States. This indicates that obesity is an unintended side effect of economic development.

Technological innovation also led to a decline in time costs of food preparation. In 1965, women spent over two hours per day preparing, cooking and cleaning up meals. Nowadays, the same tasks take less than half an hour. 'Technological change – including vacuum packing, improved preservatives, deep freezing, artificial flavors and microwaves – have enabled food manufacturers to cook food centrally and ship it to consumers for rapid consumption' (Cutler et al., 2003, p.94). This shift from individual to mass preparation led to a decline in the time costs of food preparation and thus food consumption.

Next to the expansion on the supply side of food, technological developments also influence the demand side. Technological change raised the costs of physical activity by making household and market work more sedentary; think of an increase in desk work, all kinds of household appliances, developments in transportation and increasing use of devices as TV's and computers. These factors lower the need for calories and thus the demand for food, while simultaneously raising the costs of physical activity. Lakdawalla & Philipson (2009) use multiple examples to show that in an agricultural society the worker is paid to exercise, while in advanced societies people pay to exercise (in monetary and forgone leisure terms).

However, technological change in itself cannot explain the rise in obesity rates. Firstly, an increase in income due to economic growth will lead to an increase in the demand for food. This indicates that richer individuals demand more food and will be more likely to be obese. But studies show that income and BMI are negatively correlated nowadays (Cutler et al., 2003). Secondly, in the traditional economic view the standard price mechanism holds: lower prices of any good (monetary as well as time costs) will lead to better welfare – and not worse as recent numbers indicate. But if people struggle with impatience or self-control issues, lowering the costs of food consumption may lead to an intensification of these problems and provoke overeating. In this study, these issues are indicated by time-preferences. Nevertheless, it is theoretically possible that some people do not care much about the future and therefore deliberately make choices leading to obesity.

3.3 Time preferences

Cutler et al. (2003) argue that technological change cannot be the sole explanation for the rise in caloric intake over the last years. When looking at the elasticity of caloric intake respective to price/costs of food, typical price elasticities for total food consumption are lower than needed to justify the observed increase in caloric intake (Blundell, Browning & Meghir, 1994). The traditional economic model concerns rational individuals deciding their optimal consumption pattern on costs and benefits, fully taking any possible health consequences of their actions into account. But like other purchase decisions, food consumption is not completely rational. People under- or overeat; think of all the individuals struggling with emotional eating disorders as anorexia, bulimia and binge-eating. Likewise, obesity can be the outcome of some sort of emotional eating disorder. The causes and effects of these disorders can be rated as unhealthy and impulsive behavior. So here time preferences may come into play; impulsive individuals may consume more (or less) than is optimal.

There is empirical evidence that demonstrates a relationship between time preference and unhealthy behavior (Scharff & Viscusi, 2009) and time preference and impulsive behavior (De Wit et al., 2007; Kirby, Petry & Bickel, 1999). As stated above, obesity can also count as a result of unhealthy or impulsive behavior; the utility gain from consuming food outweighs the future utility loss of its health consequences. We have to keep in mind though, that 'current food consumption' is a certainty, while 'future health consequences' are a possibility. So food indulgence can be seen as a form of *decision making under uncertainty* or an *intertemporal choice*, 'a decision involving tradeoffs among costs and benefits occuring at different times' (Frederic et al., 2002, p.351).

Already in 1836, Senior (p.109) stated that 'to abstain from the enjoyment which is in our power, or to seek distant rather than immediate result, are among the most painful distortions of the human will'. People struggling with self-control issues or impatience won't be (or will be less) able to resist immediate enjoyment and therefore rationalize their indulgence in foods by time preferences. Time preference has simply to do with the preference for immediate utility over delayed utility, 'rather sooner than later' (Frederick et al., 2002). An individual with a relatively high rate of time preference will have a relatively low demand for future health capital (Fuchs, 1986; Scharff, 2009), since the present counts heavier than the future.

A very simplified model of time preference in this context includes an individual's lifetime utility, a certain discount function, the utility gain from consuming food and the utility gain of his or her health status:

$$U = \sum_{t=0}^{T} \theta(t) \cdot u\ (eating, health) \tag{1}$$

$\theta(t)$ is the discount function at time t and can be seen as a measure for (im)patience, $U\ (eating, health)$ is this person's utility function. Now let's assume we only have two time periods, today (t=0) and tomorrow (t=1), and lifetime utility solely depends on the discount function, food consumption and health status. Individuals only need to make decisions on how much food they will consume today and tomorrow, while taking into account the possible health consequences of these decisions. For example, if person A consumes a lot today (t=0), his utility of food consumption today will be high but his health status today will be unaffected. However, tomorrow (t=1) the utility derived from his health status will be lower due to his excessive food consumption the time period before, while utility from food consumption might still be high. When translating this situation into equation (1), it will look as follows:

$$U = \theta(0) \cdot u\left(eating_{today},\ health_{today}\right) + \theta(1) \cdot u\ (eating_{tomorrow}, health_{tomorrow}) \tag{2}$$

To start with the last part of the formula, the utility function can be roughly described as 'the happiness one derives from consuming a good', i.e. food consumption and health status in this situation. As argued in previous section, technological change in the food industry influences this part of the formula by increasing the utility of consuming foods due to lower food prices and time preparation costs. In 1950, food consumption was relatively expensive (time-wise as well as price-wise). Nowadays, it can be relatively inexpensive which automatically increases the utility of food consumption. Individuals with a low level of impatience (a high $\theta(1)$) will not be much affected by this, while people with a high level of impatience will and therefore they will be more likely to be overweight or obese. Therefore, the rise in obesity rates in recent years might be due to changes in the utility of food consumption due to technological change, or differences in the discount function (individuals with a high level of impatience versus a low level of impatience), or both.

Let's assume $\theta(0)$ is 1 and $\theta(1)$ is unknown, since we do not know how much value this person attaches to the future consequences of his or her behavior. We do know however, that the higher $\theta(1)$ the more this individual cares about his or her utility tomorrow. Therefore, the discount factor can be 'used to measure the present value of future utility an individual gets through consuming a good' (Zhang & Rashad, 2008, p.100). If $\theta(1)$ equals 1, this would indicate that the individual is extremely patient and equally values the present and future consumption of a good, e.g. the utility of consuming a bar of chocolate today is equal to consuming the chocolate bar tomorrow. But individuals are impatient, the discount function of each time period is usually not the same. The lower $\theta(1)$, the less value the individual attaches to future gains and losses, and the more he or she is focused on the immediate situation. Since individuals always 'give extra weight to well-being now over any future moment' (O'Donoghue & Rabin, 1999, p.104), most individuals will behave in a manner that indicates $\theta(t) > \theta(t+1)$.

In this study, $\theta(t)$ is a number, not a function. But theoretically it could be any discount function, for example constant discounting in the form of $\theta(t) = \frac{1}{1+\alpha}^{t}$ or hyperbolic discounting in the form of $(1+\alpha t)^{-\beta/\alpha}$ with $(\alpha, \beta > 1)$, when allowing for different levels of impatience (e.g. distinguishing between discounting the near and far future) as thoroughly discussed in Loewenstein & Prelec (1992). The data used in this study is too limited to distinguish between different models or different levels of impatience, so therefore the variable used to indicate time preferences will imply $\theta(1)$. The data will give an indication on whether $\theta(1)$ is high or low. Individuals who are impatient will discount the future heavily and therefore have a low value of $\theta(1)$.

When discussing situations concerning the value of future utility, different models with different lines of thought can be used. The discounted utility model of Samuelson (1937) is commonly used and dominated the world of intertemporal choices over the last 80 years. He proposed that people discount the utility of future events at a constant rate of time preference – therefore also referred to as *constant discounting*. Constant discounting implies constant impatience in all time periods and that individual's preferences are time-consistent. This model assumes individuals are rational and always strive to maximize their utility. Therefore, impulsive behavior in this model is referred to as *rational impatience*. However, empirical evidence shows that individuals consistently violate this model, including anomalies like the common-difference effect, absolute magnitude effect, gain-loss asymmetry and delay-speedup asymmetry (Loewenstein & Prelec, 1992; Thaler, 1981). The evidence indicates that individuals do not always behave in a rational manner and 'preferences between two delayed rewards can reverse in favor of the more proximate reward as the time to both rewards diminishes' (Frederick et al., 2002, p.361). For example, someone may prefer excellent health in 31 days over a chocolate cake in 30 days, but also prefer a chocolate cake now over excellent health tomorrow. This leads to a model of hyperbolic discounting as described by Strotz (1956), Laibson (1997) and Loewenstein & Prelec (1992). The hyperbolic discounting model implies decreasing impatience. Individuals are seen as irrational and time-inconsistent, since their preferences change over time. Scharff (2009) states: 'Individuals are myopic, they will make risk choices inconsistent with long-term utility maximization' (p.5). Therefore the best option from today's perspective might not be the best choice from tomorrow's perspective anymore. Impulsive behavior in this model is described as *irrational self-control issues*.[1]

The framework used in this study concerns rational time-preferences. But when talking about the phenomenon of intertemporal choices, one could argue to use the *time-inconsistent preferences* of hyperbolic discounting as a framework instead, as briefly mentioned above. In other words, $\theta(t)$ could be time consistent (concerning individuals maximizing their utility), but $\theta(t)$ could just as well be time inconsistent (concerning individuals failing to maximize their utility). The latter concerns the anomaly

[1] Even though Farmer & Geanakoplos (2009) argue that hyperbolic discounting can also be seen as rational behavior, it is still treated as irrational in this study.

that people make time-inconsistent decisions; a choice that would not have been made occurring in a different point in time, for being rejected in advance and possible regretted after the fact (Hoch & Loewenstein, 1991). An example is to decide to lose weight in the morning but at the same time eating a whole bag of chips during the movies at night. You would have rejected the bag of chips in the morning and most likely will regret eating it after you finished. The individual's preferences change over time in such a way that they can become inconsistent. This usually occurs when an individual makes a commitment concerning the future (losing weight in this case) and plans to stick with it, but 'the incentive to keep the commitment is significantly less than making the commitment' (Kling, 2009, para. 2).

This inconsistency does not occur in time preferences, for time preferences are rational. Individuals deliberately make trade-offs between consuming food and health status. For example, even though this individual may regret eating the bag of chips afterwards, he or she still thinks rational at the moment of acting and hereby maximizing current utility.[2] Therefore, time-inconsistency can be seen as irrational behavior, while time preferences can be looked at as pure rational impatience. Although the reasoning behind the two frameworks differs, the data used in this study is too limited to distinguish between time preferences and time-inconsistency. The observed outcome of both models will be the same in this study (which is illustrated in Appendix A). Therefore the widely used framework of time preferences is an adequate measure for the abovementioned problems.

3.4 Conflict of interest

3.4.1 Dopamine system

We have to keep in mind that obesity is not just a behavioral or economical problem of individuals lacking self-control or willpower. Ever since 1990, research reveals that obese people have an imbalance in their dopamine system which makes them 'addicted' to food on such a level that they can be compared to chronic drug abusers (Baik, 2013; Kenny 2013). Among scientists it is generally known that 'repeated exposure to addictive substances [such as food], adaptive changes occur at the molecular and cellular level in the dopamine pathway' (Baik, 2013, p.1). The dopamine system influences many physiological activities, including 'the control of coordinated movements and hormone secretion, as well as motivational, emotional and contextual behaviors' (Baik, 2013, p.1) and seems to be crucial for the reward system and addictive behaviors.

Energy dense foods (high in added fat and sugar, becoming widely available through technological change) lead to a decrease in the functionality of D2 receptors (D2R) in the human brain, which are needed to activate specific dopamine signaling pathways (Small, Jones-Gotman & Dagher, 2003). A reduced functionality of these D2R leads to a lower sensitivity to the natural reward of food (feeling 'full, satisfied'), which these individuals try to overcome by eating even more. Next to that, food has a high reinforcing value to overweight individuals (Saelens & Epstein, 1996), so the more they eat, the more they want (Kenny, 2013). They get 'addicted' to food. Reductions in D2R are

[2] I have to stress that theoretically it is possible that overweight individuals are rational and just maximizing lifetime utility, even though this means they become overweight or obese.

also associated with decreased metabolism in mechanisms involved in 'salience attribution, inhibitory control/emotion regulation, and decision making' (Volkow, Wang, Fowler, Tomasi, & Telang, 2011, p.15037). Dysregulation of this system leads to 'loss of control'. The complex changes in D2R could partly explain the improper decision making of overweight individuals concerning food consumption.[3]

In this study, influences from a dopamine system imbalance could cause an endogeneity problem. This study looks at the effect of time preferences on weight (brain $\rightarrow$ BMI), but through the dopamine pathway weight also seems to influences the brain (brain $\leftarrow$ BMI). However, an increase in BMI would change the utility from food consumption $[u\ (eating)]$ and does not directly influence an individual's discount rate $[\theta(t)]$.

3.4.2 Obesity paradox

As discussed in the introduction, obesity is generally linked with all kinds of (chronic) medical conditions including diabetes, cancer, cardiovascular diseases and premature death. But to put this subject into perspective, during the last 15 years a significant number of studies showed that obesity may give a survival advantage; the so-called 'obesity paradox'. This paradox suggest that "despite the adverse effects that obesity has on the risk factors associated with cardiovascular diseases and many other chronic diseases, patients with cardiovascular diseases and overweight or obesity often have a better prognosis than leaner patients (underweight as well as patients with a 'normal' BMI) with similar diagnoses" (Lavie, De Schutter & Milani, 2015, p.1).

Not only do obese individuals have a survival advantage compared to leaner patients with similar diagnoses, a recently conducted study related to abovementioned phenomenon shows that 'overweight is associated with significant lower all-cause mortality' (Flegal, Kit, Orpana & Gaubard, 2013, p.79). In other words: individuals who are too heavy actually live longer than their healthy-weight counterparts.[4] Another recent study shows that overweight individuals are at less risk of dementia (18-29% lower dementia risk compared to individuals with a healthy weight) (Qizilbash et al., 2015).

These findings are interesting but hard to explain. Considering the obesity paradox, the researchers indicate that some of the potential reasons could be the greater metabolic reserve of obese individuals or better nutritional status (Schmidt & Slahudeen, 2007), increased muscle mass and muscular strength, lower prevalence of smoking (La Vie et al., 2015) and the younger age of the obese population (Wu et al., 2010). But some researchers suggest the abovementioned is simply the result of a selection bias in the studies demonstrating this phenomenon (Banack & Kaufman, 2013). Others criticize the use of BMI as a measure of adiposity; a higher BMI could also indicate a greater muscle mass which is associated with higher fitness and thus a more favorable health status (Kragelund & Omland, 2005). As regard to the explanation why overweight individuals are at less risk of dementia, researchers are still operating in the dark.

[3] It is to mention that brain functionality changes back to its natural state once obese individuals reach a healthy weight.
[4] However, severe obesity is still associated with higher mortality risk.

4. Methodology

For this study, data from the LISS panel will be used, collected by CentER (Tilburg University, the Netherlands). The LISS panel – Longitudinal Internet Studies for Social Sciences – contains a representative sample of the Dutch population who regularly fill out online surveys voluntarily in order to contribute to science projects. In May 2014 a survey was conducted (commissioned by H. Koç and H. van Kippersluis) among 3527 Dutch individuals containing questions about food choice, health knowledge and health valuation. This survey was set up as a Discrete Choice Experiment and conducted in two phases. Phase 1 focused on the trade-offs respondents would make between different kind of meals varying in price, time, taste and health attributes. The second phase contained additional questions regarding health knowledge and health valuation. For this study only phase 2 is used. More specific, the questions regarding time preference, health valuation, health knowledge, food knowledge and food choice will be used.

Additional to abovementioned survey, use is made of the background variables gender, age, household income per household member and education, obtained from the background variables survey of May 2015 as well as the LISS Core Study – Health (November, December 2013) to acquire information about height and weight (BMI) of the respondents. After merging the three different datasets, 2358 participants responded to all three questionnaires. Even though multiple datasets had to be merged, the used dataset still has a significant number of respondents, contains a representative sample of the Dutch population and a variation of applicable variables to choose from.

Some respondents did not answer the questions related to their household income [N=209] or education [N=6], therefore they are deleted from the dataset. Also individuals with an unsound height or weight are eliminated [N=5]. A significant number of participants did not seem to understand the time preference questions, so unreasonable answers also have to be removed from the dataset. But before eliminating respondents, first a decision should be made on which time preference variable to use. The data contains three different time preference questions, all framed differently. The first variable contains information about health-related time preferences, the second concerns money-related time preferences and the last variable is a statement to which the respondent could agree or disagree. The three different variables are framed as follows.

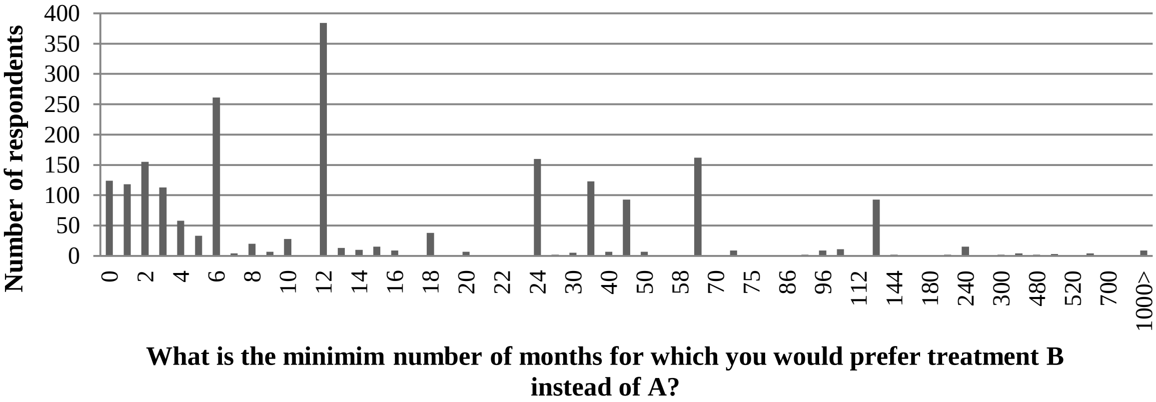
Time preference 1, health (months) **|** Participants were asked to imagine the following situation:
You have some difficulty with your daily activities (e.g. work, housework and other activities), and you have a little pain or experience some discomfort. You have no problems walking or with washing and dressing, and you are not depressed or anxious.

There are two treatments available. Treatment A ensures that you are completely healthy again for a period of 12 months, and has direct effect. Treatment B ensures that you are completely healthy again for a period of X months, but has effect in two years.

What is the minimum number of months X for which you would choose Treatment B instead of Treatment A?

As shown in Figure 1, most participants (18%) answered 12 months, followed by 6 months (12%), 24 months (7,6%) and 60 months (7,5%). The lowest amount of months answered was 0 (5,7%). Nine individuals answered 1000 months or more (the highest 10 trillion). It seems likely that participants giving answers which appear to be unreasonable (less than 10 months [N=893] or 1000 months or more [N=9]) did not understand the question. It could be argued that therefore they should be eliminated from the dataset (42% of the sample). I chose to include participants who responded to this question with 10 months or more, since it might be possible that individuals also experience some sort of utility while looking forward to an event and therefore accept a healthy period of less than the initial given 12 months.

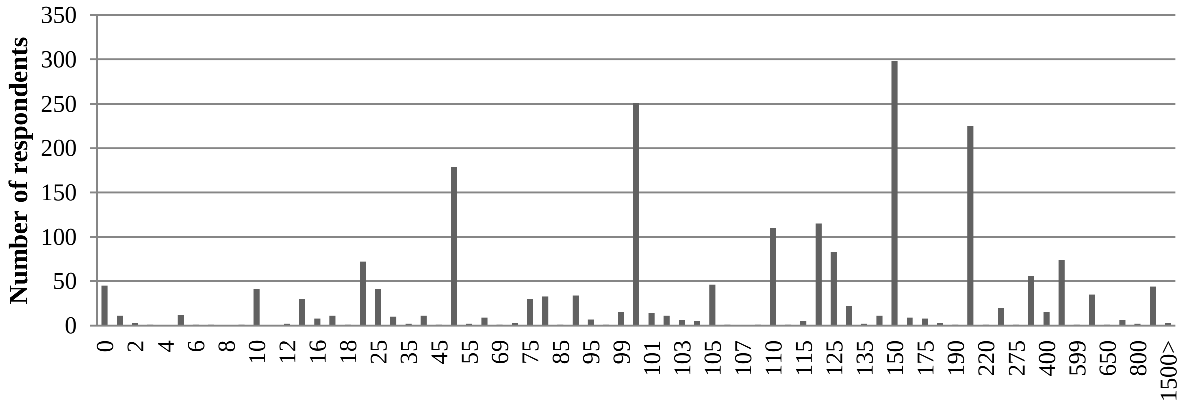
Figure 1: Health-related time preference



Time preference 2, money (euros) **|** Participants were asked to imagine the following situation:
If offered € 100,- now or € X,- in 6 months, what would be the smallest amount of money (X Euro) you would accept rather than the immediately available € 100,-?

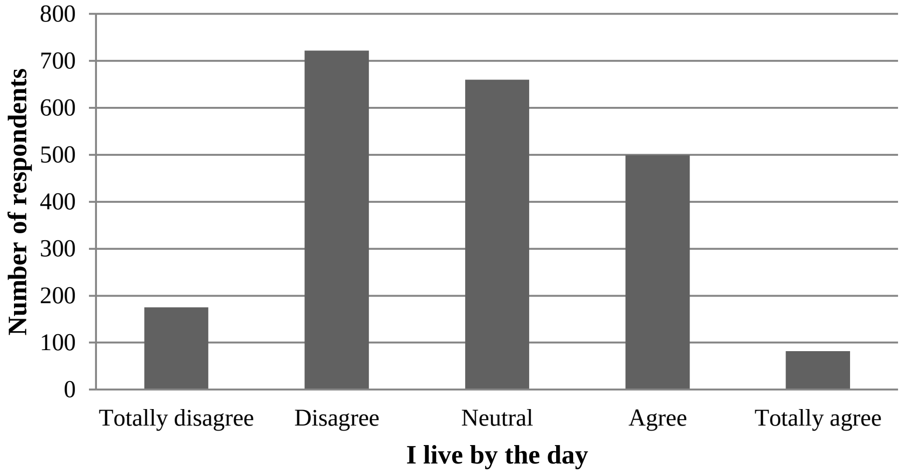
The average amount participants accept rather than the immediately available 100 euros is 4883 euros, with 0 euros being the lowest and 10 million being the highest. As Figure 2 shows, most participants (14%) answered €150, followed by €100 (12%), €200 (11%) and €50 (8%). 28% of the participants gave an answer of less than 100 euros. It seems likely that they did not understand the question and therefore should be eliminated from the dataset when including this variable.

Figure 2: Money-related time preference



Time preference 3, statement (ordinal, 5 points scale) **|** To the statement 'Nowadays, a person has to live pretty much for today and let tomorrow take care of itself.', respondents could answer totally disagree (8%), disagree (34%), neutral (31%), agree (23%) or totally agree (4%). A visual representation of these results is shown in Figure 3. This statement is very easy to understand for participants and can be seen as an indicator of the individual's time preference – totally agreeing hints towards a high discount rate (impatience).

Figure 3: Time preference - statement



A large number of respondents gave answers which appear to be unreasonable, but a high correlation between the three abovementioned variables would indicate at least some sort of understanding of the matter. Spearman's correlation coefficients were computed to assess the relationship between the three variables and a very low to almost no correlation was found (ρ = 0.2182*** for the health- and money-related time preference variable; ρ = –0.0442** for the health-related time preference and statement variable; ρ = –0.0649*** for the money-related time preference and statement variable).

Most papers concerned with time preference studies use ‘money now versus money later’ comparisons or tests. But ‘[a] person may discount the future heavily when it comes to one thing [e.g. health status], and yet not discount it when it comes to another [e.g. money]’ (Zhang & Rashad, 2008). The low correlation coefficients above show that there are indeed different kinds of impatience. Since this study focusses on health-oriented time preferences, it makes more sense to actually use a comparison regarding health trade-offs instead of money preferences. However, due to the high number of unreasonable answers of the health-related time preference variable (N=902), the statement variable (time preference 3) will be used as leading indicator.

After deciding on the leading time preference variable, a total of 220 respondents are eliminated from the dataset due to incomplete answers to the questions regarding income and education or unsound BMI outcomes. Leaving a sample of 2138 individuals for the final analysis (including all the participants giving answers which appeared to be unreasonable for the variables ‘time preference 1; health’ and ‘time preference 2; money’). I refer to the remaining participants as *regression sample 1*. For comparability, another sample is composed to be able to incorporate the health-related preference variable: *regression sample 2,* including 1236 individuals.[5] In this sample, 902 respondents from regression sample 1 are deleted due to unsound answers concerning the ‘time preference 1; health’ variable (participants answering less than 10 months [N=893] and 1000 or more months [N=9] were eliminated from the dataset).

Summary statistics of regression sample 1 are presented in Table 1. It shows that the non-overweight individuals in the sample are indeed more patient than the overweight population: they are willing to wait on average 7 months more for the same health-related outcome. The overweight individuals also indicate to live more by the day, but the difference is not very pronounced. Compared to the healthy weight individuals, the overweight respondents display a higher health valuation, but slightly lower health and food knowledge, and a lower education level. It is also to mention that the overweight sample is on average a bit older and contains fewer women than the non-overweight sample.

[5] Spearman’s correlation coefficients for regression sample 2: ρ = 0.4895*** for the health- and money-related time preference variable; ρ = –0.0632** for the health-related time preference and statement variable; ρ = –0.0693** for the money-related time preference and statement variable.

Table 1: Summary statistics of sample 1 (N = 2138)

Variable	Definition	Non-Overweight N = 1039	Overweight N = 1099
BMI	Weight (kilograms) divided by height (meters) squared.	22.421***	28.841
Time preference; health[1]	Variable indicating health-related time preference (months).	50.679*	43.317
Time preference; statement	Ordinal variable indicating to what extent the respondent lives by the day (1 = totally disagree; 5 = totally agree).	2.772*	2.843
Health valuation	Ordinal variable indicating the agreement to the statement of the importance of good health (1 = totally disagree; 5 = totally agree).	3.864***	4.069
Health knowledge	Ordinal variable indicating self-reported knowledge about health matters (1 = very low; 5 = very good).	3.462**	3.400
Food knowledge	Variable indicating the score regarding food knowledge statements.	-1.263*	-1.489
Food choice; soft drinks	Ordinal variable indicating the frequency of soft drink consumption (1 = never; 6 = every day).	2.584	2.778
Food choice; take-out	Ordinal variable indicating the frequency of a take-out meal as dinner option (1 = never; 6 = every day).	1.701	1.680
Education	Level of education in CBS categories.	3.684***	3.417
Income	Monthly household income per household member in euros (x1000).	1.322	1.311
Age	Age of the respondent (years).	51.370***	57.238
Gender	Binary variable that equals 1 if respondent is female.	0.573***	0.457

Difference between the overweight and the non-overweight for the given variable is statistically significant at the 1%-level (***), 5%-level (**) and 10%-level (*).
[1]: For regression sample 2 [N=1236].

Each of the remaining variables and control variables will be clarified and discussed in more detail below. The measurement scale of each variable is displayed within brackets. Additional descriptive statistics can be viewed in Appendix B.

BMI (continuous) **|** The outcome variable of this research is Body Mass Index (BMI). BMI is calculated with the formula $\frac{\text{weight (kg)}}{\text{length (m)}^2}$. This study uses the following categorization of BMI:

Classification	**BMI**
Underweight	<18,5
Normal weight	18,5 - 24,9
Overweight	25 - 29,9
Obese	≥ 30

Of the 2138 participants,1% are underweight, 48% have a normal weight, 37% are overweight and 14% are obese. This is comparable to the trend of the Dutch population, 48% of the Dutch population is overweight or obese according to a study of the RIVM (2014).

Health valuation (ordinal, 5 points scale) **|** To the statement 'There is nothing more important than good health', participants could answer totally agree, agree, neutral, disagree or totally disagree. It is important to know how the respondents value their health, for the level of valuation will most likely influence the manner in which they take care of themselves (e.g. healthy lifestyle).

Health knowledge (ordinal, 5 points scale) **|** To the question 'How would you rate your knowledge about health matters?', participants could answer very good, good, intermediate, low and very low. The self-assessed level of health knowledge will most likely have consequences for the health-related choices the individual makes.

Food knowledge (continuous) **|** Participants had to indicate whether they think several statements about food and health are 'true' or 'false'. Of these 12 statements, I conducted an overall score which increases by 1 if they got the answer right and decreases by 1 if they had it wrong or answered 'I don't know', as both answers indicate a shortcoming of food-related knowledge. Therefore, the highest score possible is 12, the lowest possible score is -12.

This question is relevant due to the fact that food knowledge will influence the food choices the respondents make. If a person is unaware that experts recommend eating many different types of vegetables or that the intake of excessive sodium can lead to cardiovascular disease, he or she will also not be able to act upon it.

The statements are:

1. Depending on age and physical activity level, experts recommend that an adult male should consume around 2500 calories, and an adult female should consume around 2000 calories, per day. (True)
2. According to experts around 30% of the calories in a day should come from saturated fat. (False)
3. For a healthy adult it is recommended to limit sodium intake at dinner to at most 1500 mg. (False)
4. There are health benefits of limiting those foods which contain high levels of added sugar such as soft drinks, cordial and biscuits. (True)
5. Experts advise to eat a variety of vegetables, especially dark green, red and orange vegetables. (True)
6. Meat, chicken, fish and eggs should make up the largest part of our diet. (False)
7. Choosing wholemeal bread provides no health benefits. (False)
8. A high intake of saturated fat can protect against cardiovascular diseases.(False)
9. Even in the absence of overweight, poor diet is associated with cardiovascular disease, hypertension, and type 2 diabetes. (True)
10. Sodium is a form of sugar. (False)
11. Consumption of fruits and vegetables is associated with reduced risk of many chronic diseases. (True)

12. Overconsumption of sodium can lead to hypertension and cardiovascular diseases. (True)

Food choice 1 (ordinal) **|** To the question 'How often do you drink soft drinks and energy drinks?', participants could choose between the options 'every day', '5-6 times a week', '3-4 times a week', '1-2 times a week', 'less than once a week' and 'never'. It is generally known that soft drinks and especially energy drinks are not a healthy choice, due to the sugars, calories and caffeine they contain. Consuming these drinks never of less than once a week is preferred to the other options.

Food choice 2 (ordinal) **|** To the question 'How often do you choose the option 'take out or delivery meal' for dinner?', participants could choose between the options 'every day', '5-6 times a week', '3-4 times a week', '1-2 times a week', 'less than once a week' and 'never'. Usually, a take-out or delivery meal does not mean a salad or a load of vegetables with some whole-grain rice. According to Just Eat (2013), pizza, shoarma and snacks are the most popular delivery meals and, in general, take-out meals contain more added salt, sugar and fats than freshly home-made meals. It is safe to conclude that the options '1-2 times a week' and above are not the most healthy food choice to make.

Education (ordinal) **|** Participants were asked to indicate their level of education in CBS (Statistics Netherlands) categories; 1: primary school, 2: vmbo (intermediate secondary education), 3: havo/vwo (higher secondary education), 4: mbo (intermediate vocal education), 5: hbo (higher vocational education) and 6: wo (university).

Income (continuous) **|** I used the variables 'household income' divided by the variable 'number of household members' to calculate the household income per household member, for I am interested in the amount of money each household member is able to spend. A relatively high household income does not tell the whole story if the family consists of 12 members. This new created variable is a better indicator but still not perfect, e.g. the family composition and age of the family members also matter. To be able to say more about the effect of income, I divided this variable by 1000. Income-squared is also included in the analysis, due to the inverted U-shaped relationship of income and BMI (see Section 2).

Age (continuous) **|** The age of the participant in years. Since a non-linear relation is to be expected, age-squared is also included in the analysis. This will control the analysis for the phenomenon that the older an individual, the higher his or her BMI is allowed to be (Halls, 2015).

Gender (binary) **|** In the survey, respondents could answer 1 for male, 2 for female. In order to be able to use this variable in the analysis, I rewrote this variable as a dummy (0 = male; 1 = female).

Using the data from the LISS panel, I estimate the following specification using STATA while controlling for heteroscedasticity.

Regression 1 using sample 1 (N=2138):

$$BMI = \alpha + \beta_1(time\ preference) + \beta_2(health\ valuation) + \beta_3\ (health\ knowledge) + \beta_4(food\ knowledge) + \beta_5(food\ choice\ 1) + \beta_6(food\ choice\ 2) + \beta_7(education) + \beta_8(income) + \beta_9(income^2) + \beta_{10}(age) + \beta_{11}(age^2) + \beta_{12}(gender) + \mu$$

Regression 2 using sample 2 (N=1236):

$$BMI = \alpha + \beta_1(time\ preference\ 1) + \beta_2(time\ preference\ 2) + \beta_3(health\ valuation) + \beta_4\ (health\ knowledge) + \beta_5(food\ knowledge) + \beta_6(food\ choice\ 1) + \beta_7(food\ choice\ 2) + \beta_8(education) + \beta_9(income) + \beta_{10}(income^2) + \beta_{11}(age) + \beta_{12}(age^2) + \beta_{13}(gender) + \mu$$

*Time preference 1: health related
*Time preference 2: statement

5. Results

Table 2 presents the sample regression results of the effect of the independent variables on body mass index for both samples. For alternative models of this regression, I would like to refer to Appendix C, Table 4 and 5. The findings show different results for both samples. The results of sample 1 show that a higher health valuation is positively related to BMI, which indicates that individuals who value their health more also have a higher BMI. This is quite counterintuitive but might be explained in a way that individuals with a relatively high BMI also have more health issues which raises their awareness of the importance of good health. Next to health valuation, the food choice of a take-out or delivery meal as dinner option also has a positive effect on BMI. Thus the more often the individual indicates to eat a take-out or delivery meal, the higher his or her BMI. This makes sense, since this dinner option is usually not the most healthy option to go for.

Education is negatively associated with BMI, which indicates that a higher education level implies a lower BMI and vice versa. This result is consistent with the literature, showing well established evidence that education levels are strongly linked to health, directly as well as indirectly (Feinstein, Sabates, Anderson, Sorhaindo & Hammond, 2006; Grossman, 2006). Also income in negatively related to BMI. This corresponds with the literature showing that the higher an individual's income, the higher his or her demand for health (Kenkel, 1991; Lakdawalla & Philipson, 2009). Gender is negatively associated with BMI, which indicates that females have a lower BMI compared to males. This might be due to the lower number of overweight women in the sample (see Table 1) or the fact that women in general are more concerned with their weight and appearance (Kashubeck-West, Mintz & Weigold, 2005). On the other hand, age is positively related to BMI – someone with a relatively high age is more likely to be overweight. This finding also corresponds with the literature showing a strong correlation between age and BMI – especially body fat mass (Meeuwen, Horgan, Elia, 2010).

Concerning regression sample 2, it shows that all the variables still have the same sign as sample 1, though the values and significance differ. This might indicate that eliminating almost half of the data does not lead to immense problems. We see a significant positive relationship between the time preference statement and BMI. This indicates that a higher discount rate (being relatively more impatient) implies a higher BMI. It is difficult to explain why we see a statistically significant effect of time preference on BMI when adjusting the sample and adding another time preference variable. It is possible that people who had troubles with the health-related time preference question also struggled with the time preference statement, even though the statement question was relatively easy to understand. Next to this, also food knowledge has a significant influence on BMI. The negative sign indicates that better food knowledge entails to a lower BMI. This makes sense, considering food knowledge will most likely influence the food choices the respondents make into a healthier direction. Also soft- and energy drink consumption shows to have a weakly significant positive effect on BMI. The effects of the take-out meal as a dinner option, education, income and age remain roughly the same. The variables health valuation and gender are not statistically significantly related to BMI anymore in this sample.

Table 2: The effect of the dependent variables on body mass index.

	Sample 1 R^2=0.0661	Sample 2 R^2=0.0768
Time preference; health related	-	-0.002 (0.002)
Time preference; statement	0.140 (0.097)	0.243* (0.125)
Health valuation	0.21 ** (0.105)	0.197 (0.128)
Health knowledge	0.002 (0.137)	0.211 (0.191)
Food knowledge	-0.027 (0.031)	-0.080* (0.042)
Food choice; soft drinks	0.078 (0.059)	0.141* (0.080)
Food choice; take-out	0.282* (0.147)	0.341* (0.185)
Education	-0.184*** (0.070)	-0.227** (0.089)
Income	-0.858*** (0.252)	-0.798*** (0.282)
Income^2	0.176*** (0.039)	0.164*** (0.036)
Age	0.254*** (0.029)	0.288 *** (0.038)
Age^2	-0.002*** (0.000)	-0.002*** (0.000)
Gender	-0.308* (0.185)	-0.022 (0.247)

Note: Sample 1: N=2138; sample 2: N=1236. Estimated coefficients in an OLS regression. Value of Standard Deviation in parentheses. Significance levels at 1% (***), 5% (**) and 10% (*).

In order to further examine the relationship between time preference and being overweight, a logit model is used testing the same independent variables as the previous regression, yet using a dependent variable which equals 1 if the participant is overweight (BMI of 25 or more) and 0 otherwise. It is possible that a BMI of 25 is an alarming number to individuals – in the sense of 'being officially overweight' – and they really try to stay under that value. This could also imply large differences in behavior of individuals with a BMI of 24.5 and 25.5. To be able to see whether this is the case, Figure 9 and 10 in Appendix D show the distribution of the BMI variable across the different BMI values. For sample 1, a peak is noticeable in the frequency just before the BMI value of 25, while this effect for sample 2 is apparent just after a BMI value of 25. The results of the logit regression are presented in Table 3. It shows that the results for both samples approximately align. The findings of sample 1 show that a higher discount rate – e.g. agreeing with the statement of living by the day – gives a higher probability of being overweight; each higher level of agreeing to the statement increases the probability of being overweight by 1.9 percentage points. It is interesting to see that the time preference variable in this logit model is weakly significant (p-value = 0.072), while the abovementioned OLS regression of the same sample did not show a significant result. Whereas the opposite effect is apparent for sample 2; the time preference statement is not significant anymore in this model while it was significant in the previous model.

The variables health valuation and food knowledge still align with the previous regression. A higher health valuation in sample 1 still gives a higher probability on being overweight (2.9 percentage points per higher valuation), although this conclusion cannot be drawn from sample 2. The variable food knowledge is still negatively related to being overweight for sample 2, while there is no significant effect concerning sample 1. It is also noteworthy that, for both samples, consuming soft-drinks in this model has a weakly significant effect on being overweight – consuming more soft-drinks increases the probability of being overweight by 1.2 and 1.9 percentage points respectively, while having take-out as a dinner option does not align with the findings of previous model anymore.

The control variables in the two samples still have the same signs as in previous model. For both samples, an older age gives a higher probability on having a BMI of 25 or more (3.2 and 3.5 percentage points increase respectively per year). Education level, income and gender have a negative effect on the probability of being overweight, in other words: an individual with a higher education level has a lower probability of being overweight (-1.8 and -2.2 percentage points respectively); an individual with a higher income has a lower probability of being overweight (-0.1 percentage point for de variable income itself. But as income increases this effect is lessened: 0.02 percentage points for $income^{2)}$, and being female decreases the probability of being overweight by 10.4 and 8.7 percentage points respectively, ceteris paribus.

Table 3: The effect of the dependent variables on being overweight or not.

	Sample 1 R^2=0.0607		Sample 2 R^2=0.0638	
Variable	Coefficient	Marginal effects	Coefficient	Marginal effects
Time preference; health related	-	-	-0.001 (0.000)	-0.0001 (0.000)
Time preference; statement	0.082* (0.046)	0.019* (0.011)	0.101 (0.061)	0.023 (0.014)
Health valuation	0.125** (0.051)	0.029** (0.012)	0.039 (0.067)	0.009 (0.015)
Health knowledge	-0.029 (0.072)	-0.007 (0.017)	0.055 (0.097)	0.013 (0.022)
Food knowledge	-0.016 (0.015)	-0.004 (0.003)	-0.037* (0.021)	-0.008* (0.005)
Food choice; soft drinks	0.053* (0.030)	0.012* (0.007)	0.084** (0.042)	0.019** (0.009)
Food choice; take-out	0.093 (0.078)	0.021 (0.018)	0.096 (0.099)	0.022 (0.023)
Education	-0.078** (0.034)	-0.018** (0.008)	-0.097** (0.045)	-0.022** (0.010)
Income	-0.419** (0.183)	-0.096** (0.042)	-0.472* (0.249)	-0.108* (0.057)
$Income^2$	0.088** (0.044)	0.020** (0.010)	0.102* (0.058)	0.023* (0.013)
Age	0.140*** (0.003)	0.032*** (0.004)	0.155*** (0.023)	0.035*** (0.005)
Age^2	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)
Gender	-0.452*** (0.094)	-0.104*** (0.021)	-0.382*** (0.124)	-0.087*** (0.028)

Note: Estimated coefficients and margins in a logit regression. Value of Standard Deviation in parentheses. Significance levels at 1% (***), 5% (**) and 10% (*).

6. Discussion

Despite numerous national, local and individual efforts, the number of people struggling with overweight and obesity in the Netherlands continues to grow – mainly due to an increase in daily caloric intake. In this study, I tried to explain this recent obesity epidemic by a combination of time preferences and technological innovation. I proposed an explanation based on the Grossman Model of Health Capital, arguing that technological change together with individual time preferences could have caused this rise in caloric intake. The decrease in food prices and the decline in the time costs of food preparation in combination with the preference of immediate utility over delayed utility might explain why more and more individuals become overweight. Data shows all individuals are affected by industrial development, but not all of these individuals have severe weight gain and therefore become overweight – e.g. more than half of the Dutch population still has a healthy weight. Therefore, something else besides technological change should be a factor as well. Various researchers have studied the topic of obesity and time preference in recent years using mainly samples from the United Kingdom and the United States, but their studies show ambiguous results. Therefore, this study examined the possible relationship between obesity and time preferences for the Dutch population. The aim of this study was to see to what extent overweight individuals and individuals with a healthy weight display different rates of time-discounting.

Two different samples (N=2138 and N=1236) were used with different measures of time preferences to determine whether BMI is related to time discounting. To the best of my knowledge, this is the first study with an all Dutch (adult) sample to demonstrate some sort of relationship between time preferences and obesity. The findings show that time preferences do have an influence on body mass index, but it all depends on which time preference measure and what kind of regression analysis is used. When using a simple to understand statement as indicator and a logit regression, I can conclude that a higher discount rate increases the probability of being overweight (having a BMI of 25 or higher). But this conclusion cannot be drawn from the OLS regression, using BMI as a continuous dependent variable. When including health-related time preference, we see the reverse. When including BMI as a continuous dependent variable, the time preference statement has a positive significant effect and therefore conclusions can be drawn regarding the influence of the discount rate. However, when using BMI as a binary dependent variable, the regression shows no significant effect for the two time preference variables. These results are interesting, but difficult to explain. But even though the p-values of the variables vary, it is reassuring that the sign of the effect is always the same.

There are some limitations to this study. Firstly, the survey was conducted in an uncontrolled environment and the high number of unreasonable answers regarding the time preference variable indicates that respondents had difficulties answering the questions. This might have implications for the other variables as well. Concerning the time preference variables, the data also shows that participants strongly anchor on the given value in the question. Secondly, even though the participants get paid for each completed questionnaire, they still self-select into the experiments (by agreeing to participate, they can also reject the request) and are aware of participating in a data pool. This might influence their behavior towards giving more socially acceptable answers and hereby not revealing their true self. Next to possibly giving different answers than intended, self-reporting measures do not always reveal true behavior which may give validity problems (Stone et al., 2000). More importantly, an increasing number of men and – especially – women lie about their weight, the *self-reported weight bias*, and overestimate their height (Shiely, Hayes, Perry & Kelleher, 2013). These together are the main variable of this study and this bias might have severe implications for the results. Third, this study used a very simple measure of time preference by solely depending on $\theta(t)$, therefore it is not possible to distinguish between different kinds of impatience. Individuals might disagree with the statement 'I live by the day', but still be very focused on the near future.

This study used time preferences as indicator for impatience. As briefly discussed, other alternative ways to model impulsive behavior may also be useful to study this subject – e.g. time inconsistency (Strotz, 1956) or the dual-self model of Thaler & Shefrin (1981). Future studies should focus in more detail on the distinguishable differences between time preferences and time-inconsistency, and whether the displayed behavior can be gathered into one of these frameworks. A possible alternative hypothesis could be that overweight and obese individuals show a higher degree of time-inconsistency than individuals with a healthy weight. Next to a very simple measure of time preference, this study also used a simplified model of lifetime utility. Future research should focus on more extensive models as well as alternative models, e.g. utility functions accounting for visceral influences (Loewenstein, 1996, 2000); anticipation (Caplin & Leahy, 2001); the projection bias (Loewenstein, O'Donoghue & Rabin, 2003); or reference-dependent utility (Köszegi & Rabin, 2006).

Due to a numerous amount of factors involved regarding the obesity epidemic (e.g. economical, behavioral, neurological and psychological), it is troublesome to study only one particular factor, namely time preferences, and draw solid conclusions of it. Depending on the time preference variable and regression analysis used, overweight and obese individuals do show a higher rate of discounting than individuals with a healthy weight. Hereto the null-hypothesis of this study can be cautiously rejected. However, univocal conclusions cannot be drawn from this study and further research is needed to be able to draw more solid conclusions. This study shows that time preferences do have an influence on BMI, but it depends strongly on the indicator for time preference, the sample and regression analysis used. Nevertheless, it is a strong attempt to improve the study of Nederkroon et al. (2006), while including the confounding factors education and income, using a larger Dutch sample and using multiple indicators for time preference.

Most papers studying the subject of time preference and health use a money-related type of discounting (especially the Iowa Gambling Task (Bechara, Damasio, Damasio & Anderson, 1994) is widely used) in order to draw health-related time preference conclusions. Findings of this study show that the three different measures of time preference indicators have a low to almost no correlation, which imply different kinds of impatience (as also shown by Zhang & Rashad (2008)). Therefore, I would strongly suggest to use health-related time preference indicators when studying health-related subjects. When using large-scale surveys, it might be useful to include an easy to understand statement regarding time discounting. Such a setting is less controlled and exact time preference indicators might be misinterpreted or misunderstand by the respondents. For that reason, a simple statement might be more reliable. Research shows that such a simple survey measure of impatience represents ‘a meaningful proxy for time preferences’ (Vischer et al., 2012, p.4). Their study provides a validation of using a qualitative, ultra-short survey measure as proxy for (im)patient behavior.

Current policy interventions aimed at fighting obesity are mainly focusing on educational programs promoting healthy diets and exercise. This study reveals that (unhealthy) food choices have a strong influence on BMI, which indicates that emphasizing healthy foods and good diets is indeed convenient. However, this study also reveals that impatience or self-control issues might play a role in becoming overweight or obese. Therefore, more attention should be paid to this impulsive behavior. Some say, increasing the costs of impulsive decisions through so-called ‘fat- and sugar taxes’ might be an important step to fight obesity (Lustig, Schmidt & Brindis, 2012; Nestle, 2013) – especially considering the significant effects of soft-drink consumption and take-out meals of this study. In turn, these taxes can cover the costs of obesity-related healthcare. Other researchers point out the drawbacks and unintended side-effects of such an intervention (Richards, Patterson & Tegene, 2007). However, these policy measures ignore important aspects related to the process of behavioral change, which is needed to successfully fight the obesity epidemic. Measures aimed at self-regulation or commitment mechanisms might be a more valuable addition to existing policy programs.

Appendix A

As stated, the data used in this study is too limited to distinguish between the time-preference and time-inconsistency frameworks. Even though the data used does not give me the ability to distinguish between the different frameworks presented, it is safe to say that if we were to reject time preferences, we automatically reject time-inconsistency as well. I will illustrate these indistinguishable differences using the two variables marked in this study as ‘time preference; health’ and ‘time preference; statement’. The variable ‘health valuation’ is added to this appendix to show that only differences in utility are not sufficient to explain the recent rise in obesity.

Time preference; health | To the question: ‘*What is the minimum number of months X for which you would choose Treatment B instead of Treatment A?’* rational but impatient individuals will answer a number of more than 12 months, just as irrational individuals with self-control issues will. So answers given to this question cannot help distinguishing between the two frameworks.

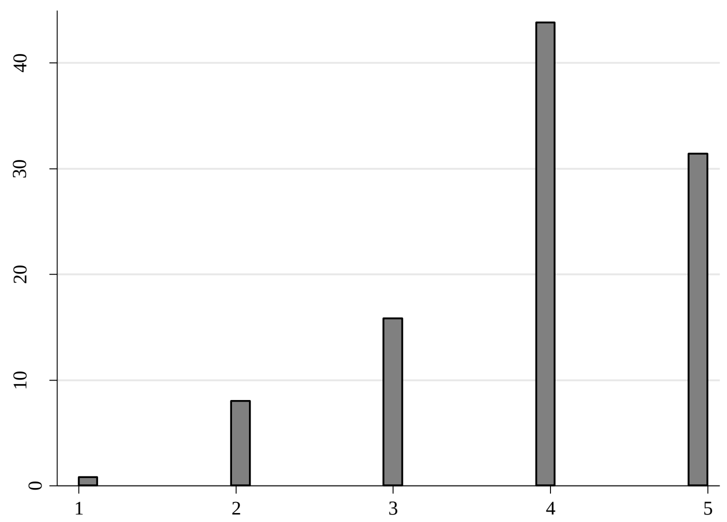
Time preference; statement | To the statement: ‘*Nowadays, a person has to live pretty much for today and let tomorrow take care of itself*’ a rational individual will most likely totally agree, while it is not clear what irrational individuals will answer – for they are irrational. It is possible that they also totally agree to this statement, but it can be just as well that they give a neutral answer. So also this variable cannot give a distinguishable difference between the two frameworks.

Health valuation | It can also be said that time preferences are not even an issue and only differences in utility derived from consuming food or health status cause obesity. Since the level of health valuation will most likely influence the way individuals think about consuming food and the health consequences that come with it, there is a significant relation between this statement and the variable ‘health valuation’, whereas there is no sensible relation between this statement and the time preference variables. But if obesity is solely caused by differences in utility, imagine the following situation: Imagine two individuals with a healthy weight, both enjoying the utility gain of the recent technological changes (Section 3.2) and both striving to maximize their utility. Person A has a rather low health valuation and derives a high utility from consuming a bag of chips - which he indeed does every day; person B has a relatively high health valuation and does not enjoy chips that much. They both know eating large amounts of chips is unhealthy, but still person A keeps eating it every day. Why? Because he likes chips so much (the high utility gain)? It is true that food gives immediate gratification (Cutler et al., 2003), but due to the diminishing marginal utility of consuming food this cannot be the reason he keeps eating chips every day – e.g. after a couple days/weeks the utility you derive from consuming that bag of chips declined remarkably and might be at the same level as person 2 gets from eating chips. Together with the health consequences that come with eating large amounts of unhealthy foods (and thus the lower utility of this person’s future health status, see also Section 3.3), this person is highly failing in maximizing his utility. Therefore, food indulgence cannot solely be explained by differences in utility. Discount functions are shown to have a significant influence, so the obesity epidemic should have something to do with $\theta(1)$.

Appendix B

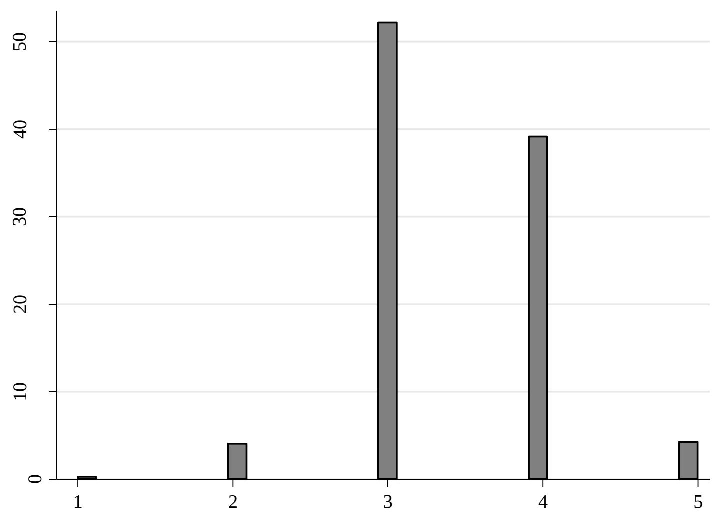
Descriptive statistics of regression sample 1 of the variables health valuation, health knowledge, food knowledge, food choice 1 (soft drinks) and food choice 2 (take out as dinner option). The y-axis scale is in percentages for all figures.

Figure 4: Health valuation
'There is nothing more important than good health'



Scale: 1 = totally disagree, 2 = disagree, 3 = neutral, 4 = agree; 5 = totally agree.

Figure 5: Health Knowledge
'How would you rate your knowledge about health matters?



Scale: 1 = very low; 2 = low; 3 = intermediate; 4 = good; 5 = very good.

Figure 6: Food knowledge

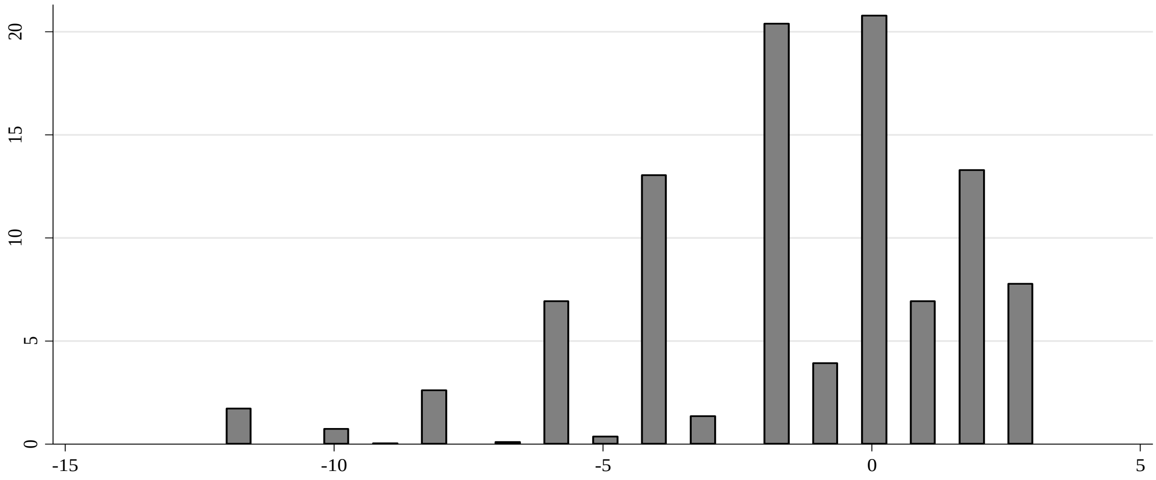


Figure 7: Food Choice 1

'How often do you drink soft- and energy drinks?'

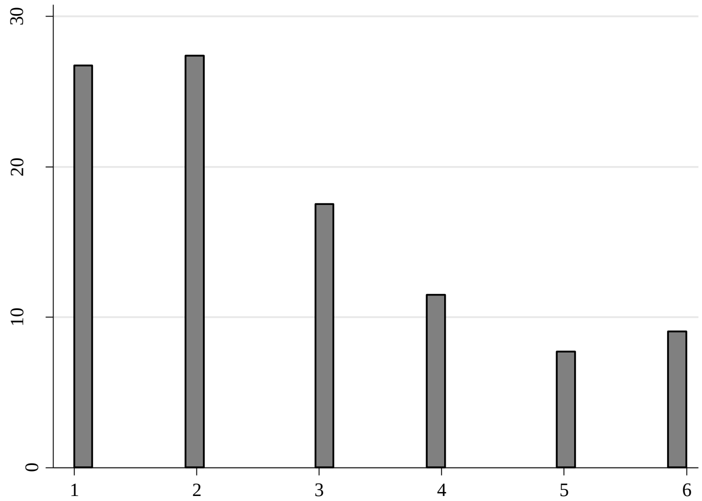
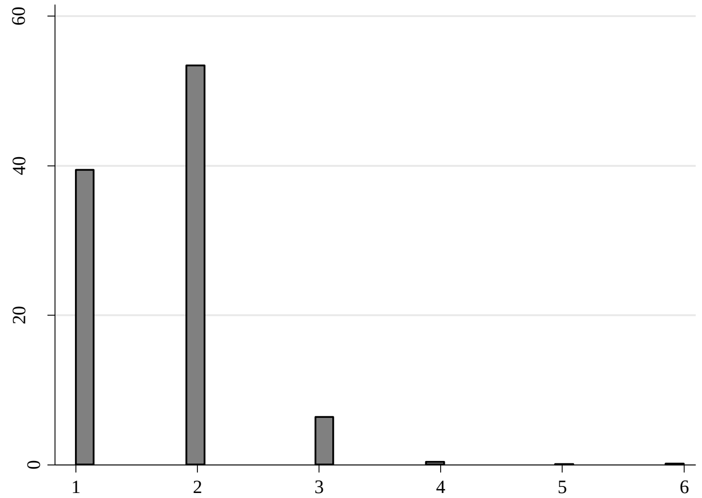


Figure 8: Food Choice 2

'How often do you have a take-out or delivery meal as dinner option?'



Scale for Figure 7 & 8: 1 = never; 2 = less than once a week; 3 = 1-2 times a week; 4 = 3-4 times a week; 5 = 5-6 times a week; 6 = every day.

Appendix C

Table 4 shows an overview of the different regression models. Model C is the preferred model and used in this study.

Table 4: The effect of time preference on body mass index, sample 1 (N = 2138)

	Model A $R^2 = 0.0613$	**Model B** $R^2 = 0.0642$	**Model C** $R^2 = 0.0661$
Time preference; statement	0.150 (0.097)	0.143 (0.091)	0.140 (0.097)
Education	-0.219*** (0.068)	-0.207*** (0.069)	-0.184*** (0.070)
Income	-0.833*** (0.250)	-0.861*** (0.252)	-0.858*** (0.252)
Income^2	0.170*** (0.039)	0.175*** (0.039)	0.175*** (0.039)
Age	0.256*** (0.028)	0.260*** (0.028)	0.254*** (0.029)
Age^2	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Gender	-0.409** (0.183)	-0.312* (0.185)	-0.308* (0.185)
Food knowledge		-0.025 (0.031)	-0.027 (0.031)
Food choice; soft drinks		0.082 (0.059)	0.078 (0.059)
Food choice; take-out		0.268* (0.147)	0.282* (0.147)
Health valuation			0.211** (0.105)
Health knowledge			0.002 (0.137)

Note: Estimated coefficients in an OLS regression. Value of Standard Deviation in parentheses. Significance levels at 1% (***), 5% (**) and 10% (*).

Table 5 shows the estimated coefficients of the different models including the health-related time preference variable and therefore using regression sample 2.

Table 5: The effect of time preference on body mass index, sample 2 (N = 1236)

	Model A $R^2 = 0.0660$	**Model B** $R^2 = 0.0742$	**Model C** $R^2 = 0.0768$
Time preference; health-related	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Time preference; statement	0.262** (0.125)	0.241 (0.125)	0.243* (0.125)
Education	-0.280*** (0.085)	-0.242*** (0.087)	-0.227** (0.089)
Income	-0.755*** (0.283)	-0.801*** (0.282)	-0.798*** (0.282)
$Income^2$	0.156*** (0.037)	0.164*** (0.037)	0.164*** (0.036)
Age	0.282*** (0.038)	0.289*** (0.037)	0.288*** (0.038)
Age^2	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Gender	-0.192 (0.240)	-0.019 (0.246)	-0.022 (0.247)
Food knowledge		-0.071* (0.042)	-0.080* (0.042)
Food choice; soft drinks		0.133* (0.080)	0.141* (0.080)
Food choice; take-out		0.325* (0.184)	0.341* (0.185)
Health valuation			0.197 (0.128)
Health knowledge			0.211 (0.191)

Note: Estimated coefficients in an OLS regression. Value of Standard Deviation in parentheses. Significance levels at 1% (***), 5% (**) and 10% (*).

Appendix D

Figure 9 and 10 show the distribution of the BMI variable across the different BMI values. For sample 1, a peak is noticeable in the frequency just before the BMI value of 25, while this effect for sample 2 is apparent just after this particular BMI value. For convenience, a black reference line is drawn at a BMI value of 25.

Figure 9: Distribution of BMI variable
Regression sample 1

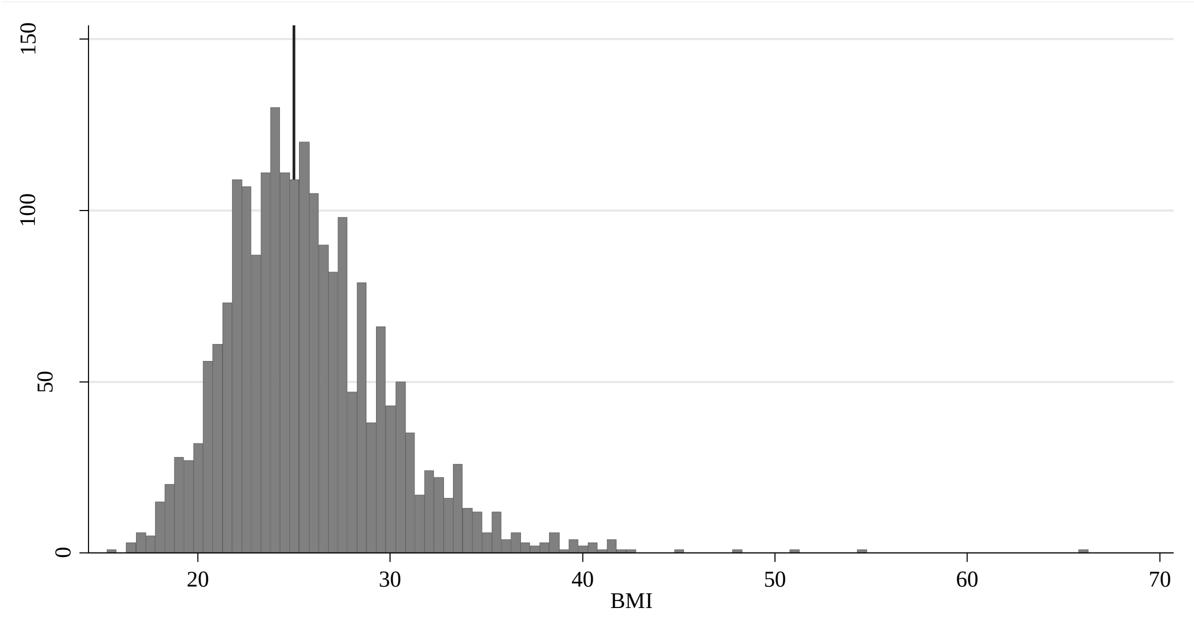
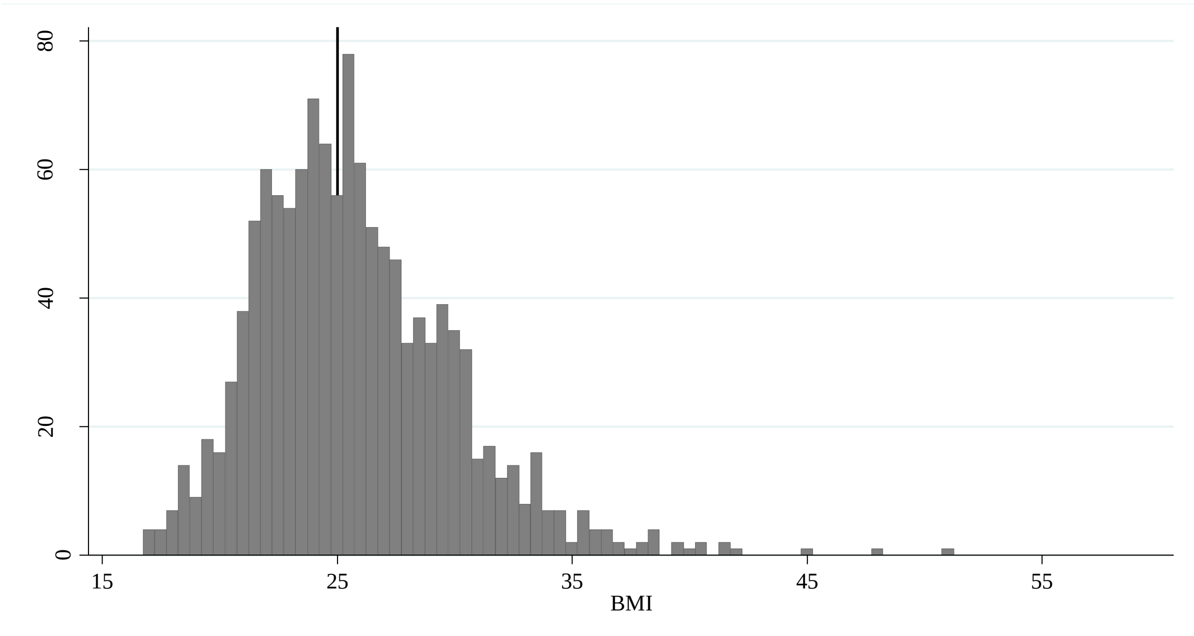


Figure 10: Distribution of BMI variable
Regression sample 2



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