Essays on consumer self-control and its interventions

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Essays on Consumer Self-Control and Its Interventions

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To Amma, Nana, and Vinay:
We did it.

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Essay 2 investigates how bariatric surgery impacts a form of self-control that involves trade-offs with the cost of time called delay discounting (DD), its temporal stability, and its domain differences for food and money. Two longitudinal studies show that obese people are more impatient for food (but not money) than lean individuals and that surgery reduces impatience. A third study with lean and obese BMIs eliminates alternative explanations to DD differences across reward domains.

Essay 3 proposes to study how the brain's ability to integrate value impacts self-control. Before and after noninvasive brain stimulations, OCD patients complete a set of economic experiments that gauge general executive function and their ability to create value and exert self-control. I contribute to neuroeconomics and psychiatry by showing how behavioral economics experiments can measure the efficacy of treatments beyond clinical measures and behavioral decision-making literature by exploring the impact of valuation on the ability to exert self-control.

FRANÇAIS

L'essai 1 mesure l'hétérogénéité des effets des étiquettes nutritionnelles sur le devant de l'emballage (FOP) sur les choix alimentaires dans des contextes d'épicerie réels. Je quantifie la façon dont l'efficacité des FOP varie en fonction des caractéristiques du panier, magasin et produit. Les FOP ont la réponse la plus forte des consommateurs qui achètent les produits les plus chers, qui sont probablement des consommateurs à revenu élevé, créant encore plus d'inégalités en termes de salubrité des choix alimentaires entre les consommateurs riches et pauvres. Les détaillants, avec leur assortiment et leurs choix de prix, ont un impact substantiel sur l'efficacité du FOP.

L'essai 2 étudie l'impact de la chirurgie bariatrique sur une forme de maîtrise de soi qui implique des compromis avec le coût du temps, sa stabilité temporelle et ses différences de domaine. Deux études longitudinales montrent que les personnes obèses sont plus impatientes de manger (mais pas d'argent) que les personnes maigres et que la chirurgie réduit l'impatience. Une troisième étude élimine les explications alternatives aux différences entre les domaines.

L'essai 3 propose d'étudier comment la capacité du cerveau à intégrer la valeur influe sur la maîtrise de soi. Avant et après les stimulations cérébrales non invasives, les patients de TOC effectuent une série d'expériences qui évaluent la fonction exécutive générale et leur capacité à créer de la valeur et à exercer une maîtrise de soi. Je peux montrer comment les expériences économiques peuvent mesurer l'efficacité des traitements cliniques et comment l'intégration de la valeur influe sur différents aspects de la maîtrise de soi.

EXTENDED ABSTRACT IN ENGLISH

Self-control governs day-to-day life, from financial decision-making to adherence to regulations, especially in this dissertation, dietary decision-making. In this dissertation, I explore how different interventions to promote self-control for healthier lifestyles in both marketing and medical practices promote self-control provide insights into the mechanisms and boundary conditions of self-control.

Essay 1 measures the heterogeneity in the effects of two pre-selected front-of-pack (FOP) nutrition labels on food product choices in real-life grocery shopping settings. Previous literature has measured the average impact of FOP labels but does not explain in what conditions these labels work better or worse. Using a data set of more than 1.1 million purchases resulting from over 200,000 labels placed in two food categories, I quantify how the effect of FOP labels varies with (1) consumer basket characteristics, (2) store characteristics, and (3) product characteristics. I find that FOP labels have the strongest response by consumers that buy the most expensive products, who are very likely the higher-income consumers, creating even more inequality in terms of the healthiness of food choices between rich and poor consumers. I also show evidence that retailers, with their assortment and pricing choices, have a substantial impact on the effectiveness of the FOP labels.

Essay 2 investigates how bariatric surgery impacts a form of self-control that involves trade-offs with the cost of time (intertemporal choice), its temporal stability, and its domain differences for food and money. In two longitudinal studies, I ask obese weight loss surgery patients before and after surgery to make financial and dietary decisions to pick between smaller rewards, either food or money, offered sooner and larger rewards, again, either food or money, offered later. In money decisions, obese patients consistently act like lean counterparts in that they are willing to wait for larger

rewards. However, in identical decisions involving food, before surgery, obese patients are much less inclined to wait for larger rewards than lean individuals compared to comparable financial choices. After surgery, these differences disappear, and obese patient participants are much more willing to wait for food rewards. I eliminate alternative explanations to intertemporal choice differences across reward domains. Participants of lean or obese BMIs again make similar decisions with various food types. Participants discount less for monetary rewards than any food rewards, independent of weight status, and discount the value of future food rewards than for money, regardless of the type of food choice.

Essay 3 proposes to explore how a direct intervention on the brain's ability to integrate value impacts self-control and economic decision-making. Psychiatric disorders and their targeted treatments provide natural manipulations of deficits and changes in decision-making. Before and after a course of targeted, noninvasive brain stimulation, obsessive-compulsive disorder patients will complete a set of economic experiments that gauge their ability to create value, their ability to exert self-control by making trade-offs between goals and their ability to wait for future rewards, and their overall executive function abilities. I contribute to both neuroeconomics and psychiatry research by showing how behavioral economics experiments can measure the efficacy of clinical treatments beyond clinical experiments, especially for a self-control disorder like OCD.

RÉSUMÉ ÉTENDU EN FRANÇAIS

La maîtrise de soi régit la vie quotidienne, depuis la prise de décision financière, le respect des réglementations et la prise de décision alimentaire. Grâce à la fois au marketing et aux pratiques médicales, les interventions visant à promouvoir la maîtrise de soi pour des modes de vie plus sains et plus avantageux donnent un aperçu de ses mécanismes et des conditions limites nécessaires pour réussir l'effort de maîtrise de soi. Dans cette thèse, j'explore les sources de l'efficacité d'interventions allant du médical au managérial pour lutter contre les troubles de la maîtrise de soi comme l'obésité et le trouble obsessionnel-compulsif (TOC) afin d'éclairer les mécanismes sous-jacents à l'utilisation de la maîtrise de soi.

L'essai 1 mesure l'hétérogénéité des effets de deux étiquettes nutritionnelles présélectionnées sur le devant de l'emballage (FOP) sur les choix de produits alimentaires dans des contextes d'épicerie réels. La littérature précédente a mesuré l'impact moyen des FOP mais n'explique pas dans quelles conditions ces étiquettes fonctionnent mieux ou moins bien. En utilisant un ensemble de données de plus de 1,1 million d'achats résultant de plus de 200000 FOP placés dans deux catégories d'aliments, je quantifie comment l'effet des étiquettes FOP varie avec (1) les caractéristiques du panier de consommation, (2) les caractéristiques du magasin et (3) les caractéristiques du produit. Je trouve que les étiquettes FOP ont la réponse la plus forte des consommateurs qui achètent les produits les plus chers, qui sont très probablement les consommateurs à revenu élevé, créant encore plus d'inégalités en termes de salubrité des choix alimentaires entre les consommateurs riches et pauvres. Je montre également que les détaillants, avec leur assortiment et leurs choix de prix, ont un impact substantiel sur l'efficacité des étiquettes FOP.

L'essai 2 étudie l'impact de la chirurgie bariatrique sur une forme de maîtrise de soi qui implique des compromis avec le coût du temps appelé actualisation des délais (DD), sa stabilité temporelle et ses différences de domaine pour la nourriture et l'argent. DD for money a été identifié comme une mesure potentielle de l'impulsivité dans les dépendances, y compris les troubles de l'alimentation et l'obésité. La littérature actuelle fournit peu de preuves d'un effet causal de la DD par le poids corporel. La DD n'a pas été étudiée dans l'obésité morbide, et il n'est pas clair si l'impulsivité liée à l'obésité est spécifique à un domaine. Je demande aux patients obèses chirurgicaux de perte de poids avant et après la chirurgie de choisir entre des récompenses plus petites, soit de la nourriture, soit de l'argent, offertes tôt et des récompenses plus importantes, encore une fois, de la nourriture ou de l'argent, offertes plus tard. Dans les décisions financières, les patients obèses agissent systématiquement de la même manière que leurs homologues maigres en ce sens qu'ils sont prêts à attendre des récompenses plus importantes. Cependant, avant la chirurgie, les patients obèses sont beaucoup moins enclins à attendre des récompenses plus importantes que les personnes maigres par rapport à des choix financiers équivalents dans des décisions identiques concernant la nourriture. Après la chirurgie, ces différences disparaissent et les patients obèses sont beaucoup plus disposés à attendre des récompenses alimentaires. J'élimine les explications alternatives aux différences DD entre les domaines de récompense. Les participants ayant un IMC maigre ou obèse répètent des tâches DD avec différents types de récompenses. Les participants remettent moins pour les récompenses monétaires par rapport à toutes les récompenses alimentaires, indépendamment de leur poids. Les participants ignorent davantage les récompenses futures pour la nourriture que pour

l'argent, quel que soit le type de compromis comme la nourriture ou la quantité par rapport à la qualité.

L’essai 3 vise à explorer comment orienter l’intervention sur la capacité du cerveau à intégrer la valeur des impacts sur la maîtrise de soi et la prise de décision économique. Les troubles psychiatriques et leurs traitements ciblés permettent des manipulations naturelles des déficits et des changements dans la prise de décision. Avant et après un cours de stimulation cérébrale non invasive, les patients atteints de TOC effectuent une série d'expériences économiques qui évaluent la fonction exécutive générale et leur capacité à créer de la valeur et à exercer une maîtrise de soi. Je contribue à la neuroéconomie et à la psychiatrie en montrant comment les expériences d'économie comportementale peuvent mesurer l'efficacité des traitements cliniques au-delà des expériences cliniques, en particulier pour un trouble de la maîtrise de soi comme le TOC. Je contribue à la littérature sur la prise de décision comportementale en explorant l'impact de l'évaluation sur la capacité d'exercer la maîtrise de soi.

INTRODUCTION

Do you prefer chocolate cake over a fruit salad as dessert? Individuals often successfully pursue a goal such as dieting by choosing the fruit salad in the face of the temptation of the chocolate cake – a process often referred to as *self-control.* Self-control arises when there is the need to override behavior, thoughts, compulsions, and emotions that satisfy a visceral objective in favor of a goal with a more considerable value. Everyday examples include whether to spend money on a trip today or save for retirement, to maintain vegetarianism or succumb to a bacon sandwich, and—during the (current) global COVID-19 pandemic—to follow government-imposed social distancing guidelines or secretly host a birthday party. For the average individual, more self-control is desirable. Higher self-control has been correlated positively with higher grades in school, psychological adjustment, less binging on food and addictive substances, better social relationships, and positive emotional responses (Tangney, Baumeister, and Boone 2004).

A perfectly economically rational human being would automatically take actions towards their overall well-being and not perceive the steps necessary to be costly. Such a human being would stick to a healthy diet plan, regularly contribute towards a retirement fund, and—in the current pandemic—adhere to shelter-in-place policies without a second thought and no feeling of inconvenience. Such a human being is hard to come by.

Thinking of self-control as a muscle that can be strengthened and fatigued provides a framework to the general reasoning behind lower exertions of self-control in the face of choice conflict (Baumeister 2002). Using a body-building metaphor, the muscle of self-control needs first to be exercised with resistance that is possible to overcome. The exertion of the muscle must feel rewarding. Over time, continual

practice with the same resistance makes self-control easier to the point that overcoming the resistance becomes a habit (Wood and Rünger 2015). The self-control "muscle" becomes harder to exercise when more resistance is applied, from increasing the weight needed to resist to impede the muscle's range of motion. Conversely, the muscle becomes easier to exercise with lower resistance used or with increased muscle motion. Interventions to improve self-control find ways to decrease the resistance that makes self-control difficult to exert. For example, to reduce frivolous expenditures, one could automate their bank to allocate a maximum amount per month to a checking account and to transfer the rest of the money into a savings account, thus limiting expenditures per month. Because of automation, the individual does not have to actively remember to manage the account limits, thus decreasing the effort, and therefore the resistance, to control their spending.

Research has often framed self-control as the conflict between two internal selves: a planner (a "future self') and a doer (the "present self') (Milkman, Rogers, and Bazerman 2008; Thaler and Shefrin 1992), and the *dual-selves theory* elicits the idea that individuals see themselves as both (Milkman, Rogers, and Bazerman 2008). The present self favors immediate visceral rewards and the satiation of proximate goals. On the other hand, the future self prefers the achievement of more significant, overarching goals despite the up-front cost. The objectives of both these selves seek pleasure at different points in time, contradicting previous research that self-control and pleasure are mutually exclusive (Vosgerau, Scopelliti, and Huh 2020).

Sources of motivation are critical to the adherence to and effectiveness of self-control interventions. External motivators, or those where the desire to pursue action comes from outside the self, can lead to desirable short-term outcomes. For example, manipulating one's surroundings that favor resisting temptation help enforce self-

control (Wood and Rünger 2015). A savings plan with mandated contributions into a retirement fund, social liability through a declaration on social media, and steep police fines for gatherings are perfect examples of situational self-control (Ariely and Wertenbroch 2002; Duckworth, Gendler, and Gross 2016). However, the continual use of external motivators can backfire and make self-control harder to practice in the long run and lead to self-control failures (Muraven, Rosman, and Gagné 2007). Savings plan changes may cap contributions, social media commentary can be harmful, and uneven enforcement of government policies can deter the continual practice of behaviors to achieve larger goals.

Considering this, external motivators to exert self-control can be dangerous. In dietary decision-making, external motivators like social pressure and body image can lead to negative food choices, which can lead to eating disorder behaviors like anorexia (starvation of food) and bulimia (purging behaviors around food), and body dysmorphia (Hartmann, Dohle, and Siegrist 2015). Self-determination theory shows that individuals with self-determination are more likely to engage in behaviors that are in line with their goals because the actions to achieve said goals are in line with their interests (Deci and Ryan 2012). Literature has shown that smokers who have higher internal than external motivation to quit smoking were more likely to achieve it (Curry, Wagner, and Grothaus 1990). From a managerial perspective, it is much more effective to encourage healthier food choices by finding pleasure rather than deterrents from unhealthy food, thus nudging consumers to pay more for less (Cornil and Chandon 2015). Therefore, it is more effective in the long-term to encourage self-control with internal motivators, or those based on inner values and goals and actions that define free will.

This dissertation aims to explore whether interventions designed to increase self-control work and, if so, how. The first essay of this dissertation explores a marketing intervention designed to facilitate shoppers in making conscientious food choices for improved health. This essay motivates to examine in controlled settings individual factors contributing to the success of such interventions through clinical populations, which serve as natural manipulations on the mechanisms of self-control. The second essay of this dissertation explores whether a physiological intervention towards weight loss impacts a form of self-control that involves participants having to wait for a large reward. The third essay sets up a study that explores the mechanisms of self-control success through a physiological intervention that affects the subfunctions of decision-making surrounding self-control like value integration, goal trade-off, risk aversion, and executive function. The first essay explores how an intervention increases self-control based on the economic factors critical to its success. The second and third essays, physiological interventions to improve self-control, determine whether the interventions impact the economic factors in controlled environments.

ESSAY 1: MEASURING THE HETEROGENEITY IN EFFECTS OF FRONT-OF-PACK LABELS ON THE NUTRITIONAL QUALITY OF SUPERMARKET FOOD PURCHASES

INTRODUCTION

Several marketing tools influence food choices and, therefore, health, from targeted food marketing to children to food descriptions and nutritional information in restaurant menus (Curry, Wagner, and Grothaus 1990). Some food marketing strategies can clash with health policy aimed at healthier diets, specifically when a product's consumption may not be in the best interest of the consumer's health; others can work in synch with policy goals to encourage individuals to make decisions better for their well-being (Kozup, Creyer, and Burton 2003). Within the different marketing tools, nudges—changes in choice architecture that shape behavior without explicitly forbidding behavior—are used by governments and companies to promote healthy food choices (Enax et al. 2015).

Front-of-package (FOP) nutrition labels are examples of cognitive nudges that are the most direct interventions to promote healthy dietary choices (Thaler and Sunstein 2008). FOP labels are advantageous to managers because these nudges are minor additions to packaging and do not change the product formulation. Previous literature has shown that consumers are responsive to and become more informed by FOP labels (Cadario and Chandon 2020). Still, their effectiveness is dependent mainly on their styling and location. Previous work has also shown that traffic-light FOP labels are generally effective at informing consumers, but their impact on choices in natural settings is weak (Graham, Orquin, and Visschers 2012).

Given this positive but small effect of FOP labels, there is a need to explore the factors that drive the effectiveness of FOPs to inform managers and policymakers about the conditions that lead FOP labels to be or not to be effective, which could

therefore guide FOP labels' targeted usage in certain products, stores, or contexts. Our objective with this paper is to explore what factors increase or decrease the effectiveness of FOP labels on consumer food decisions. Our approach could be applied in other areas beyond the dietary decision-making realm, as manufacturers in multiple consumer product categories, from electronics to fashion, use information labels, for example, to signal energy efficiency and responsible sourcing of materials.

Our data comes from a randomized control trial across 60 stores of three national grocery chains in France, where four different FOP labels were tested. We use grocery store information and transaction information by loyalty card carriers and nutritional information of products purchased in various food categories to quantify which covariates – product characteristics, shopper basket characteristics, and store characteristics – play a role in the effectiveness of the labels. We measure this effectiveness by contrasting the difference in the number of healthy purchases and the number of unhealthy purchases made between treatment and control stores. To do so, we use the causal forest method in a difference-in-difference approach to generate individual treatment effects for the thousands of customers in the data set and to determine which covariates are most important in identifying heterogeneity in treatment effects.

Our main results have two essential facets. First, our findings suggest that the consumers benefiting from the additional information choose more expensive products and hence, likely have higher incomes. In other words, this result seems to offer evidence that FOP labels lead to healthier choices for higher-income consumers and have very little to no impact on consumers of low income, exacerbating the inequality that exists in terms of healthy food choices (Dubois et al. 2020; Roberto et al. 2012). Second, we find that for FOP labels to have a more significant impact, assortment and

pricing done by retailers play an essential role. For consumers to shift their patterns in the presence of the FOP labels, enough products in the healthier tercile must be made available at accessible prices. At the same time, a smaller choice set of unhealthy products also should be considered. These findings highlight the role that retailers play in the healthiness of food choices of consumers.

HETEROGENEITY IN EFFECTS OF FOP LABELS

Previous work that studied how FOP labels influence consumer choices in natural settings has found a slight improvement regarding choices of healthier products (Pechey and Monsivais 2016). We aim to go beyond the measurement of the average effect of FOP labels on choices, which was the focus of previous literature, by instead studying how three dimensions that characterize a shopping trip – product, basket, and store characteristics – explain differences in the effectiveness of FOP labels on making healthy purchases. These three aspects are the most relevant categories of covariates. The literature has provided support, and we give an overview below on how these factors could contribute to mechanisms by which FOP labels impact consumer purchases. For literature on the average effect of FOP labels, please see Dubois et al. 2020.

Product characteristics

Product characteristics like price and brand can influence the responsiveness of individuals to FOP labels in several ways. Price reduction strategies in food marketing can promote discounted choices compared to their alternatives, and these effects are generalizable to most food categories (French et al., 2012). While reducing prices on healthy foods as a public health strategy is an effective way to encourage their purchase, decreasing prices in unhealthy competitive alternatives can undermine such efforts, as customers are price-sensitive when making choices about healthy

choices but not as much so when making choices about unhealthy foods (Talukdar and Lindsey, 2013). The conflict in the effectiveness of price reduction strategies could be reconciled with how price-sensitive customers decide on food purchases, as low-income families purchase foods when they perceive “value for money spent,” such as low prices for large volumes of foods (Burns, Cook, and Mavoa, 2013). A high price can also inhibit the willingness to buy if the price is associated with premium branding, certifications, or even healthiness (Anselmsson, Johansson, and Persson 2007; Delmas and Grant 2014). FOP labels may change price sensitivity, as consumers are willing to pay more for healthy food than unhealthy food in the presence of nutritional claims in behavioral settings (Anselmsson, Johansson, and Persson 2007; Delmas and Grant 2014). (López-Galán and de-Magistris 2020) find that customers become less price-sensitive when presented with FOP-labeled foods; however, they consider price sensitivity within the category of foods and not a customer’s general price sensitivity, as in for products outside of a target category.

Brands are undeniably one of the most important factors underlying product choice, but there is little work on how they interact with FOP labels to influence food choices. Brands are overall perceived first as a sign of quality and then lead customers to the evaluation of other criteria (Vranešević and Stančec 2003), with packaging design influencing the choice and perception of specific brands, including private brands (Vranešević and Stančec 2003). Directly related to package labels and their contents, a study on South African consumers showed that brand preferences depend on the demographics of populations, like education, which may in part be attributed to a consumer’s ability to interpret label information (Wells, Farley, and Armstrong 2007). However, younger consumers also use food choices to construct their image towards others and fit within a group (Wyma et al. 2012), highlighting the importance of brand

choice and packaging of foods in this context. It is not well known if FOP labels benefit or work against branding. The mere presence of an FOP label can serve as part of a government-created brand, creating a sense of trust and notion of quality for products and brands that a customer may not initially consider (Stead et al. 2011). An FOP label's effectiveness could also benefit store brands or little-known brands as they compete with national brands. Our study evaluates if FOP labels have a more substantial impact on choices when present in national brands versus private brands.

Store characteristics

Store location and socioeconomics have been explored extensively in their relationship to consumer dietary choice, often with conflicting results, as seen in wealth-obesity paradoxes across several countries (Janssen and Hamm 2014). Store accessibility has driven the conversation around how supply and demand impact consumers purchasing healthy food. The literature on food deserts, or areas where it is difficult to buy affordable or good-quality fresh food due to distance traveled, is conflicted about their impact on obesity and health. For example, when comparing residents inside and outside of Detroit, a notorious food desert city in the United States, obesity was not correlated with residents living in a food desert but instead to health status and sociodemographic factors (Aitsi-Selmi et al. 2012; Dinour, Bergen, and Yeh 2007; Dinsa et al. 2012). Research in agricultural economics has shown that consumers from lower-income backgrounds are more willing to travel further to supermarkets than to spend at closer farmers' markets for food, even though consumers can utilize food subsidies at farmers' markets and smaller grocery stores (Budzynska et al. 2013). A structural demand model showed that food deserts and other supply inequality variables like differences in prices and product availability do

not contribute to differences in nutritional inequality, and raising food subsidies for lower socioeconomic groups would decrease nutrition access inequality (Taylor and Villas-Boas 2016). However, increasing food subsidies to decrease nutritional inequality differences may backfire. Experimental evidence has shown that creating budget allocations for food would reduce spending on food. At the same time, a slight increase in wealth for below poverty line households under malnutrition does not necessarily improve spending to solve malnutrition (Allcott et al., 2018).

A possible reconciliation of this conflict between socioeconomics and the desire to make healthier choices is that, while food subsidies provided to low-income households directly increase purchasing power for food to prevent hunger, the subsidies do not directly promote healthy options. Food stamp literature that focuses on health choices shows that the informed consumer intends to make healthier choices. Still, uninformed consumers could continue making the same, and maybe worse, choices if they are provided with a wealth allocation (Colson-Sihra and Bellet 2018).

Customers' visit frequency and behavior in grocery stores can also impact their product choice. For example, customers who spend more time in stores tend to explore less amongst the variety of products a store carries (Guthrie et al. 2007; Wiig and Smith 2009). A study on the frequency of grocery store visits in food stamp recipients has shown that, for individuals who are less frequent shoppers, those who visit towards the end of a month (i.e., close to when benefits run out for the month) have low average calories of food purchases. However, the recipients who regularly shop throughout the month maintain the average calories of purchased items (Hui, Bradlow, and Fader 2009).

In conclusion, it is likely that store characteristics, possibly through location, size of the store, and the respective socio-economical levels of the store's consumers, influence the strength of the impact of FOP labels because these characteristics impact stocking decisions (quantity, quality, and categories available) and pricing decisions (promotions and price differences because of location), thus impacting how shoppers evaluate products and make their decisions.

Basket characteristics

Marketing literature has explored how variation in grocery baskets is essential in explaining choices. For example, basket sizes of consumers relate to pricing sensitivity, where those who have larger baskets (i.e., who buy items more items in a single visit) are less sensitive to prices when considering individual products but are more conscientious of price when considering the expected cost of their basket (Wilde and Ranney 2000). Multi-category choice models have shown that correlations in preferences across and within different food categories can help predict attribute preferences for existing and new food categories, from nutritional composition to brand names (Bell and Lattin 1998).

However, policies that have increased the amount of healthy food available in low-income area stores have yielded insignificant results in increasing the number of healthy purchases in baskets. For example, when an ordinance in the Minneapolis and St. Paul metropolitan area mandated the stocking of minimum quantities and varieties of various nutritious foods and beverages, researchers found that the healthfulness of consumer purchases did not significantly change, despite store adherence to the new policies (Singh, Hansen, and Gupta 2005). In fact, in an analysis on sources of nutritional inequality differences in the United States using Nielsen metrics, (Laska et al. 2019) found that supply differences (i.e., what a store stocks and

therefore impacting what a consumer puts in her basket) account for only 10 percent of nutritional inequality disparities. It remains to be explored whether other nudges towards making healthy choices can improve upon policies.

Frequent shoppers tend to shop closer to their home, buy fewer items, and use alternative modes of transportation (ex. walking and public transit), while infrequent shoppers tend to drive to make purchases, buy more, and spend more per visit (Jiao, Vernez Moudon, and Drewnowski 2016). Integrated with the previous discussion on basket sizes and store location on food choices, the introduction of FOP labels could have different impacts on individuals. On the one hand, an FOP label may introduce new habits to shoppers who shop frequently (Abrams, Evans, and Duff 2015); on the other hand, the presence of an FOP label may not be enough to change the food preferences of frequent customers due to previous habits or inertia, as seen with graphical packages aimed at decreasing smoking (Van Dessel, Smith, and De Houwer 2018). To shed some light on some of these issues, we explore if basket size and the number of visits to stores, among other variables, change the effect of FOP labels on food choices.

In short, based on the previously described literature, the answer to the following question is still unknown: what are the (1) product characteristics, (2) store characteristics, and (3) basket characteristics that influence the effects of FOP nutrition labels on consumer choice in natural conditions and by how much?

DATA

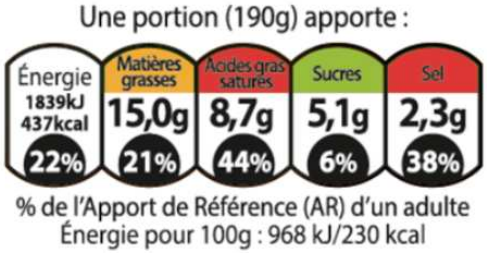
The field experiment that led to the collection of the data took place from September 26 to December 4 of 2016, where research assistants placed four types of FOP labels on food products in 40 randomly selected supermarkets from three of the largest retail chains in France, with 10 supermarkets per labeling system, during the

10-week treatment period. Besides the 40 treatment stores, 20 additional supermarkets were randomly chosen to serve as control stores in which the product labels remained as before with no additional FOP label. Because the manufacturers would opt into receiving an FOP label, not all products received an FOP label, thus allowing for us to explore the effects of labeling when customers can opt out of purchasing items without the FOP label. Store selection per treatment condition and the control group was balanced by two criteria: chain of the store (Carrefour, Simply, and SuperCasino) and whether the store was in an area of economically privileged or underprivileged area. This metric was determined by whether the store fell into areas in the bottom two quintiles of proportion of unskilled laborers. This protocol is publicly available on the website of the French Ministry for Solidarity and Health (Dubois et al. 2020), and the experiment was authorized by ministerial decree. The field experiment was registered at the International Standard Randomized Controlled Trials Number Registry (ISRCTN 58212763).

In this paper, we focus on evaluating the impact of the NutriCouleur and NutriScore labels, displayed in Figure 1, which have been shown to be the most significant in influencing consumer choices (Reanudin et al. 2016).

Figure 1: (a) The NutriCouleur and (b) NutriScore front-of-package labels

(a)



(b)

The retailers provided purchase data for four product categories: canned foods, fresh foods, industrial baked goods, and pastries, from their loyalty cardholders, identified in the dataset only by their store card number, for two time periods: the ten

weeks during which the study was implemented, from September 26 to December 4, in 2016, and the corresponding ten weeks in the previous year, 2015. We focus in our analysis on the two largest categories of the four: canned foods, which includes products such as canned ravioli and stews, and fresh foods, comprised of products like prepared salads and sandwiches. After removing transactions where product information was missing, our data set contains information about 2,809,261 purchases of 4612 products, of which 1285 were products that received labels in the treatment stores. These transactions were made by 132,621 consumers. On average, customers visited the stores 4 times within the 10 weeks, purchasing on average between 2 and 3 items in these four categories, and spending €4.62 per basket with an average price of €2.43 per item. Customers tended to visit the same store throughout the 10-week period, as less that 1% of customers visited multiple stores of different treatments or of no treatment.

To quantify the nutritional quality of purchased food, we used the Ofcom nutrient profiling score developed by the British Food Standards Agency (FSA score). The FSA score assigns positive points between 0 and 10 according to the amount of four nutritional components typically considered unhealthy: energy, sugars, saturated fat, and sodium per 100 g or 100 mL (Dubois et al. 2020); and negative points between -5 and 0 according to the amount of three nutritional components usually considered healthy: percentage of fruits, vegetables, and nuts, fibers, and proteins. Hence, when adding all these components, the FSA score can range from -15 (best) to 40 (worst nutritional quality). As in previous papers (e.g., (UK Department of Health 2011), this score was chosen because it has previously been used in scientific literature and is also the only system validated by associations with the onset of disorders related to poor dietary choices, such as diabetes and cardiovascular disease (Labonté et al.

2018). The information to compute the FSA score for each product was based on the nutrient and energy information available through mandatory food packaging labeling. We were able to compute the FSA for 3,914 products out of our total of 4,612 products.

As the dependent variable, our approach looks at the change between the two 10-week periods in the purchase incidences of products of different degrees of healthiness based on their FSA scores. To do so, we created three terciles of all products purchased across all stores within each food category based on their FSA. The first tercile includes the healthiest products that range from -8 to 0 in FSA score for canned foods (-7 to 2 for fresh foods); the second tercile includes products with FSA scores between 1 and 2 for canned foods (3 and 8 for fresh foods); finally, the third tercile includes the least healthy products, with FSA scores larger than 3 for canned foods (larger than 8 for fresh foods). We then measured the total purchase incidences of products, measured by the number of unique items within a category and tercile of healthiness, during the 10-week period in each tercile, at the individual level, for the treatment and control stores during the treatment year as well as in the corresponding 10 weeks before the treatment. We explore purchase incidences rather than the number of items purchased within a category and tercile to account for large volumes of purchase of any single product, which would not necessarily be representative of improving healthy decisions (ex., size of household leading to purchases of large volumes of a single product). We study the aggregate behavior over the 10-week period compared to matching behavior of corresponding weeks because customers may not visit in the same corresponding week between treatment and control periods, thereby not allowing for a complete picture about behavior during the treatment period.

Summary statistics for the average purchase incidences by food category, store treatment, tercile, and labeling decision can be found in Table 1. As seen by the larger average number of products purchased, the fresh foods category was the most purchased category of food in both 2015 (the pre-treatment year) and 2016 (the treatment year). Healthy and unhealthy fresh foods were generally purchased in equal amounts and much more than those of mid-range health. While we observe that healthy product consumption (tercile 1) went down significantly in the control stores from 2015 to 2016, that reduction was reduced or eliminated in most of treatment stores. In tercile 3, the unhealthiest, we observe a stronger decline in consumption in the treatment stores, in 2016, than in the control stores.

Table 1: Average purchase incidences by food type, treatment, tercile, and year

Food Type	Treatment	Year	Tercile 1	Tercile 2	Tercile 3
Canned Foods	Control (No Label)	2015	0.260 (0.003)	0.095 (0.002)	0.045 (0.001)
		2016	0.238 (0.003)	0.090 (0.002)	0.049 (0.001)
	NutriCouleur	2015	0.291 (0.006)	0.107 (0.003)	0.053 (0.002)
		2016	0.271 (0.005)	0.107 (0.003)	0.052 (0.002)
	NutriScore	2015	0.262 (0.004)	0.101 (0.002)	0.046 (0.002)
		2016	0.235 (0.004)	0.087 (0.002)	0.042 (0.001)
Fresh Foods	Control (No Label)	2015	0.862 (0.007)	0.277 (0.003)	0.838 (0.005)
		2016	0.833 (0.006)	0.301 (0.003)	0.777 (0.005)
	NutriCouleur	2015	0.785 (0.011)	0.269 (0.004)	0.780 (0.008)
		2016	0.803 (0.011)	0.294 (0.004)	0.742 (0.008)
	NutriScore	2015	0.765 (0.009)	0.273 (0.004)	0.782 (0.007)
		2016	0.763 (0.008)	0.279 (0.004)	0.677 (0.006)

The descriptive statistics of purchases, separated by tercile, labeling decision, and food category, can be found in Table 2. The products had an average FSA of 6.58 (SEM = 0.13), ranging from a minimum of -8 to a maximum of 27. Heterogeneity in the average healthiness, however, existed across the two categories, and branding. Canned foods had healthier nutritional quality, with an average FSA score of 2.91 (SEM = 0.35), while the FSA score of fresh foods was 5.49 (SEM = 0.29). Average prices did not differ extensively across terciles of foods and within labeling decisions and food category.

Table 2 :Descriptive statistics and FSA scores

Tercile	1	2	3
Canned Foods			
Number of Products	181	68	47
Min (FSA)	-8	1	3
Max (FSA)	0	2	20
Mean Price (€) (s.d.)	2.47 (0.08)	2.38 (0.12)	2.60 (0.28)
% Store Brand Products	64%	65%	79%
Fresh Foods			
Number of Products	382	152	187
Min (FSA)	-7	3	9
Max (FSA)	2	8	23
Mean Price (€) (s.d.)	2.70 (0.06)	2.80 (0.09)	2.21 (0.08)
% Store Brand Products	54%	63%	59%

A comparison of store locations (major city, urban, suburban, and rural settings) showed differences in the average healthiness, price of products purchased, and basket sizes. Summary statistics can be found in Table 3. Generally, stores in major cities had lower average prices for both canned and fresh foods, while stores in suburban areas had the highest average price. For the canned foods category, stores in major cities had the lowest average FSA of items purchased and the highest in

suburban settings. For the fresh foods' category, stores in rural settings had the lowest average FSA of items purchased and the highest in stores in major cities. The largest percentage of store brand loyalty was found in major city and urban settings and the lowest in rural settings. On average, more items within the sampled categories were bought per basket in rural stores compared to stores in urban settings. Some of these characteristics may lead to a different response by consumers to FOP labels.

Table 3: Descriptive statistics by store location

	Store Location	Major City	Urban	Suburban	Rural
Basket Characteristics	Mean (Basket Size) (SE)	2.01 (0.001)	1.97 (0.005)	2.29 (0.005)	2.55 (0.006)
	Mean (Store Brand Loyalty) (SE)	50% (0.2%)	50% (0.1%)	42% (0.1%)	39% (0.1%)
Canned Foods	Mean Price (SE)	2.51 (0.02)	2.43 (0.01)	2.77 (0.01)	2.78 (0.01)
	Mean FSA (SE)	6.55 (0.04)	6.39 (0.02)	6.48 (0.01)	6.68 (0.01)
Fresh Foods	Mean Price (SE)	2.06 (0.01)	2.15 (0.01)	2.26 (0.01)	2.21 (0.01)
	Mean FSA (SE)	0.76 (0.05)	1.36 (0.02)	1.63 (0.02)	1.57 (0.05)

METHOLOGY

The Causal Inference Problem

In the following discussion, we adapt to our setting the description of how to quantify the effects of treatment through causal inference present in (Labonté et al. 2018). Consider the case of one food category *r*. For a set of i.i.d. customers $i = 1, \ldots, n$, we observe a vector of features X_i, for example, the average price of their groceries, the number of visits per week, and the size of the store they visit; a response metric Y_i, i.e., some measure of choices; and a treatment indicator $W_i \in \{0, 1\}$ for whether a customer was shopping in a treatment store ($W_i = 1$) or not ($W_i = 0$). We observe $Y_i =$

$Y(W_i)$, i.e., the change in the shopping behavior of customers, depending on the store where they purchase their groceries.

The causal inference problem involves estimating the conditional average treatment effect (CATE) for an individual as

$$\tau_i(x) = E[Y_i(1) - Y_i(0) \,|X_i = x]. \quad 1$$

The CATE describes the effect of the treatment, given that customer *i* has a particular set of observable features x_i. If we assume that the treatment is unconfounded with the explanatory variables, then whether a customer is in the treatment or control group is independent of their observable features, or

$$W_i \perp \{Y_i(0), Y_i(1)\} \mid X_i. \quad 2$$

In our case, over 99 percent of customers, identified by their loyalty card ID number, visit only one store, so the treatment effect is estimated over a population of customers with similar observable features across the two groups. To compare the effects of the treatment between customers in the treatment group and the behavior of customers in the control group, the first step involves estimating the treatment propensity for each customer, or, in other words, the probability the customer visited the treatment or the control store, given their observable characteristics. The probability to receive a treatment given an individual's set of features *x* can be defined as

$$e(x) = P[W_i = 1 \mid X_i = x]. \quad 3$$

As a customer can only be part of the treatment or the control group, if the propensity score $e(x)$ can be estimated, then (1) can be rewritten using inverse propensity score weighting as such:

$$\tau_i(x) = E\left[Y_i\left(\frac{W_i}{e(x)} - \frac{1 - W_i}{1 - e(x)}\right) \mid X_i = x\right]. \quad 4$$

The propensity score can be measured with conventional processes like likelihood estimation from a regression. The second step would then be to match customers between the treatment and the control groups based on their propensity scores so that comparing individuals with similar propensity scores would be akin to controlling for individual differences in behaviors and estimating the effect of the treatment. However, when more covariates are added, estimating propensity scores and matching individuals can become cumbersome, and the propensity scores" ability to recover heterogeneous treatment effects can be limited.

The Causal Forest Method

The causal forest method is a supervised machine learning method that combines the method of regression forests with causal inference (Athey and Imbens 2016; Wager and Athey 2018). Specifically, in a causal tree, observations are split into smaller groups based on their feature values until each leaf of a tree (i.e., a terminal node) contains at least one treatment and one control group observation. Aggregating the trees created a causal forest, where each tree is drawn from the dataset with replacement. Though the trees differ in how they split the data, be it by the covariates chosen or the subset of data drawn, the average of the differences in the leaves of the trees will identify the average treatment effect as if controlling for individual differences.

For example, assume we create a forest with *B* trees, and we look at a tree *b*, created with a subsample of the data S_b. In the first stage of the causal forest method, in a tree *b*, the within-leaf treatment effect is estimated as the difference between the expected outcomes for customers with properties *x* who shopped at a store with an FOP label and the expected outcomes of those who did not and within the same leaf

(i.e., also with properties *x*). Let $N_{l,\,W=1}$ be the number of customers within a leaf *l* who shopped at a treatment store and $N_{l,\,W=0}$ be the number of customers within a leaf *l* who did not. The conditional average treatment effect for an individual at a leaf would then be the following:

$$\hat{\tau}_i = \frac{1}{N_{l,W=1}} \sum_{i=1}^{N_{l,W=1}} Y_{i|W=1} - \frac{1}{N_{l,W=0}} \sum_{i=1}^{N_{l,W=0}} Y_{i|W=0} \qquad 5$$

The first summation is the average of outcome Y_i for individuals in the leaf *L* who were in the treatment group, and the second summation is the average of outcome Y_i for individuals in the leaf *L* who were in the control group. In terms of causal inference, observations that are together in each leaf are analogous to having similar propensity scores because they are grouped with observations with similar properties; thus, individuals can receive estimates of treatment effects, as estimated in Equation 4. These treatment effects are averaged across all the leaves of a tree and then across all *B* trees of the forest, where each tree is created with a different subsample of the data S_b in a process called bootstrap aggregation, or "bagging." We run the causal forest on 16 covariates of store characteristics, shopper basket characteristics, and product characteristics, which can be found in the Appendix in Table 7. Regression forests using the covariates below to estimate the propensity scores indicated that the probability a customer who was selected shopped at either treatment or nontreatment stores was as unbiased as possible for the sample sizes.

The causal forest method's benefits come from its nonparametric approach, in which the properties of the study population are not assumed to follow the assumptions of a specific statistical model. The trees can split observations at multiple combinations of value thresholds for a covariate of interest at multiple stages of the tree, so the causal forest can define complex subsets of the data and help estimate

nonlinear interactions between covariates and the outcome (for example, when the outcome value may increase for low covariate values but decrease for higher covariate values).

Of particular interest to the contribution of this paper, the forest also provides an interpretable description of heterogeneity. The estimation of heterogeneous individual treatment effects, in this case, from different consumer basket characteristics, store characteristics, and product characteristics, upon the observed outcome, is equivalent to a data-driven search for important moderators to the effectiveness of the treatment, which is in the policymaker's best interest. Furthermore, this search is principled in the sense that the estimated effects should generalize rather than being just data-mined relationships unique to the current dataset. The causal forest model does not overfit to a specific study population and can potentially discover what drives treatment effects in related study designs.

To explore the heterogeneity of the treatment's effectiveness across different FOPs, we defined as our dependent variable the change from the pre-treatment period to the post-treatment period in the purchase incidence of products with different levels of healthiness T, separated into terciles, i.e., the number of unique products purchased in each tercile *T.* We explore this dependent variable to gauge the effectiveness of a label by the magnitude of the increase in the number of "healthy" (i.e., first tercile) purchases and the magnitude of the decrease of the number of "unhealthy" (i.e., third tercile) purchases. That way, the treatment effect estimation is akin to a difference-in-difference design, as the treatment effect would be exploring the difference in the difference in purchases incidences between the treatment year and non-treatment year. To implement the causal forest, we followed the method similar to the one proposed by (Athey and Imbens 2016; Wager and Athey 2018)), which follows the

double machine learning approach (Chernozhukov et al. 2018). First, out-of-sample propensity scores $\hat{e}^{(-i)}$ and out-of-sample predicted outcomes $\hat{m}^{(-i)}$ are separately estimated with regression forests to compute residuals between the observed and predicted outcomes $Y_i - \hat{m}^{(-i)}(X_i)$ and between the observed treatment vector and propensity scores $W_i - \hat{e}^{(-i)}(X_i)$. These residuals are then used to constrain the out-of-bag estimates of individual treatment effects by the causal forest and prevent overfitting. We imposed "honesty" for each tree, where half of the data is used to generate the tree partitions and the other half of the data to estimate treatment effects. We used the generalized random forest software package in R, which provides a way to estimate the parameters of interest and a detailed description of the estimation algorithm (Chernozhukov et al. 2018).

We estimated each causal forest using the covariates whose splits determined the most heterogeneity (i.e., those with the highest variable importance), as suggested by (Athey, Tibshirani, and Wager 2019) These variables of importance will be useful later to explore the moderating factors of the treatment effects. We ran forests separately for each category of food *r* and each FOP label type *l*, akin to accounting for fixed effects of categories of foods on the outcomes and to evaluating each label from a baseline condition of no label.

RESULTS

We applied the causal forest method to evaluate the impact of two labels, the NutriScore and the NutriCouleur labels, which, as previously mentioned, have been shown to have the more significant average impact on choices (Dubois et al. 2020). We start by discussing the average treatment effect (ATE), followed by the results related to the heterogeneity of the impact of FOP labels on consumer choices.

Average Treatment Effect of FOP Labels

The average treatment effect, as seen in Table 4, shows significant changes in the number of purchase incidences of healthy, mid-range healthy, and unhealthy foods. For the number of purchases of healthy fresh foods, tercile 1, with the NutriScore label, the ATE was 0.0397, a 14.9% increase, while the ATE for mid-range healthy purchases was -0.0186 (a 21.2% decrease) and the ATE for unhealthy purchases was -0.0221 (an 8.38% decrease). For the number of purchases of healthy fresh foods with the NutriCouleur label, the ATE was 0.0249, a 9.2% increase, while the ATE for mid-range healthy purchases was -0.0096 (a 10.9% decrease) and the ATE for unhealthy purchases was -0.0302 (an 11.5% decrease).

Table 4: Mean conditional average treatment effects for food type r*, tercile* t*, and label* l*. All treatment effects are significant after Bonferroni correction of p = 0.0042 for 12 comparisons with* $\alpha = 0.05$*.*

Food Type *(r)*	Tercile *(t)*	Label *(l)*	$\hat{\tau}_{r,t,l}$	S.E.	t value
Canned Foods	1	NutriCouleur	0.0253	0.0003	79.9
		NutriScore	0.0357	0.0003	122.05
	2	NutriCouleur	0.0117	0.0002	75.1
		NutriScore	0.0014	0.0002	9.435
	3	NutriCouleur	-0.0073	0.0001	-107.1
		NutriScore	-0.0073	0.0001	-120.8
Fresh Foods	1	NutriCouleur	0.0249	0.0004	58.4
		NutriScore	0.0397	0.0004	101.5
	2	NutriCouleur	-0.0096	0.0001	-79.2
		NutriScore	-0.0186	0.0001	-200.6
	3	NutriCouleur	-0.0302	0.0003	-92.5
		NutriScore	-0.0221	0.0003	-73.9

The effectiveness of FOP labels in the canned foods category is similar, which is evidence that the effect of FOP labels is not restricted to one category. For the number of purchases of healthy canned foods with the NutriScore label, the ATE was

0.0357, an 11.2% increase, while the ATE for mid-range healthy purchases was -0.0014 (a 1.2% decrease) and the ATE for unhealthy purchases was -0.0073 (a 13.2% decrease). For the number of purchases of healthy canned foods with the NutriCouleur label, the ATE was 0.0253, a 7.9% increase, while the ATE for mid-range healthy purchases was 0.0117 (a 10.1% increase), and the ATE for unhealthy canned food purchases was -0.0073 (a 12.9% decrease).

A natural question from the introduction of a FOP is whether the change in purchases in labeled items is significantly different from that of unlabeled items. Both the NutriCouleur and NutriScore labels led to a significant increase in the purchase labeled healthy (tercile 1) fresh foods compared to unlabeled foods. These results can be found in Table 16.

These results are in line with previous work (Dubois et al., 2020) and suggest that, in both categories, the impact of the FOP labels increased the purchase incidence of healthier (tercile 1) products at the expense of a reduction in the purchase incidence of the less healthy (tercile 3) products. The mid-range healthy (tercile 2) products were the ones least impacted by the presence of the two FOP labels.

Heterogeneity in the Impact of FOP labels on Food Choices

Besides obtaining the ATE, the goal of using the causal forest method is to explore the relationships between covariates of interest and individual treatment effects to identify possible reasons behind the differences in treatment effects. We use variable importance, a weighted sum of how many times a particular variable was split at each level of the causal forest, to identify the relative importance of the three different categories of variables. The variable importance captures whether a variable has enough explanatory power to the desired outcome variable. It has been adopted

by policy-makers to create benchmark models to explore sources of variation in policy outcomes (Dubois et al. 2020).

Table 5 shows the results for the variable importance measure, aggregated to the three buckets that were outlined previously: shopper basket, product, and store-related variables. Overall, across both label types, food categories, and terciles, product characteristics were the most important variables in explaining heterogeneity (54.5% on average), followed by basket characteristics (38.8%), and store variables were the least important (6.8%). These values are consistent for each of the causal forests run. It is important to highlight that the store-level variables are more important to explain the heterogeneity in the results of the NutriScore label.

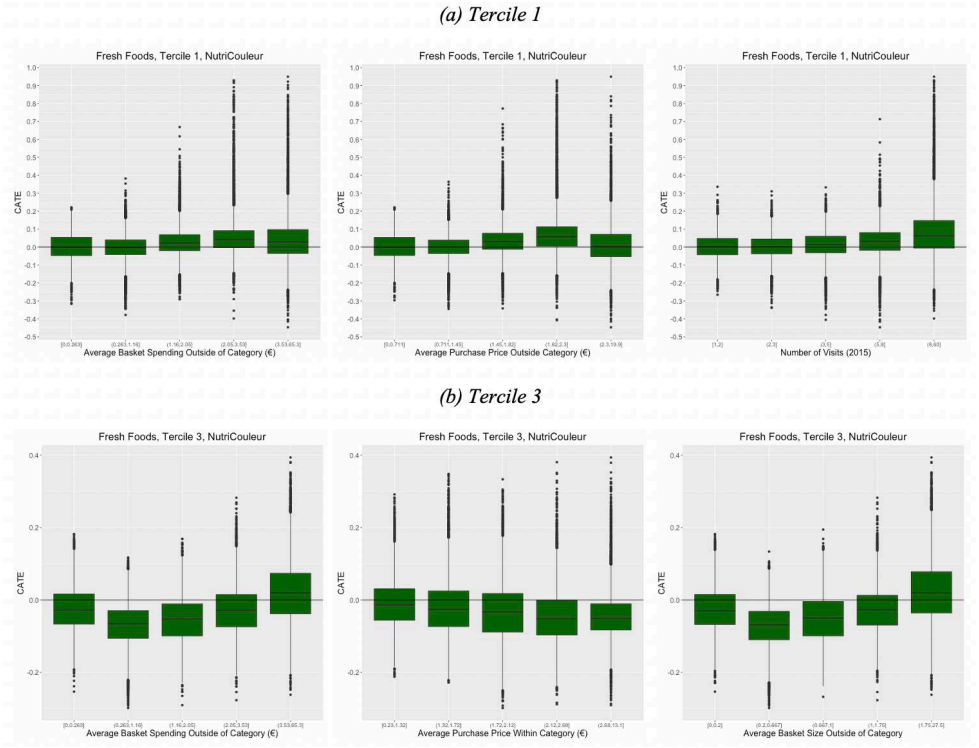
To go into more detail about the conditions that lead to better or worse performance of each label, in Figure 2, based on the individual treatment effects, we display the heterogeneity of response to the FOP labels for the incidence of purchases of tercile 1, the healthiest products, and tercile 3, the least healthy, for different values of the variables with most heterogenous effect. For succinctness, we discuss here the results for the fresh foods category, which is the largest in our data set. As a basis of analysis, note that the average effects for the NutriCouleur and NutriScore labels for tercile 1 products were increases in purchase incidence by 0.025 and 0.040, respectively, and decreases in purchase incidence for tercile 3 products by -0.03 and -0.022, respectively.

Table 5: Variable importance in identifying heterogeneity of treatment effect for food type r*, tercile* t*, and label* l.

Food Type	Tercile	Label	Basket Variables	Product Variables	Store Variables
Canned Foods	1	NutriCouleur	0.444	0.527	0.029
		NutriScore	0.410	0.545	0.044
	2	NutriCouleur	0.423	0.552	0.025
		NutriScore	0.332	0.595	0.073
	3	NutriCouleur	0.347	0.598	0.054
		NutriScore	0.379	0.579	0.042
Fresh Foods	1	NutriCouleur	0.439	0.530	0.031
		NutriScore	0.357	0.446	0.197
	2	NutriCouleur	0.386	0.576	0.038
		NutriScore	0.343	0.610	0.047
	3	NutriCouleur	0.500	0.437	0.063
		NutriScore	0.289	0.539	0.172

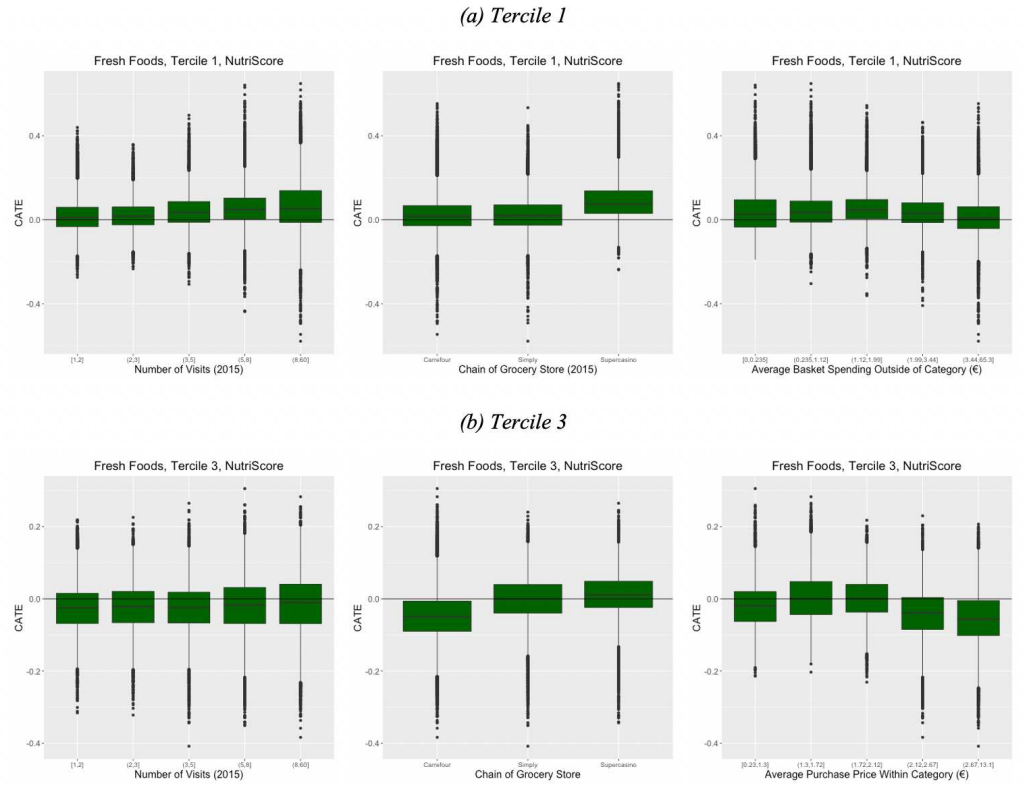
Looking at the top panel of Figure 2, for NutriCouleur, we show the three variables that show the highest variation across quintile of covariate, in terms of impact variation on the purchase incidences of tercile 1: the average basket size, the average purchase price, and the number of visits. The main conclusion to be drawn here is that the NutriCouleur label works significantly better for consumers that have larger baskets, with the average effect in the two highest quintiles almost doubling, compared to the average of the individual treatment effects. We see a similar effect in terms of the number of visits, with this FOP label working better for consumers that visit the store more often. These results suggest that consumers that have more experience with the store and larger shopping baskets, either because they buy more per visit or because they make more visits, are likely to have more opportunities to notice the NutriCouleur label and consider healthier products more often, which then leads to a larger impact on the choice of healthier products.

Figure 2: Distribution of the treatment effect for three important covariates, in terciles (1) and (3) for Fresh Foods, NutriCouleur label



Similarly, if we look at the bottom panel of Figure 2 that focuses on products in tercile 3, the unhealthiest products, we observe that NutriCouleur has highest impact on consumers with average-sized baskets (second and third quintile). The average price paid by consumers shows an interesting effect of the FOP label on choices. In both terciles 1 and 3, consumers that purchase items of higher prices respond more to the presence of NutriCouleur. For example, for quintiles 4 and 5 in the unhealthier tercile, the effect of NutriCouleur was close to -0.05, close to doubling the average effect. These results suggest that the consumers benefiting from the additional information are the ones choosing more expensive products, and hence likely to have higher income. In other words, this result seems to offer evidence that the FOP label leads to healthier choices by higher income consumers, and no impact on consumers of low income, exacerbating the inequality that exists in terms of healthy food choices (Chen and Hsiang 2019; O'Neill and Weeks 2018).

Figure 3: Distribution of the treatment effect for three important covariates, in terciles (1) and (3) for Fresh Foods, NutriScore label



We do a similar analysis for NutriScore, as we would like to highlight the role of store variables to explain the heterogeneity. For this FOP label, the variables that mostly explain the variation of impact on choices are the number of visits, the supermarket chain, and prices. Figure 3 and a regression considering each chain as a factor shows the results. As with the NutriCouleur label, consumers that visited the stores more often and that paid higher prices on average are the ones more affected, in a positive way, by the NutriScore label. In terms of retailer chains and looking at the top panel and middle graph of Figure 3, Carrefour has the lowest average treatment effect (albeit positive) amongst the three chains (0.024, $\beta = 0.0348\ (SE = 0.0006)$) in terms of the healthiest tercile, while the chain SuperCasino has the highest treatment effect (0.093, $\beta = 0.0987\ (SE = 0.001)$), almost four times as strong. Looking at the bottom row and middle graph of Figure 3, Carrefour has the largest reduction in the average treatment effect (-0.047, $\beta = -0.012\ (SE = 0.0006)$), while SuperCasino

shows a small increase in the average treatment effect (0.001, $\beta = 0.0432$ ($SE = 0.007$)). We display the summary statistics by chain in Table 6 to provide reasons for these differences.

Table 6: Descriptive statistics by chain of control stores and NutriScore-treated stores

Chain	Average Basket Spending	Tercile of Fresh Food Healthiness	1	2	3
Carrefour	2.92 (0.02)	Average Number of Products	263	127	195
		Mean Price (SEM)	2.20 (<0.01)	2.43 (0.01)	1.99 (<0.01)
Simply	2.05 (0.01)	Average Number of Products	242	151	201
		Mean Price (SEM)	2.37 (<0.01)	2.53 (<0.01)	1.88 (<0.01)
SuperCasino	1.65 (0.02)	Average Number of Products	305	212	226
		Mean Price (SEM)	2.04 (<0.01)	2.43 (0.01)	1.92 (<0.01)

Overall, SuperCasino stores offered, on average, a larger variety of healthier products when compared to Carrefour (305 versus 263), and available at lower prices (€2.04 versus €2.20). This will make it easier for consumers to change to a healthier choice if they notice the FOP labels. In tercile 3, the differences between chains are still in the same direction, with Carrefour offering fewer products than SuperCasino of this unhealthier tercile (195 vs. 226), at a more expensive price (€1.99 versus €1.92. Hence, the lower variety and more expensive products of the tercile 3 product motivate consumers to avoid them more often when in the presence of the FOP label.

We also observe lower average basket spending by SuperCasino shoppers (€1.65 per basket) than Carrefour shoppers (€2.93 per basket), which suggests that the NutriScore label is most effective at nudging customers who spend less per visit

(SuperCasino shoppers) towards healthy choices and nudging customers who have more income (Carrefour shoppers) away from unhealthy choices. We note that these are just averages, because, unfortunately, we do not have demographic information at the individual level. We do corroborate these results in a regression, nesting for store chain as a factor variable (healthy foods, NutriScore: $\beta_{basket\ spending} = -0.0040\ (SE = 0.000148), t = -26.96$, a 1.5% increase in healthy foods purchased per €1 less spent per basket; unhealthy foods with the NutriScore label: $\beta_{prive} = -0.0170\ (SE = 0.000302), t = -55.77$, a 6.5 % decrease in unhealthy foods purchased per €1 increase in willingness to pay).

The results seem to suggest that for the FOP labels to work, the choice set available at the stores has a role to play. For consumers to shift their patterns in the presence of the FOP labels, an increased availability of products in the healthier tercile in conjunction with a smaller choice set of unhealthy products could increase the number of healthy purchases. These findings highlight the role that retailers play in the healthiness of food choices of consumers.

CONCLUSION

This paper explored the sources of heterogeneity of the effects of front-of-package labels on food choices. We used the causal forest method to estimate individual treatment effects for thousands of customers of three of the largest grocery chains in France during a national field experiment of various front-of-package food labels. Using these retail data in a realistic setting, we identified sources of heterogeneity in the effectiveness of two labels in two different categories of foods. We proposed ways for managers and policymakers to improve the effectiveness of the labels.

In the fresh food category, the largest in our analysis, the NutriCouleur label, a chromatic label that contains nutritional detail, was most effective at encouraging healthy choices for experienced shoppers, be they shoppers who visited the stores more often or would spend more per visit. This finding would suggest to managers and manufacturers that healthy products that would benefit from receiving the NutriCouleur label would be part of larger baskets. In contrast, the NutriScore label, also a chromatic label but with nutritional recommendations synthesized into a letter score, worked best for customers who frequently visited stores but spent less per visit, possibly making fewer purchases per visit. The sources of differences in the effectiveness of labels are per the numerous papers on which style of FOP label is the most effective at consumer comprehension (for example, Egnell et al. 2018).

This dataset posed some limitations that could lead to future research. First, promotional information such as discounts and products were sold as bundles were not available in the transaction data. Second, this dataset only contains data for transactions in four food categories that receive the labels and not in other categories that could realistically have FOP labels like dairy and canned vegetables. The insight from the current dataset is the importance of labels for the purchase of somewhat ready-to-eat items, so their interaction with items that require preparation would add another layer of analysis about product substitution effects. Third, we only have data from loyalty cardholders; though research has shown that loyalty cardholders could have different demographics from nonparticipants (those who do not have loyalty cards) (Nevalainen et al. 2018; Vuorinen et al. 2020), the causal forest method estimates treatment effects using many different combinations of splits on our covariates, which could encapsulate the behavior of nonparticipants as if they were in the forest, thus estimating individual treatment effects robust. Nevertheless, further

research would have to explore ways to include purchases by customers without loyalty cards.

The most relevant implications of these findings involve the relationship between the effectiveness of the labels and marketing mix variables that actions can change from manufacturers, retailers, and policymakers. All three have incentives to use front-of-package labels. Retailers benefit from the encouragement of consumers to purchase new products because of the salience of the label, and labels incentivize manufacturers to keep improving their products (Lim et al. 2020). Policymakers like government agencies want to encourage individuals to eat healthier to decrease public health care costs related to metabolic health conditions like obesity, heart disease, and diabetes. These costs can be challenging for consumers where the marginal cost of healthcare is high, like in low-income areas. Our findings show that both labels worked best to decrease unhealthy purchases for consumers that purchased the most expensive items, who are very likely the higher-income consumers. This difference in purchase power creates even more inequality regarding the healthiness of food choices between rich and poor consumers. FOPs, therefore, need to be used in conjunction with changes to marketing mix variables by each of these three groups—retailers, manufacturers, and policymakers—to ensure their effectiveness.

Retailer decisions drive most of the found correlations between the identified covariates of interest and label effectiveness. First, with regards to product assortments, retailers can change their assortments to include more healthy products that are labeled and fewer unhealthy products, in general. Because habituation variables like basket size and spending correlated strongly with the effectiveness of labels, the retailer should consider stocking assortments of labeled products found in similar baskets. Second, pricing is a retailer's decision. Retailers can decrease the

prices and offer more promotions for healthier labeled products, making the willingness to pay less of a deciding factor in the purchase decision of a healthy item.

However, lowering the price of healthy products may not always be in the best interest of retailers. Policymakers can intervene in several ways. First, they can implement mandates about nutritional content. Policies in the United States have shown some success in this with mandatory *trans*-fat labeling, decreasing some types of fats in snack foods (Van Camp, Hooker, and Lin 2012). Still, such policies need to be specific enough to force manufacturers to improve their products' nutritional content genuinely. Second, front-of-package labels need to be regulated not to deceive consumers about the nutritional quality of products, thus ensuring that consumers can trust front-of-package labels (Rao and Wang 2017). Third, regarding price accessibility to healthy foods, policymakers can subsidize retailers to keep prices low for items that meet healthy nutritional standards and implement FOP labels, thereby promoting products that are healthy and educating consumers about choosing healthy products. Though food subsidies can decrease nutritional inequality problems between low-income and high-income consumers (Allcott et al. 2018), current food subsidy programs struggle with subsidizing by caloric content rather than nutritional quality. Governments should shift the focus of direct-to-consumer food subsidies from caloric intake to nutritional quality, both in content and promotion (Dinour, Bergen, and Yeh 2007; Townsend 2006). We hope that such suggestions, in conjunction with FOPs, can genuinely help consumers make healthier food decisions.

THE NEURAL BASIS OF INDIVIDUAL DIFFERNCES IN SELF-CONTROL IN DIETARY DECISION-MAKING

This chapter will focus on laying out what we know from neuroeconomics about the psychological underpinnings and individual differences in exercising self-control through willpower. Against this background, in this chapter, we present an interdisciplinary exercise between behavioral science and neuroscience to capture individual differences in dietary decision-making and its control. We first discuss the computational approaches to capture individual differences in self-control and reward impatience studied in behavioral economics and their neural underpinnings. Next, we discuss boundary conditions provided by studying self-control-related diseases such as obesity, eating disorders, drug addiction, and gambling. Finally, we conclude our chapter by calling for an interdisciplinary model of dietary decision-making and its control.

MODEL-BASED APPROACHES TO DIFFERENCES IN SELF-CONTROL

Higher self-control has been correlated positively with higher grades in school, better psychological adjustment, less binging on food and addictive substances, better social relationships, and positive emotional responses (Tangney, Baumeister, and Boone 2004), but what are the mechanisms underlying such outcomes? Research in economics and neuroeconomics has studied self-control using different models. The most prominent ones are discussed in the next section.

Evolution of Models to Capture Individual Differences in Impatience in Behavioral and Neuroeconomics

Behavioral economics adds insight into the understanding of preference for immediate rewards through formal models of *intertemporal choice* and *delay discounting* (Laibson 1997; Loewenstein and Thaler 1989). Such models refer to

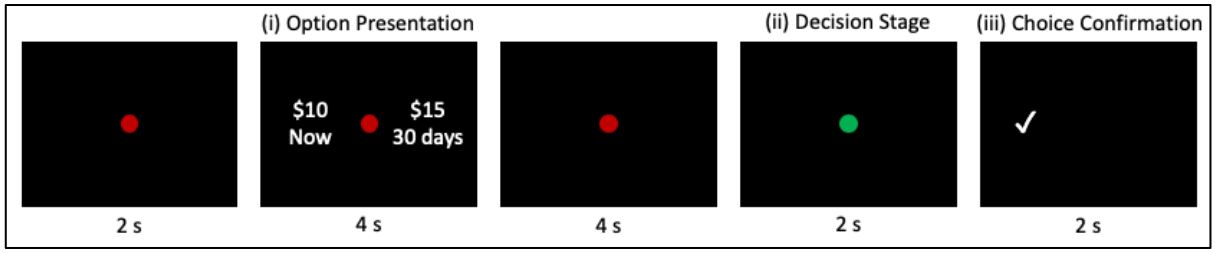
decisions that involve trade-offs between different outcomes at different points in time. Traditionally, these models capture preference for immediate monetary payoffs, but more recent research has attempted to investigate discounting for other rewards such as drugs and food (Ainslie 1975; Odum and Rainaud 2003).

Generally, in these choices, the value or utility of chosen rewards that are further away in time (later in the future) is devalued more than that of options closer in time (sooner in the future) because time is considered a cost to receive the reward. For example, one can spend on a new car or invest the same money in a retirement fund. Such decisions affect consumption patterns for months or years to come and therefore have consequential long-term effects on well-being. However, people have individual perceptions of durations of time. One person may exaggerate the length of time until retirement and therefore perceive the utility of a retirement fund as lower than another, a more cautious person does. The decreased perceived utility increases the difficulty of choosing between a new car and a retirement fund. Both options might have close perceived values to each other, though distinctly different economic values.

Quantitative models of intertemporal choice allow researchers to formally describe how individuals construe larger rewards in the future due to the delay in time to the reward. These models equate the perceived value of a reward as a function of the delay to the reward and the actual value of the reward. The literature on intertemporal choice has developed several computational models to describe how time construal impacts the valuation of delayed rewards. These computational models have evolved through behavioral economics and psychology literature as more experimental methodologies have elucidated the process of *temporal* (or *delay*) *discounting*, defined as the act of discounting rewards with time delays. In tasks to estimate delay discounting behavior, a subject repeatedly chooses between a smaller

but more immediate reward and a larger but later reward (Figure 4), with varying differences between the rewards and the times offered. The delays, differences between rewards, and multiple choices made by participants are incorporated into these models to allow for statistical fits of these delay discounting models. The model will estimate a measure that describes each participant's behavior, called a parameter.

Figure 4: A Delay Discounting Task. (i) Different monetary rewards offered at different points in time are presented to a participant in a decision period. (ii) The participant is prompted to make a choice. (iii) The participant's selection is indicated in the choice mode, and the reward is delivered in the time indicated from the choice period. Durations of each stage are in seconds (s) and indicated at the bottom of each panel.



The binary choices allow for a statistical fit on the discounting models. For each participant, the model will contain a measure that describes their behavior, called a parameter. This discounting parameter can be seen as an individual difference; comparing parameters between certain groups (e.g., people with a relatively low vs. high income or IQ) can provide insights into behavior. For example, Petry (2001) showed that pathological gamblers showed more impulsivity; they had higher average discounting rates in a delay discounting task for money rewards than healthy, non-gambling individuals. Pathological gamblers who had substance abuse disorders had higher average discounting rates than gamblers without substance abuse disorders. Compared to a task with money, the addictive stimulus for gamblers means that pathological gamblers exert less self-control than healthy individuals. Among gamblers, those with substance abuse disorders have worse self-control than those who do not have substance abuse disorders. Therefore, Petry (2001) suggests that

pathological gambling and substance abuse disorders are related to self-control disorders, which will be discussed further in this chapter.

The first computational model, the exponential model, derives its base from traditional economics research and the normative (ideal) assumption that humans discount the utility of future rewards by a fixed percentage over time (Samuelson 1937). That is, for every increment of time further away, the reward is discounted by a constant amount. *Subjective value* refers to the perceived utility of the future reward by the individual. To mathematically describe this model, let *SV* represent the subjective value of the reward, *A* the objective amount of the reward, δ the discount factor between 0 and 1, and *t,* the amount of time until the reward. The representation of the subjective value based on exponential discounting is:

$$SV = A\delta^t \qquad 6$$

In this model, lower values of δ, the discounting parameter, represent higher discounting of future rewards and, therefore, a smaller subjective value of future rewards. Higher discounting of future rewards implies less self-control. So, a higher discounting parameter for a participant (closer to 1) indicates more self-control.

However, while this model is normative in economics, it is not an accurate representation of actual human behavior, as not only humans but also animals (Samuelson 1937) do not perceive time in such a linear manner. Behavioral research overwhelmingly supports that humans and animals do not exponentially discount future rewards (Mazur 2001). People will strongly discount any future rewards when a time delay exists, but as the choice becomes more offset, the discounting of the reward will not be at a rate directly proportional to time. For example, if a choice were €10 today versus €11 in one day, the discounting rate would be much steeper than if the choice were between €10 in one month from today versus €11 in one month and one

day from today. In model terms, the discount rate for an intertemporal choice made in the present would be higher than if the same intertemporal choice were made in the future, which violates the exponential model's assumption of a constant discount rate.

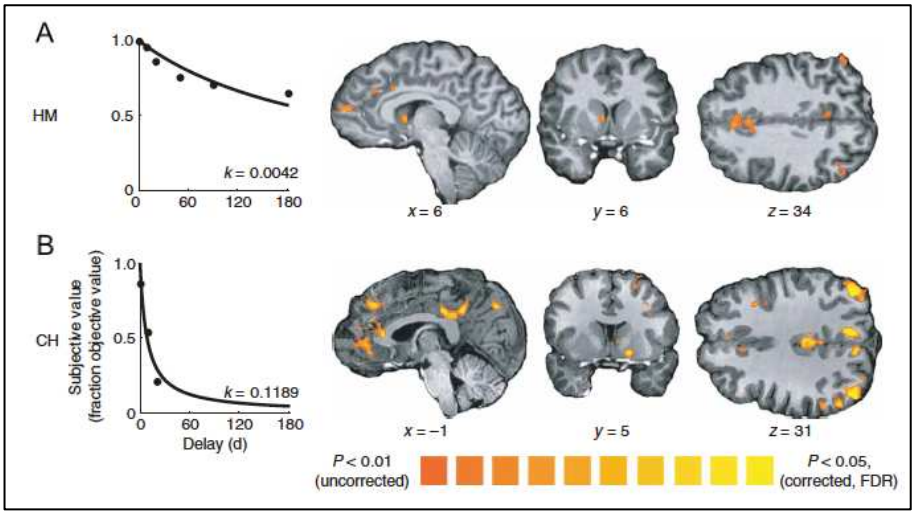
The hyperbolic model addresses that empirical evidence of non-exponential discounting. Once again, let *A* and *SV* have their same representations as in the exponential model, but let *t* represent the delay until the reward and *k* represent the discounting parameter. The hyperbolic model is then described as:

$$SV = \frac{A}{1 + kt} \qquad 7$$

In this model, more impulsive individuals have higher *k* parameters. The single parameter of the model makes it the preferred model for studying impulsive behavior. In .

Figure *5*, more activity in the brain in the medial prefrontal cortex (mPFC) and the ventral striatum (vStr) can be seen with participants who have higher discounting parameters (towards subfigure B) than in participants with lower discounting parameters (towards subfigure A).

Figure 5: Graphical representations of how the discounting parameter changes the hyperbolic subjective value model. (A) Less discounting of future value. (B) Higher discounting of future value. Adapted from (Takahashi 2005)*.*



However, the hyperbolic model does not explicitly account for people having a strong preference for immediate rewards and therefore showing a present bias. The quasi-hyperbolic model (Laibson 1997) explicitly captures impulsivity (the "present bias") and also the lower discounting of temporally further rewards for a more "patient" rational system. Once again, let *A* and *SV* represent objective and subjective values of the reward, respectively. Then, the quasi-hyperbolic model is represented as:

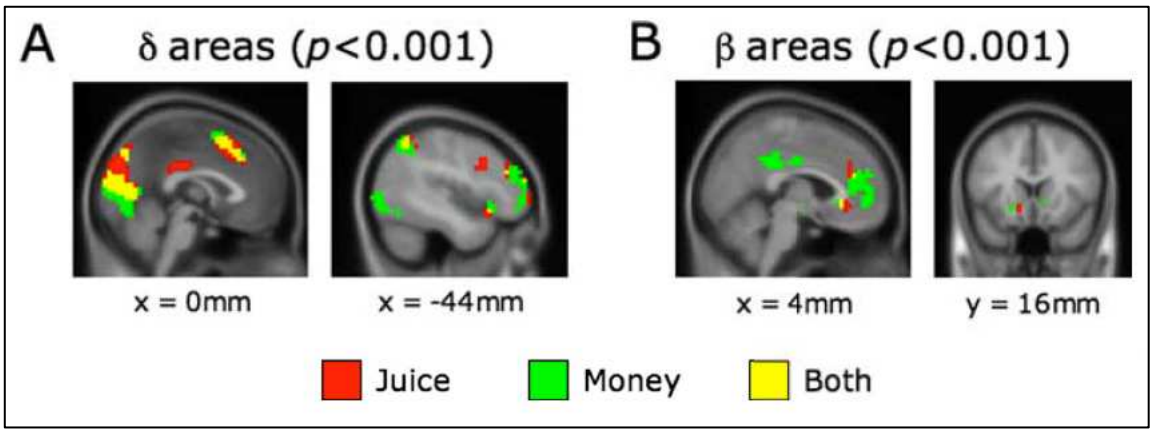
$$SV = A * \beta * \delta^t \qquad 8$$

In this model, β represents the first competing system involved in intertemporal choice: an impulsive emotional system. The second parameter δ represents a patient rational system that accounts for the value of both immediate and future rewards. For both parameters, the lower the parameter, the more impulsive and less patient the individual is. This model indicates that when both rewards are delayed in time, there is a preference reversal between smaller-sooner and larger-later rewards, that a smaller-sooner reward will be selected when provided immediately but the larger-later reward will be selected if there is also a delay in the smaller-sooner reward.

The quasi-hyperbolic model is most in line with the theory of dual selves. When making an intertemporal choice, an individual would think of both a doer when considering a nearer but smaller reward and a planner when considering a later but larger reward. Hence, the conflict between these two selves can be interpreted as the conflict between the impulsive, emotional system and the patient, rational system. These systems have somewhat analogous neural correlations. McClure *et al.* (2004) and McClure *et al.* (2007) showed both behavioral and neurological evidence of these competing systems. The first system, the visceral system encoding immediate rewards, consists of the posterior cingulate cortex (PCC), the ventral Striatum (vStr),

and the ventromedial prefrontal cortex (vmPFC). The second system, the self-directed reflective system, recruits the dorsolateral prefrontal cortex (dlPFC), the right intraparietal cortex (RPar), and the lateral orbitofrontal cortex (lOFC), along with visual and motor regions. The quasi-hyperbolic model has been applied to intertemporal choices with food rewards; overlaps in brain activity for food and monetary rewards suggest that the valuation systems between domains of rewards share brain regions, as shown in **Error! Not a valid bookmark self-reference.**.

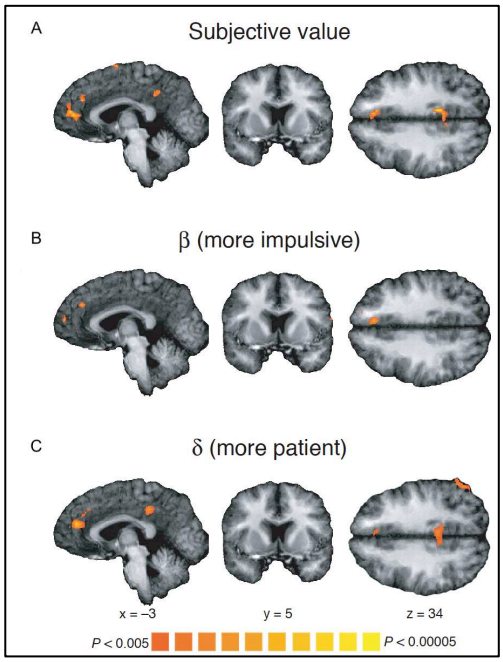
Figure 6: Separate regions of brain activation for impatience (A) and impulsivity (B) systems in intertemporal choice for food (red) and monetary (green) rewards. The yellow regions show an overlap in brain activity for both rewards. Adapted from Samuel M. McClure et al. 2007.



Kable and Glimcher (2007) investigated the question of whether the brain contains a single system or two distinct systems encoding immediate and delayed rewards. They could not find enough evidence of "competing systems" in intertemporal choice that encode the values of immediate and delayed rewards. If one were to compare the sagittal planes (the cross-section brain images on the left of each subfigure of Figure 7), one would notice that all three cross-sections have warm spots in the same area of the brain, which indicates that the regions in these systems — subjective valuation, impulsivity, and patience — overlap with each other, meaning that these systems are not independent of each other.

Figure 7: Representations of subjective value of future rewards (A), the "impulsive" system (B), and the patience system (C). The regions of activity across all three conditions have strong

overlap, indicating that the two systems of self-control are not independent of each other. Adapted from Joseph W. Kable and Glimcher 2007.



Assume an individual had to choose between €10 today and €15 in a week, and then between €10 in a week and €15 in two weeks. The quasi-hyperbolic model would predict that for the first choice set she would pick €10 today because the "impulse" system would have a preference for today (the choice set is framed with a reward in the present, so one must be a "doer" to consider a possible immediate outcome), and for the second choice set she would pick €15 in two weeks because a "patience" system would be activated (the choice set is framed with the outcome always in the future, so one must be a "planner"). To have two independent discounting parameters would indicate that these systems work independently of each other. Kable and Glimcher (2010) further added to the 'dual systems' theory of delay discounting by considering that an individual will discount relative to the soonest possible reward. To capture both the "impulse" system and the "patience" system, they proposed the as-soon-as-possible (ASAP) model, whose basic intuition is that individuals will choose the soonest available option of greater perceived value. The ASAP model form captures the "impulse" system to account for the desire for the

soonest-possible reward, while estimating the discounting parameter to account for the "patience" system, and neither system acts independently of the other. This model suggests that there exists no preference reversal when a smaller-sooner reward versus a larger-later reward choice is shifted in time (i.e., there is no preference reversal if a choice made in the "now" condition is repeated in a "not now" condition because the frame of reference for the choice is based on the soonest possible time of the reward).

The ASAP model is a modification of the hyperbolic model (with the *SV, A, k,* and *D* represented as before) with the inclusion of the following gain function g, which is a function of the delay to the soonest possible reward, represented as D_{ASAP}:

$$g(D_{ASAP}) = \frac{1}{1 + k * D_{ASAP}} \quad 9$$

Then, the ASAP model is represented as follows:

$$SV = g(D_{ASAP}) \frac{A}{1 + k(D - D_{ASAP})} \quad 10$$

Interestingly, some economists have argued that discount rates are stable across time and independent of the specific context (Kirby 2009; Odum 2011, 2012). Behavioral economists and psychologists, however, argue differently and have found that delay discounting is context dependent. For example, poverty has psychological consequences that can make individuals more present-biased and short-sighted and have higher discounting rates (Haushofer and Fehr 2014). Different age groups also discount future rewards differently; younger adults are steeper discounters than older adults (Jimura et al. 2011).

One caveat to note is that the utility curve for the rewards is assumed to be linear throughout the literature that has developed these models. This linear assumption can be applied when an intertemporal choice task is a two-alternative

forced choice task. However, if more than two rewards are offered, linear utility cannot be assumed, as this can lead to biased estimation of the delay discounting parameters (Cheung 2016). Some intertemporal choice model estimations will consider constant relative risk aversion and apply a risk aversion parameter α as an exponent to the objective value of the reward. Equation *7*, for example, would then be rewritten as $SV = \frac{A^{\alpha}}{1+kt}$.

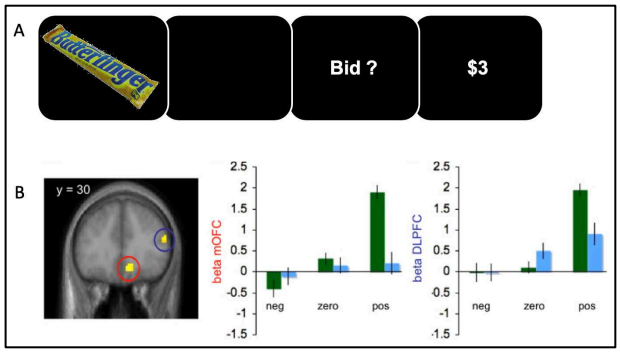
Another stream of literature in neuroeconomics has investigated models of dietary decision-making and its self-control. These models have also investigated how the specific context matters. They are discussed in the next section.

A Neuroeconomic Model to Capture Subjective Value Coding and Its Control for Dietary Choices

Early work in neuroeconomics has studied how the human brain encodes subjective value for foods using tasks from behavioral economics to ensure "true" value coding while participants' brains were scanned (Plassmann, O'Doherty, and Rangel 2007, 2010). As seen in

Figure *8*, this work found that neural activity in two regions in the brain, the ventromedial prefrontal cortex (vmPFC, the bottom yellow dot on the brain image in section B) and the dlPFC (the right-side yellow dot on the brain image in section B), correlates with the subjective appetitive and aversive value of foods. Notably, as seen previously, both areas, which positively correlated to impulsivity and patience systems in intertemporal choice, respectively, are active when evaluating dietary choice.

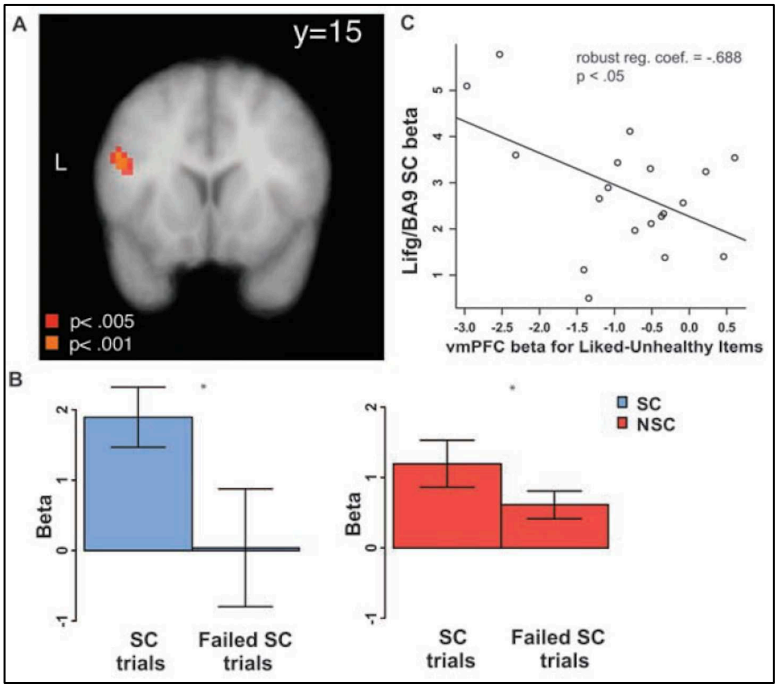
Figure 8: (A) Participants were asked the amount they were willing to pay to consume snack items of varying levels of healthiness. (B) Activity in the right vmPFC and the dlPFC was correlated with participants' bidding for foods (green) to consume ('pos') or avoid ('neg'). This implies that valuation of appetitive and dietary-choices goals will involve action by the dlPFC. Adapted from Plassmann et al. 2010.



Several later meta-analyses found that the vmPFC and the vStr form the brain valuation system for different rewards, including money, foods, and products such as trinkets (Bartra, McGuire, and Kable 2013; Levy and Glimcher 2011; Rangel and Clithero 2013). So what role does the dlPFC play in food valuation and its control? Camus *et al.* (2009) provided evidence for the necessary role of the dlPFC in the valuation of foods by temporarily inhibiting activity in the dlPFC using transcranial magnetic stimulation and showing decreased valuations of foods. Follow-up research investigating how one could control the assignment of subjective values to food leveraged a choice between fruit salad and chocolate cake, for example, into how much weight the consumer put on either the health or the taste of food (Hare, Camerer, and Rangel 2009; Hutcherson et al. 2012; Rangel and Hare 2010). Hare *et al.* (2009) proposed a neural model of self-control that does not necessarily involve competition of two different systems but rather the strengthening and weakening of the value coding system in the vmPFC-vStr valuation system through an interaction with the dlPFC. They showed that self-control is implemented in the brain through an increased correlation or “co-activation” in neural activity between the vmPFC and dlPFC. When contrasting brain activity between participants who were more “successful” at implementing self-control (i.e., those who were picking more healthy choices) compared to others, the difference in brain scans was in the increased activity in the dlPFC, as seen by the red area in **Error! Not a valid bookmark self-reference.**,

where warmer colors indicate more activity in the area. This implies that activity in the dlPFC positively correlated to more control to make healthy food choices.

Figure 9: (A) The dlPFC is more active in successful self-control trials for participants who were asked to exert self-control than in those who were not asked. (B) The differences in dlPFC activity between self-control individuals and no-self-control individuals. (C) Activity in the dlPFC is correlated negatively to activity in the vmPFC, indicating that the dlPFC acts as a "self-control brake" to activity for the vmPFC's role as the common valuation region of the brain. From Hare et al. 2009.



The results from these self-control studies and the research on models of intertemporal choice are further proof that the two systems are involved in self-control choice. The valuation system (akin to the β system of intertemporal choice and 'emotional' self of the dual-selves theory) and the control system (akin to the δ system of intertemporal choice and the "patient" self of the dual-selves theory) do not compete. The dlPFC modulates activity in the vmPFC when one exerts self-control by communicating information involving health and other facets that would inhibit choosing visceral rewards that satisfy a visceral need to consider options superlative (in this case, health) goals with some cost.

These are in line with Kable and Glimcher (2010), which shows that the vmPFC is involved in the valuation of reward, regardless of when the reward arrives. Through this model of cognitive regulation, or actively using control processes to regulate the decision-making process with food rewards, humans can increase and decrease their cravings when choosing food. Activity in the vmPFC and dlPFC correlates with this value strengthening and weakening (Hutcherson et al. 2012). Some findings suggest that the dlPFC first involves itself in dietary self-control through filtering attention (i.e., reducing attention from goal-distracting cues like tastiness). Then it regulates the value assigned to the food (Harris, Hare, and Rangel 2013). Intertemporal choice contributes to this notion of self-control. A higher subjective value for a future reward implies either regulating the present reward's value or increasing the future reward's value.

Anatomically, recent research has found that individual differences in grey matter volume in the vmPFC and dlPFC could predict success in dietary regulation; individuals with more grey matter volume in these regions were better at exerting dietary self-control (Schmidt et al. 2018). Given this clue to how more stable neural markers play a role in explaining individual differences in self-control, we will discuss in the next section other research helping to provide a better understanding of self-control success and failure.

WHAT FACTORS IMPACT THE ABILITY TO EXERT SELF-CONTROL?

We have explored the neural mechanisms through which self-control occurs in the brain, but what how individuals actively resist temptations? Specifically, what behaviors and manipulable mechanisms will consequently impact how the brain processes temptations and fights them? Psychology research can provide insights into what behaviors strengthen (or weaken) our ability to exert self-control. A better

understanding of control-related disorders such as addiction, obesity, and eating disorders might provide insight into what biological mechanisms disrupt our ability to exercise self-control.

Consumer decision-making literature has explored how depleted mental resources lead to increased efforts to exert self-control (Masicampo, E.J.; Baumeister 2008). Neuroscience literature has helped to cleanly identify what processes contribute to such "depleted mental resources." Self-control relies on interconnected processes involving working memory, executive function, and value integration. As mentioned before, numerous studies have shown how manipulating activity in the dorsolateral prefrontal cortex (dlPFC) changes how the brain's valuation system (BVS) weighs important factors in value-based decision-making, as both regions are involved in working memory and *executive function* (Camus et al. 2009; Tusche and Hutcherson 2018). Below we discuss how individual psychological differences that lead to depleted mental resources, per se, are essential to decision-making impact the ability to exert self-control.

Self-Control and Executive Function

The cognitive processes that contribute to cognitive control, such as attention, working memory, and cognitive flexibility are part of *executive function*. The cognitive control system (CCS) regions most often associated with executive function include the dlPFC and the anterior cingulate cortex (ACC). Two executive functions essential to cognitive control discussed below are the roles of *cognitive flexibility* and memory.

Cognitive flexibility refers to an individual's ability to switch between ideas and think about multiple concepts, ideas, and tasks simultaneously. Simple examples of cognitive flexibility include the ability to integrate information from various sources,

learn from the environment, and adapt to changes when making decisions. Neurodevelopment research has shown that cognitive flexibility develops until a human adult's mid-twenties and that increased abilities to implement cognitive flexibility are very much related to functional connectivity in the prefrontal cortex of the brain (Masicampo, E.J.; Baumeister 2008). The developmental research implies that dysfunctions in functional connectivity between areas of the brain in the CCS and the brain's valuation system (BVS) would be important for physicians to explore such functional connectivity differences to explore deficits in cognitive control. Because of its role in learning, common disorders related to self-control deficit through cognitive flexibility are also disorders in learning like attention deficit and hyperactivity disorder (ADHD and ADD), Parkinson's' disease, and obsessive-compulsive disorder (OCD).

Much related to cognitive flexibility is the role of memory in self-control, specifically *working memory*, or the amount of temporary information to remember. To temporarily store information and integrate information from previous experiences ties into learning and making decisions. Examples of the increased use of working memory in daily settings that can impede self-control include working through a list of purchases in a grocery store, making decisions in high stimulation environments (ex., those with a lot of sensory input like a trendy clothing retail store), and having increased stressors and responsibilities, which would lead to fewer "mental resources" to exert self-control.

Increased working memory is related to self-control, as it negatively correlates to temporal discounting (Morton, Bosma, and Ansari 2009). The region of the brain most associated with working memory is the dlPFC (Hinson, Jameson, and Whitney 2003), which, as discussed before, also overlaps with regions related to delay discounting (Goldman-Rakic 1995). The executive processes for working memory

detract resources from the intertemporal decision-making process, making it necessary to assess choices in an economically suboptimal process, like assessing only the time to the reward rather than the actual values of the reward.

This notion ties itself to later research on episodic future thinking, or the capacity to vividly imagine future personal events, which, for example, has been shown to help adolescents with reducing impulsive decision-making (Wesley and Bickel 2014). Episodic future thinking reduces delay discounting as self-projection into the future through visualizing the self in the future engages the hippocampus, which is involved in the decision-making process by evaluating future payoffs by mental simulation (Bromberg, Wiehler, and Peters 2015). Episodic future thinking was also positively correlated with activity in the dlPFC.

Self-Control and Affect

In the same light, positive affect promotes forward-looking and high-level thinking, increasing a consumer's willingness to wait, thus decreasing delay discounting behavior (Peters and Büchel 2010). On the other side of the emotion spectrum, imagining negative future events makes individuals pick more smaller-sooner rewards (Pyone and Isen 2011). Financially, individuals make worse financial decisions, opting for smaller-sooner rewards when they are sad (Liu et al. 2013). Negative emotions can elicit altered time perception, making individuals more present-oriented (Lerner, Li, and Weber 2013), though the exact neural mechanisms remain unknown. Related to this, increased perceived stress of future events, which shares certain aspects of negative emotions, can increase the influence of immediately satiating attributes of reward stimuli and decrease self-control, as stress increases functional connectivity between the vmPFC and the amygdala, which is involved in stress response (Guan et al. 2015). Likewise, increased perceived stress in the

present offsets the preference for immediate choices to those set in the future (Maier, Makwana, and Hare 2015).

Memory and affect, or the underlying experiences of feelings, emotions, and mood, can interact to improve self-control. For example, positive memories can reduce delay discounting (Lempert et al. 2012). How people perceive their future self will impact whether they tend to make present-oriented or future-oriented choices (Lempert et al. 2017). If the present self feels shared similarities with their future self (i.e., seeing themselves as they currently are in the future), they will make more choices today that benefit their future self.

Research in cognitive-behavioral theories of depression shows that, during learning tasks, depression patients recall less positive feedback and more negative feedback than negative controls, thus creating biases in learning rates (Hershfield 2011). The integration of different types of feedback is associated with other regions of the orbitofrontal cortex, part of the brain valuation system (BVS) (Nelson and Craighead 1977). The interlinked roles of memory and affect, therefore, play a role in the exertion of self-control by not only impacting how value is modulated through the recall of relevant information, beliefs, and emotions about aspects of the decision but also through how this information integrates with the valuation system as part of the brain's ability to integrate such modulated information to generate value.

SELF-CONTROL IN HEALTH AND DISEASE

Dopaminergic disorders can lead to increased delay discounting, as evidenced not only by fundamental research on how dopamine influences value-based decision-making (Monterosso et al. 2007) but also by research on how drug exposure leads to disorders in delay discounting (Dreher et al. 2009; Guitart-Masip et al. 2012; Kayser et al. 2012; Wallace et al. 2014). Choosing larger-later responses in a delay

discounting task requires steady dopamine signaling to the striatal and prefrontal regions of the brain, while smaller-sooner choices are prompted by shorter dopamine signals that focus attention on the visceral reward; modulation through the orbitofrontal cortex (OFC) can allow dopamine to shift the decision from smaller-sooner to larger-later choices (Volkow and Morales 2015).

The vStr and vmPFC, common regions in value-based decision-making tasks (Volkow and Baler 2015), rely on the dopaminergic system and are regions vital to subjective value computation in delay discounting and self-control. Considering that obesity is typically associated with behaviors like a lack of self-control around food, a proclivity for high-calorie foods, and normatively unhealthy diets (Bartra, McGuire, and Kable 2013; Rangel and Clithero 2013), the same processes of addictive behaviors apply to obesity and dietary decision-making in general.

Dopamine contributes to obesity and addictive disorders, as both share common mechanisms through the reinforcement of reward cues (e.g., response to the taste of the food), the motivation and self-regulation to seek the reward (e.g., the continual seeking of similarly tasting foods), and the increased habitual response because of the reward cues (e.g., the habit of consuming foods of similar taste) (Baler and Volkow 2006; Volkow, Wise, and Baler 2017). Eating disorders can be treated by improving the function of dopamine-modulated reward circuits to solve the glucose addiction or food insensitivity problem, which alludes to obesity being treated like a pathological eating behavior and a food addiction problem (Volkow, Wise, and Baler 2017). Obesity has also been seen as a reward deficiency syndrome for glucose due to the impairment of brain reward circuitry, resulting in low dopamine function (Volkow et al. 2013). In that sense, if addiction treatments aim to reduce the rewarding attributes of drugs while increasing inhibition and cognitive control (Blum, Thanos, and

Gold 2014) and if eating disorders are also based on dopamine circuits, one option in the fight against obesity could be to implement therapies similar to those used in treating addictions and eating disorders, which involve focusing on reducing the rewarding attributes of unhealthy foods, increasing the focus on rewarding characteristics of healthy foods, and increasing an individual's ability to exert cognitive control and inhibition.

Chemical markers beyond neurotransmitters are important to the study of self-control, considering that chemical markers in the body communicate with neurotransmitters, which would guide decisions involving self-control. In dietary decisions, metabolic processes seem prime candidates for essential drivers of the self-control network in the brain. On the one hand, metabolic processes are involved in the basic homeostatic control of eating; that is, we eat when our energy resources are depleted. We abstain from eating when our energy levels are sufficient. Findings that humans have dedicated hormonal regulators of hunger, satiety, and fat levels, such as leptin, ghrelin, and insulin, among others, support this model (Baler and Volkow 2006). Such hormones communicate with lower-level brain systems that represent a "homeostatic regulator." On the other hand, more recent research suggests that metabolic processes go beyond maintaining an energy balance and also influence higher-order motivational systems linked to eating for pleasure rather than calories (Dagher 2012; Morton, Meek, and Schwartz 2014; Williams and Elmquist 2012). For example, increased sleep deprivation was associated with decreased activity in appetite evaluator regions, which then was associated with increased food choices that, if consumed in excess, would trigger weight gain (Dagher 2012; Morton, Meek, and Schwartz 2014; Zheng and Berthoud 2007).

An exciting new stream of research, primarily based on animal models, on metabolic processes investigating the bacteria in the gut suggests that the richness of gut bacteria of the host can be linked to the host's brain systems involved in homeostatic regulation, emotion, and cognition (Greer, Goldstein, and Walker 2013), the so-called "gut-brain axis") and also to eating and dieting behavior (Le Chatelier et al. 2013; Cotillard et al. 2013). For example, research had shown that when the gut microbiota of germ-free mice was replaced with those with Parkinson's, the previously germ-free mice started showing the same motor symptoms of Parkinson's disease (Le Chatelier et al. 2013; Cotillard et al. 2013). Given that Parkinson's disease is a dopamine deficit disorder behaviorally characterized by low motivation and reward valuation, that most Parkinson's patients suffer from gastrointestinal disorders, and that the gastrointestinal symptoms often precede the motor symptoms of the disease, this finding is preliminary evidence of how gut microbiota and changes in the gastrointestinal system impact the brain's reward valuation system.

SUMMARY

Taken together, we discussed work in a variety of disciplines that study the rewarding and hedonic aspects of decision-making and its control, yet why we choose what and how much we eat is still poorly understood. We think this is partly due to the lack of communication between different disciplines studying decision-making in the context of self-control. Bridging various areas that have been co-existing separately for too long could substantially advance current theories about decision-making and its control (Sampson et al. 2016). First, experimental economics and real-world consequences of behavior can map their findings to physiological manifestations, thus advancing utility models in behavioral economics. Second, the treatment of self-

control disorders can further refine psychological theories of self-control Third, research in medicine, nutrition science, and microbiology can lead to a bottom-up decision-making model and its self-control (i.e., from gut to brain to behavior). The following two essays explore how physiological changes translate to changes in self-control measured through behavioral and experimental economics approaches from a bottom-up approach.

ESSAY 2: THE EFFECTS OF BARIATRIC SURGERY ON DELAY DISCOUNTING MODELING FOR FOOD AND MONEY: A LONGITUDINAL STUDY

INTRODUCTION

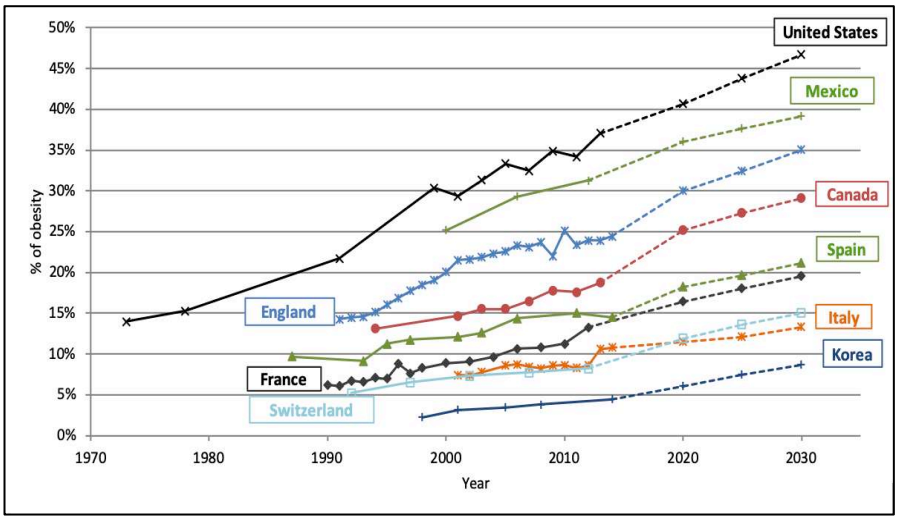
Obesity is a global epidemic (Berthoud 2011; Rangel 2013), given its prevalence and its impact on the risk of cardiovascular disease, type 2 diabetes, and cancer. Countries are vastly heterogeneous in obesity rates; for instance, 38.2 percent of U.S. adults versus 15.3 percent of French adults are obese, according to the OECD ((Caballero 2007), Figure 10). Yet obesity rates are continually increasing in all developed countries, with projections for 2030 estimated at 47 percent of the population in the United States, 35 percent in England, and 21 percent in France, making it critical to understand the causes and possible cures of obesity.

Individual differences in exercising self-control could be one contributing factor to the obesity epidemic. Dietary temptation is everywhere, from the prevalence of international chain restaurants competing with local cuisines to the strategic placement of foods on supermarket shelves. Unfortunately, these everyday societal facets do not contribute to a sustainable lifestyle. Previous research has established a link between self-control failure and being overweight and suffering from obesity (Jasinska et al. 2012; Weller et al. 2008), as well as the ability to keep weight off after a diet (Jasinska et al. 2012; Weller et al. 2008).

Globally, people can lose weight, as evidenced by the size of the weight loss industry, the persistent suggestion of new diets, and the success of reality TV shows such as “The Biggest Loser” and “My 600-lb Life” in the United States. However, the outcomes of such efforts are often merely temporary – it is hard not to regain weight after a “successful” weight loss intervention (Weygandt et al. 2013). A study from the U.S. National Institutes of Health tracked sixteen participants on “The Biggest Loser”

six years after their participation, and found only one participant had not regained any weight (Thomas et al. 2013). This research suggests that individual differences in one's neurobiology and psychology might have a big impact on the ability to not only lose weight but also keep it off.

Figure 10: Current and projected obesity rates (defined as BMI ≥30 kg/m^2) in select countries (Fothergill et al. 2016)



Bariatric surgery, or surgery on the gastrointestinal (stomach and intestines) tract, remains one of the most effective interventions against obesity. Previous literature has shown that Roux-en-Y gastric bypass surgery (RYGB), a bariatric procedure that in addition to restricting the size of the stomach, physically remove parts of the digestive tract, is the most effective form of weight loss surgery, compared to other forms of bariatric surgery like lap banding, which only restricts the size of the stomach through physical pressure. RYGB patients exhibit not only more the obvious physical weight loss results from physical restrictions on the stomach but physiological changes including reduced hedonic responses to food, and changes in food preferences and hunger, changes in cognitive function, and changes in reward and motivation processing (Handley et al. 2016; Volkow, Wise, and Baler 2017). Gastrointestinal changes, therefore, could mediate changes to behavioral responses to food because of how changes to the "gut-brain" axis directly impact gut hormones,

which interact with neurotransmitters involved in reward valuation, which then impacts behavior (Handley et al. 2016; Volkow, Wise, and Baler 2017).

Intertemporal choice and obesity

Impulsivity, which can be measured by delay-discounting, has been identified as a potential psychological factor of obesity. Compared with lean subjects, overweight and moderately obese subjects exhibit greater discounting behaviors (Behary and Miras 2015; Scholtz et al. 2014). The impact of obesity on delay discounting behaviors has been studied as well through the hyperbolic model (Fields, Sabet, and Reynolds 2013; Meule and Blechert 2017) and predominantly with monetary rewards (Scharff 2009; Schiff et al. 2016). Obesity has been shown to correlate with the quantity (though not frequency) of ready-to-eat foods and take-away items consumed (Weller et al. 2008), while the increased impulsivity to eat healthy foods provides a protective effect on healthy food consumption by preventing the hunger that will increase the desire for unhealthy food.

The study of self-control and obesity, therefore, becomes a chicken-or-egg problem. Does a decreased ability to exert self-control lead to obesity, or do the physiological effects of obesity lead to problems with exerting self-control? The former question implies that the general lack of self-control exertion, independent of reward domain, leads to obesity. The second implies that the physiological processes underlying obesity would lead to deficiencies in the ability to exert self-control, which also implies context dependence for self-control (i.e., that the struggle to exert self-control may be limited to food). Thus, to understand how obesity is related to self-control and how lean and obese individuals differ in their ability to exert self-control, a controlled manipulation of the physiological processes around obesity like weight loss

can shed light into this. In this project, gastric bypass surgery serves as the controlled measure of weight loss.

Our current paper seeks to address how morbid obesity is correlated with delay discounting and whether weight loss, specifically with a direct intervention on the gastrointestinal tract through bariatric surgery, will change the relation between morbid obesity ad delay discounting. In each of the three studies, we address the following hypotheses using different types of intertemporal choice tasks, each method contributing something that drives insight into the efficacy of bariatric surgery in promoting self-control. First, we hypothesize that before surgery, obese patient participants will be much more impatient for food rewards than lean control participants. After surgery, the difference in patience for food rewards will decrease for the obese patient participants. Second, we hypothesize that the obese patient participants will behave similarly to the lean control participants for food rewards after surgery.

The literature remains inconclusive about the differences in delay discounting for monetary rewards because of the different reward types offered in such delay discounting studies, such as in hypothetical studies that cannot be truly incentive-compatible (Miranda-Olivos et al. 2021; Schiff et al. 2016; Tang et al. 2019; Weller et al. 2008). Thus, we also hope to explore potential mediators to explain why weight loss surgery would lead to changes in behavior and the boundary conditions for the limits of surgery impacting behavior. Considering the marginal utility differences for food versus for money, we hypothesize that individuals should be discounting future healthy food rewards less than future unhealthy food rewards and discounting less in trade-offs based on quality rather than quantity.

STUDY 1

Overview

The purpose of this experiment is, one, to study the differences in discounting behavior between lean individuals and morbidly obese individuals and, two, to understand the effect of gastric bypass surgery on delay discounting behavior in morbidly obese patients through delay discounting models.

Participants

Data was collected between March 2011 and October 2017 from female obese patients (N=17, BMI 44±2.5) and lean control participants (N=45, BMI 22.2±1.8). Obese patient and lean control participants repeated the task 6 months later, the obese patients after bariatric (RYGB) surgery (N=17, BMI = 34.2 ± 1.2), and the lean, once again, six months after baseline (N = 35, BMI 22.1 ± 0.43) to confirm stability of their behavioral results between sessions. Before the task, all participants needed to agree to not eat at least three hours prior to the task and have only a light meal before. An obese non-patient participant pool (N = 29, BMI 31.8 ± 0.5) was also recruited to control for how weight and not being on a controlled diet would impact behavior, as obese patient participants were in consultation with physicians and had to lose weight to qualify for surgery.

Experiment

In an incentive-compatible delay-discounting task under functional MRI, participants were asked to choose between a smaller but sooner (SS) reward or a larger but later (LL) reward of money (Euros) or chocolates of equal monetary value. The study was adapted from a previous delay discounting study that only used monetary rewards (Appelhans et al. 2012). The SS rewards were either offered immediately (the “now” condition) or with a delay of 14 days (the “not now” condition)

while the LL rewards were offered at 14 or 28 days after the SS reward. The values of the rewards as well as the percentage difference between the SS and LL rewards were varied through the experiment. Participants performed 36 rounds each of the "now" and "not now" conditions for a total of 72 rounds per reward type (food and money). Overall, the participant completes 144 trials (2 ("today" or "in 2 weeks" for the time of delivery of the SS reward) by 2 (a two week or four-week time interval between the SS and LL reward) by 18 (the number of relative differences in reward magnitudes between the SS and LL rewards) by 2 (food versus money rewards)). The reward pairings with their respective delays can be found in the Appendix in Table 8. Participants were also asked before and after the experimental session three questions about how hungry they felt (Cronbach's $\alpha = 0.9119$), as pre-task hunger could contribute to how participants make food decisions by integrating satiety cues. These questions can be found in the Appendix in Table 10.

Behavioral Results

Analyses were performed using both MATLAB Version 2019b and Stata Version 16.1.

Participants would select either the larger-but-later or smaller-but-sooner reward in the delay discounting task. The variation in the time intervals of rewards, relative differences between rewards, and absolute differences in rewards allowed us to estimate intertemporal choice behavior with delay discounting models. Based on the literature supporting the model, we took a constrained maximum likelihood estimation approach to estimate the discounting behavior with the "as soon as possible (ASAP)" delay discounting model (Decker, Figner, and Steinglass 2015), a revised version of the traditional hyperbolic discounting model that accounts for choices with immediate or offset consequences, in Equations 9 and 10. Estimation of individual

discounting parameters allowed us to compared differences in the discount parameter *k* between groups, across time, and between reward types.

We ran a mixed effects regression with the covariates subject type, time point of measurement, and their interaction term, and the dependent variable was the discounting parameter for the reward (food or money). We found that obese patients exhibited greater impatience for food rewards than lean individuals (β_{group} = 0.066 ($SE_{group,\ mean}$ = 0.019), Z_{group} = 3.56, [0.030, 0.103]) and that this difference was most pronounced before surgery ($k_{obese,\ T0}$ = 0.0912 ($SE_{obese,\ T0,\ mean}$ = 0.023) > $k_{lean,\ T0}$ = 0.0296 ($SE_{lean,\ T0,\ mean}$ = 0.007), T_{T0} = -2.48, [-0.114, -0.01]). While we did not find a significant interaction effect between participant group and time ($\beta_{groupXtime}$ = -0.011 ($SE_{groupXtime,\ mean}$ = 0.011), $Z_{groupXtime}$ = -0.96 [-0.070, 0.010]), a planned contrast for the difference in discounting before and after surgery showed that the obese patients became less impatient after the surgery ($M_{difference}$ = 0.041, ($SE_{difference,\ mean}$ = 0.018), χ^2=5.62, [0.006, 0.075]).

Obese non-patient participants had a mean discounting rate between those of lean control and obese patient participants, but their mean discounting rate for food rewards was not significantly different from the patient group before surgery ($M_{obese\ patients,\ T0}$ = 0.0913 ($SE_{\ obese\ patients,\ T0}$ = 0.0237) > $M_{obese\ control}$ = 0.0525 ($SE_{obese\ control}$ = 0.0147), t = 1.40, p = 0.174, [-0.018, 0.096]; $M_{lean\ control,\ T0}$ = 0.0296 ($SE_{\ lean\ control,\ T0}$ = 0.0075) < $M_{obese\ control}$ = 0.0525 ($SE_{obese\ control}$ = 0.0147), t =-1.38 , p = 0.174, [-0.0560, 0.0104]). We found no significant differences in delay discounting behavior across groups and over time for monetary rewards. These results can be seen in Figure 11 (food rewards) and Figure 12 (monetary rewards). The figures and the differences in delay discounting also show that the discounting of larger-later rewards was much

more for food rewards than money rewards (M_{food}=0.0439 (SE=0.00586)>M_{money} (SE = 0.0129 (SE = 0.0020), t = 5.57, p <0.001, [0.020, 0.042]).

Figure 11: Group mean comparisons of the ASAP model discounting parameter k_{ASAP} for food rewards. Times are at baseline and 6 months after baseline collection.

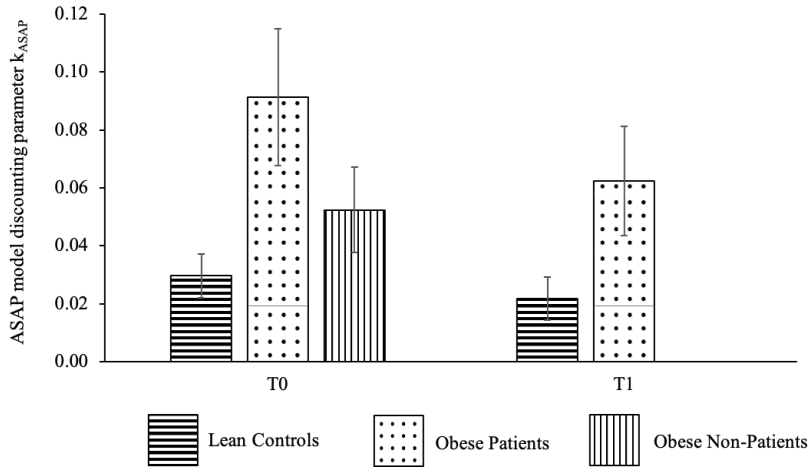
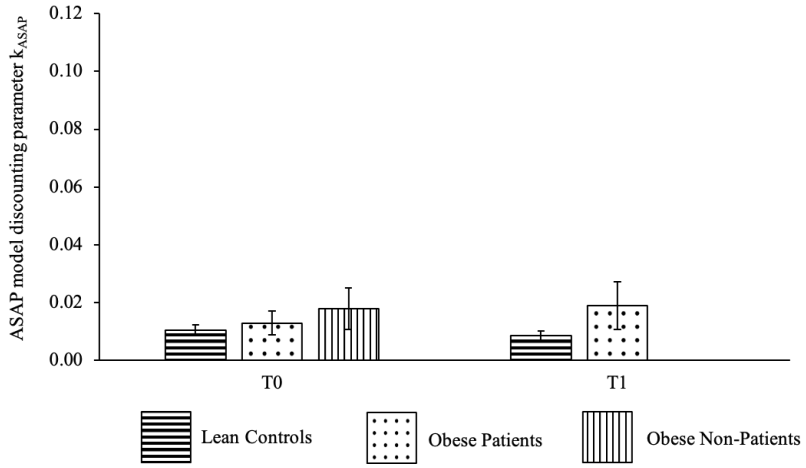


Figure 12: Group mean comparisons of the ASAP model discounting parameter k_{ASAP} for money rewards. Times are at baseline and 6 months after baseline collection.



Discussion

Overall, obese patient participants before surgery are much more impatient for food rewards than lean control participants. After weight loss surgery, the obese patients became much more patient for food rewards than they were before surgery. These effects do not exist for monetary rewards. The latter finding undermines past research where obese individuals discount future monetary rewards more than lean individuals (Weller et al. 2008). We think the differences lie in the incentive-compatible

nature and, subsequently, the scale of rewards for our experiment compared to Weller et al. 2008. Obese and lean participants are comparable in their discounting behavior for monetary rewards and remain consistent over time (i.e., their discounting behavior does not significantly change). These results show that physiology impacts the stability of discounting behavior, and discounting behavior differences do exist between domains of rewards.

This study has its limitations. First, we have a limited number of obese patient participants who performed the behavioral tasks compared to the lean participants, which generates noise in the estimates. Second, large quantities of chocolate could drive the behavior of participants to select smaller-but-sooner rewards more often. We hope that the next studies can ameliorate some of the limitations faced to explore delay discounting and intertemporal choice in-depth.

STUDY 2

Overview

The purpose of this experiment is to determine whether impatience for monetary and food rewards are different between obese patients and lean controls and whether weight loss through bariatric surgery impacts the indifference points in obese patients. This experiment was part of a battery of tasks provided to the participants during a broader experimental protocol.

Participants

Like in the previous study, participants were recruited between March 2011 and October 2017. Obese patients (N = 74, BMI = 45.6 ± 0.66) participated in the task before weight loss surgery. After twelve months, 60 participants returned to repeat post-surgery medical follow-ups, but 12 leaving the behavioral task due to a lack of

interest and 4 leaving because of pregnancy, leaving 44 patient participants (BMI = 33.1 ± 1.05). Lean control participants (N=41, BMI = 22.2 ±0.25) repeated the task six months (N = 35, BMI = 22.1 ± 0.43) after initial experimentation to confirm stability of their behavioral results between sessions. Before the task, all participants needed to agree to not eat at least three hours prior to the task and have only a light meal before. Obese patients were sampled as well at three months after surgery, and a non-patient obese participant group was recruited to perform the behavioral tasks to control for the effects of pre-surgery consultation and pre-surgery weight loss on behavior. Their information can be found in the Appendix in Table 9.

Experiment

We used a simplified version of a delay discounting procedure adapted for food and money (Weller et al. 2008). Participants made a series of binary choices between four Celebration® chocolates now and an equivalent or larger number of chocolates (incrementing by one unit up to 12 units) one week later. The task was repeated with Euros. The dependent variable is defined as the indifference point, or the minimum number of chocolates (or Euros) a participant is willing to take to wait a week for the reward. The indifference point is, therefore, the participant's point of indifference between the smaller but sooner reward and the larger but later reward. If a participant were offered a value of X now or a value of Y, where $Y \geq X$, in one week and selects X, and if the participant were then offered X now or the value of Y+1 in one week and selects the latter choice of value Y+1, then the indifference point would be defined as Y+1. Participants who answered €4 for all questions (hence not exhibiting an indifference point with the given range and having an indifference point greater than €12) were asked to self-report their indifference point.

Results

Analyses were performed using Stata Version 16.1.

The first question we sought to answer was whether there were differences between the participant pools in their indifference points per reward type. Next, we asked whether the indifference points would change in the obese patient participant pool after bariatric surgery and how their indifference points would compare to the lean and obese non-patient participant groups. Finally, we asked whether psychological measures could explain indifference point differences.

We had two exclusion criteria for the analyses of indifference points. First, we only included participants who answered the indifference point task without exhibiting quantity aversion to foods. That is, if a participant preferred 6 candies in a week to 4 candies today in one trial but preferred 4 candies today to 7 candies in a week in another trial, then that participant's session was not only not included in analysis but also their other sessions throughout the protocol. If a participant's behavior changes to perceivably exhibit less or more impatience, then we cannot rule out that their behavior change is due a change in their relationship to food that is not related to self-control. Second, given that self-reported indifference points could range from close to the experiment's limit (e.g., 15 candies) to extremely far from the limit (e.g., 1000 candies), we had to determine a reasonable cut-off for analysis of the indifference point. While a large range of inputs was not an issue for monetary indifference points, it became so for candy indifference points. We determined outlier measures of indifference points by adding the interquartile range (measure of seventy-fifth percentile minus twenty-fifth percentile) to the median indifference point measure across all subject types and across all time points (Li 2008). The cut-off for the analysis was 21 candies in the food task and 12 Euros for the money task.

To account for repeated measures for some participants, we regressed model per reward type the indifference points on groups, time, and their interactions, controlling for repeated measures by participants. The dependent variable, the number of candies to wait one week, was regressed against subject type (lean control or obese patients), time of measurement (baseline versus post-baseline/surgery measurement), and the interaction between subject type and time. For surgery patients, we consider the 12-month time point as the post-baseline to account for stabilization of the effects of surgery rather than any acute responses that may be felt three months after surgery. Like in the previous study, we control for pre-task hunger (Cronbach's α = 0.9158).

Overall, obese patients exhibited greater delay discounting for food (i.e., they asked for more chocolates in exchange of waiting one week) compared to lean individuals (β_{group} = 2.68 (SE_{group} = 0.91), Z_{group} = 2.69, p = 0.003, [0.90, 4.46]). These differences were particularly pronounced at T_0, that is, when comparing pre-surgery obese patients and lean individuals ($M_{obese,\ T0}$ = 10.5 ($SEM_{obese,\ T0}$ = 0.64) > $M_{lean,\ T0}$ = 7.73 ($SEM_{lean,\ T0}$ = 0.64); $T_{group,\ T0}$ = 3.02, [0.93, 4.55]) (Figure 13). In a mixed-effects model, where we account for the participant's identification number for repeated measures, delay discounting for food was attenuated post-surgery among obese patients but remained stable over time among lean subjects, as shown by the significant interaction effect between participant group and time ($\beta_{Group\ X\ Times0\text{-}1}$ = -2.51 ($SE_{group\ X\ Times0\text{-}1}$ = 1.16), $Z_{\ Group\ X\ Times0\text{-}1}$ = -2.15, [-4.79, -0.25]) (Figure 13). We found no difference between obese and lean subjects for monetary rewards and no change post-surgery (Figure 14). We think this contradicts previous findings on monetary delay discounting differences between obese individuals and lean individuals because

*Figure 13: By-group indifference point means comparisons for food rewards. Times are latest collection (6 months for lean controls; 12 months for obese patients). *p<0.05*

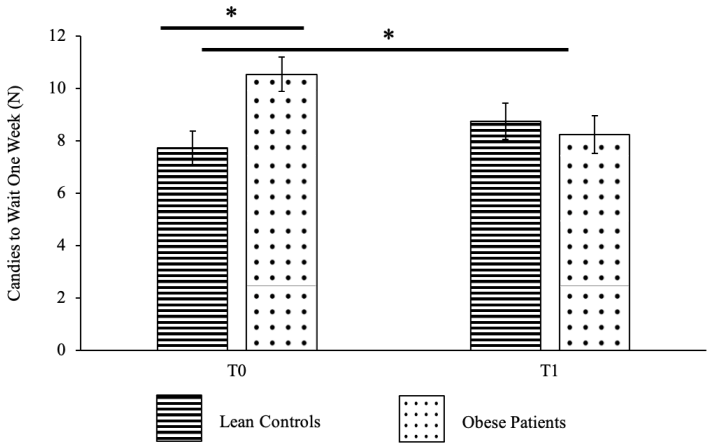
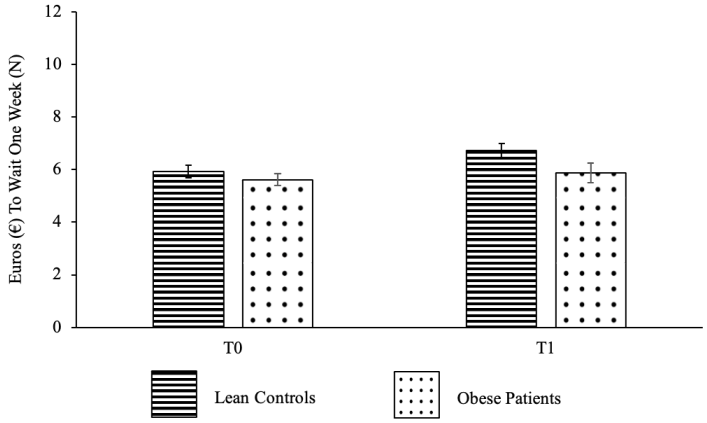


Figure 14: By-group indifference point means comparisons for money rewards. Times are latest collection (6 months for lean controls; 12 months for obese patients).

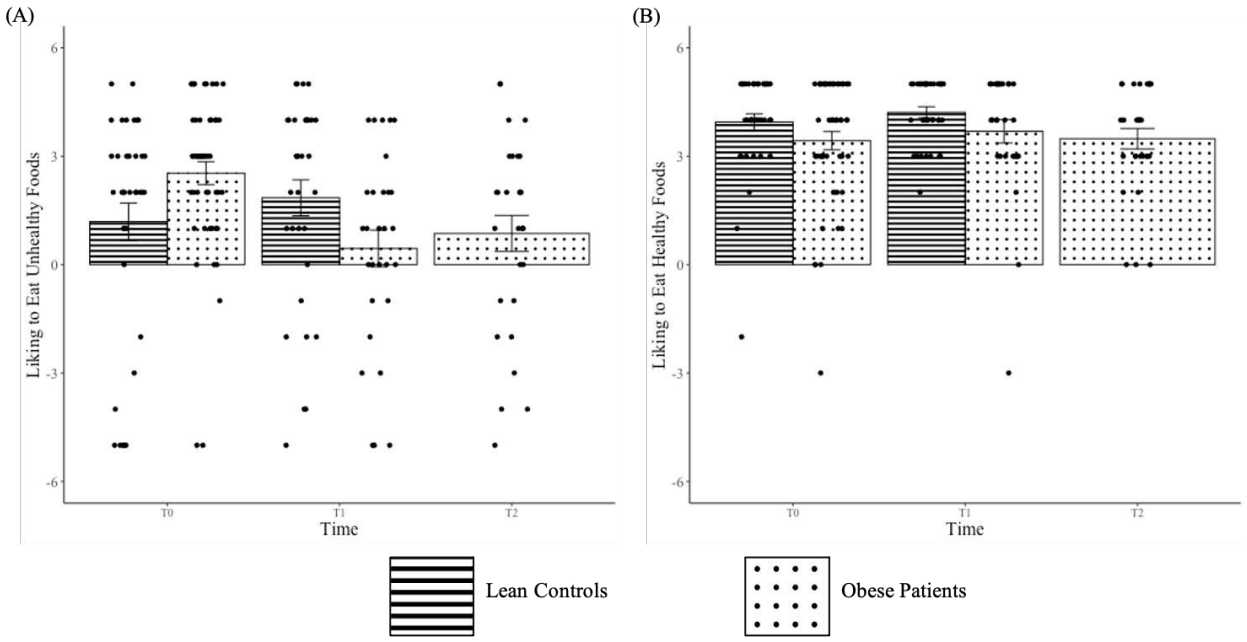


We investigated possible behavioral and metabolic mediators to understand why surgery patients had a decrease in indifference point after surgery to understand the mechanisms that drive the changes in behavioral measures of self-control.

In addition to questions about participants' feeling of hunger, we asked participants directly how much they liked eating healthy and unhealthy foods and other rewarding activities linked to addictive behaviors such as smoking, drinking, gambling, and shopping using a visual analog scale ranging from -5 to 5. The questions can be found in the Appendix in Table 11. The means of the ratings for unhealthy and healthy foods can be found in Figure 15. In a difference-in-difference analysis of the liking of

unhealthy foods between obese patients and lean controls, where post-surgery measures are considered 12 months after surgery, obese patients show a significant decrease in their liking of unhealthy foods ($\beta_{group\ X\ time} = -2.21\ (SE = 0.80), t = -2.78, p = 0.006, [-3.78, -0.64]$), while neither group or time differences nor the same interaction effect for healthy foods were significant ($\beta_{group\ X\ time} = -0.17\ (SE = 0.42), t = -0.40, p = 0.687, [-1.00, 0.66]$). To begin to explore mediation of how the wanting of foods impacts indifference points, we regressed the change in food indifference points to changes in the liking of unhealthy foods, but the regression was not significant for obese patients (β = -1.16 (SE = 1.66), t = -0.70, p = 0.492, [-4.61, 2.30]). We could not find mediation either in a full mediation model ($\beta_{subject \rightarrow liking\ change} = -1.54\ (SE = 0.64), p\ 0.016, [-2.79, -0.292]; \beta_{liking\ change \rightarrow indiff\ pt} = -3.03\ (SE = 4.55), p = 0.505, [-12.0, 5.89]$).

Figure 15: Distribution and group means of categorical liking for (A) eating unhealthy foods and (B) eating healthy foods.



Using the same cohort of patients, we explored two possible metabolic marker mediators of indifference points. First, we explored how changes in the residual leptin of an individual, a hormone released from fatty (adipose) cells that acts in a negative feedback loop to the brain to signal a lower need for food, mediates changes in the indifference point, since leptin communicates with dopamine neurons, and excessive leptin, a marker of desensitization by the neurons that communicate with it, is correlated with lower executive function task performance (DiLeone 2009; Morrison 2009; Warren, Hynan, and Weiner 2012). Second, we controlled for the homeostatic model assessment for insulin resistance (Ruano et al. 2006), which is evidence of slowed metabolism, thus an indicator of the role of the hypothalamus in the decision process. Because metabolic markers were collected once for lean control participants, we created three factors as the covariate of interest: lean controls (baseline), obese patients before surgery, and obese patients after surgery, thus providing three coefficients per pathway in the mediation model. We did not find significant relationships between these measures and food indifference points. These mediation paths can be found in the Appendix in Figure 21 and Figure 22.

Discussion

Obese patients show increased patience to wait for food after bariatric surgery, while their preferences for monetary rewards stay constant over time and comparable to the behavior of matched lean individuals. Once again, we do not find significant differences in behavior for monetary rewards. We explored a mediation model based on neuroscientific models of self-control, that changes to self-control can be explained by changes in the valuation of stimuli involved in choice. While we find initial evidence that surgery changes the valuation of eating unhealthy foods, we cannot find evidence

that the change in the valuation of eating unhealthy foods leads to a change in food indifference points.

This study, too, has its limitations. First, a limited return of participants to follow-up sessions, as well as their elimination from the study due to responses that indicated quantity aversion for food or extreme food desires, also reduced the number of datapoints available, as we could only take differences for participants who not only returned one year later for assessment and metabolic panel data. Second, post-surgery behavioral results could be biased by the nature of participants who completed multiple sessions of the study. However, this limitation is undermined by the results from Study 1, where all obese patient participants returned to complete the second session of the study six months later, and the findings of a reduction in impatience for future foods rewards was found in both studies. Third, though the quantities of rewards during in the indifference point task are reduced to reasonable quantities, chocolate (unhealthy foods) could be counterproductive as reward stimuli for bariatric surgery patients who must follow a regimented diet and lose weight before surgery, like in Study 1. It is necessary to explore the boundary conditions of intertemporal choice for food through changing the reward stimuli type, which we aim to do in Study 3.

STUDY 3

Overview

The results of Study 1 and Study 2 have led to new questions. First, what happens in a food intertemporal choice task that avoids quantity aversion to food? While money has linear utility (more value from more money), the same cannot be said for food, considering that it takes a finite amount of food for satiety, and individuals could actively choose smaller quantities of foods to avoid having the temptation of

consuming large amounts of food, even in spaced intervals and in the future. Quantity aversion could serve as an alternative explanation to the main effect of higher discounting rates for food rewards than monetary rewards. Second, what would happen if the choices in the delay discounting task were not for chocolates but instead a healthier food? We hypothesize that individuals would exert more patience (i.e., have less delay discounting) for healthier foods because of less aversion to eating large amounts of food. Third, would the same trade-offs exist with non-economic differences (i.e., a trade-off in personal preferences rather than a trade-off in quantity)? We expect that participants would be willing to wait longer for tastier foods, given the fixed quantities of foods. In general, we expect that obese participants will be less willing to wait for later food rewards compared to lean participants.

This follow-up study, administered in a battery of tasks, explores the boundaries of the delay discounting task in Study 1 and helps address the exclusion of quantity averse participants in Study 2.

Participants

We decided to eliminate alternate explanations through studying participants of various BMI classifications. Lean (N = 29, 14 females; BMI 22.3±0.34) and obese (N = 17, 10 females; BMI 34.2 ±0.97) participants were recruited for this study from a German population. To ensure honest responses to dietary choices in this study, participants could not be on a vegetarian or vegan diet, have religion-related restrictions such as kosher or halal, have intolerances or allergies such as against gluten or lactose, have a history of diabetes or other metabolic diseases, have a history of other diseases that require a specific diet, be diagnosed with eating disorders like bulimia or anorexia, or be pregnant.

Experiment

Participants were first asked to rate 70 foods on how healthy and how tasty they perceived the foods, each on a visual analog scale from 1 (extremely unhealthy or "untasty") to 7 (extremely healthy or tasty). For ten foods the participants rated of average tastiness (around a rating of 5) and of average healthiness (around a rating of 5.5) and average unhealthiness (around a rating of 2.5), participants were asked to complete incentive-compatible second-price auctions for each of the foods to determine their willingness to pay for the foods. The unhealthy and the healthy foods that were closest in value to €1 were used as stimuli for delay-discounting tasks.

Participants performed several incentive-compatible delay discounting tasks adapted from Study 1. All smaller-sooner rewards were offered after the experiment, and all larger-later rewards were offered in either 14 or 28 days. Overall, there were 20 trials (10 different percentage differences with two different delays). While percentage differences stayed relatively consistent from Study 1, magnitudes of rewards were decreased to account for possible aversion to large magnitudes of food rewards in the delay discounting task that would bias results towards smaller-sooner rewards in Study 1. The reward values used can be found in the Appendix in Table 13. To determine whether differences in delay discounting existed beyond monetary and unhealthy food rewards, participants performed the delay discounting task with a healthy food stimulus. The stimulus was determined individually for each participant based on personal healthiness and taste ratings completed earlier in the battery of tasks.

Participants also performed a modified delay discounting task, where participants were asked to pick between a less tasty food offered at the end of the experiment and a tastier food offered either 14 or 28 days after the experiment. Stimuli

were selected per individual based on their individual taste and healthiness ratings. Smaller-sooner and larger-later pairings were made between foods of similar healthiness ratings but differing taste ratings, and both food rewards were rated positively on taste (i.e., the participant must like the food, and dislike would not force a participant's choice between the two foods). There were twenty trials, ten per delay.

To control for whether risk preferences impacted delay discounting, participants performed a choice task between two lotteries: one with a 100 percent probability of receiving a reward corresponding to those of the smaller-sooner options in the non-taste delay-discounting tasks, and one with a probability between 50 and 80 percent of receiving a reward corresponding to those of the larger-later options in the non-taste delay-discounting tasks. A table of lotteries menus can be found in the Appendix in Table 14.

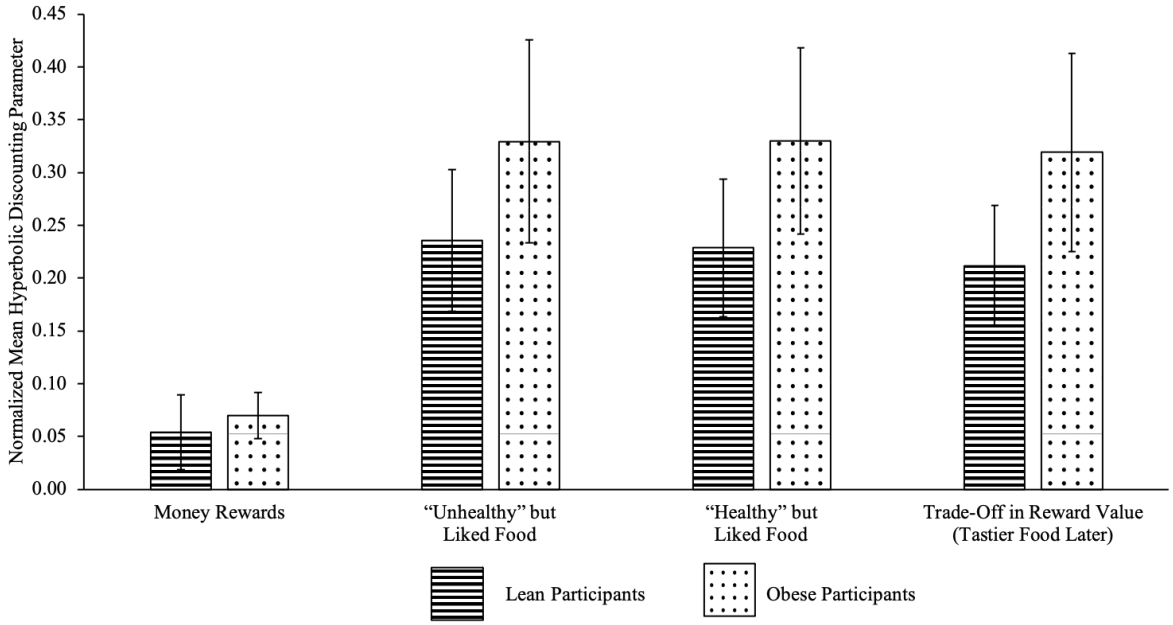
Results

An estimated hyperbolic discounting parameter, as seen in Equation 7, was used as the dependent variable, where higher discounting parameter corresponded to higher impatience. To account for scale differences between the monetary, unhealthy food, and healthy food discounting parameters, where stimuli differences were consistent quantities across all participants, and the taste discounting parameters, where stimuli differences were differences in subjective taste preferences, discounting parameters were scaled to be between 0 and 1 for a scaled discounting parameter $k_{HYPnorm}$.

Overall, participants discounted significantly less for monetary rewards compared to any food rewards, independent of weight status (i.e., they were more patient for future rewards). Delay discounting behavior was consistent within groups between unhealthy and healthy food choices ($k_{unhealthy,\ obese}$ = 0.329 (*SE* = 0.088) <

$k_{healthy,\ obese}$ = 0.330 (*SE* = 0.096), *t* = 0.018, *CI* = [-0.085, 0.083]; $k_{unhealthy,\ lean}$ = 0.236 (SE = 0.067) > $k_{healthy,\ lean}$ = 0.229 (*SE* = 0.065), *t* = 0.0942, *CI* = [-0.144, 0.158]) and when taste (quality) was a trade-off rather than quantity ($k_{unhealthy,\ obese}$ = 0.329 (*SE* = 0.088) > $k_{taste,\ obese}$ = 0.319 (*SE* = 0.093), *t* = 0.074, *CI* = [-0.283, 0.304]; $k_{unhealthy,\ lean}$ = 0.236 (*SE* = 0.067) > $k_{taste,\ lean}$ = 0.211 (*SE* = 0.058), *t* = 0.297, *CI* = [-0.143, 0.191]). A logistic regression with the dependent variable of whether the participant picked the risky option and covariates of group, the relative difference between rewards, the probability to win the risky reward, and their interaction showed that the groups are not significantly different in their risk aversion ($\beta_{group} = -0.269\ (\mathrm{SE} = 0.697), \mathrm{z} = -0.39, \mathrm{p} = 0.700, [-1.64, 1.10]$).

Figure 16: Group mean comparisons of the normalized hyperbolic model discounting parameter ($k_{HYP,norm}$) for all reward types between lean and obese participant groups in the follow-up pilot study.



The behavioral results with the discounting parameters show that participants indeed discount future rewards more for food than money, regardless of trade-off type like food healthiness, quantity of food, or quality of food. These results can be found in Figure 16.Risk preferences between groups were comparable, as obese

participants and lean participants had similar probabilities in choosing the riskier lottery, as seen in a mixed-effects logistic regression of choosing the risky lottery on the probability of winning the larger-later reward, the group of the participants (lean or obese), and the relative difference between rewards ($\beta_{group} = -0.261\ (SE = 0.700), z = -0.37, p = 0.708, [-1.63, 1.11]$).

Discussion

We find significant differences between money and food discounting, independent of food type, which confirms that delay discounting differences exist between monetary and food rewards. We were not able to find significant differences between groups and within reward types for discounting behaviors. Specifically, delay discounting in quantity trade-offs between healthy and unhealthy foods are not significantly different, and delay discounting for quantity trade-offs for unhealthy foods and trade-offs in reward value, to control for quantity aversion, were not significantly different. This result is promising because it shows that the trend of higher discounting for foods rewards is consistent for any reward modality of food (quantity or value), implying true impatience for larger-later food rewards. Obese participants showed generally higher discounting for food rewards compared to the lean participants, yet this difference does not exist for monetary rewards.

GENERAL DISCUSSION

We provide novel evidence that differences in self-control for food but not money between lean controls and morbidly obese patients diminish after bariatric surgery by contrasts of both indifference points and intertemporal choice model discounting. We show such differences in self-control are food-specific and do not extend to other rewards like money.

Neuroimaging data can shed light into correlates of brain activity to changes in delay discounting for obese patients after surgery. Data in Study 1 was collected under functional MRI, so imaging data during the delay discounting task does exist. However, because of the low participant count for the obese patients (at least half of the number of lean control participants), a traditional full-factorial analysis on whole-brain scans will probably not be the best approach to analyzing the data. Thus, neuroimaging analysis will require further work to explore changes in impatience for food versus money while accounting for noise due to small sample sizes.

One aspect of this study that has not been extensively studied is the correlation between gut bacteria diversity and delay discounting behavior (Clément, 2011; Poitou et al., 2005; Turnbaugh & Gordon, 2009). It is known that gut bacteria diversity changes because of gastric bypass surgery, but how this would correlate to behavioral measures remains unknown. Evidence suggests that less gut bacteria diversity is associated with obesity and with the presence of bacteria that are highly efficient at energy extraction from the diet (Menni et al., 2017). Though the obese patients are on strict healthy diets and have had lost significant weight before surgery, we expect less gut microbiota richness before surgery than after surgery for obese patients and for the obese patient gut microbiota to, overall, be less diverse than that of the lean controls. Future work into exploring the role of gut microbiota on delay discounting and self-control include, but are not limited to, studying how noninvasive changes to the gut microbiota (i.e., a probiotic and other supplement that aim to diversity the gut flora) impact self-control behavior over time and whether large readily available cohorts of participants through publicly collected gut microbiota and twin databases can provide insights into self-control behavior.

Overall, we hope this research sheds light on the effects of obesity on one major aspect of dietary behavior and consumption and its control. The impact of bariatric surgery indicates that there is behavioral evidence that consumption behavior is driven by the “gut-brain” axis, as this type of surgery is a direct intervention on the gastrointestinal tract. We hope that these results, along with the future directions of this current project, will help with gaining insight into interventions against not only obesity but also other disorders in intertemporal choice like addiction, eating disorders, and gambling.

ESSAY 3: THE EFFECTS OF CENTRAL OFC RTMS THERAPY ON ECONOMIC DECISION-MAKING IN OBSESSIVE-COMPULSIVE DISORDER

INTRODUCTION

Pathologies involving the deficit of self-control and possible subfunctions of self-control provide natural manipulations to understand the role of these subfunctions in self-control. Research in health and disease on eating disorders, controlled substance abuse, smoking, and gambling have provided a wealth of information on how treatments to these diseases change self-control (see “SELF-CONTROL IN HEALTH AND DISEASE”). These diseases provide indirect and untargeted manipulations of the brain’s valuation system (BVS), the brain regions that integrate value, and the cognitive control system (CCS), the areas of the brain that are important to modulation of valuation.

A prevalent technique to manipulate activity noninvasively and directly in the brain is repetitive transcranial magnetic stimulation (rTMS). Through electromagnetic induction (changing a local magnetic field to change electrical currents), rTMS can either decrease activity (inhibitory stimulation) or increase activity (excitatory stimulation) in regions of the brain. Extensive research has been able to explore how direct manipulation of the dorsolateral prefrontal cortex (dlPFC), a region of the CCS with accessible proximity to the surface of the brain, impacts self-control. Inhibitory rTMS in the dlPFC has been shown to decrease valuation during food choices (Tukey 1977). Excitatory rTMS in the dlPFC (excitatory rTMS) has served as an effective therapy against substance dependence and cravings for highly palatable food (Camus et al. 2009) and against anorexia nervosa involving the limitation of food intake (Jansen et al. 2013).

However, because of the importance of the BVS, directly manipulating the BVS, namely in the orbitofrontal cortex (OFC) is extremely difficult without either creating lesions in animal subjects such as monkeys or studying the effects of previous brain damage or neurological conditions in patients (Fellows 2006; Noonan et al. 2017). Thus, finding natural manipulations of activity in the BVS through diseases and direct therapies that target activity the BVS are critical to understand how changing activity in the BVS impacts self-control.

Our main question in this study is to determine how changing the ability to assess the value of different choices impacts self-control. This study bridges the gap between the biological basis of self-control and the day-to-day mental processes that guide how people makes choices. Understanding the mechanisms that contribute to self-control through the brain's valuation system can reveal what happens within people with insufficient self-control and guide strategies for improving human behavior, particularly because the BVS and CCS share information with each other during the decision process and, therefore, imply that these regions act in a feedback loop with each other (McClelland et al. 2016).

In this study, a cohort of patients suffering from obsessive-compulsive disorder (OCD) and their accompanying therapy provides the natural manipulation of altered activity of the BVS and its manipulation. OCD is a disorder of self-regulation and behavioral inhibition, characterized by repetitive actions, high cognitive control associated with performing very exact actions, and ritualistic organizations and behaviors (e.g. frequent, excessive hand washing, continually checking if a door is locked, constant rearranging of items), affecting around 100 million people globally (Sokol-Hessner et al. 2012). As of 1990, the annual financial cost of OCD to the U.S. economy was $8 billion, around 6 percent of national mental health spending; indirect

costs of OCD, due to lost work productivity, were estimated at $6.2 billion (Sasson et al. 1997). These remain conservative estimates, given the difficulty in detection, diagnosis, and its often coupling with other mental health disorders.

OCD rises from cognitive control and decision process deficits (DuPont et al. 1995), but its exact psychological and neuroscientific mechanisms remain poorly understood. In studies applying various methodologies ranging functional brain imaging (fMRI) to measuring intrinsic connectivity of the brain when thinking of nothing specific (i.e., resting state connectivity) on impulse control (Maltby et al. 2005) and response to pictures showing compulsive control behavior triggers (Maltby et al. 2005), OCD patients exhibit heightened activity in parts of the BVS (i.e., the OFC, medial prefrontal cortex, anterior cingulate cortex, ventral striatum (Adler et al. 2000) as well as the CCS (i.e., the dlPFC) (Abbruzzese et al. 1995; Hou et al. 2014; Jung et al. 2013). Studies measuring white matter connectivity strength in the brain show that OCD patients have altered white matter connectivity in those two systems amongst others, however, the exact mechanisms remain inconclusive (Koch et al. 2014).

Interestingly, we do not know whether OCD systematically impacts general decision-making abilities of everyday decisions and their control unrelated to OCD symptoms such as food and monetary decisions. OCD's most common treatments focusing on symptom control include medication and cognitive-behavioral therapy. More recently, however, first evidence has been provided that noninvasive stimulation therapy like rTMS could provide a more permanent treatment to OCD, focusing on the cause rather than on its symptoms. Specifically, work from Bruno Millet's group showed that rTMS inhibitory stimulation over the right central OFC in the BVS reduced (1) clinical symptoms of OCD, measured by the Yale-Brown Obsessive-Compulsive Scale and (2) resting state metabolic activity in the OFC (Koch et al. 2014). A meta-

analysis has shown that inhibitory rTMS applied to BVS was more effective in reducing OCD-related symptoms as compared to those that applied rTMS to the CCS (Berlim et al. 2013).

To approach our main question of how altered activity in the BVS and its manipulation impact self-control, we have two subgoals of this study in the context of the OCD patient cohort. The first goal of this project is to investigate whether OCD patients also exhibit struggles to exert self-control in everyday decision-making tasks as compared to healthy controls. Specifically, we aim at understanding whether such differences in control behavior would stem from deficits in controlling relevant valuation processes and whether these self-control deficits can be linked to deficits on cognitive function that are more generally linked to decision making and its control. The second goal of this project is to understand whether rTMS therapy applied to the BVS (i.e., the OFC) would improve potential dysfunctionalities in valuation processes and/or their control at the behavioral and neural levels. To investigate the latter, we plan to examine whether changes in behavior are mediated by changes in resting-state activity before versus after the therapy.

SUBJECTS

Between 45 and 15 days before the first day of therapy, OCD inpatient and outpatient cohorts in two hospitals in France undergo clinical examination to determine whether they qualify to receive inhibitory (1 Hz) rTMS therapy on the bilateral lateral OFC over the course of 20 sessions in 10 days: one session in the morning where rTMS applied with a butterfly coil was applied to the left (or right) lateral OFC and another session in the afternoon applied to the other side. Previous literature has shown that the targeting of the right lateral OFC decreases glucose metabolism in the brain's valuation system, as seen with resting state PET (for voxels and Brodmann

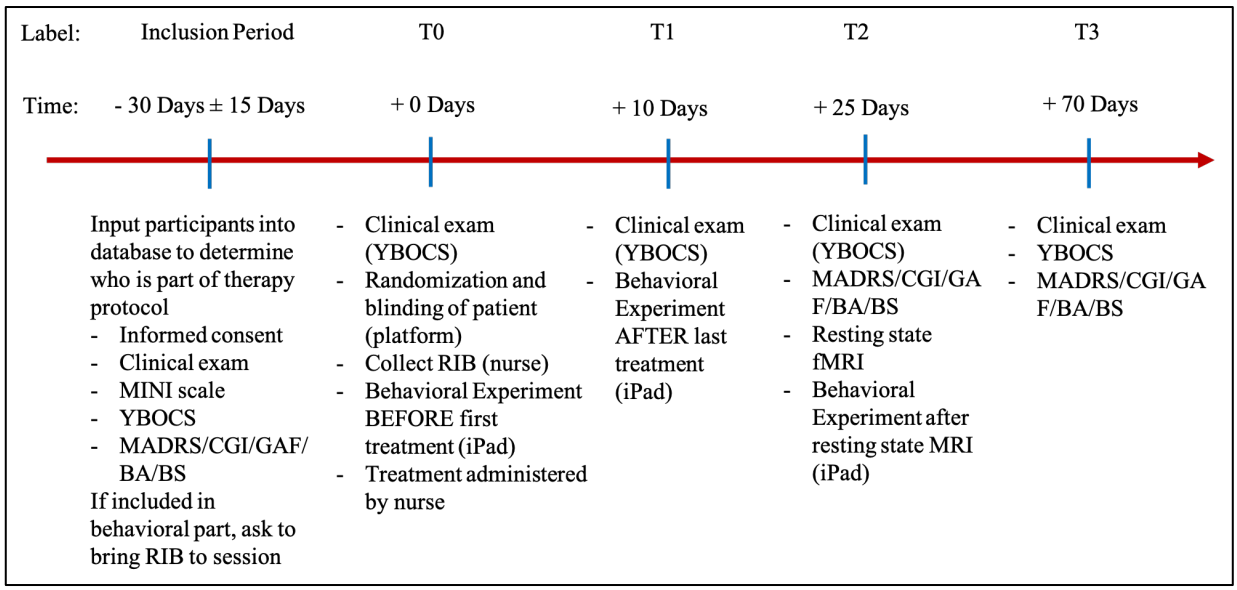
areas, please refer to Nauczyciel et al. 2014). Targeting of the bilateral lateral OFC will be based at Fp1 and Fp2 on the 10-20 system of an EEG cap. Patient inclusion into the therapy will be of adults ages 18 to 65, already receiving treatment by at least a selective serotonin reuptake inhibitor (SSRI) and cognitive behavioral therapy, and a Yale-Brown Obsessive Compulsive Scale score of over 25 (indication of moderate to severe OCD symptoms), and exclusion would include another psychiatric disorder (except for anxiety) and a negative reaction to rTMS. If a patient qualifies for treatment, a computerize database will randomly assign patients to either an active rTMS arm (where the inhibitory rTMS will be applied) or a sham rTMS arm.

On the first day of therapy, participants will first undergo a 30-minute resting-state imaging session to assess regional interactions across the brain. After the imaging session, participants will undergo the first round of behavioral experiments, all administered on an iPad. After the behavioral experimental session, the first rTMS therapy session of 20 will begin. A timeline of patient participant recruitment and completion of tasks can be found in Figure 17. Participants will repeat the behavioral experiment after their twentieth rTMS session, and fifteen days after the last day of treatment, participants will return for another resting state fMRI session followed by a behavioral experiment session. Seventy days after the first day of treatment, participants will return for clinical evaluation.

We estimated the sample size required for our study based on a literature review on the effects of brain stimulation on non-OCD related cognitive control such as intertemporal choice and goal trade-off. Assuming an effect size of 0.4 (β=0.95, α=0.05), we computed a minimum sample size of 70 OCD patient participants randomly assigned to the active and sham treatment arms of the rTMS therapy (35 in

each group) as well as 35 healthy control participants, which will be matched to the patient population.

Figure 17: A timeline of inclusion, evaluation, therapy, imaging, and behavioral experiment administration over the course of the treatment and evaluation period.



METHODOLOGY

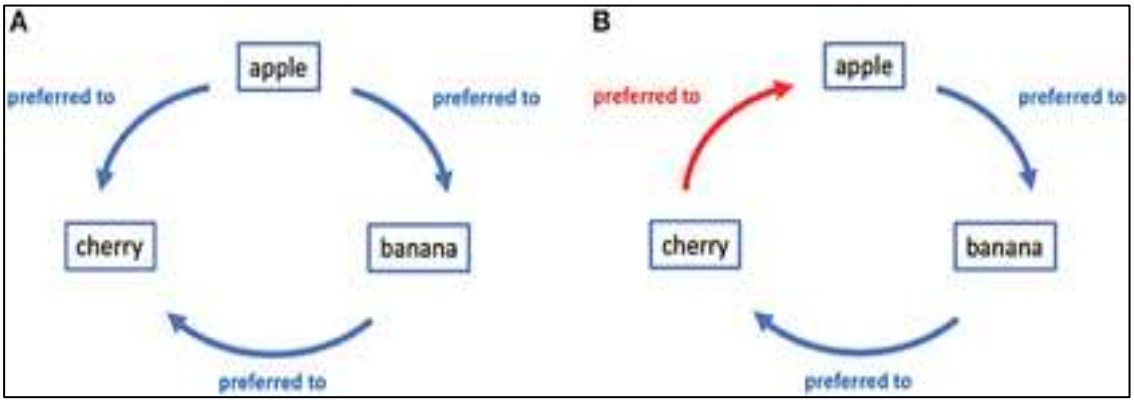
Participants will participate in three categories of tasks: to evaluate the ability to integrate value, the ability to exert self-control, and cognitive function abilities. All experiments below were made incentive-compatible; participants are not told beforehand from which of the experiments the computer would draw their reward and, thus, were incentivized to make choices to the best of their abilities. All behavioral experiments are administered on an iPad and without any writing devices. Participants are incentivized to participate in each hour-long behavioral session with €6, as per institutional IRB protocol. All experiments are administered in French.

Normative Economic Valuation and Self-Control

An important axiom of rational decision-making theories is that people have transitive preferences (Arrow 1958). This axiom suggests that, if one chooses an apple over a banana, and a banana over an orange, when one is offered the choice of apple or orange, one should choose the apple if basing the choice on some consistent

subjective value metric. Choosing the orange instead would constitute a violation of transitivity of preferences. Research has shown that patients who suffer from lesions in the BVS make transitivity violations which, therefore, represent irrationality in assigning value to options and, therefore, struggle to make decisions (Arrow 1958). Examples of preference transitivity and its violation can be seen in Figure 18.

Figure 18: Examples of transitivity violations in the NEVT Task. (A) A representation of rational economic thinking with transitivity of preferences holding. (B) A representation of transitivity violations.



Previous literature has shown that OCD patients are making more inconsistent choices, which, in turn, implies they might have issues assigning economic values that are assigned in the BVS (Pushkarskaya et al. 2017). We extend upon this literature to determine whether rTMS therapy that decreases hyperactivity in the OFC has a positive impact on their transitivity of preferences. We adapt methodologies from (Fellows and Farah 2007) to create a set of tasks that would determine whether OCD patients make violations in the transitivity of preferences under three conditions: when they are asked to make choices under free will (the “natural condition”), when they are asked to make choices with a superlative goal in mind with low conflict between options (i.e., to achieve the goal requires little resistance), and when they are asked to make choices with a superlative goal in mind but with high conflict between options. Because of the incentive-compatible nature of the task, where participants understand

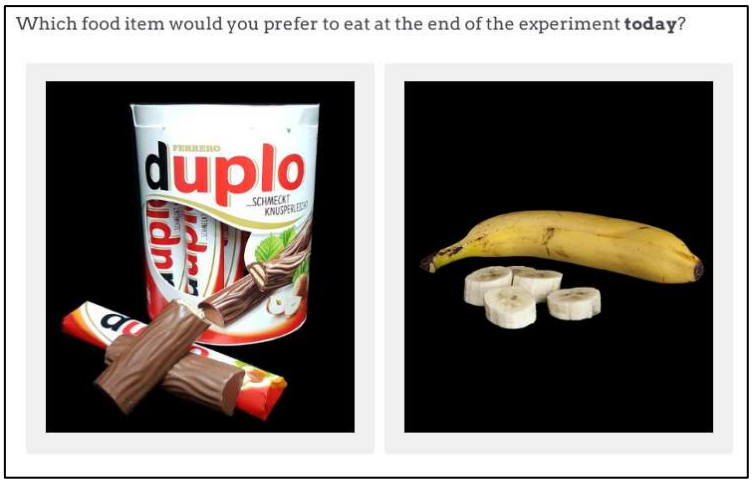
they could receive any outcome of their choices, we elicit the ability to exert self-control in their ability to trade-off between visceral and long-term goals.

Participants first rate 51 different foods based on how healthy they think the food is (the criteria for healthiness are up to them) and how tasty they think the food is. Three sets of six foods were chosen from their ratings. The first two sets of six foods were selected based on transitivity of health and taste attributes. For the low-conflict condition, if food A were rated healthier than food B, then food A was also rated tastier than food B. In the high-conflict condition, if food A were rated healthier than food B, then food A was rated less tasty than food B. For the natural condition, the third set of six foods was chosen randomly from the remaining of the 51 foods that were not selected in the first two conditions. Participants are then asked to rank within each set of foods their most liked (ranked 1) to least liked (6) to indicate a ranking of natural preferences for the foods.

After a delay of another task in the experimental protocol to mask the prime of the ranking task on decisions, participants then are asked under incentive-compatible conditions to pick the food that they prefer between all 15 pairwise combinations of the 6 foods per set of foods for a total of 45 choices (15 choices per each of 3 conditions). In the natural condition, participants are asked to simply choose which food they prefer, independent of their health preferences or taste preferences. For the low- and high-conflict categories, participants are asked to choose to the best of their ability the healthier food amongst the options presented. In the low-conflict category, choosing the healthier item is trivial because the healthier item was also deemed tastier. In the second category of choices, the healthier item was considered the less tasty of the two foods, thus presenting a conflict between perceived tastiness and perceived healthiness of the two items. A visual example of low- and high-conflict

choice conditions can be found in Figure 19. We hypothesize that, before treatment, OCD patients would exert less self-control than healthy control patients, and these differences should reduce after treatment.

Figure 19: Example of food choice task to explore self-control. The picture represents what a participant sees, and the table below represents the health and taste ratings the participant would have assigned if the food choice were presented in a low-conflict or a high-conflict condition.



	Duplo Chocolates		Banana	
	Health Rating	Taste Rating	Health Rating	Taste Rating
Low-Conflict Choice	2	4	5	5
High-Conflict Choice	2	6	5	5

Intertemporal choice self-control

Intertemporal choices—choices between a larger but later (LL) reward versus smaller-but-sooner reward—involve self-control because it involves the need to experience the inconvenience of waiting to achieve a superlative goal (more). Past literature remains conflicted on whether OCD patients have impairments in self-control, such as with delay discounting: Some papers find that OCD patients exhibit higher discounting for future rewards than healthy controls (Sohn et al. 2014), while others do not (Sohn et al. 2014). In the context of obsessive-compulsive personality disorder (Pinto et al. 2014), patients exhibit lower discounting than healthy controls.

A possible resolution to discrepancies in delay discounting research on OCD patients is to simultaneously estimate risk preference with intertemporal choice. Traditional binary intertemporal choice tasks assume a linear utility for rewards for the identification of time preference parameters. While this is useful for low stakes choices, time preferences and utility curvature can be confounded with one another when the "stakes" for choices are not perceived as low. "WEIRD" populations (Henrich, Heine, and Norenzayan 2010) may not think about waiting for a future reward as a risky endeavor, but this is not the case for other populations that experience uncertainty in their lifetime, such as living through extreme duress like trauma or poverty (Pinto et al. 2014).

The effects of such stressors can also be caused by the same physiological underpinnings of OCD. Research has shown that OCD patients show high amounts of risk aversion and deliberation time for gambling tasks (Bommier 2006). The high amount of risk aversion is caused by exaggerated responses to threats and diminished responses to rewards, as seen in deficits in functional connectivity between limbic and prefrontal pathways, or connectivity between areas of the brain that generally process threat and areas of the brain that generally process reward value; the deficiencies in these pathways correlated strongly with the severity of OCD symptoms (Sip et al. 2018). Similar muted responses to rewards and punishment have been seen in individuals who have experienced stress due to terrorist attacks (Admon et al. 2012). Thus, risk aversion can be an important factor to making decisions involving time for OCD patients and, therefore, intertemporal preference. It becomes necessary to assess risk aversion along with intertemporal choice preferences together to avoid errors in the estimation of time preference parameters (Ling, Kalenscher, and Plassmann 2019).

The Convex Time Budget Task (CTB), a multiple-choice budgeting task with rewards, is able to measure both temporal preferences and risk preferences of participants (Cheung 2016). Participants are asked to pick amongst 6 bundles of rewards with differing reward magnitudes. In each bundle, one reward is offered sooner in time (i.e., at the end of the experiment or offset in time by 5 weeks), and the other reward is offered later in time (either 5 or 9 weeks after the sooner reward). As the sooner reward decreases, the larger reward increases, and the total sum of the sooner and larger rewards increase the larger the later reward becomes, thus creating a convex budget curve.

Participants in total made 24 incentive-compatible choices. The maximum reward is €20, and the minimum reward is €9. A linear combination of the sooner and later rewards will always equal €20, where the sum of the larger reward and a budget factor times the sooner reward equals €20. A table of the reward menu, schedule of rewards, and the budget factor that determines the convexity of the budget curve can be found in the Appendix in Table 15.

Executive function

Executive function has been linked to OCD (Chamberlain et al 2007), specifically in tasks that measure working memory abilities and cognitive flexibility. The dlPFC, in conjunction with its role in modulating value, plays a major role in working memory. Impairments in neural circuits related to working memory may underlie the difficulties that patients with OCD have in deflecting from an established course of thought or action, which may be based on modulation of activity in the dlPFC. Reduced cognitive flexibility corresponds to errors in working memory tasks and increased response times in task performance. Thus, it is necessary to measure

executive function capacities to investigate whether the potential discrepancies in self-control and valuation tasks are due to differences in valuation and/or its control and not more generally linked to a limitation in cognitive function frontal lobe.

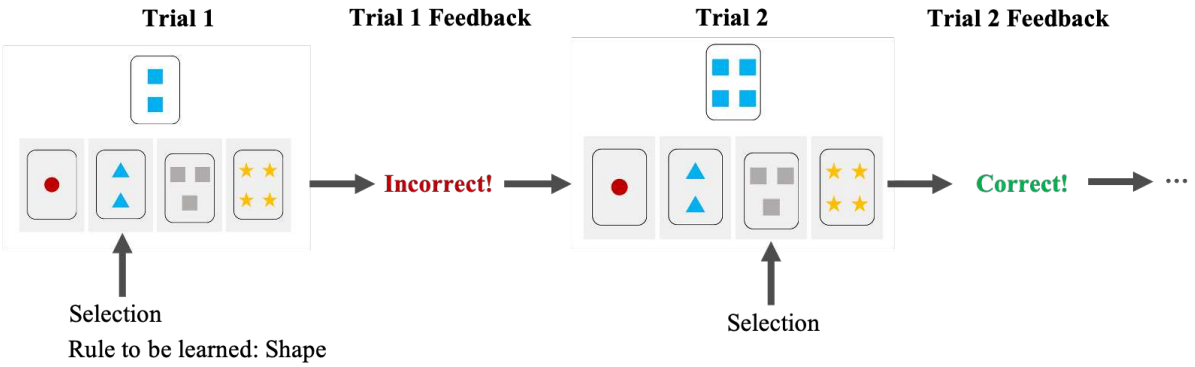
The Wisconsin Card Sorting Task (WCST) is a card matching task where participants are asked to learn a matching rule, match a target to stimuli, and adapt as the matching rules change (Berg 1948). Patients with obsessive-compulsive disorder (OCD) exhibited impaired rule-shifting abilities in the WCST (Fontenelle et al 2001). The number of errors made during the game serve as metrics of working memory, while specific types of errors—preservation errors that are created when rules change and errors that are not related to trials around rule changes—can elaborate on the sources of underlying deficits in executive function.

We implemented a computerized WCST of 60 trials, where accuracy is incentivized for participants with €0.05 per correct response. Participants are required to identify sorting principles of the top card by color, shape, or number for a set of cards and respond to feedback based on accuracy. The sorting rule will change during the task, and participants will be required to adapt to the sorting rule.

For example, refer to Figure 20. The cards at the bottom of the screen represent the rules which the participant must match. If the rule is by color or number, then the participant will have to pick the second card. If the rule is by shape, then the participant will have to pick the third card. Participants receive feedback for whether they picked the correct card or not, which will help them learn the matching rule of the trial. The participants will have to learn the rule changes throughout the experiment, which are not offered at regular intervals throughout the task. The dependent variables of interest would be the number of errors the participant makes, the number of preservation errors the participant makes (a metric of a struggle to learn a new sorting rule), and

the number of non-preservation errors that participant makes (a metric of a struggle to adhere to a sorting rule).

Figure 20: Example trials of the Wisconsin Card Sorting Task. The top card represents the target card, and the four cards below represent different rules: color, shape, and number. The participant must learn with feedback the matching rule of the round.



Control measures

In addition to the above experiments, we ask all participants to complete three questions to assess hunger before each session (see Table 10), the Positive and Negative Affect Schedule (PANAS) after each session to assess positive and negative affect (Berg 1948; Nakao et al. 2009), education, household income, and, after the final experiment session, what they think was the purpose of the study. After the final experimental session, we ask patient participants whether they think they received the active or sham treatment and whether they found the treatment effective, should they think that they received the treatment.

ANALYSIS PLAN

French pension strikes in December 2019 and, as of the writing of this manuscript, the ongoing COVID-19 pandemic has delayed patient recruitment and control participant matching and, therefore, data collection. Analyses will be performed using both MATLAB Version 2019b and Stata Version 16.1. In general, we implement

analyses for a 3 by 3 full factorial design of group (OCD patients with active therapy, OCD patients with sham therapy, and healthy controls) and time (T0, T1, and T2). Depending on the significance of group and time differences for performance in each of these tasks, we can run mediation models to explore how the valuation and executive function tasks mediate discrepancies in self-control tasks.

Below is the analysis plan for each of the behavioral experiments.

Food Choice Analysis Plan

The main goal of designing normative economic valuation tasks is to determine whether participants can preserve transitivity of preferences when making a series of choices, an indicator of the ability to assess value in a rational way. In the context of this experiment, we can measure transitivity of preferences in several ways. The first way, as commonly done during previous transitivity preference studies, during the 15 pairwise choices of the 6 foods, we can measure the number of transitivity violations—or three-item preference loops—participants make in their preferences, as in (Watson, Clark, and Tellegen 1988). By counting the number of transitivity loops made per condition (natural, low-conflict, and high-conflict), we can determine whether patients before treatment, compared to healthy controls, create more violations in preference and whether these violations occur during goal trade-offs.

We can run the following regression per choice condition (natural choice, low-conflict choice, high-conflict choice), where $N_{i,t,c}$ is the number of violations for an individual i at time point t for condition c.

$$N_{i,t,c} = \beta_1 * Group + \beta_2 * Time + \beta_3 * Group * Time + \epsilon \quad (11)$$

The first two coefficients determine whether there exist group and time effects *t* on the changing of the number economic violations, which control for having OCD

and undergoing treatment. Changes in the interaction coefficient β_3 determine whether the treatment was effective at decreasing violations of transitivity. Comparisons between choice conditions c of the coefficient β_3 can explain whether changes in the number of violations exist when a participant makes choices naturally or must consider a superlative goal with little or more effort.

The second way is whether the participant changes their preferences during the binary choice task compared to their previous indications of preference. Based on the condition of the task (natural choice, low conflict, high conflict), we can categorize a choice as whether the choice was made in accordance with the ranking task, whether the choice was made in accordance with taste preferences, and whether the choice was made in accordance with health preferences. Then, the dependent variable is an indicator variable $\mathbb{I}_{i,t,c,n,r}$ of whether the participant *i* in condition c and time point *t* made a violation per choice rule *r* (natural ranking, choosing between health and taste) during the trial *n*. We can run the mixed effects logistic regression (controlling for participant ID to account for repeated measures) as per Equation 12 per each rule.

$$\begin{aligned}\mathbb{I}_{i,t,c,n} = \beta_1 * Group + \beta_2 * Time + \beta_3 * Group * Time + \beta_4 * Condition + \beta_5 \\ * Group * Time * Condition + \beta_6 * Distance + \beta_7 * Distance \\ * Group * Time * Condition + \epsilon\end{aligned} \quad 12$$

Coefficients β_1 to β_3 are group-treatment main effects and interactions to explore whether treatment changes violations of adherence to the instructions given. Coefficient β_4 explores the effect of choice condition (natural choice, low conflict, or high conflict) on violations, and β_5 explores the three-way interaction. Coefficient β_6 explores whether the violation was made depended on the difference in the attributes of the food (i.e., the "distance" between the options), and coefficient β_7 explores the

interaction between treatment and distance. For the natural choice, the distance would be the difference in ranking between foods. For the health choice conditions, this would be the normalized distance between the two options depending on health and taste attributes (i.e., if option 1 had attributes (H_1, T_1) and food 2 had attributes (H_2, T_2), then the distance would be $\sqrt{(H_1 - H_2)^2 + (T_1 - T_2)^2}$).

Convex Time Budget Analysis

The convex time budget experiment's benefits come from the ability to compute risk aversion and intertemporal choice preference in one experiment. We explain the estimation process of risk aversion and intertemporal choice parameters below based on Andreoni, Kuhn, and Sprenger 2013.

Considering risk aversion for rewards α, the utility for a smaller-but-sooner reward c_t can be written as:

$$U(c_t) = \frac{(c_t)^\alpha}{\alpha} \qquad 13$$

The utility for the larger-but-later reward c_{t+D} offered D away from current time point t can be expressed as a quasi-hyperbolic function modified from Equation 8 with present bias parameter β and discount parameter δ as such:

$$U(c_{t+k}) = \begin{cases} \beta\delta^k \frac{(c_{t+D})^\alpha}{\alpha}, t = 0 \\ \delta^k \frac{(c_{t+D})^\alpha}{\alpha}, t > 0 \end{cases} \qquad 14$$

We choose the quasi-hyperbolic model of delay discounting for estimating intertemporal choice preferences due to its tractability and use in previous literature; more research needs to be done on how inferences from a convex time budget task change based on the choice of intertemporal choice model. For the convex time

budget task, the utility for receiving the bundle of two rewards offered at two different times can be written as the sum of Equations 13 and 14.

$$U(c_t, c_{t+k}) = \frac{1}{\alpha}(c_t)^{\alpha} + \frac{1}{\alpha}\beta\delta^{k}(c_{t+D})^{\alpha} \quad 15$$

This utility curve is subject to the linear budget constraint in the experiment in Equation *16*, where P is the ratio between rewards to sum the total reward value to €20.

$$c_{t+D} + Pc_t = 20 \quad 16$$

Maximizing the utility function subject to the budget constraint leads to the following tangency condition between the two rewards.

$$\frac{c_t}{c_{t+D}} = \begin{cases} (\beta\delta^{D}P)^{\frac{1}{\alpha-1}}, t = 0 \\ (\delta^{D}P)^{\frac{1}{\alpha-1}}, t > 0 \end{cases} \quad 17$$

To convert this equation into a linear form for estimation of the parameters β, δ, and α, we can take the natural logarithm of Equation *17* to obtain the following linear function for multiple independent participants, where $\mathbb{I}_{t=0}$ is an indicator for time period $t = 0$ and error ϵ.

$$\boldsymbol{ln}\left(\frac{\boldsymbol{c_t}}{\boldsymbol{c_{t+D}}}\right) = \left(\frac{\boldsymbol{ln(\beta)}}{\boldsymbol{\alpha - 1}}\right) * \mathbb{I}_{\boldsymbol{t=0}} + \left(\frac{\boldsymbol{ln(\delta)}}{\boldsymbol{\alpha - 1}}\right) * \boldsymbol{D} + \left(\frac{\boldsymbol{1}}{\boldsymbol{\alpha - 1}}\right) * \boldsymbol{ln(P)} + \boldsymbol{\epsilon} \quad 18$$

The regression to estimate would then be as follows.

$$\boldsymbol{ln}\left(\frac{\boldsymbol{c_t}}{\boldsymbol{c_{t+k}}}\right) = \boldsymbol{\hat{\gamma}_1} * \mathbb{I}_{\boldsymbol{t=0}} + \boldsymbol{\hat{\gamma}_2}\, \boldsymbol{D} + \boldsymbol{\hat{\gamma}_3} * \boldsymbol{ln(P)} + \boldsymbol{\epsilon} \quad 19$$

The nonlinear parameter estimates of α, β, and δ would be easily estimated from the coefficients in Equation 19 as the following.

$$\hat{\alpha} = \frac{1}{\hat{\gamma}_3} + 1\ ;\ \hat{\delta} = \exp\left(\frac{\hat{\gamma}_2}{\hat{\gamma}_3}\right)\ ;\ \hat{\beta} = \hat{\delta} = \exp\left(\frac{\hat{\gamma}_1}{\hat{\gamma}_3}\right) \quad 20$$

The log of the ratio between rewards is censored by corner solution responses, where a participant decides to wait for the full reward value ($c_t = 0$ and $c_{t+k} = €20$) or

not wait for any reward ($c_t = 20/P$ and $c_{t+k} = 0$), thus motivating a two-limit censored interval regression approach. The interval bounds are determined by the midpoints of the log ratios of rewards adjacent to the selected rewards, while the upper bound for choosing the smallest budget and the lower bound for the largest budget would be censored, respectively. If a participant only picks corner solutions, then a nonlinear estimation of the quasi-hyperbolic model in Equation 8 with assumed $\alpha = 1$ can be used to estimate parameters β and δ. The parameter estimates can then be used for factor analyses to perform a full-factorial analysis on the effects of the rTMS treatment on self-control and risk aversion for OCD patients (active versus sham treatment) versus healthy controls and over the treatment time. Discounting and risk aversion parameters can also be correlated to clinical measures of OCD symptoms (Y-BOCS) collected during each session and their changes over sessions.

Wisconsin Card-Sorting Task

The goal of using the WCST is to determine whether OCD patients, before treatment, have more deficits in executive function than healthy controls and whether deficits in executive function could explain changes in task performance. The main dependent variable of interest for the WCST is the total number of errors made. We expect everyone to have errors through the task because errors are what help a participant learn the sorting rules through the task. However, we can break down the errors into two types. The first are preservation errors; if OCD patients are struggling with rule shifting, we expect a higher number of preservation errors made by participants before treatment. This type of error would reflect a difficulty in shifting behaviors after negative feedback. The second type of error is non-preservation error, which arises after correctly identifying a rule shift, which would indicate struggles to adhere to patterns. The second dependent variable of interest during the task would

be the reaction time of participants for correct and incorrect responses, which relates to the speed for applying a sorting rule.

IMPLICATIONS AND CONTRIBUTIONS

This project has several important and novel contributions to society as well as to different research fields.

From the societal angle, the project aims at uncovering novel mechanisms underlying OCD, a common psychiatric disease with a significant impact on economic health care costs. Current OCD research remains ambiguous why clinical therapies neuroscientifically and psychologically reduce OCD symptoms and how these therapies' effects extend to daily decision-making processes. This project intends to shed light on where exactly patients' decision-making and control deficits stem from: the valuation in the BVS, its modulation by the CCS to exercise control, or related cognitive functions.

Along with the societal impact, this project will also advance theorizing in behavioral decision-making (BDM) and decision neuroscience in several ways. The ability and set-up to conduct rTMS stimulation applied to the BVS is rare and novel, as almost all previous studies in decision neuroscience have applied rTMS to the CCS instead. This project will contribute to our understanding of the causal role of the BVS through its manipulation using rTMS for decision-making and its control in human primate participants. It also allows us to explore why rTMS therapy might lead to a behavioral change by measuring its potential impact on more permanent resting state imaging in the brain. A better understanding of the causes of OCD through physiological treatment rather than with pure symptom reduction approaches is pivotal for designing more efficient treatments.

Lastly, we also add insight to BDM research by challenging the norms underlying value-based decision processes. BDM research often frames that some choices that stem from habits and excessive effort are optimal, but the excessive deliberation underlying these processes can be a harmful, as shown by OCD and other related mental health disorders. Our experiments can reveal the biological mechanisms underlying self-control and its interrelated systems. Because we work directly with patients, our results would directly reveal insights into how deficits in human behavior translate beyond clinical measures and potentially influence day-to-day consumer decision making.

FUTURE WORK IN CONSUMER SELF-CONTROL

In this dissertation we explore consumer self-control and its interventions with a top-down approach. We first determine under what conditions front-of-package labels encourage consumers to purchase healthier products. The marketing variables explored to improve dietary choice are akin to studying individual differences of self-control like assessing value, habituation, attention, socioeconomics, and memory. Next, we explore the boundary conditions of successful self-control through medical interventions. We investigate whether and why dietary self-control changes due to weight loss. Finally, we set up a study that directly manipulates the brain's valuation system to explore whether self-control is improved in a cognitive control disorder and whether the change is a function of changes in subprocesses of decision-making.

Findings from these interdisciplinary projects show the interdisciplinary nature of society's challenges that involve self-control deficits. Essay 2 proved that intertemporal choice, once thought to be a stable trait, is context and biology-dependent; individuals exhibit differences in self-control between food and money, and changes in physiology would change behavior for food but keep preferences for money stable. These findings, in conjunction with results from Essay 1, highlight the role economics play in the battle against self-control disorders like addiction and obesity. We discussed the role stressors play on self-control, that perceived stress in the future creates biases for choices favoring visceral goals. Poverty and the economics underlying low socioeconomic status contribute to making decisions focused on short-term goals, from purchasing groceries based on prices, regardless of healthiness because of the need to eat, and the locations that are frequented for shopping to access lower prices. The consequences of such purchases incrementally contribute to metabolic syndrome disorders and obesity, which becomes an

economics challenge. Estimated health care costs of obesity to economies range significantly through its direct and indirect costs, from health care expenditures to reduced workplace productivity, but the magnitudes of costs are consistent. For example, the cost of obesity in China ranges is estimated between 3.58 and a projected 8.73 percent of the gross national product in 2020 and 2025, respectively; meanwhile, estimates in the United States range from US$89 billion to US$212 billion (Schneider et al. 2020). In the context of dietary choice, the proposed studies in Essay 3 should provide insight into what subprocesses of self-control can have the most impact (valuation, choice conflict, memory, and attention) if manipulated through marketing tools like front-of-package labels in Essay 1, which may or may not improve attention to and valuation of health attributes.

Beyond the natural application of this research to obesity, and looking beyond a post-COVID-19 world, an interdisciplinary approach to studying self-control research will be extremely critical. Increased false information that has undermined science and government policies and psychological and economic fatigue from continual shelter-in-place policies have led to defiance of shelter-in-place measures and vaccine uptake necessary to recover from the current pandemic. The psychological and economic characteristics of those who defy and those who do not defy policies would advance research into the effects of long-term exertion of self-control, self-control under different perceptions of the future, self-control with different levels of trust, self-control with social influences, and self-control with different perceptions of risk. To prepare for the next pandemic or similar disaster, self-control research would inform how governments create and apply marketing campaigns to combat distrust and adherence to policies to keep people safe despite an acute cost; governments will

need to find metrics of individual differences that impact self-control so that they selectively target the campaigns to create the most impact.

Such foundations may eventually result in new ways of addressing disadvantageous psychological and economic behaviors of importance for society at large that are at least partly characterized by a lack of self-control. With a better understanding of the information processes underlying self-control at our disposal, the ability of companies to design products and communication strategies to increase “better-for-you” choices of their consumers and deter consumers from damaging choices could advance. Similarly, the ability of policy makers to design more efficient public policy interventions could increase. Such an interdisciplinary approach might also help to inform clinical research and health sciences to improve current interventions to treat disorders that are linked, at least partly, to self-control failures.

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APPENDIX

Table 7: Covariates explored in causal forest estimation

Variable	Unit	Category of Variable
The average price of items purchased within category	Euro (€) ≥ 0	Product
The average price of items purchased outside of target category	Euro (€) ≥ 0	Product
Percentage of store brand items bought within category	$\mathbb{R} \in [0,1]$	Product
Percentage of store brand items bought outside of target category	$\mathbb{R} \in [0,1]$	Product
Number of labeled items bought outside of category	$\mathbb{Z} \geq 0$	Product
Number of unlabeled items bought outside of category	$\mathbb{Z} \geq 0$	Product
Average Caloric Density of Items Purchased Within Category	$\mathbb{R} \geq 0$ in kilojoules	Product
The average number of items purchased per basket outside of target category	$\mathbb{R} \geq 0$	Basket
The average basket spending on items outside of target category	Euro (€) ≥ 0	Basket
The number of visits within the 10-week period	$\mathbb{Z} \geq 1$	Basket
The average visit week	$\mathbb{R} \in [1, 10]$	Basket
Percentage of weeks visited with weekend visits	$\mathbb{R} \in [0,1]$	Basket
Number of Labeled Items Purchased Within Tercile and Outside of Category	$\mathbb{Z} \geq 0$	Basket
Economic Status Group	Factor Variable: Lower, Upper	Store
Store Location	Factor Variable: Major City, Urban, Suburban, Rural	Store
Chain	Factor Variable: Carrefour, Simply, SuperCasino	Store

Table 8: Counts of participants, average recruitment age, and average BMI per participant group and time point for Study 1 of Essay 2.

Participant Group	Age at Recruitment	Baseline (T0)	Post-surgery + 6 months (T1)
Obese Patients	34.6 ± 1.8	N = 17 $\overline{\text{BMI}}$ = 44 ± 2.5	N = 17 $\overline{\text{BMI}}$ =
Lean Controls	38 ± 13	N = 45 $\overline{\text{BMI}}$ = 21.7 ± 1.4	N = 34 BMI:
Obese Non-Patients (No surgery)	37.6 ± 2.4	N = 29 $\overline{\text{BMI}}$ = 31.8 ± 0.5	-----

Table 9: Counts of participants and average BMI per group and time point and before and after exclusions for Study 2 of Essay 2.

	Lean Controls		Obese Patients			
	Baseline (T0)	Baseline + 6 Months (T1)	Before Surgery (T0)	Post-Surgery + 3 months (T1)	Post-Surgery +12 months (T2)	Obese Non-Patients (T0)
N, before exclusion	41	35	74	47	43	29
N, Food after exclusions	34	28	40	28	24	23
N, Money after exclusions	41	35	68	45	39	25
BMI, before exclusions	22.1 (0.27)	22.0 (0.47)	45.6 (0.66)	38.9 (0.86)	33.2 (1.06)	31.8 (0.5)
BMI, after exclusions	22.0 (0.27)	21.8 (0.42)	46.2 (0.80)	38.0 (1.20)	32.3 (1.43)	33.5 (0.69)

Table 10: Questions to assess participants' hunger in Essays 2 and 3 in visual analog scales. Each question was scored out of 100 in Study 2 of Essay 2, and all other studies were scored between 1 and 7.

Original French Question	English Translation
Avez-vous faim maintenant?	Are you hungry now?
Éprouveriez-vous du plaisir à manger maintenant ?	How much would you enjoy eating now?
Quelle quantité de nourriture seriez-vous capable de manger maintenant ?	How much food would you enjoy eating now?

Table 11: Questions to assess explicit liking of eating foods and other addictive behaviors. Each question was answered on a visual analog scale from -5 to 5.

Original French Question	English Translation
Dans quelle mesure aimez-vous jouer (jeux d'argent, poker) ?	How much do you enjoy gambling (for money, poker)?
Dans quelle mesure aimez-vous fumer ?	How much do you enjoy smoking?
Dans quelle mesure aimez-vous faire du shopping ?	How much do you enjoy shopping ?
Dans quelle mesure aimez-vous boire de l'alcool ?	How much do you enjoy drinking alcohol ?
Dans quelle mesure aimez-vous manger des fruits ou légumes, comme des fraises ?	How much do you enjoy eating fruits and vegetables, such as strawberries?
Dans quelle mesure aimez-vous manger quelque chose de sucré et riche, comme un pain au chocolat ?	How much do you like to eat something sweet and rich, like *pain au chocolat*?

Table 12: Delays and rewards for the discounting task of Study 1.

Time of Smaller Reward (days)	Time of Larger Reward (days)	Smaller Reward Value (€)	Larger Reward Value (€)
0	14	23.5	23.7
0	14	21	21.25
0	14	23	25.75
0	14	17.5	20.5
0	14	8	10
0	14	27	36
0	14	22.5	32.5
0	14	28	56
0	14	8	32
0	28	17.1	17.2
0	28	14	14.2
0	28	12	13.5
0	28	21	24.5
0	28	31	39
0	28	15	20
0	28	16	23
0	28	12	24
0	28	24	96
14	28	21.1	21.2
14	28	10.15	10.3
14	28	15.75	17.5
14	28	28	33
14	28	35	44
14	28	18	24
14	28	17	24
14	28	11	22
14	28	14	56
28	42	14.05	14.1
28	42	22.25	22.65
28	42	26	29
28	42	9	10.5
28	42	11	13.75
28	42	24	32
28	42	28	40
28	42	22	44
28	42	18	72

Table 13: Delays and rewards for the discounting task of Study 3.

Time of Smaller Reward (days)	Time of Larger Reward (days)	Smaller Reward Value (€)	Larger Reward Value (€)
0	14	12	13
0	14	10	11
0	14	12	14
0	14	8	10
0	14	9	12
0	14	5	7
0	14	6	9
0	14	8	16
0	14	6	18
0	14	3	12
0	28	14	15
0	28	8	9
0	28	6	7
0	28	15	19
0	28	6	8
0	28	14	20
0	28	12	18
0	28	4	8
0	28	1	3
0	28	5	20

Table 14: Lotteries for risk preference task of Study 3.

Certain Reward	Risky Reward	Reward Difference (%)	Prob (Win)	EV(Reward)
12	13	0.0769	0.8	10.4
10	11	0.0909	0.75	8.25
12	14	0.1429	0.7	9.8
8	10	0.2000	0.6	6
9	12	0.2500	0.5	6
5	7	0.2857	0.8	5.6
6	9	0.3333	0.75	6.75
8	16	0.5000	0.7	11.2
6	18	0.6667	0.6	10.8
3	12	0.7500	0.5	6
14	15	0.0667	0.8	12
8	9	0.1111	0.75	6.75
6	7	0.1429	0.7	4.9
15	19	0.2105	0.6	11.4
6	8	0.2500	0.5	4
14	20	0.3000	0.8	16
12	18	0.3333	0.75	13.5
4	8	0.5000	0.7	5.6
1	3	0.6667	0.6	1.8
5	20	0.7500	0.5	10

Table 15: Convex time budget task reward bundles and times of reward for the bundles.

Trial	Times of Payment	Payoff 1	Payoff 2	Payoff 3	Payoff 4	Payoff 5	Payoff 6	Ratio (P)
1	Payment TODAY	19	15.2	11.4	7.6	3.8	0	1.05
	Payment in 5 Weeks	0	4	8	12	16	20	
2	Payment TODAY	18	14.4	10.8	7.2	3.6	0	1.11
	Payment in 5 Weeks	0	4	8	12	16	20	
3	Payment TODAY	17	13.6	10.2	6.8	3.4	0	1.18
	Payment in 5 Weeks	0	4	8	12	16	20	
4	Payment TODAY	16	12.8	9.6	6.4	3.2	0	1.25
	Payment in 5 Weeks	0	4	8	12	16	20	
5	Payment TODAY	14	11.2	8.4	5.6	2.8	0	1.43
	Payment in 5 Weeks	0	4	8	12	16	20	
6	Payment TODAY	11	8.8	6.6	4.4	2.2	0	1.82
	Payment in 5 Weeks	0	4	8	12	16	20	
7	Payment TODAY	20	16	12	8	4	0	1
	Payment in 9 Weeks	0	4	8	12	16	20	
8	Payment TODAY	19	15.2	11.4	7.6	3.8	0	1.05
	Payment in 9 Weeks	0	4	8	12	16	20	
9	Payment TODAY	17	13.6	10.2	6.8	3.4	0	1.18
	Payment in 9 Weeks	0	4	8	12	16	20	
10	Payment TODAY	15	12	9	6	3	0	1.33
	Payment in 9 Weeks	0	4	8	12	16	20	
11	Payment TODAY	12	9.6	7.2	4.8	2.4	0	1.67
	Payment in 9	0	4	8	12	16	20	

	Weeks							
12	Payment TODAY	9	7.2	5.4	3.6	1.8	0	2.22
	Payment in 9 Weeks	0	4	8	12	16	20	
13	Payment in 5 Weeks	19	15.2	11.4	7.6	3.8	0	1.05
	Payment in 10 Weeks	0	4	8	12	16	20	
14	Payment in 5 Weeks	18	14.4	10.8	7.2	3.6	0	1.11
	Payment in 10 Weeks	0	4	8	12	16	20	
15	Payment in 5 Weeks	17	13.6	10.2	6.8	3.4	0	1.18
	Payment in 10 Weeks	0	4	8	12	16	20	
16	Payment in 5 Weeks	16	12.8	9.6	6.4	3.2	0	1.25
	Payment in 10 Weeks	0	4	8	12	16	20	
17	Payment in 5 Weeks	14	11.2	8.4	5.6	2.8	0	1.43
	Payment in 10 Weeks	0	4	8	12	16	20	
18	Payment in 5 Weeks	11	8.8	6.6	4.4	2.2	0	1.82
	Payment in 10 Weeks	0	4	8	12	16	20	
19	Payment in 5 Weeks	20	16	12	8	4	0	1
	Payment in 14 Weeks	0	4	8	12	16	20	
20	Payment in 5 Weeks	19	15.2	11.4	7.6	3.8	0	1.05
	Payment in 14 Weeks	0	4	8	12	16	20	
21	Payment in 5 Weeks	17	13.6	10.2	6.8	3.4	0	1.18
	Payment in 14	0	4	8	12	16	20	

	Weeks							
22	Payment in 5 Weeks	15	12	9	6	3	0	1.33
	Payment in 14 Weeks	0	4	8	12	16	20	
23	Payment in 5 Weeks	12	9.6	7.2	4.8	2.4	0	1.67
	Payment in 14 Weeks	0	4	8	12	16	20	
24	Payment in 5 Weeks	9	7.2	5.4	3.6	1.8	0	2.22
	Payment in 14 Weeks	0	4	8	12	16	20	

Table 16: Mean conditional average treatment effects for changes in labeled items purchased versus unlabeled items purchased for food type r, tercile t, and label l. All but one difference in treatment effect is significant after Bonferroni correction of p = 0.0042 for 12 comparisons with $\alpha = 0.05$.

Food Type *(r)*	Tercile *(t)*	Label *(l)*	$\hat{\tau}_{r,t,l}$	S.E.	t value
Canned Foods	1	NutriCouleur	-0.0083	0.0003	-24.15
		NutriScore	-0.0404	0.0002	-172.68
	2	NutriCouleur	0.0295	0.0003	106.92
		NutriScore	0.0097	0.0001	67.32
	3	NutriCouleur	0.0055	0.0001	36.89
		NutriScore	0.0304	0.0002	150.43
Fresh Foods	1	NutriCouleur	0.0053	0.0005	11.74
		NutriScore	0.0261	0.0004	59.22
	2	NutriCouleur	0.0004	0.0002	1.74
		NutriScore	-0.0050	0.0001	-38.25
	3	NutriCouleur	0.0117	0.0004	27.71
		NutriScore	-0.0019	0.0005	-4.03

Figure 21: Mediation model between bariatric surgery and changes in indifference point with residual leptin (i.e., leptin corrected for body fat percentage) as a mediator.

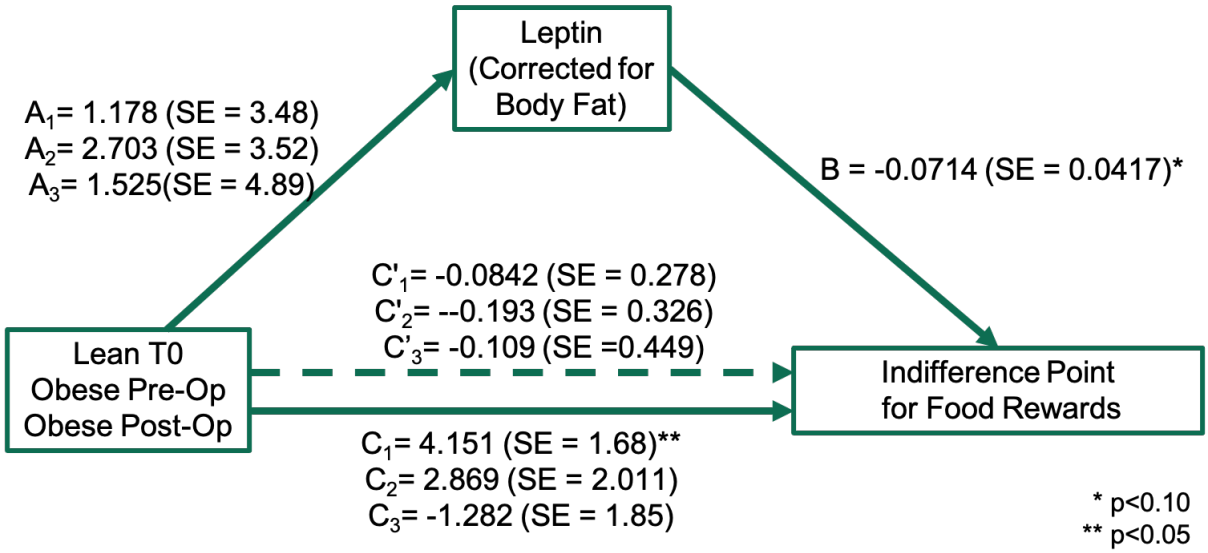

Figure 22: Mediation model between bariatric surgery and changes in indifference point with homeostatic regulation of insulin resistance (HOMA-IR) as a mediator.