BMI, Food Purchase, and Promotional Sensitivity*

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Abstract

In this paper, we examine the relationship between obesity and sensitivity to in-store promotions and price discounts using a dataset that links individual-level food purchases, store-level price and promotion exposures, and individual-level obesity status. We estimate the structural model of category attention and product purchase on 12 vice and 12 virtue product categories, and find that low-income individuals with obesity are more promotion-sensitive than low-income individuals without obesity. This difference in promotional sensitivity across obesity status is especially strong in vice food categories. Our findings provide field support to laboratory work that documents a relationship between obesity, sensitivity to food cues, and impulsive purchase.

KEYWORDS: *Obesity, health data, scanner data, marketing and health*
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Disclaimers:

The Findings and Conclusions in This Preliminary Presentation Have Not Been Formally Disseminated by the U. S. Department of Agriculture and Should Not Be Construed to Represent Any Agency Determination or Policy.

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Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

Obesity is the second-leading cause of preventable death in the U.S. (Goldman, 2020, link). For example, adults suffering from obesity were at greater risk for hospitalization and death during the COVID pandemic (CDC Report, link). In addition to health concerns, obesity also leads to increased health insurance premiums (Bhattacharya and Sood, 2011), increased medical expenses (Cawley and Meyerhoefer, 2012), and productivity losses in the labor market (Fletcher et al., 2011). These facts make it clear that our society needs better strategies to address this public health crisis.

While many factors contribute to obesity, including genetics, medications, and physical inactivity (CDC Report, link), the role of diet should not be overlooked.[1] Certainly, it cannot be denied that a large share of groceries sold in American stores are considered unhealthy (NPR Report, [link]). And to make matters worse, in-store promotions are more frequent for unhealthy foods[2] (Houben et al., 2014; Nederkoorn, 2014; Castellanos et al., 2009; Werthmann et al., 2011; Ferriday and Brunstrom, 2011). However, previous literature suggests that, in the case of the U.S., supply side explanations alone may not fully explain consumers' dietary choices (Dubois, Griffith, and Nevo, 2014 [3]; Allcott et al., 2019 [4]). It is there-

[1] As a recent NPR Morning Edition piece illustrates through the story of Bruce Caldwell, it is possible to completely reverse Type 2 diabetes through a change in diet. [link]. Recognizing the importance of diet, the White House has recently (September 2022) hosted a conference on hunger, nutrition, and health. One of its stated goals include, "... increase healthy eating ... by 2030, so that fewer Americans experience diet-related diseases like diabetes, obesity, and hypertension." [link]

[2] In the United States, expenditures for in-store marketing increased from 28% of marketing budgets in 1968 to 68% (about $75 billion) in 2009 (Cohen and Lesser, 2016).

[3] In comparing food purchases across U.S., France, and the UK, the findings in this paper show that while prices are important in influencing dietary choices in the US, they cannot explain compositional patterns. Rather, consumer preferences in addition to the economic environment serve an important role.

[4] There is substantial literature suggesting that nutritional inequality contributes to the obesity epidemic. In this paper, the authors study the phenomenon of food deserts. They find that neighborhood environments do not meaningfully contribute to nutritional inequality. More specifically, "Counterfactual simulations show that exposing low-income households to the same products and prices available to high-income households reduces nutritional inequality by only about 10%, while the remaining 90% is driven by differences in demand. These findings counter the argument that policies to increase the supply of healthy groceries could play an important role in reducing nutritional inequality.

fore essential to also understand how demand side forces influence diet and health outcomes. In particular, understanding dietary preferences of individuals along the body weight spectrum may substantially contribute to policy designs aimed at addressing the obesity epidemic.

This paper uses a structural demand model to quantify the sensitivity to in-store price discounts and product promotions for consumers across the entire body weight spectrum. We exploit a rich and unique combination of data sets, including Nielsen Homescan – a nationally representative panel of weekly household grocery purchases, MedProfiler Survey – an annual comprehensive survey on body weights[5] and health conditions administered to Nielsen household members, and Nielsen's Retail Measurement Services (RMS) – a national panel of UPC-level sales data covering close to 40% of all U.S. grocery purchases. We match the MedProfiler health survey to the Nielsen Homescan data to capture a profile of food purchases to the individual's body weight status. We then further create the food environment faced by each panelist by linking the purchases to the RMS data. The resulting dataset provides a rich setting to study the relationship between food demand of consumers – across the weight distribution – and promotional cues they face in a real world setting. Furthermore, we analyze this relationship across many food categories, both vice goods (i.e., food seen as tempting and unhealthy) and virtue goods (i.e., food seen as non-tempting and healthy).

We begin our analysis by establishing two stylized facts underlying demand of consumers across the weight distribution. First, for products in the vice categories, the data reveals that individuals suffering from obesity, on average, spend a larger share of their budget on vice goods. On the other hand, they do not show the same behavior in the virtue categories. This suggests that analyzing vice and virtue categories separately may help identify behavioral differences in purchases of vice versus virtue goods. Second, consumers suffering from obesity purchase from vice categories more frequently, but in smaller sized packages. This affirms findings documented in previous literature showing individuals purchasing small package sizes of vice goods as a commitment device (Wertenbroch, 1998). But it also hints

[5]The MedProfiler Survey elicits both height and weight information for each household member, allowing us to calculate individual's body mass index (BMI), a standard way to identify obesity.

at a positive relationship between impulsive purchase and obesity. If true, policies regulating intertemporal price variations, such as the one proposed in the U.K., could be impactful, as they aim to remove the temptation for vice foods[6].

Our main analysis uses a structural model to disentangle demand preferences of households across the weight spectrum, for vice and virtue categories, in the presence of price discounts and product promotions. To accommodate a large selection of product categories, we rely on a structural model that allows for both category attention and product choice within a category (Ching et al., 2009, 2014). In the model, a consumer's decision process takes place in two steps: in the first stage, called the *consideration stage*, attention to a category may be governed by consumer needs (e.g., inventory) as well as cues which may act as triggers that will lead a consumer to purchase. Allowing for category-level consideration is important, as category-level cues such as promotions may prompt purchases of vice products, particularly when consumers' mental resources become limited and for consumers who suffer from obesity (Dhar et al., 2005). We operationalize this idea by interacting weight status with in-store promotions at this stage of the model. In the second stage of the model, called the *purchase stage*, conditional on considering a food category, a consumer makes a deliberate decision of what product to choose following a standard random utility model. We model unobserved preference heterogeneity and state dependence in product choice (Dubé et al., 2010). Relevant to the topic at hand, our model allows consumers' weight status and income to directly affect their price sensitivity.

We use this structural model to analyze food shopping behavior in 20 different product categories, half vice and half virtue. Estimates from our model show a number of policy-relevant patterns. First, in-store promotions have differential impact on individuals across the body weight spectrum. Individuals suffering from obesity are more likely to be affected by these marketing strategies. Exacerbating this effect, this increased promotional sensitivity occurs more often in vice categories, as compared to virtue categories. Second, in line with previous findings (Allcott

[6]In the U.K. policymakers have called for regulating supermarket price promotions due to concerns that they may be increasing consumption of unhealthy food. [link] #maincontent: "Special offers on unhealthy food and drinks should be restricted in an attempt to curb Britain's expanding waistlines, experts have said."

et al., 2019), the data reveals an unquestionable income effect. More specifically, low income individuals are more sensitive to promotional activities, such as in-store displays and sales, when they consider whether to make a purchase in a category. The effect we observed before – individuals suffering from obesity are more susceptible to in-store promotions than their counterparts – is stronger for individuals who are constrained by income. The same pattern is also found for individuals less constrained by income, but to a lesser extent.

Our paper adds to the combined set of knowledge on contributing factors to the obesity crisis by providing insights into the heterogeneous demand preferences of individuals along the body weight spectrum. Our findings are of interest to researchers, policymakers, and business managers keen to find effective solutions to curb obesity, particularly strategies involving in-store promotions. More specifically, regulating promotional activities such as display and feature in vice categories may serve to eliminate unwanted temptation disproportionately affecting individuals on the higher end of the weight distribution. Equally important are considerations for low-income individuals, particularly those suffer from obesity, as they may be less able to mitigate the adverse health effects.

We structure the remainder of the paper as follows. In Section 2, we discuss how our paper contributes to the existing literature. Section 3 describes the data and its construction. Section 4 presents stylized facts found in the data. We present the structural model of consumer attention in Section 5 and estimation results in Section 6. Section 7 concludes.

2 Literature Review

Our paper contributes to a small but growing literature that relates observed food purchase behavior to health outcomes. To the best of our knowledge, we are one of the few papers that examines the relationship between body weight and food purchase empirically using observed purchase data and store-level exposures. This research gap is mainly due to data limitations as most health datasets typically do not include information on food purchase (the closest is the NHANES data, which has information on food purchase through recall, but does not link observed purchase to health outcomes). Some more recent work has linked observed purchase behavior to one-time surveys containing information on BMI (Allcott et al., 2019; Hut and Oster, 2018; Department of Health and Social Care (DHSC), 2018b). In contrast, in our work we observe health information for a large sample of consumers over a six year period.

As we will describe in more detail in section 3, our combined data links the Nielsen Homescan consumer purchase panel to Nielsen's store scanner data, and a survey on Homescan panelists performed by IRI called Medprofiler. There are a few papers which have analyzed older versions of the data we use (Medprofiler). For example, Okrent and Sweitzer (2016) uses five years of IRI data to examine how expenditures and price sensitivity for a broad set of product categories vary with BMI. We contribute beyond their analysis by quantifying how obesity affects in-store promotional sensitivity, and tying behavior to a structural model of attention.[7] Ma et al. (2013) use an earlier version of the IRI data to examine how household food consumption responds to diagnosis of diabetes. They find that households decrease sugar consumption, but households with higher measures of self-control offset the lower sugar consumption with more consumption of healthy categories.[8] Moreover, Chen et al. (2016) use IRI's consumer panel and the MedProfiler data, but only investigate how aggregate food-purchase measures relate to obesity status. More importantly, they did not combine purchase data with store exposure data, and so could not quantify the relationship between BMI and price/promotional exposure as we do. Our newer dataset, which also links household food purchase data to the MedProfiler survey, contains many more households than the older data and we focus on a different research question, in particular, how consumers with different obesity status responds to the in-store promotional cues.

Our analyses are motivated, in part, by the existing laboratory findings on impulsive behavior, food purchase and obesity. Our findings provide some field validation on laboratory studies relating obesity and promotional sensitivity. We emphasize that the lab literature we draw on involves hypothetical purchase deci-

[7]Their analysis relies on the IRI store panel provided to USDA, rather than Nielsen's. The IRI store panel provided to USDA does not contain store feature and display information.

[8]Oster (2018) finds in Nielsen's panel that individuals who start purchasing diabetes testing strips do not consume substantially less unhealthy foods.

sions. As DellaVigna and Linos (2022) point out, there are many reasons that the results of laboratory experiments may not always scale to the field: for example, people may behave differently in actual choice situations rather than hypothetical ones, or the sample of individuals in a lab study may not reflect the general population.

Our work contributes to an emerging literature examining the relationship between obesity and impulsive behavior, particularly in the context of food cues and advertising. Store factors (i.e display and price promotions) have been found to be more important than any customer level factors in influencing purchases (Cohen and Lesser, 2016). It has also been well documented that cheap relative prices (Epstein et al., 2012), television commercials, and sales promotions (Hawkes, 2009) of food may contribute to increased food consumption. The fact that obesity is correlated with impulsive behavior, and that in-store cues such as promotions can also lead to impulsive purchase, suggests that individuals with obesity may be more responsive to in-store food promotions. Indeed, a correlation between obesity and higher attention/responsiveness to food cues has been demonstrated in lab settings (Castellanos et al., 2009; Werthmann et al., 2011; Ferriday and Brunstrom, 2011). For instance, there is evidence that food cues, such as promotions, are especially salient to individuals with obesity when the product categories are snack foods (Nederkoorn, 2014).

In terms of impulsive behavior, one approach that has been taken to measure it is to quantify an an individual's geometric and/or present bias discount factors. In particular, individuals with lower measured discount factors will consider the future less, and may behave more impulsively. This stream of literature has found an association between lower discount factors and higher BMI (Chabris et al., 2008; Richards and Hamilton, 2012; Ikeda et al., 2010; Courtemanche et al., 2014). An alternative approach has been to measure impulsive behavior directly through questioning, and to relate it to current BMI or future weight gain. For example, Nederkoorn et al. (2010) measure response inhibition in female undergraduate students in a lab study and measure weight gain one year later. They find a positive relationship between lower inhibitory control and future weight gain.

Our paper also contributes to the literature examining the relationship between obesity and impulsive behavior, especially in vice food categories. Vice foods are defined as unhealthy goods which a consumer purchases impulsively, and feels regret after purchasing (Rook, 1987; Thomas et al., 2012). Reseachers also find that consumers exhibit less self-control and greater impulsive urges when faced with vice goods (Rook, 1987; Hoch and Loewenstein, 1991; Shiv and Fedorikhin, 1999). On the empirical side, some work in marketing has examined the impact of in-store promotions on vice and virtue categories, with mixed results: Narasimhan et al. (1996) find no relationship between category impulsivity and promotion response, while Yan et al. (2017) find promotion response is stronger in vice categories than virtue categories for a smaller set of goods. Moreover, neither of them examined how interaction between promotion sensitivity and food category is moderated by obesity. Work in consumer psychology suggests that such a relationship may exist in the field: Bublitz et al. (2010)'s review notes that past work in consumer psychology has found that impulsive consumers are more likely to adopt a promotion focus when exposed to vice foods than healthy foods. This is directly tested in the lab by Nederkoorn (2014), who finds the interaction between weight status, in-store promotional cues and self control disproportionately affects the purchase of snack foods in a hypothetical purchase setting.

The literature documenting a correlation between obesity and enhanced promotion sensitivity is consistent with work on cognitive load effects and self-regulation. It finds that when cognitive resources are limited, a shift in attention away from cues signaling the need to exert control and toward cures signaling gratification leads to reduced self-control (Luck and Vogel, 1997; Pashler et al., 2001; Inzlicht and Schmeichel, 2012; Inzlicht et al., 2014). In our setting, such cues will arise both from the hedonic nature of vice goods, as well as promotions drawing consumers' attention to these categories. In the face of such cues, consumers may need to exert extra cognitive effort to resist the temptation to purchase them. The lab literature suggests that obesity is a function of reduced ability to self-regulate. Moreover, we expect (and find) particularly large effects for obese consumers who are also facing scarcities or coping with other activities that would demand their attention. In our context, having a lower income may be correlated with more mental stress, and hence greater exhaustion of internal resources.

We thus view part of our contribution as providing field support for both the lab results cited above, as well as the theoretical literature on self-regulation, with a novel dataset. While the papers investigating obesity and impulsive behavior mainly rely on student samples, the papers on obesity and social factors use more macro-level data without having individual level food purchase data. Our rich panel data allow us to investigate the research question regarding obesity, food purchase and income from a large scale but granular field data. Understanding the answer to this question about scale is critical for researchers and policy-makers who wish to build on the results of smaller interventions to plan larger implementations.

Our research also contributes to the understanding of obesity, impulsive behavior, and social economic factors, in particular, income. Prior literature suggests impulsive behavior may be related to scarcity of cognitive resources (Mischel et al., 1972; Vohs and Faber, 2007; Iyer et al., 2020). In particular, the cognitive system has a finite capacity (Luck and Vogel, 1997; Pashler et al., 2001). As indicated by Inzlicht and Schmeichel (2012) and Inzlicht et al. (2014), with a shift in attention away from cues signaling the need to exert control and toward cues signaling gratification may lead to suboptimal outcomes. For example, Shah et al. (2012, 2019) find that scarcity leads to overborrowing, and in eye tracking studies, Zhao and Tomm (2018) find evidence that resource scarcity increases cognitive demands on individuals and may overly focus their attention aspects such as a product's overall price, to the detriment of other product features. Additionally, limited cognitive resources may be exacerbated by external mental, financial or physical factors. In our context, having a lower income may be correlated with more mental stress, and hence greater exhaustion of internal resources. As argued by Kim and von dem Knesebeck (2018), one's financial situation will not only affect one's food choice, but also psychosocial factors that derive from relative deprivation such as control over life, insecurity, and stress. Prior literature has also documented evidence that the price sensitivity for sugar-sweetened beverages varies across different income groups. For example, Guerrero-López et al. (2017) found that price elasticity of demand for soft drinks was higher for lower-income consumers, as compared to higher-income consumers. Higher-income consumers were less sensitive to changes in prices, and continued buying soft drinks even after price increases. If financial constraints (resource scarcity) increase cognitive load, we expect those consumers with lower income to be more promotional sensitive. In our setting, both vice goods and in-store promotional cues impose immediate grafication which consumers might attend more to. Therefore, they need more cognitive effort to resists the temptation and regulate themselves. The effect is particularly large for those who are facing scarcities or are coping with other activities that demand their attention.

3 Data and Sample Selection

Our analysis makes use of three datasets: the Nielsen Homescan Consumer Panel, the Nielsen Retail Scanner data, and the IRI MedProfiler survey which is a health survey linked to the Nielsen Homescan Consumer Panel data.[9] All three panels span the years 2010 to 2015. The first two are fairly standard and have been used extensively in past empirical work in industrial organization and marketing. Specifically, the Homescan panel tracks individual purchases of grocery products over time. The Nielsen Retail Scanner dataset tracks store level prices and quantity data. We link the two datasets to complement the prices of purchased goods recorded by the IRI households with the prices and in-store promotion information of non-chosen available products in stores documented by the Nielsen Retail Scanner data.

In addition to the two well known scanner data sets, we make use of a unique and comprehensive health survey, the IRI MedProfiler survey. The MedProfiler survey is a large-scale survey administered by IRI to all Homescan panelists. The survey includes a broad range of health-related questions, which collect information about an individual's weight and height, eating/exercise habits, as well as different kinds of health conditions. About two thirds of households complete the MedProfiler survey: The number of households in the panel, and those who are in the MedProfiler data, are shown in columns one and three in Table 1.

Linking the combined consumer purchase panel and Medprofiler survey to Nielsen's retail store panel provides two important advantages over using only the IRI data, as earlier work has done (Ma et al., 2013; Chen et al., 2016; Okrent and Sweitzer, 2016; Ailawadi et al., 2018). First, the IRI store panel provided by USDA

[9]The Homescan panel is maintained as part of a joint venture by both Nielsen and IRI.

does not contain feature or display variables, making it more difficult to measure how they affect demand in a discrete choice model. Second, the IRI version of the consumer panel provided by USDA does not precisely identify the store where the consumer shops, and rather identifies only the chain. Thus, matching a consumer trip to a store (which is necessary to estimate a discrete choice demand model) is often not possible. Moreover, for larger chains, prices are provided not at the individual store level, but aggregated up to the level of a Retail Market Area. These latter reasons may be why Okrent and Sweitzer (2016)'s work focuses on estimating aggregate demand, rather than product-level demand as we do.

We limit the sample in our analysis to one-person households who complete the MedProfiler survey. We use one-person households because in much of our analysis, we will quantify the relationship between a shopper's BMI and his/her purchase behavior. The Nielsen Homescan panel does not identify which household member is shopping during a given trip, so we can only match purchases to household members in one-person households. As we will discuss below, the BMI distributions and purchase behavior of one-person households is similar to that of multi-person households (Okrent and Sweitzer, 2016), suggesting our findings should generalize. Furthermore, we exclude households who never make purchases in the six-year period of the data, as well as individuals who appear to have had a baby during the sample period. Regarding the latter exclusion, we wish to focus our analysis on individuals who are obese for reasons other than pregnancy, which is temporary. Even with these sample selection mechanisms, as can be seen in the fourth column of Table 1, we still retain about eight to ten thousand households every year.

Table 1: Number of Households in Nielsen Homescan Panel

Year	Homescan # of Households	1 Person Homescan # of Households	MedProfiler # of Households	1 Person MedProfiler # of Households
2010	60,658	15,483	38,750	8,009
2011	62,092	15,859	48,701	9,534
2012	60,538	15,303	39,651	8,570
2013	61,097	15,615	47,040	10,574
2014	61,557	15,703	41,573	9,828
2015	61,380	15,424	45,264	9,942

We compared the distributions of several demographic variables in our sample of one-person households compares to that of the entire MedProfiler sample. Overall, both samples are similar, for example, ethnicity, Hispanic origin and education.[10] The samples differ somewhat in age and gender composition, with over 70% of one-person households being female and around 50% of individuals in all households in the MedProfiler dataset being female. Moreover, about 28% of one-person households are over the age of 65, while in the entire MedProfiler dataset, only 19% of individuals are above 65. Full tables of the comparisons are presented in Web Appendix Tables W1 through W7 of Web Appendix A.

A comparison of the distributions of BMI, one of our main variables of interest, between the complete MedProfiler dataset and one-person households is shown in Table 2. The BMI is defined as an individual's body mass, measured in kilograms, divided by the square of the individual's height, measured in meters, and is a commonly used measure of obesity in clinical practice.[11] Individuals are typically classified into one of five BMI brackets, which are shown in the first column of the

[10]In multi-person households, we measure household level education and age as the maximum value of these variables across the female and male household head. Ethnicity is measured as ethnicity of the household head.

[11]According to the U.S. Center for Disease Control, "The correlation between the BMI and body fatness is fairly strong", and "The accuracy of BMI as an indicator of body fatness also appears to be higher in persons with higher levels of BMI and body fatness" (https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html, retreived on Nov 11, 2021).

Table 2: Distribution of BMI Brackets (Person-year level)

BMI Bracket	BMI Ranges	U.S. Population	MedProfiler Percent household-years	One-person MedProfiler Percent household-years
Underweight	< 18.5	1.5	1.79	1.71
Healthy	$18.5 - 24.9$	28.3	28.39	27.61
Overweight	$25 - 29.9$	32.5	33.64	32.16
Obese	$30 - 39.9$	30.0	28.44	29.36
Extremely Obese	≥ 40	7.7	7.74	9.16

table. The second column shows the BMI cutoffs used to assign an individual to a particular bracket. The third column shows the distribution of BMI in the U.S. population (Center for Disease Control, 2015; The National Institute of Diabetes and Digestive and Kidney Diseases Health Information Center, 2017), while the distribution of the complete MedProfiler sample and of the one-person sample[12] are shown in columns four and five respectively. In our analysis, we will use both BMI and individual's obesity status, derived from his or her BMI bracket, to describe one-person households.

There are two important points to take away from this table: First, the distributions of BMI brackets are similar for both the complete MedProfiler and the one-person household sample. Second, the BMI distribution presented in the table is very similar to the population distribution of BMI in the United States during this period from the third column of Table 2. This latter point is notable, because although individual weight is self-reported, the fact that BMI as measured in the survey mimics the nationalwide distribution of BMI suggests that there are not systematic biases in how individuals report their weight. We also compared the densities of weight in pounds, as well as BMI, for individuals over 20 years old for both samples, finding that the BMI distributions are similar for the one-person and complete MedProfiler samples. We present figures comparing these distributions across both samples in Web Appendix Figures W1 and W2.

In the empirical analysis for this paper, we will conduct separate analyeses for consumers who are above 65, versus below 65, for a number of reasons. First,

[12] We exclude individuals under the age of 20 for all analysis in this paper. This is because the typical BMI bracket designations do not apply to individuals under that age.

the BMI calculation may not be a good indicator of health for the elderly (Diehr et al., 2008), meaning that our measure of obesity may have more noise for older individuals. Second, an individual's lifestyle may change significantly after the age of 65, when most people in the United States retire.[13] Retired individuals may exhibit substantially different behavior than those who are working. Third, our data oversamples individuals above the age of 65, and thus there may be concern our findings would be less representative of the general population if their behavior is substantially different from younger people. However, we do find similar qualitative patterns in behavior when comparing under 65 individuals to over 65 individuals, mitigating the latter concern.

4 Stylized Facts

We estimate our model of category consideration on 20 different Nielsen product categories, ten vice categories and ten virtue categories. To define categories as vice or virtue, we mainly rely on the work of Thomas et al. (2012), who conduct a survey asking consumers about their perceptions of (a) how healthy a particular food category is, and (b) how impulsive (tempting) the category is, for 100 food categories. Each category was then rated by 78 undergraduate students and an overall vice index was constructed for each category which averaged the students' perceptions of category unhealthiness and impulsiveness. We chose the top vice and top virtue categories for analysis, where we could find an appropriate mapping to a Nielsen category with sufficient data suitable for discrete choice demand analysis.

It is not straightforward to direct map Thomas et al. (2012) to Neilson categories as we encounter several chanllengs when we do the mapping exercise. In particular, some of the categories in Thomas et al. (2012) are debatable, for example, lunchmeat has been listed in the virtue, but it has shown up in many unhealthy list and has been critized to contain lots of sodium and sometimes fat as well as some preservatives like nitrites.

[13] About 70% of the US population aged 65 or above is retired, see https://www.bls.gov/opub/btn/volume-4/people-who-are-not-in-the-labor-force-why-arent-they-working.htm.

To overcome this shortcoming, we supplement our category selection with Oster (2015), who surveyed 17 doctors to rank food modules as "a good source of calories," "a bad source of calories" or "neither good nor bad." Although most of results in Oster (2015)'s survey are consistent with the list in Thomas et al. (2012), some of the categories receive opposite vice or virtue ratings. For example, fresh bread, which received high virtue rank in Thomas et al. (2012), has received 12 votes for "bad source" and only 1 vote for "good source", indicating that fresh bread is not very healthy. Given these inconsistency, we exclude fresh bread and lunch meat from our virtue list. Consulting and using a combination of Thomas et al. (2012) and Oster (2015), we pin down ten vice categories and ten virtue categories that span from frozen, storable to persible goods.

We describe our procedure for category selection in detail in Web Appendix B with tables showing exact mappings in Web Appendix Tables W8 and W9.

4.1 Food Purchase and Obesity, by Category

We now turn to descriptive analysis of how category-level food purchase varies with obesity status. First, we investigate the relationship between category food expenditure shares and individual's weight status. In Table 3, we present expenditure shares (as a share of a household's total grocery bill) for vice and virtue categories we select. For vice categories, it is almost universally the case that expenditure shares increase with BMI bracket. One exception is regular soda, which is lower for extremely obese individuals. For virtue categories, we generally observe decreases in expenditure shares with some categories showing mixed patterns, such as eggs and dry pasta. We note that Table 3 is for the sample of individuals below age 65. We present expenditure shares for the over 65 consumers in Web Appendix Table W10, and observe generally similar patterns.

We also explored how purchase behavior related to overall purchase quantity, frequency and brand choice differed for individuals along the body weight distribution across all categories. The results of our analysis showed that for vice categories, individuals with obesity purchase higher overall quantities, make purchases more frequently, purchase smaller sizes within a trip, and switch brands more than

Table 3: Monthly spending shares, by food category and BMI bracket

Vice Categories					
Category	Underweight	Healthy	Overweight	Obese	Extreme Obese
Non Chocolate Candy	0.8865	0.8535	0.8635	0.9743	1.0953
Cookies	1.3632	1.3006	1.3739	1.3980	1.4014
Donuts	0.1879	0.1400	0.1644	0.1822	0.2068
Frozen Novelties	0.5017	0.6264	0.7303	0.8248	1.0436
Dessert Cakes	0.4409	0.4371	0.4831	0.5296	0.5472
Potato Chips	1.0338	1.0620	1.1870	1.2872	1.4232
Pudding	0.1161	0.0936	0.1040	0.1232	0.1429
Ice Cream	1.3728	0.9818	1.1418	1.1172	1.2910
Regular Soda	2.0877	2.0072	2.0725	2.1030	1.8755
Frozen Pizza	0.7425	0.9719	1.0294	1.0347	1.0763
Virtue Categories					
Category	Underweight	Healthy	Overweight	Obese	Extreme Obese
Dry Beans	0.0648	0.0460	0.0403	0.0314	0.0311
Rice	0.2385	0.1634	0.1174	0.1067	0.0920
Fresh Salad	0.4573	0.8051	0.8433	0.8154	0.7912
Frozen Vegetables	1.0837	0.7968	0.7336	0.7399	0.6910
Eggs	0.7409	0.9033	0.8824	0.8825	0.8831
Tea Bags	0.2890	0.3023	0.2591	0.2512	0.1867
Milk	2.3043	2.5846	2.4742	2.2904	2.1055
Hot Cereal	0.4050	0.4079	0.3173	0.2732	0.2440
Canned Vegetables	1.1163	1.0379	0.9209	0.9285	0.9170
Dry Pasta	0.3046	0.3367	0.3050	0.2848	0.3009

Notes: This table shows average monthly shares of food expenditures for single-person households who are under 65. Categories correspond to the vice and virtue categories defined in Tables W8 and W9.

non-obese individuals. The results suggest that although individuals with obesity purchase more often, and more overall, they tend to choose smaller package sizes, perhaps as a means of controlling consumption. Wertenbroch (1998) also documents that consumers may purchase smaller package sizes of vice goods as a way of controlling consumption of them. Notably, we did not find systematic differences like this (outside of more brand switching) for virtue categories. We present these summary statistics in Web Appendix Tables W11 and W12.

5 Structural Model

For our primary analysis in the paper, we will estimate a structural model of category consideration in the style of Ching et al. (2009, 2014). We will use the model to explore the implications of the laboratory literature, which suggests that promotions may disproportionately heighten the salience of food for the obese, especially for vice categories. The model we use is called the "price consideration" model of brand choice, and it captures consumer attention to a category as well as choice of product within a category. In the model, a consumer's decision process proceeds in two steps. The first stage, called the *consideration stage*, models whether a consumer considers a product category or not. In the second stage, called the *purchase stage*, which occurs only if a consumer considers a category, the consumer decides which product (if any) to purchase. Category consideration is driven by consumer need for the category (for example, if a consumer's inventory is running low the likelihood of consideration may be higher), as well as cues such as advertising or price promotions that may increase category salience. If a consumer considers purchasing in the category, the consumer will make a purchase decision by choosing the option which maximizes utility (this includes not purchasing any product in the category). According to Ching et al. (2014), the behavioral motivation for the consideration model is a boundedly rational multi-stage decision process. Additionally, it is consistent with the previously cited theoretical framework of self-regulation and internal resources, with limited cognitive resources, a shift in attention away from cues signaling the need to exert control and toward cues signaling gratification leads to reduced self-control (Luck and Vogel, 1997; Pashler et al., 2001; Inzlicht and Schmeichel, 2012; Inzlicht et al., 2014), and higher probability of purchase consideration.

We specify consumer i's utility from purchasing product $j = 1, ..., J$ in time t as

$$\begin{aligned} U_{ijt} &= \alpha_{ij} - \beta p_{ijt} + x_{ijt}^{Choice}\lambda + \varepsilon_{ijt} \qquad (1) \\ &= \overline{U}_{ijt} + \varepsilon_{ijt}, \end{aligned}$$

where α_{ij} reflect's consumer i's persistent preference for product j, β_i reflects the consumer's sensitivity to the price of product j in the store the consumer shops at in time t, x_{ijt}^{Choice} is a vector of consumer product and brand characteristics which we describe below, and ε_{ijt} is a type 1 extreme value error that is independently and identically distributed across products, consumers and periods. $\overline{U}_{ijt}$ denotes consumer i's utility net of the idiosyncratic error. We denote the no-purchase option as option J and normalize $\overline{U}_{iJt}$ to zero: $U_{iJt} = 0 + \varepsilon_{iJt}$. Conditional on category consideration, we can express the probability consumer i chooses product j in time t as:

$$P_{it}(j|C) = \frac{\exp\left(\overline{U}_{ijt}\right)}{\sum_{k=1}^{J} \exp\left(\overline{U}_{ijt}\right)}. \tag{2}$$

Next, following Ching et al. (2009, 2014) we denote the probability of category consideration as $P_{it}(C)$. The unconditional probability consumer i purchases a product $j < J$ in period t will then be given by

$$P_{it}(\text{purchase } j) = P_{it}(C)P_{it}(j|C), \tag{3}$$

while the unconditional probability of no purchase is made is

$$P_{it}(J) = (1 - P_{it}(C)) + P_{it}(C)P_{it}(J|C). \tag{4}$$

5.1 Econometric Model Specification

In this section we describe the details of our model specification, and how we will use it to test our hypotheses. We specify the category consideration probability as follows:

$$P_{it}(C) = \frac{\exp\left(x_{it}^{Cons}\gamma_c\right)}{1 + \exp\left(x_{it}^{Cons}\gamma_c\right)}, \tag{5}$$

x_{it}^{Cons} is a vector of individual demographic variables, variables capturing category-level promotional activity, a proxy for inventory, and interactions between promotional activity, the inventory proxy and demographics. Our exact specification includes the following regressors:

- Low income: Indicator if individual i is below median income.
- High income: Indicator if individual i is above median income.
- Obese $\times$ Low Income: Interaction between obese indicator and low income indicator.
- Obese $\times$ High Income: Interaction between obese indicator and high income indicator.
- Feature, display: Indicators for whether any alternative in the category is on feature (display) in week t in the store consumer i shopped at.
- Deal: Average number of alternatives in the category where a price deal is inferred in week t in the store consumer i shopped at.
- Obese $\times$ low income $\times$ feature (display, deal): Interactions between obese indicator, low income indicator, and promotional variables.
- Obese $\times$ high income $\times$ feature (display, deal): Interactions between obese indicator, high income indicator, and promotional variables.
- Purchase Gap: Number of weeks elapsed since the previous time an inside good was chosen in the category.
- Purchase Gap $\times$ Obese (High Income): Interactions between purchase gap, and obese/high income indicators.

The first four variables allow the main effect of consideration to vary with both income and obesity status. The feature and display variables are 1 if any altnernative j is on feature or display during the time consumer i visits the store in week t. The deal variable is constructed somewhat differently than feature or display: It is the average number of alternatives in the category that appear to have price deals. Price deals are not recorded in the Nielsen store data, so we must infer them. We use a procedure that follows Hendel and Nevo (2006). For each UPC and store in the data, we find the quarterly modal price of that UPC in the store. Then, we identify a product as being on deal if its price is more than 5% below the modal price.[14] In the consideration probability, we use the average number of price deals in a category as a regressor rather than an indicator for whether there is any deal or not, because it is very often the case that there is at least one product in the category with a low price: such an indicator would have too little variation.

The interactions between the three in-store promotional variables, obesity, and income are key to testing the implications of lab findings in the field. We expect that obesity may be correlated with higher resource constraints, which will imply higher sensitivity of consideration to promotions for individuals with obesity, especially in vice categories which are perceived as more tempting. The impact of obesity on category purchase may be moderated by income, which is why in our main specifications we include interactions between obesity and income. For example, if vice goods are non-essential then lower income individuals may be less likely to consider them. Positive interactions between obesity and in-store promotion variables would be consistent with more obese individuals being more sensitive to advertising cues; if vice categories are harder to resist, then this effect should be especially strong in those. Individuals with lower income may also face higher cognitive constraints, and thus, we may find the strongest effects among individuals with low income.

The final sets of variables we include are the purchase gap, and interactions between purchase gap and obesity/income. Following Ching et al. (2009, 2014), purchase gap is defined as the number of weeks elapsed since the last purchase made in the category, and is included to capture inventory effects. In particular, Ching et al. (2014) argue that the interpurchase time is an approximation to inventory that allows consumption rates to vary over time. Such an approximation is useful in our case since some product categories we study may have consumption rates that vary with inventory (Ailawadi and Neslin, 1998; Bell et al., 1999; Sun, 2005). We include interactions between purchase gap and obesity, because individuals with obesity may have different consumption rates than non-obese individuals, which may be expected if there is a correlation between obesity and impulsive consumption.

[14] In Hendel and Nevo (2006)'s work, they varied the threshold for defining a deal and found results were similar across different thresholds.

Before discussing the variables we include in the second stage of product choice, we make some comments on the feature, display and deal variables. First, the feature and display variables are only recorded for around 30% of the stores in the Nielsen data, and are missing for the rest. In order to use the entire sample to estimate the model, we set the feature and display variables to zero when they are missing (this approach has been taken in other papers using this data, such as Shapiro et al. (2021)). A consequence of setting the in-store promotion variables to 0 when they are missing is that the coefficients on these variables, as well as the interactions between them and obesity or income, will be biased towards zero, and thus a conservative estimate of their true effects. We include the deal variable to help mitigate the issues resulting from missing data. Recall that this variable captures the number of products for which the price is low, relative to the product's historical price. Typically, low prices are promoted using features or displays, and as a result this variable will be correlated with promotions we cannot observe in the data.

In the product choice part of the model, we include in x_{ijt}^{Choice} interactions between alternative-specific constants and obesity, feature and display indicators for product j, along with interactions between feature, display and price with obesity and high income indicators. We note that our model includes both unobserved heterogeneity in preferences through allowing random coefficients, α_{ij}, and state dependence through including a lag choice indicator in x_{ijt}^{Choice} that is 1 if alternative j is the same as the last one the consumer purchased (Dubé et al., 2010). We also include an interaction between the state dependence term and obesity, since we found in the previous section individuals with obesity tended to switch brands more than non-obese individuals.

5.2 Construction of Choice Sets and Estimation Data

To estimate our choice model, we need to make decisions on how to construct the choice set for consumers. Because we estimate our model on many categories, the exact way we construct choice sets will depend on category-specific characteristics, but we follow the following general principles: First, we want to differentiate between different package sizes, so in each category we tabulate the different sizes available. We then tabulate the distribution of available sizes, and define size categories for a particular UPC. For example, for most product categories we define large sizes as those above the 75th percentile, small sizes as those below the 25th, and medium as those in between.[15] Second, we wish to differentiate between leading national branded goods, private labels, and smaller share brands, which we call other brands. The options in our choice sets are then typically defined as small, medium or large sizes of the top few manufacturer brands, small, medium, and large private label, and small, medium, or large sizes of other brands, and no purchase (we note that some brands are not available in some sizes). To construct prices, feature and display variables for other brands, we use share-weighted averages of these variables across brands. If a particular national brand has multiple sizes in a particular size category, or multiple flavors or variations, we similarly average over prices, features and displays. As an example, in the ice cream category, the small size is anything less than or equal to 28.5 ounces, the medium between 28.5 and 56 ounces, and large 56 ounces or above. To protect confidentiality of the companies who provide data to Nielsen, we denote the top national brands we include in the choice set as Brands 1-7. Not all these brands are available in all sizes, so our final choice set is (in order of purchase frequency): (1) medium private label, (2) medium Brand 1, (3) small Brand 2, (4) large private label, (5) medium Brand 3, (6) small Brand 4, (7) medium Brand 5, (8) small private label, (9) medium Brand 6, (10) large Brand 7, (11) small other brands, (12) medium other brands, (13) large other brands, (14) no purchase. The details on how the choice sets are constructed in all categories are available upon request.

Our model is estimated at the weekly level. To construct our estimation sample, for each category we construct choice variables for each week, store and product. For consumers, we merge purchase data from the purchase panel with weekly trip data, so we know when a visit happened with no purchase. Then, we merge in the choice sets to construct our final estimation data. We also restrict the time window where we estimate the model to a 3 month window around November, when

[15] All the options for each category are available upon request. In some categories, such as soda, consumers often purchase multipacks so we use that to define size as well if applicable.

the Medprofiler survey is taken (October 1 through December 31). We make this restriction for two reasons: First, to reduce measurement error in the BMI measurement. An individual's BMI in May, for example, may be less reflective of the BMI measurement in November, which is closer to when the survey is taken. Second, making the window shorter will reduce a potential endogeneity concern with the measure of BMI. In particular, BMI in November may be a function of consumption in earlier months, leading to spurious positive correlation between BMI and category purchase (and spurious correlation with the BMI interactions we are interested in). To show evidence that this source of endogeneity will not be severe, we first show that changes in BMI seem relatively unresponsive to quarterly consumption in Web Appendix Table W13. This table shows estimates of the log of BMI from the November survey on log quarterly consumption of a number of broad food categories (corresponding to Nielsen department codes) from the prior year, as well as the prior year's BMI and individual fixed effects. Two facts are notable in this table. First, the impact of quarterly consumption on BMI is extremely small: for example, focusing on quarter 1's frozen food expenditures, the results show that a 1% increase in frozen food expenditures in January through March will increase BMI in November by only 0.187%. Second, there is no significant effect of food consumption in Quarter 4 (when BMI is actually measured) on BMI. As a result, there should be very little spurious correlation between a purchase of a package of ice cream in October, for example, and the BMI measurement in November.

In Table 4, we present some of the characteristics of our estimation datasets. The number of alternatives includes the outside option, and varies from 8 to 29. Many of our estimation datasets are large, including one or two hundred thousand observations. The final column of the table presents the fraction of individuals in each dataset who are under 65, which is about 70% of the sample.

6 Estimation Results

Recall that our main parameters of interest are the interactions between obesity and sensitivity to in-store promotional variables (feature, display and price deals) for high and low income individuals, in the category consideration part of the model.

Table 4: Sample Information for Estimation Datasets

Category	Number of Alternatives	Number of Osbervations	Number of Households	Fraction HHs Under 65
		Vice Categories		
Non Chocolate Candy	14	140458	11010	70.1%
Cookies	14	154027	11890	70.2%
Donuts	12	75480	5423	70.2%
Frozen Novelties	14	137825	9824	69.9%
Dessert Cakes	14	125339	9336	69.4%
Potato Chips	14	152401	11286	70.9%
Pudding	13	59951	3975	68.4%
Ice Cream	14	158958	10824	68.8%
Regular Soda	16	153779	11042	70.5%
Frozen Pizza	14	138630	9588	70.3%
		Virtue Categories		
Dry Beans	8	41476	2992	64.4%
Rice	14	75832	5419	70%
Fresh Salad	14	132618	9611	69.5%
Frozen Vegetables	29	147944	10202	69.6%
Eggs	13	156756	11963	69.1%
Tea Bags	14	93238	6888	67.4%
Milk	14	161281	11853	70.1%
Hot Cereal	14	117541	8589	67.7%
Canned Vegetables	17	141461	11604	69.1%
Dry Pasta	14	138277	10251	70.2%

These interaction terms will inform us about whether individuals with obesity are more or less sensitive to promotions than non-obese individuals. Motivated by the researches which suggests income may moderate the sensitivity of individuals with obesity to promotions(see Pickett et al., 2005; Kim and von dem Knesebeck, 2018; Zhao and Tomm, 2018; Shah et al., 2012, 2019 and so on), our preferred specification includes three-way interactions between obesity, promotional variables, and a high income (above median) indicator. We also present our main set of findings for the under 65 population, because as we have discussed earlier, BMI may be a worse measure of obesity for individuals above 65. However, we will show that our main set of findings, which is that the consideration decisions of individuals with obesity are more sensitive to promotions in vice categories than virtue categories, still holds in a number of robustness checks we discuss later in this section.

We present the interaction terms of interest for vice categories in Table 5. We present the categories in each row, and the corresponding model estimates for that category in the columns. The first three columns show the impact of obesity on the sensitivity of category consideration for feature, display and price deals, conditional on the consumer being low income (below the median).The results for Chocolate Candy, for example, demonstrate that, for individuals with low income, thsoe with obesity are significantly more likely to consider the category in response to increases in these in-store promotional variables than the non-obese. The fourth column shows a check mark for when at least one coefficient in columns 1-3 is positive and significant at the 10% level. The fourth column indicates strong support for the theory that individuals with obesity are more promotion sensitive: in eight of twelve vice categories, at least one interaction coefficient is positive and significant. Moreover, no interactions are negative and significant. We also note that compared to other categories, pudding is less frequently purchased so that the non-significant result is not surpring. Columns 5-7 of Table 5 show the estimated interaction terms for high-income consumers. Although we observe some evidence in support of the theory that individuals with obesity are more promotion-sensitive, the effects are weaker than for consumers with low income for two reasons. First, we only find at least one positive interaction in four categories, rather than eight. Second, there are even more categories where the interaction between obesity and a promotional variable is negative and significant (cookies, donuts, frozen novelties, potato chips, ice cream, and regular soda), indicating mixed or lower promotional sensitivity for individuals with obesity and high income (relative to high income non-obese individuals).

Table 5: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Vice Goods

	Low Income				High Income			
Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Non Chocolate Candy	0.087	-0.042	0.943**	✓	0.042	0.046	1.159***	✓
	(0.1004)	(0.1182)	(0.3876)		(0.0888)	(0.1125)	(0.38)	
Cookies	0.054	-0.14	-0.514		0.058	-0.366**	-0.864**	
	(0.1283)	(0.1701)	(0.5239)		(0.0921)	(0.1517)	(0.4113)	
Donuts	-0.042	0.162	1.922**	✓	-0.687**	0.116	2.151**	✓
	(0.3572)	(0.2335)	(0.9101)		(0.3227)	(0.2562)	(1.0672)	
Frozen Novelties	0.023	0.043	-0.032		-0.236***	-0.453***	-1.234***	
	(0.0892)	(0.0858)	(0.3414)		(0.0744)	(0.0715)	(0.3017)	
Dessert Cakes	-0.092	0.247	2.36***	✓	-0.222	-0.265	0.432	
	(0.1753)	(0.1864)	(0.7203)		(0.1452)	(0.1675)	(0.5728)	
Potato Chips	0.014	0.243*	0.277	✓	0.075	0.037	-1.12***	
	(0.1132)	(0.1377)	(0.3942)		(0.0968)	(0.1216)	(0.3527)	
Pudding	-0.576	-0.417	-0.914		-0.576	-0.417	-0.914	
	(4.35)	(1.3016)	(9.0235)		(4.35)	(1.3016)	(9.0235)	
Ice Cream	0.018	0.119	0.357		-0.232***	0.209**	-0.412	✓
	(0.1016)	(0.099)	(0.3452)		(0.0853)	(0.0888)	(0.2884)	
Regular Soda	2.401**	1.786	-16.275	✓	-6.633**	-2.271	9.001**	✓
	(1.2086)	(2.1149)	(10.5053)		(2.9608)	(2.2693)	(3.5252)	
Frozen Pizza	0.325**	0.168	1.218***	✓	0.15	0.032	0.196	
	(0.1471)	(0.1536)	(0.4489)		(0.1017)	(0.1018)	(0.352)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income. For the Pudding category, the high income interactions were not identified and so were not included in the model.

Next, we turn to discussing the estimated interactions terms in the virtue categories, which are presented in Table 6. Focusing on the first three columns of the table, for consumers with low income, there seems to be some evidence consumers with obesity and low income are more promotion sensitive, but it is somewhat weaker than vice categories for two reasons. First, we find at least one positive and significant interaction a smaller fraction of categories: only four out of twelve categories for virtue goods, relative to eight of twelve for vice goods. Second, although in vice goods there were no negative interactions between promotion sensitivity and obesity for consumers with low income, in virtue goods there are two categories where a negative effect is observed: hot cereal and canned vegetables. Thus, comparing our findings to those of vice goods, we find consumers with obesity are more likely to be promotional sensitive to the vice categories. We also note that some of the categories where stronger effects are found are likely to be the less healthy virtue categories: for example, canned vegetables (Oster, 2015) and yogurt. We also note that in terms of the purchase frequency, compared to other virtue categories, tea bags and hot cereals are purchased less often, which may make identification of interaction effects more difficult. For consumers with high income, we again observe results that are weaker than those for consumers with low income. We only find at least one positive estimated coefficient in three categories, rather than five. Moreover, there are more categories where a negative and significant interaction is observed: two, relative to zero in columns 1-3. Relative to virtue goods, we do not find evidence that individuals with obesity and high income are more promotion sensitive. In fact, in vice categories there are more categories with negative coefficients (six) and less with at least one positive (one).

Table 6: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Virtue Goods

	Low Income				High Income			
Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Dry Beans	1.909	0.966	-0.321		1.909	0.906	4.017**	✓
	(3.0963)	(1.0451)	(1.508)		(3.0963)	(0.819)	(1.7498)	
Rice	0.288	0.317	0.836		0.07	0.043	-0.615	
	(0.6206)	(0.3951)	(1.6264)		(0.445)	(0.2655)	(1.2299)	
Fresh Salad	0.02	0.141	0.516		-0.033	0.237	0.21	
	(0.1297)	(0.1994)	(0.4101)		(0.1)	(0.1546)	(0.3121)	
Frozen Vegetables	0.08	0.169	0.195		0.011	0.12	-0.859***	
	(0.1111)	(0.1289)	(0.3721)		(0.0801)	(0.0945)	(0.2667)	
Eggs	-0.154	-0.081	0.468*	✓	-0.196*	-0.134	-0.234	
	(0.149)	(0.1381)	(0.2758)		(0.1149)	(0.0997)	(0.1957)	
Tea Bags	-0.123	-0.044	1.959**	✓	-0.096	-0.246	0.832	
	(0.2602)	(0.2303)	(0.9697)		(0.1995)	(0.1654)	(0.7319)	
Milk	0.209	-0.062	-0.76		0.113	-0.14	0.188	
	(0.1535)	(0.1514)	(0.6252)		(0.1156)	(0.1157)	(0.4927)	
Hot Cereal	-0.433**	-0.008	-0.043		0.119	0.154	1.817***	✓
	(0.2181)	(0.2048)	(0.7907)		(0.1748)	(0.1697)	(0.6193)	
Canned Vegetables	-0.43***	0.171*	0.289	✓	0.052	0.052	-0.168	
	(0.0864)	(0.0978)	(0.3658)		(0.0685)	(0.0767)	(0.2761)	
Dry Pasta	-0.009	-0.261	0.377		0.576***	-0.112	-0.337	✓
	(0.1788)	(0.1701)	(0.5994)		(0.1593)	(0.158)	(0.4414)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income. For the Yogurt and Bottled Water categories, the high income interactions were not identified and so were not included in the model.

To get a sense of the overall magnitudes of the effect of obesity on promotional sensitivity, in Tables 7 and 8 we provide the predicted impact of obesity on the derivative of the consideration probability with respect to the promotional variables for consumers with low income:

$$\frac{\partial P(C|Obese)}{\partial x} - \frac{\partial P(C|Non-Obese)}{\partial x}, \quad x \in \{Feature, Display, Deal\}.^{16}$$

Entries in bold correspond to interaction effects that are statistically significant at the 10% level. The results in the tables indicate that individuals with obesity are often much more sensitive to promotions than non-obese individuals. For example, in regular soda, a feature will increase the consideration probability of an consumer with obesity and low income by 18% more than a non-obese consumer with low income. Many other estimated effects are of similar magnitude - diet soda, non chocolate candy, donuts, cakes, and frozen pizza, for example.

In Tables 9 and 10 we present predicted category level purchase probabilities for obese and non-obese individuals. When we compute predicted purchase probabilities, we hold all other covariates fixed at their averages in the data. Focusing on Table 9, we can see that predicted purchase probabilities for consumers with obesity in vice goods are higher for eleven of the twelve categories. For virtue goods, which are presented in Table 10, we can see that purchase probabilities are higher for consumers with obesity for only three out of twelve categories, and overall the differences between obese and non-obese consumers is not large.

We present the estimates of the rest of the coefficients that enter the consideration probabilities in Web Appendix Tables W14 and W15 for vice and virtue goods, respectively. A note we make on the estimates in these tables is that the purchase gap parameter is negative for many categories (especially vice ones), which suggests a potential alternative source of dynamics in category choice to inventory: addiction, or habit formation. Importantly, the interactions with obesity suggest that in vice categories, individuals with obesity have more negative purchase gap coefficients, meaning these goods are more addictive for them. For virtue categories,

[16] When computing these derivatives, we hold all the other covariates fixed at their average values in the data.

Table 7: Difference in Sensitivity of Consideration Probability to Promotional Variables for Obese vs Non-Obese Consumers, Vice Goods

Category	Feature	Display	Deal
Non Chocolate Candy	0.022	-0.017	**0.262**
Cookies	0.015	-0.036	-0.139
Donuts	0.019	0.035	**0.372**
Frozen Novelties	0.007	0.014	0.017
Dessert Cakes	-0.019	0.053	**0.503**
Potato Chips	0.003	**0.059**	0.068
Pudding	0.08	-0.11	0.226
Ice Cream	0.004	0.027	0.071
Regular Soda	**0.184**	-0.227	-6.4
Frozen Pizza	**0.081**	0.042	**0.304**

Notes: This table shows, for a particular promotional variable, the derivative of the consideration probability for consumers with obesity minus that of non-obese consumers. For example, row 1 column 2 shows that the increase in consideration probability that occurs when a display happens is 5% higher for an obese consumer than a non-obese consumer, in the chocolate candy category. Categories with statistically significant interactions from Table 5 are shown in bold.

Table 8: Difference in Sensitivity of Consideration Probability to Promotional Variables for Obese vs Non-Obese Consumers, Virtue Goods

Category	Feature	Display	Deal
Dry Beans	0.393	0.21	-0.049
Rice	0.057	0.062	0.164
Fresh Salad	0.007	0.032	0.146
Frozen Vegetables	0.021	0.042	0.051
Eggs	-0.037	-0.02	**0.113**
Tea Bags	-0.017	-0.007	**0.352**
Milk	0.044	-0.016	-0.153
Hot Cereal	**-0.106**	0.001	-0.004
Canned Vegetables	**-0.098**	**0.038**	0.066
Dry Pasta	-0.002	-0.066	0.088

Notes: This table shows, for a particular promotional variable, the derivative of the consideration probability for consumers with obesity minus that of non-obese consumers. For example, row 1 column 2 shows that the increase in consideration probability that occurs when a display happens is 21% higher for an obese consumer than a non-obese consumer, in the dry beans category. Categories with statistically significant interactions from Table 6 are shown in bold.

Table 9: Category-Level Purchase Probability and Overall Elasticity, Vice Goods

Category	Category Purchase Probability	
	Obese	Non-Obese
Non Chocolate Candy	0.143	0.116
Cookies	0.178	0.152
Donuts	0.034	0.026
Frozen Novelties	0.13	0.09
Dessert Cakes	0.04	0.033
Potato Chips	0.085	0.077
Pudding	0.02	0.015
Ice Cream	0.082	0.074
Regular Soda	0.01	0.046
Frozen Pizza	0.122	0.114

Notes: For consumers with low income only.

Table 10: Category-Level Purchase Probability and Overall Elasticity, Virtue Goods

Category	Category Purchase Probability	
	Obese	Non-Obese
Dry Beans	0.105	0.105
Rice	0.025	0.028
Fresh Salad	0.148	0.116
Frozen Vegetables	0.19	0.191
Eggs	0.364	0.383
Tea Bags	0.032	0.039
Milk	0.284	0.296
Hot Cereal	0.048	0.047
Canned Vegetables	0.092	0.098
Dry Pasta	0.057	0.051

Notes: For consumers with low income only.

many of the interactions are positive, suggesting consumers with obesity are less addicted to them, which is intuitive.

We present most of the coefficients that enter product choice probabilities in Web Appendix Table W16 for vice categories and Web Appendix Table W17 for virtue categories. For simplicity of presentation, we do not present the means and variances of the alternative specific coefficients (recall that these coefficients are allowed to be random parameters), as well as their interactions with the obesity dummy.[17] We note however that for many products we do find significant and large variance parameters, indicating there is important unobserved taste heterogeneity. The signs of many other parameters (e.g., price, feature, display and income interactions) are as expected.

Last, we consider the results of our robustness exercises. First, we present the interaction terms from running the models on the over 65 sample in Web Appendix Tables W18 and W19, for vice and virtue goods respectively. For consumers with low income, in vice goods we observe positive interactions of promotional

[17]Presenting these parameters would entail presenting 30 to 90 additional parameters for each category.

variables with obesity in eight of the twelve categories, and in three of the twelve virtue categories. The results mirror those for the under 65 sample. Last, Web Appendix Tables W22 and W23 present the estimated interactions when three-way interactions between income, obesity and promotional variables are excluded. For vice categories, eight of twelve display positive interactions, while we observe five of twelve virtue categories having positive interactions. Thus, it still appears that overall, consumers with obesity are more sensitive to promotions in vice categories than virtue ones.

7 Discussion and Conclusion

Although a significant amount of research in laboratory settings has documented both a correlation between obesity and impulsiveness, as well as between obesity and sensitivity to in-store promotions, field support for these findings has so far been lacking. Better understanding how these lab findings extend to the field will be of fundamental importance in understanding how to combat rising obesity rates, which may be at least partially driven by promotion of unhealthy foods. Our work documents a broad relationship between obesity and increased sensitivity to in-store promotions that is strongest among vice foods, which are typically unhealthy foods that policymakers may aim to curb consumption of. This correlation between obesity and increased promotion sensitivity in vice goods is strongest for low-income consumers, which is significant from a policy perspective as such consumers may be less able to mitigate adverse health effects from obesity.

Turning to the implications of our findings, managers in grocery retailing have recently been implementing policies designed to help consumers make healthier food choices. Most of these policies have focused on providing information: For example, in the United States, the grocery chain Raley's rearranged shelf placement of cold cereals to emphasize those with less added sugar, and eliminated candy from the checkout aisle, while the grocery chain Giant Food launched a program called "Nutrition Made Easy."[18] Our finding that individuals with obesity are also more sensitive to promotions in some virtue categories suggests that a complementary

[18] See https://www.supermarketnews.com/health-wellness/connecting-customers-wellness.

strategy may be for retailers (and national brand manufacturers who set trade promotions) to shift in-store promotions to healthier products. For policymakers, our findings supporting prior work finding a relationship between obesity and impulsive food purchase suggest that strategies designed to curb in-store promotion of vice goods may be effective, especially for stores where consumers with low income often shop. In particular, such strategies may include those proposed by the U.K. government for limiting the amount that supermarkets can promote such products (Department of Health and Social Care (DHSC), 2018b), or removing candy from checkout aisles (Department of Health and Social Care (DHSC), 2018a; Ejlerskov et al., 2018).

Our work also suggests that further research is necessary to understand the extent to which the relationship between obesity and impulsiveness is domain-specific. For example, our work suggests the relationship between increased promotion response and obesity persists across both vice and virtue categories, suggesting the relationship betwen impulsivity and obesity may not just be restricted to vice foods. This is consistent with work that relates discount factors estimated from monetary trade-offs to BMI (Courtemanche et al., 2014). However, some lab work such as Houben et al. (2014) suggests a more domain-specific relationship: individuals with obesity act impulsively with respect to snacks foods but no differently than others in different choice domains. Additional work in the lab and field could help resolve this potential inconsistency. For example, one avenue with data such as ours could be to use exclusion restrictions on structural stockpiling models to estimate discount factors in different storable goods, following techniques described in Ching and Osborne (2021). Estimated discount factors from actual choice data could then be related to BMI, and one could examine whether the correlations are larger in particular categories (e.g., vice versus virtue goods, or even non-food categories such as cleaning products).

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WEB APPENDICES FOR BMI, FOOD PURCHASE, AND PROMOTION SENSITIVITY [Intended to be made available online.]

A Additional Cross-Tabulations and Distributions

Table W1: Distribution of Household Size

Number of Members	MedProfiler Percent household-years
1	23.60
2	42.65
3	14.52
4	11.73
5+	7.50

Table W2: Distribution of household income (per person)

Income Level	MedProfiler Percent household-years	1 Person MedProfiler Percent household-years
$\leq \$15,000$	28.25	15.62
$\$15,000 - \$23,750$	22.12	18.22
$\$23,750 - \$42,500$	33.78	30.45
$> \$42,500$	15.85	35.71

Table W3: Distribution of Household Ethnicity

Income Level	MedProfiler Percent household-years	1 Person MedProfiler Percent household-years
White	81.51	81.87
Black	9.96	12.69
Asian	3.14	1.86
Other	5.39	3.59

Table W4: Distribution of Household Hispanic Origin

Income Level	MedProfiler Percent household-years	1 Person MedProfiler Percent household-years
Hispanic Origin	7.07	3.19
Non-Hispanic Origin	92.93	96.81

Table W5: Distribution of Gender (Person-Level)

Income Level	MedProfiler Percent household-years	1 Person MedProfiler Percent household-years
Male	47.36	28.31
Female	52.64	71.69

Table W6: Distribution of Household Education (Max of Male, Female Head)

Income Level	MedProfiler Percent household-years	1 Person MedProfiler Percent household-years
No High School	1.09	1.50
High School Graduate	15.37	16.92
Some College	30.10	31.20
College Graduate	36.41	33.33
Post Graduate	17.03	17.05

Table W7: Distribution of Age (Person-Level)

Income Level	MedProfiler Percent household-years	1 Person MedProfiler Percent household-years
≤ 30	17.21	15.61
$31-40$	14.64	8.88
$41-50$	17.43	10.94
$51-65$	31.73	36.67
> 65	19.00	27.91

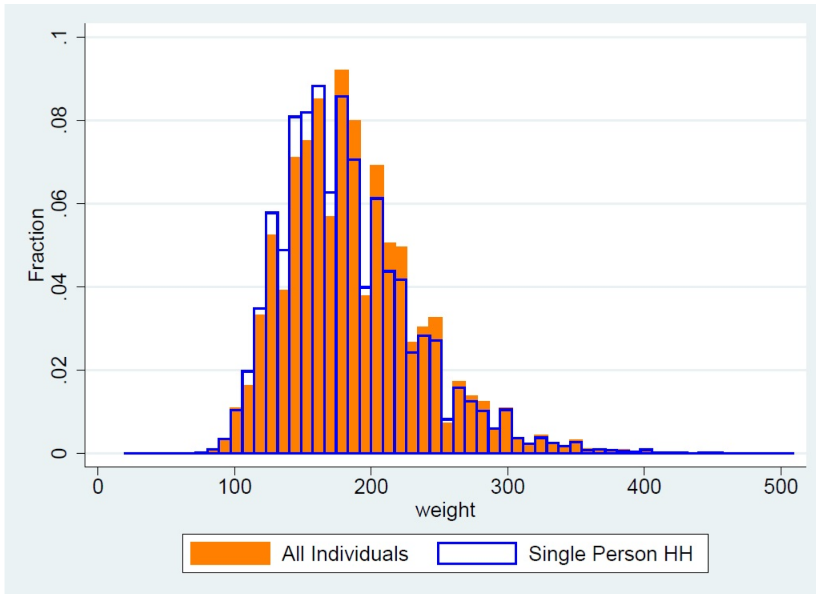

Figure W1: Weight distribution of individuals over 20 years old

B Category Selection

We estimate our model of category consideration separately for each of the 20 product categories. To define categories as vice or virtue, we rely on the work of Thomas et al. (2012), who conduct a survey asking consumers about their perceptions of (a) how healthy a particular food category is, and (b) how impulsive (tempting) the category is, for 100 food categories. In Thomas et al. (2012), food categories are defined using the definitions provided by a large grocery chain, which classifies foods according to the area where they are located in the chain's stores. Each category was then rated by 78 undergraduate students and an overall vice index was constructed for each category which averaged the students' perceptions of category unhealthiness and impulsiveness. We chose the top vice and top virtue categories for analysis, where we could find an appropriate mapping to a Nielsen category with sufficient data suitable for discrete choice demand analysis.

Although the exercise conducted by Thomas et al. (2012) is highly useful in classifying categories as vice or virtue, we found some difficulties in creating an exact mapping between their category definitions, and categories in the Nielsen data that could be used to estimate a discrete choice model. First, the categories defined in Thomas et al. (2012) often contained multiple food items, corresponding to different Nielsen product categories. Second, sometimes a particular item in Thomas et al. (2012)'s categorization may not have a clear mapping to a particular product category. Third, sometimes there is overlap in the Thomas et al. (2012) categories, presumably because stores may stock similar items in multiple places in the store (for example, chocolate bars may be in the candy aisle, and at the checkout counter). Fourth, some of the categories have extremely low purchase frequencies, or contain so many different product varieties that estimation of a choice model is not possible.[19] As an example, the top vice category is defined to be "Confectionary, gum, bars, marshmallows". Although confectionary may refer to many different food items, our interpretation of this category is that it refers to candy. In

[19]We attempted to estimate our choice model on one infrequently purchased category, popcorn, but found that due to lack of variation in the data the model did not produce reasonable parameter estimates. For example, it produced a highly positive price coefficient, and negative signs on promotional variables such as feature and display.

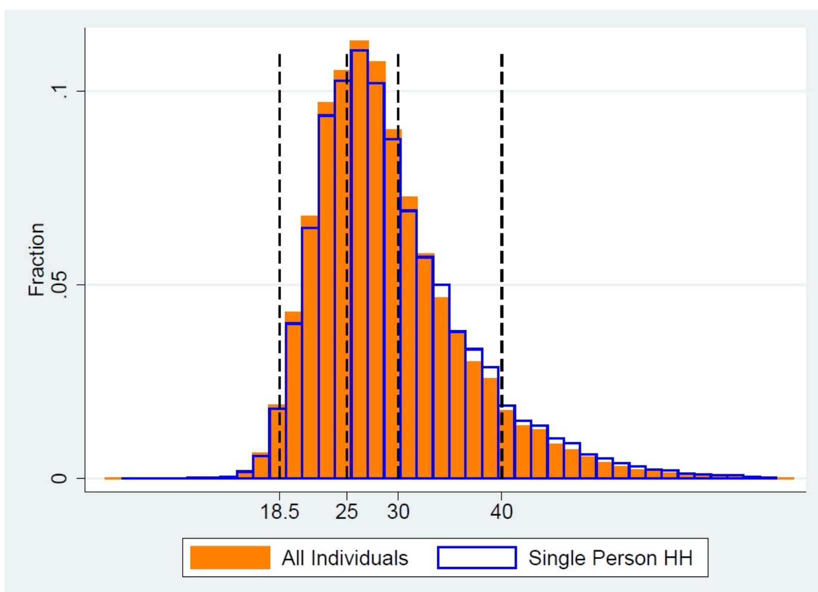

Figure W2: BMI distribution of individuals over 20 years old. Dotted lines indicate BMI bracket cutoffs.

the Nielsen data, there are two categories corresponding to candy, chocolate candy and non-chocolate candy, and a separate category for Gum, which is extremely infrequent purchased and the prices do not vary much. The exact definition of "Bars" is not clear to us, but assuming this category refers to candy, candy bars will be contained in the Nielsen categories for chocolate/non-chocolate candy. Marshmallows are an extremely infrequently purchased product category (21,836 purchases over 6 years, where 2.68% of trips contain a purchase of marshmallows). The items in this category also appear in categories with lower vice indexes: gum and confectionary are both included in the third-ranked vice category, which is "Candy-Gum, Confectionary".

Our approach is, for each vice category in Thomas et al. (2012), to find the closest Nielsen category or categories corresponding to each item, conditional on the category being frequently purchased enough that we can estimate a choice model on it. In Table W8, we show how we map each of the top 15 vice categories from Thomas et al. (2012) to Nielsen product categories. The first column of the table lists the items in each of Thomas et al. (2012)'s categories, while the second is the ranking of the category, along with its vice index. In the third, we list the Nielsen categories we include which correspond to the items in column 1. For brevity, we do not list categories in this column that have already been listed in a preceding row. For example, items 1 and 3 include both candy and gum, and thus we only list the corresponding Nielsen categories in the first row. The fourth column contains notes on why some categories were not included in our analysis, and why in some cases only one or two categories in the list were chosen. As an example, item 2 lists snacks as part of a category, and there are many categories in the Nielsen data that could correspond to snacks. We include the most popular snack category in salty snacks, which is potato chips. Finally, we note that the last category, carry out cafe products, is a reference card category, which we found does not have complete store price information. As a result, we cannot use it to estimate a choice model.

Moreover, we supplement our category selection task with Oster (2015), who surveyed 17 doctors to rank food modules as "a good source of calories," "a bad source of calories" or "neither good nor bad." Although most of results in Oster

(2015)'s survey are consistent with the list in Thomas et al. (2012), some of the categories are debatable. For example, fresh bread, which received high virtue rank in Thomas et al. (2012), has received 12 votes for "bad source" and only 1 vote for "good source", indicating that fresh bread is not very healthy. Similarly, lunch meat has shown up in many unhealthy list and has been critized to contain lots of sodium and sometimes fat as well as some preservatives like nitrites. As a result, we exclude fresh bread and lunch meat from our virtue list. By relying on Thomas et al. (2012) and Oster (2015), we pin down ten vice categories and ten virtue categories, spanning from frozen, storable to persible goods.

Next, we describe the virtue categories we use to estimate the choice model. As with the vice categories, we take the goods from the Thomas et al. (2012) paper with the lowest vice ratings, in reverse order, and find the closest Nielsen categories. One issue we face with many virtue goods, such as fresh fruit or vegetables, is that these are classified as reference card products in the Nielsen data. What this means is that for these categories, because there is no UPC information, no price information is recorded in the store data. Thus, for many of Thomas et al. (2012)'s top virtue categories, it is not possible to estimate a choice model since the prices of all the alternatives in the store (in particular, those that are not chosen by the shopper) are unavailable.

Table W8: Mapping of Vice Categories from Thomas et al (2012) to Nielsen Categories

Thomas et al (2012) Category	Thomas et al (2012) Ranking (Vice Index)	Nielsen Categories (ID Number)	Notes
Confectionary, Gum Bars, Marshmallows	1 (2.52)	Chocolate Candy, Non-Chocolate Candy,	Marshmallows and Gum are infrequently purchased.
Candy, Cookies Snacks, Popcorn	2 (2.37)	Cookies, Potato Chips, Candy is covered in item 1	Potato chips is the largest snack category. Popcorn is infrequently purchased.
Candy-Gum, Confectionary	3 (2.28)	Covered in item 1	
Donuts	4 (2.27)	Donuts	
Icecream sandwich, Pops, Fudge, Fruit bar, Choc. bars	5 (2.27)	Frozen Novelties, Choc. bars covered in item 1	
Sweet goods, Breakfast cakes, Cheese cake, Dessert cakes, Donuts, Muffins, Pies	6 (2.08)	Fresh dessert cakes, Donuts covered in item 4	We chose the largest category in this list. The rest are infrequently purchased.
Snacks - Potato chips, Tortilla chips, Corn chips, Cheese puffs, Pretzels	7 (2.03)	Potato chips covered in item 2	We chose the largest category in this list.
Cookies	8 (1.81)	Covered in item 2	
Refrigerated pudding, Gels, Cheese cakes	9 (1.66)	Refrigerated Pudding	
Cakes	10 (1.58)	Covered in item 6	
Ice Cream	11 (1.57)	Ice Cream	
Gelatin, Pudding & Other Desserts	12 (1.50)	Covered in items 2,6,9	
Carbonated Beverages	13 (1.47)	Carbonated Soft drinks, Low calorie soft drinks	
Frozen burgers, Sandwich, Pizza, Rolls, Burritos, Mozza sticks	14 (1.46)	Frozen Pizza	We chose the largest category in this list.
Carry out cafe products	15 (1.22)		The closest Nielsen category, ‘take out’, is reference card.

Notes: Categories are ordered according to the vice index in Thomas et al. (2012). Reference card categories do not have complete price information.

Table W9: Mapping of Virtue Categories from Thomas et al (2012) to Nielsen Categories

Thomas et al (2012) Category	Thomas et al (2012) Ranking (Vice Index)	Nielsen Categories (ID Number)	Notes
Fresh Cooking Vegetables	1 (-1.19)		Reference card
Beans, Barley, Rice	2 (-1.13)	Packaged beans, Packaged rice	Barley is infrequently purchased.
Fresh Carrots	3 (-1.11)		Reference card
Salad vegetables	4 (-1.11)	Precut Fresh Salad	
Baby food	5 (-1.11)		We exclude parents from the sample.
Salad vegetables	4 (-1.11)	Precut Fresh Salad	
Other fresh fruit and vegetables	6-17 (-1.09 - -0.94)		Reference card
Frozen vegetables	18 (-0.93)	Frozen vegetables	
Chicken	19 (-0.90)		Reference card
Breads	20 (-0.90)	Fresh Bread	
Eggs & Egg substitutes	21 (-0.88)	Fresh Eggs	
Tea	22 (-0.87)	Tea Bags	
Spices, seasonings, extracts	23 (-0.87)		Category is infrequently purchased and fragmented.
Milk & cream	24 (-0.83)	Refrigerated Milk	
Fresh soft fruit seasonal	25 (-0.77)		Reference card
Yogurt - refrigerated	26 (-0.77)	Refrigerated Yogurt	
Hot cereal	27 (-0.75)	Hot cereal	
Cut fruit	28 (-0.73)		Reference card
Bottled water	29 (-0.71)	Bottled water	
Fresh bread	30 (-0.67)	Covered in item 20	Not healthy (Oster, 2015)
Canned vegetables	31 (-0.64)	Corn, Tomatoes Kidney beans, Grean beans	We chose the top categories.
Lunch meat	31 (-0.64)	Lunchmeat - sliced	Not healthy
Pasta sauce	32 (-0.64)		Category is infrequently purchased.
Deli meats	33 (-0.63)	Covered in item 31	
Pasta	34 (-0.62)	Dry macaroni, Dry spaghetti	

Notes: Categories are ordered according to the vice index in Thomas et al. (2012), in reverse order. Reference card categories do not have store price information.

C Tables of Additional Model-Free Evidence

Table W10: Monthly spending shares, by vice/virtue category and household BMI bracket, 65 and over sample

Category	Underweight	Healthy	Overweight	Obese	Extreme Obese
Vice Categories					
Chocolate Candy	2.0624	1.7312	1.7815	1.8628	1.8421
Non Chocolate Candy	0.7766	0.7607	0.8230	0.9335	1.0431
Cookies	1.3523	1.4529	1.5569	1.6034	1.5678
Donuts	0.2285	0.1507	0.1786	0.1937	0.2004
Frozen Novelties	0.7249	0.8596	0.9450	1.0450	1.0422
Dessert Cakes	0.5495	0.4288	0.4950	0.5100	0.5539
Potato Chips	0.9971	0.8492	1.0284	1.1331	1.1692
Pudding	0.0871	0.1253	0.1473	0.1490	0.1569
Ice Cream	1.4405	1.4048	1.4617	1.3602	1.3774
Regular Soda	1.7866	1.3926	1.3310	1.2707	1.1950
Diet Soda	0.8443	1.2290	1.5638	1.9193	2.0489
Frozen Pizza	0.7647	0.7107	0.7099	0.7300	0.6411
Virtue Categories					
Category	Underweight	Healthy	Overweight	Obese	Extreme Obese
Dry Beans	0.0383	0.0487	0.0386	0.0420	0.0373
Rice	0.1340	0.1042	0.0862	0.0772	0.0788
Fresh Salad	0.7726	0.8681	0.8264	0.8716	0.8577
Frozen Vegetables	0.7890	0.8395	0.7770	0.7335	0.7126
Eggs	1.1150	1.1024	1.1073	1.1103	1.1253
Tea Bags	0.2767	0.3402	0.2908	0.2620	0.2382
Milk	2.5719	2.7194	2.6407	2.5048	2.1653
Yogurt	2.0721	2.0737	1.6672	1.4398	1.6092
Hot Cereal	0.5250	0.4785	0.4066	0.3219	0.2592
Bottled Water	0.4799	0.7121	0.7141	0.8431	0.7527
Canned Vegetables	1.2675	1.1619	1.1211	1.1686	1.0805
Dry Pasta	0.3952	0.2761	0.2639	0.2677	0.2457

Notes: This table shows average monthly shares of food expenditures for single-person households who are 65 and over. Categories correspond to the vice and virtue categories defined in Section B.

Table W11: Summary Statistics: Vice Categories

Category		Quantity per Year (Oz)	Number of Yearly Purchases	Quantity per Purchase (OZ)	Interpurchase Time (Days)	Prob. Brand Switch
Chocolate Candy	Non-Obese	87.48	8.91	10.09	43.57	0.76
	Obese	101.87	10.50	9.95	39.02	0.79
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.0043	0.0000	0.0000
Non Chocolate Candy	Non-Obese	85.03	6.46	13.36	54.18	0.69
	Obese	98.75	7.38	13.50	51.07	0.72
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.0493	0.0000	0.0000
Cookies	Non-Obese	116.81	8.01	14.47	45.32	0.66
	Obese	138.94	9.38	14.74	41.91	0.68
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.0000	0.0000	0.0000
Donuts	Non-Obese	36.19	2.45	14.71	82.79	0.32
	Obese	38.56	2.64	14.53	87.50	0.38
	P-Value (Obese - Non-Obese)	0.2451	0.1321	0.0725	0.0179	0.0000
Frozen Novelties	Non-Obese	43.49	4.56	9.58	61.36	0.52
	Obese	52.48	5.50	9.42	58.37	0.56
	P-Value (Obese - Non-Obese)	0.0001	0.0000	0.0032	0.0001	0.0000
Dessert Cakes	Non-Obese	49.60	3.34	14.76	80.32	0.49
	Obese	56.94	3.86	14.67	77.43	0.53
	P-Value (Obese - Non-Obese)	0.0001	0.0000	0.3123	0.0098	0.0000
Potato Chips	Non-Obese	73.84	6.98	10.70	47.35	0.47
	Obese	89.65	8.63	10.44	40.58	0.50
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.0000	0.0000	0.0000
Pudding	Non-Obese	55.50	2.28	23.52	86.24	0.31
	Obese	53.55	2.28	23.49	91.94	0.32
	P-Value (Obese - Non-Obese)	0.5836	0.9990	0.8490	0.0312	0.1501
Ice Cream	Non-Obese	311.51	5.73	54.35	55.83	0.45
	Obese	350.44	6.36	55.08	51.49	0.46
	P-Value (Obese - Non-Obese)	0.0001	0.0000	0.0000	0.0000	0.0004
Regular Soda	Non-Obese	1466.76	9.23	159.58	38.01	0.53
	Obese	1480.49	10.29	145.54	37.03	0.57
	P-Value (Obese - Non-Obese)	0.7990	0.0006	0.0000	0.0140	0.0000
Diet Soda	Non-Obese	1717.31	9.78	181.39	32.03	0.50
	Obese	2168.19	12.97	170.01	27.84	0.50
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.0000	0.0000	0.5451
Frozen Pizza	Non-Obese	106.40	4.74	22.09	63.45	0.48
	Obese	120.14	5.01	23.65	65.47	0.51
	P-Value (Obese - Non-Obese)	0.0001	0.0347	0.0000	0.0088	0.0000

Notes: Columns 1-2 are measured on a yearly basis across households, while the rest are measured in terms of the number of purchases.

Table W12: Summary Statistics: Virtue Categories

Category		Quantity per Year (Oz)	Number of Yearly Purchases	Quantity per Purchase (OZ)	Interpurchase Time (Days)	Prob. Brand Switch
Dry Beans	Non-Obese	34.52	1.33	25.57	183.99	0.28
	Obese	32.62	1.29	24.76	190.50	0.29
	P-Value (Obese - Non-Obese)	0.3356	0.4315	0.1057	0.2725	0.1996
Rice	Non-Obese	88.73	1.50	57.11	151.28	0.42
	Obese	74.27	1.42	50.76	164.47	0.45
	P-Value (Obese - Non-Obese)	0.0032	0.0910	0.0000	0.0001	0.0000
Fresh Salad	Non-Obese	87.48	6.69	13.19	41.93	0.38
	Obese	97.20	6.90	14.28	42.60	0.39
	P-Value (Obese - Non-Obese)	0.0024	0.2288	0.0000	0.1421	0.0000
Frozen Vegetables	Non-Obese	160.96	7.38	22.10	58.65	0.38
	Obese	158.49	7.21	21.80	62.92	0.41
	P-Value (Obese - Non-Obese)	0.6156	0.3555	0.0000	0.0000	0.0000
Eggs	Non-Obese	104.18	7.09	14.69	46.22	0.29
	Obese	117.65	7.44	15.63	44.32	0.30
	P-Value (Obese - Non-Obese)	0.0000	0.0012	0.0000	0.0000	0.0000
Tea Bags	Non-Obese	129.12	2.61	49.54	93.69	0.48
	Obese	119.87	2.30	52.40	110.65	0.47
	P-Value (Obese - Non-Obese)	0.0631	0.0001	0.0000	0.0000	0.0082
Milk	Non-Obese	1451.12	14.63	98.36	21.97	0.21
	Obese	1497.49	14.52	102.18	22.51	0.22
	P-Value (Obese - Non-Obese)	0.1591	0.6567	0.0000	0.0002	0.0000
Yogurt	Non-Obese	326.48	16.53	19.72	29.02	0.32
	Obese	290.41	14.47	19.71	34.52	0.33
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.9122	0.0000	0.0000
Hot Cereal	Non-Obese	78.59	2.95	27.96	89.44	0.33
	Obese	62.89	2.59	24.54	110.15	0.37
	P-Value (Obese - Non-Obese)	0.0000	0.0000	0.0000	0.0000	0.0000
Bottled Water	Non-Obese	1850.66	6.24	293.31	48.45	0.40
	Obese	2001.92	6.54	298.38	48.51	0.44
	P-Value (Obese - Non-Obese)	0.0329	0.1350	0.0016	0.9133	0.0000
Canned Vegetables	Non-Obese	318.32	11.50	27.20	44.63	0.55
	Obese	328.72	11.32	28.89	47.27	0.56
	P-Value (Obese - Non-Obese)	0.1422	0.3792	0.0000	0.0000	0.0000
Dry Pasta	Non-Obese	80.34	3.55	22.42	96.61	0.49
	Obese	84.56	3.71	22.88	96.41	0.49
	P-Value (Obese - Non-Obese)	0.0651	0.0445	0.0001	0.8592	0.7553

Notes: Columns 1-2 are measured on a yearly basis across households, while the rest are measured in terms of the number of purchases.

D Supplemental Estimation Results

Table W13: System GMM Regression of Log BMI in November on Log of Quarterly Category Consumption, Individual Fixed Effects, and Lagged BMI

Regressor	Estimate	Standard Error
Log BMI (Prior Year)	0.53875**	(0.21178)
Log Dry Grocery Vol, Quarter 1	-0.00136	(0.00137)
Log Frozen Foods Vol, Quarter 1	0.00187***	(0.00066)
Log Dairy Vol, Quarter 1	-0.00057	(0.00104)
Log Deli Vol, Quarter 1	-0.00003	(0.00054)
Log Packaged Meat Vol, Quarter 1	0.00018	(0.00051)
Log Fresh Produce Vol, Quarter 1	-0.00016	(0.00061)
Log Alcohol Vol, Quarter 1	0.00033	(0.00030)
Log Dry Grocery Vol, Quarter 2	0.00072	(0.00143)
Log Frozen Foods Vol, Quarter 2	0.00003	(0.00067)
Log Dairy Vol, Quarter 2	0.00166	(0.00109)
Log Deli Vol, Quarter 2	-0.00039	(0.00060)
Log Packaged Meat Vol, Quarter 2	0.00051	(0.00053)
Log Fresh Produce Vol, Quarter 2	-0.00059	(0.00068)
Log Alcohol Vol, Quarter 2	0.00005	(0.00027)
Log Dry Grocery Vol, Quarter 3	-0.00070	(0.00145)
Log Frozen Foods Vol, Quarter 3	0.00137*	(0.00077)
Log Dairy Vol, Quarter 3	-0.00218	(0.00134)
Log Deli Vol, Quarter 3	0.00051	(0.00064)
Log Packaged Meat Vol, Quarter 3	0.00096*	(0.00058)
Log Fresh Produce Vol, Quarter 3	-0.00090	(0.00064)
Log Alcohol Vol, Quarter 3	0.00117***	(0.00033)
Log Dry Grocery Vol, Quarter 4	0.00023	(0.00136)
Log Frozen Foods Vol, Quarter 4	0.00004	(0.00072)
Log Dairy Vol, Quarter 4	0.00070	(0.00106)
Log Deli Vol, Quarter 4	0.00062	(0.00052)
Log Packaged Meat Vol, Quarter 4	-0.00080	(0.00057)
Log Fresh Produce Vol, Quarter 4	-0.00106	(0.00065)
Log Alcohol Vol, Quarter 4	-0.00033	(0.00026)
Number Obs.	22676	

Notes: The dependent variable in this regression is the log of an individual's BMI in November. The regressors are lag of log BMI, the log of one plus quarterly category consumption in ounces, and individual fixed effects. The model is estimated using the System GMM estimator of Blundell and Bond, with cluster robust standard errors.

Table W14: Estimated Additional Parameters in the Consideration Probability for Vice Goods

	Low Income	High Income	Obese × L. Inc	Obese × H. Inc	L. Inc × Feature	L. Inc × Display	L. Inc × Deal	H. Inc × Feature	H. Inc × Display	H. Inc × Deal	L. Inc × P. Gap	Obese × L. Inc × P. Gap	H. Inc × P. Gap	Obese × H. Inc × P. Gap
Chocolate Candy	0.135	0.819***	0.118	-0.12	0.444***	-0.35***	4.771***	0.091	-0.652***	5.115***	-4.619***	-2.554***	-5.148***	-0.505***
	(0.0961)	(0.093)	(0.1248)	(0.1429)	(0.0664)	(0.0826)	(0.2771)	(0.0567)	(0.0838)	(0.2559)	(0.105)	(0.1797)	(0.1061)	(0.1704)
Non Chocolate Candy	0.569***	0.547***	-0.089	-0.211	0.067	-0.558***	2.914***	0.066	-0.721***	3.765***	-5.84***	0.359*	-4.805***	-0.132
	(0.1012)	(0.0943)	(0.1491)	(0.1457)	(0.0702)	(0.0817)	(0.2565)	(0.057)	(0.0695)	(0.2111)	(0.1349)	(0.188)	(0.0771)	(0.144)
Cookies	0.842***	1.161***	0.38*	0.538***	-0.197**	0.291**	1.907***	-0.22***	-0.122	1.02***	-7.239***	0.418	-6.96***	0.747***
	(0.1289)	(0.1171)	(0.2016)	(0.1996)	(0.0819)	(0.1128)	(0.3279)	(0.0552)	(0.0944)	(0.2472)	(0.1726)	(0.259)	(0.1354)	(0.1886)
Donuts	0.668***	0.227	-0.771**	-0.132	0.527**	0.061	-0.036	0.342	0.201	1.218**	-5.093***	1.984***	-3.782***	-0.902**
	(0.2432)	(0.2245)	(0.3311)	(0.3587)	(0.2602)	(0.1605)	(0.6222)	(0.2229)	(0.1577)	(0.5894)	(0.2318)	(0.2925)	(0.176)	(0.3811)
Frozen Novelties	-0.521***	-0.958***	0.428***	1.448***	0.136**	0.274***	0.649***	0.256***	0.298***	1.346***	-7.572***	-0.133	-7.549***	-2.403***
	(0.0577)	(0.0471)	(0.0746)	(0.0605)	(0.063)	(0.0643)	(0.2425)	(0.0513)	(0.0455)	(0.1842)	(0.1592)	(0.2043)	(0.112)	(0.1769)
Dessert Cakes	0.855***	-0.225	-0.657***	0.244	0.17	-0.034	-0.434	0.204**	0.555***	1.171***	-4.714***	0.25	-4.31***	-0.089
	(0.1996)	(0.1512)	(0.244)	(0.2159)	(0.1228)	(0.151)	(0.4631)	(0.0969)	(0.1077)	(0.3931)	(0.1531)	(0.2355)	(0.1259)	(0.1903)
Potato Chips	1.041***	0.673***	-0.065	0.308**	0.027	0.172*	0.216	0.028	0.199**	1.002***	-7.118***	-2.457***	-6.24***	-1.303***
	(0.1331)	(0.1028)	(0.1732)	(0.1536)	(0.0789)	(0.1004)	(0.2835)	(0.0663)	(0.0798)	(0.2232)	(0.1581)	(0.2733)	(0.1142)	(0.1816)
Pudding	2.779**	2.779**	-1.25	-1.25	1.667	-0.635	3.725	1.667	-0.635	3.725	-5.809***	-0.702	-5.809***	-0.702
	(1.0936)	(1.0936)	(1.1432)	(1.1432)	(4.2354)	(1.231)	(8.8813)	(4.2354)	(1.231)	(8.8813)	(2.0165)	(2.1787)	(2.0165)	(2.1787)
Ice Cream	0.768***	0.585***	-0.103	0.068	-0.021	-0.165**	0.979***	0.058	-0.297***	0.986***	-6.977***	-0.909***	-5.011***	-0.11
	(0.0933)	(0.0781)	(0.1289)	(0.1077)	(0.0732)	(0.0721)	(0.2404)	(0.0548)	(0.0587)	(0.1902)	(0.123)	(0.1967)	(0.0907)	(0.1318)
Regular Soda	-0.355	2.771***	-0.265	-2.443***	-0.342	1.93*	33.199***	6.64**	4.338**	1.59	-23.043***	-5.779	-35.069***	12.164
	(0.602)	(0.7551)	(0.7778)	(0.851)	(0.7361)	(1.0214)	(9.5959)	(2.9273)	(2.188)	(2.3003)	(7.2995)	(9.3749)	(10.8394)	(11.7816)
Diet Soda	1.771***	1.587***	-0.617	0.542	-0.924***	2.21***	2.99***	-0.244	1.518***	2.33***	-23.13***	-11.27**	-20.56***	-8.899***
	(0.2975)	(0.162)	(0.4064)	(0.4266)	(0.2896)	(0.2875)	(1.0542)	(0.1798)	(0.1735)	(0.621)	(2.1501)	(4.6177)	(1.1416)	(3.3034)
Frozen Pizza	1.522***	0.54***	-1.006***	-0.313**	-0.086	0.293**	-0.695**	0.056	0.281***	0.874***	-5.446***	1.676***	-5.354***	0.844***
	(0.1623)	(0.1026)	(0.2071)	(0.1505)	(0.1091)	(0.1156)	(0.3163)	(0.0693)	(0.0712)	(0.2288)	(0.1413)	(0.1977)	(0.1006)	(0.1574)

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income.

Table W15: Estimated Additional Parameters in the Consideration Probability for Virtue Goods

	Low Income	High Income	Obese × L. Inc	Obese × H. Inc	L. Inc × Feature	L. Inc × Display	L. Inc × Deal	H. Inc × Feature	H. Inc × Display	H. Inc × Deal	L. Inc × P. Gap	Obese × L. Inc × P. Gap	H. Inc × P. Gap	Obese × H. Inc × P. Gap
Dry Beans	0.304	0.318	-0.92	-0.465	-0.5	-0.544	-0.36	-0.96	-0.15	-3.372***	-1.234***	0.612	-1.879***	0.71*
	(0.9287)	(0.7629)	(0.9402)	(0.8459)	(3.9856)	(0.7176)	(1.1401)	(3.361)	(0.5544)	(1.2425)	(0.3778)	(0.4419)	(0.3196)	(0.4104)
Rice	0.322	-0.073	-0.546	-0.133	-0.055	0.011	-0.004	-0.005	-0.162	0.508	-2.431***	0.462	-2.298***	0.726**
	(0.5097)	(0.4332)	(0.9458)	(0.8938)	(0.3757)	(0.258)	(0.8801)	(0.2661)	(0.1658)	(0.6942)	(0.261)	(0.4162)	(0.2092)	(0.3641)
Fresh Salad	0.68***	0.987***	0.193	0.064	0.059	-0.024	0.761***	0.068	0.098	0.42**	-7.73***	0.329	-8.634***	1.451***
	(0.097)	(0.0642)	(0.1388)	(0.1143)	(0.0854)	(0.1191)	(0.2625)	(0.0586)	(0.0885)	(0.1753)	(0.1604)	(0.2417)	(0.1376)	(0.1851)
Frozen Vegetables	1.043***	0.64***	-0.265	0.062	0.256***	0.029	0.435*	0.019	0.093	1.715***	-3.864***	-0.521***	-4.181***	0.598***
	(0.1125)	(0.0879)	(0.1804)	(0.1367)	(0.0738)	(0.0874)	(0.25)	(0.0526)	(0.066)	(0.1743)	(0.0949)	(0.1916)	(0.0835)	(0.1262)
Eggs	1.097***	0.582***	-0.275*	0.133	0.176	-0.032	-0.323	0.087	-0.013	-0.095	-4.54***	0.652**	-3.193***	-0.255
	(0.1208)	(0.0827)	(0.1507)	(0.1128)	(0.1118)	(0.1091)	(0.2005)	(0.0811)	(0.0677)	(0.1293)	(0.2233)	(0.2926)	(0.1507)	(0.2325)
Tea Bags	0.798**	-0.014	-0.623	-0.105	-0.282	-0.05	-0.331	0.066	0.074	0.102	-3.741***	0.471	-2.995***	0.664***
	(0.3333)	(0.2266)	(0.4479)	(0.3389)	(0.1812)	(0.1476)	(0.5822)	(0.1288)	(0.1032)	(0.4412)	(0.2303)	(0.3157)	(0.1317)	(0.2039)
Milk	2.348***	2.219***	-0.159	-0.356***	-0.021	-0.075	0.234	-0.101	-0.058	-0.021	-9.236***	-1.521***	-9.138***	0.936***
	(0.0985)	(0.0719)	(0.1305)	(0.1052)	(0.1096)	(0.1171)	(0.4715)	(0.0796)	(0.0785)	(0.3354)	(0.1656)	(0.2704)	(0.1432)	(0.216)
Yogurt	2.806***	2.876***	0.35**	0.35**	1.39***	-	-2.14***	1.39***	-	-1.668***	-17.363***	-	-17.363***	-
	(0.1256)	(0.0912)	(0.1408)	(0.1408)	(0.1161)		(0.4424)	(0.1161)		(0.3089)	(0.549)		(0.549)	
Hot Cereal	0.228	0.794***	0.078	-1.074***	-0.122	0.464***	0.962*	-0.087	0.13	-0.052	-2.891***	0.502*	-2.748***	1.164***
	(0.2129)	(0.2055)	(0.3343)	(0.2968)	(0.145)	(0.1405)	(0.5128)	(0.1181)	(0.1091)	(0.3858)	(0.1809)	(0.2665)	(0.1353)	(0.1836)
Bottled Water	-0.206***	0.043	-0.584***	-0.363***	-0.062	0.321***	0.827***	0.074*	0.154***	0.442***	-10.878***	4.864**	-8.023***	3.25*
	(0.0521)	(0.0485)	(0.0626)	(0.0613)	(0.0521)	(0.0545)	(0.1769)	(0.039)	(0.0516)	(0.1527)	(1.4527)	(2.0223)	(1.0128)	(1.8532)
Canned Vegetables	-0.065	-0.436***	-0.214	-0.104	0.37***	0.207***	-0.064	0.183***	0.176***	0.761***	-3.023***	0.641***	-2.237***	0.109
	(0.0852)	(0.0648)	(0.1441)	(0.104)	(0.0597)	(0.0634)	(0.2412)	(0.0439)	(0.0473)	(0.1696)	(0.0928)	(0.1453)	(0.0572)	(0.1018)
Dry Pasta	0.521***	0.395**	-0.228	-0.079	-0.119	0.547***	1.366***	-0.308***	0.465***	1.265***	-3.648***	1.498***	-2.584***	-0.079
	(0.1868)	(0.1605)	(0.2812)	(0.2575)	(0.1289)	(0.1203)	(0.395)	(0.0962)	(0.0911)	(0.2719)	(0.214)	(0.2715)	(0.1452)	(0.2289)

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income.

Table W16: Selected Coefficients in Product Choice Probabilities, Vice Categories

Category	Price	Feature	Display	Obese × Price	Obese × Feature	Obese × Display	H. Inc × Price	H. Inc × Feature	H. Inc × Display	Lag Choice	Obese × Lag Choice
Chocolate Candy	-2.717***	0.22***	-0.222***	0.319***	0.076**	0.048*	-0.321***	0.005	0.049*	1.069***	-0.063***
	(0.0804)	(0.0266)	(0.0238)	(0.1114)	(0.03)	(0.0263)	(0.0563)	(0.0286)	(0.0258)	(0.0164)	(0.024)
Non Chocolate Candy	-0.932***	0.28***	-0.197***	0.115	0.042	0.12***	-0.179**	0.122***	-0.098**	0.983***	-
	(0.0816)	(0.0446)	(0.0378)	(0.1433)	(0.0486)	(0.0409)	(0.0762)	(0.047)	(0.0412)	(0.0166)	
Cookies	-2.098***	0.128***	0.001	0.227*	0.017	0.04	0.527***	0.07*	-0.034	1.28***	-0.134***
	(0.0954)	(0.0364)	(0.028)	(0.122)	(0.0424)	(0.0323)	(0.0897)	(0.0407)	(0.0315)	(0.0175)	(0.0268)
Donuts	-2.256***	0.371	0.068	-0.824	0.347	-0.074	0.06	-0.142	-0.137	1.837***	-0.062
	(0.3525)	(0.2379)	(0.0978)	(0.6131)	(0.2629)	(0.1219)	(0.3839)	(0.2645)	(0.1153)	(0.0667)	(0.0989)
Frozen Novelties	-4.466***	0.086	-0.029	-0.21***	0.148*	0.086	0.402***	0.011	0.051	2.043***	-0.092**
	(0.0536)	(0.0838)	(0.0716)	(0.0452)	(0.0871)	(0.0768)	(0.0484)	(0.0896)	(0.0795)	(0.0311)	(0.039)
Dessert Cakes	-0.447***	0.327***	0.011	0.048	0.074	-0.037	0.192***	0.043	-0.084	1.75***	-0.303***
	(0.0689)	(0.1131)	(0.0568)	(0.0805)	(0.1232)	(0.0644)	(0.0621)	(0.1234)	(0.0615)	(0.038)	(0.0562)
Potato Chips	-4.138***	0.138***	0.073**	-0.978***	0.03	0.023	0.187**	0.021	-0.058	1.763***	-0.24***
	(0.1123)	(0.0401)	(0.0323)	(0.1627)	(0.0453)	(0.0351)	(0.084)	(0.044)	(0.0353)	(0.0184)	(0.0264)
Pudding	-3.246***	0.131	0.244	-1.82	-0.391	-0.106	0.524	0.375	0.184	2.448***	-0.134
	(0.9907)	(0.2376)	(0.2756)	(1.2329)	(0.2833)	(0.3203)	(0.3661)	(0.2377)	(0.2835)	(0.096)	(0.1416)
Ice Cream	-14.848***	0.372***	0.198***	0.384	0.014	-0.055	0.707***	-0.055	0.038	1.85***	-0.072**
	(0.3409)	(0.0455)	(0.0377)	(0.4672)	(0.0481)	(0.0409)	(0.173)	(0.0487)	(0.0421)	(0.0198)	(0.0297)
Regular Soda	-16.284***	0.125***	-0.033	0.079	-0.021	-0.054**	-2.648***	-0.124***	-0.102***	1.752***	-
	(0.7087)	(0.0244)	(0.0201)	(1.0609)	(0.0298)	(0.0268)	(0.2566)	(0.027)	(0.0234)	(0.0118)	
Diet Soda	-38.581***	0.021	-0.105***	2.074***	-0.058**	-0.005	5.298***	0.029	-0.01	1.632***	-0.036**
	(0.3907)	(0.0264)	(0.0212)	(0.5659)	(0.0289)	(0.0248)	(0.3167)	(0.0286)	(0.0241)	(0.0107)	(0.0172)
Frozen Pizza	-4.557***	0.302***	0.204***	-0.102	-0.005	-0.095**	1.245***	-0.154***	-0.033	1.687***	-0.079**
	(0.2289)	(0.0464)	(0.0423)	(0.3197)	(0.0542)	(0.0478)	(0.1479)	(0.053)	(0.0463)	(0.0213)	(0.0332)

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income.

Table W17: Selected Coefficients in Product Choice Probabilities, Virtue Categories

Category	Price	Feature	Display	Obese × Price	Obese × Feature	Obese × Display	H. Inc × Price	H. Inc × Feature	H. Inc × Display	Lag Choice	Obese × Lag Choice
Dry Beans	-19.74***	0.82	-0.935	6.279	-2.699	0.448	0.427	2.006	-0.16	1.136***	0.006
	(4.5167)	(5.9593)	(1.5535)	(6.0139)	(6.274)	(1.421)	(4.1935)	(6.9343)	(1.1875)	(0.1465)	(0.2378)
Rice	-10.549***	0.947**	0.291	1.269	-0.629	0.319	2.686**	-0.899	0.033	1.537***	-0.105
	(1.4538)	(0.4318)	(0.2364)	(1.981)	(0.5818)	(0.2797)	(1.2914)	(0.5674)	(0.2654)	(0.0841)	(0.139)
Fresh Salad	-2.344***	0.226***	0.18	-0.391*	-0.022	-0.033	0.62***	-0.033	0.021	0.99***	-0.138***
	(0.1609)	(0.059)	(0.1139)	(0.232)	(0.0618)	(0.1129)	(0.0997)	(0.0608)	(0.1208)	(0.0227)	(0.0337)
Frozen Vegetables	-13.08***	0.117***	0.253***	1.141**	0.005	-0.023	2.232***	-0.223***	-0.048	1.305***	-0.049
	(0.3145)	(0.0388)	(0.0324)	(0.4511)	(0.0478)	(0.0368)	(0.2153)	(0.0443)	(0.0345)	(0.0212)	(0.0353)
Eggs	-4.756***	0.094	0.158**	-0.414	0.157*	0.045	1.348***	0.161*	-0.011	0.872***	-0.046
	(0.2228)	(0.0734)	(0.064)	(0.2718)	(0.0888)	(0.0726)	(0.1891)	(0.0865)	(0.0725)	(0.0229)	(0.0366)
Tea Bags	-3.924***	0.758***	0.449***	1.73**	-0.114	-0.089	2.04***	0.131	-0.131	1.927***	0.034
	(0.5768)	(0.197)	(0.1088)	(0.7117)	(0.2176)	(0.1329)	(0.4874)	(0.2184)	(0.1235)	(0.047)	(0.0797)
Milk	-54.462***	0.251***	0.113**	-1.374	-0.088	0.05	4.472***	-0.131**	-0.076	1.387***	-0.061***
	(1.0707)	(0.0489)	(0.0543)	(1.5181)	(0.0558)	(0.0629)	(0.4943)	(0.0543)	(0.0609)	(0.0132)	(0.02)
Yogurt	-32.294***	-0.113***	0.162***	-1.31***	0.037	-0.123***	2.345***	-0.047	-0.107***	2.085***	0.185***
	(0.0903)	(0.0279)	(0.0251)	(0.1369)	(0.0299)	(0.028)	(0.0717)	(0.0294)	(0.0279)	(0.0081)	(0.0148)
Hot Cereal	-1.236***	0.383***	0.274***	0.722*	0.213	-0.159*	0.327	-0.061	-0.078	1.841***	-0.077
	(0.3336)	(0.1198)	(0.0803)	(0.4363)	(0.1328)	(0.0897)	(0.2175)	(0.1319)	(0.0867)	(0.0396)	(0.064)
Bottled Water	-84.31***	-0.103**	-0.277***	17.059***	-0.008	-0.039	-1.03*	-0.13**	0.042	0.381***	-0.198***
	(0.6664)	(0.0461)	(0.0329)	(0.8564)	(0.058)	(0.0428)	(0.6062)	(0.0554)	(0.0391)	(0.0193)	(0.0334)
Canned Vegetables	-56.561***	-0.042	0.141***	-2.265*	-0.011	-0.007	4.73***	-0.107	-0.013	0.871***	-0.047
	(0.8037)	(0.0615)	(0.0464)	(1.2684)	(0.0802)	(0.0538)	(0.5459)	(0.0735)	(0.052)	(0.0269)	(0.0456)
Dry Pasta	-12.807***	0.275***	0.167***	-1.002	-0.159**	0.12**	1.188**	0.038	-0.14**	1.247***	-0.203***
	(0.5861)	(0.0609)	(0.0486)	(0.7645)	(0.0709)	(0.0575)	(0.4637)	(0.071)	(0.056)	(0.031)	(0.0484)

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income.

Table W18: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Vice Goods, Over 65 Sample

	Low Income				High Income			
Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Chocolate Candy	-0.16	-0.145	0.85*	✓	-0.018	0.014	0.382	
	(0.1014)	(0.1455)	(0.4987)		(0.1741)	(0.2947)	(0.8755)	
Non Chocolate Candy	0.328**	-0.441***	-0.361	✓	-0.249*	-0.003	0.406	
	(0.1349)	(0.154)	(0.5488)		(0.1449)	(0.1933)	(0.6358)	
Cookies	-0.042	0.512**	1.491**	✓	-0.153	0.669***	-2.194***	✓
	(0.1662)	(0.2166)	(0.7502)		(0.1856)	(0.2539)	(0.8178)	
Donuts	-0.277	0.001	0.728		-0.149	0.365	3.42*	✓
	(0.477)	(0.3084)	(1.1835)		(0.6553)	(0.4422)	(1.8422)	
Frozen Novelties	0.247**	-0.1	-0.032	✓	0.232**	-0.329***	0.195	✓
	(0.1106)	(0.1054)	(0.4441)		(0.1145)	(0.1063)	(0.4279)	
Dessert Cakes	-0.118	-0.421*	1.894**	✓	-0.207	-0.127	1.094	
	(0.1993)	(0.233)	(0.8967)		(0.2387)	(0.3002)	(1.0427)	
Potato Chips	0.342**	-0.078	-0.535	✓	-0.042	-0.028	-0.437	
	(0.1738)	(0.1861)	(0.5954)		(0.1769)	(0.2459)	(0.6163)	
Pudding	1.188	-0.648	-0.932		1.188	-0.648	-0.932	
	(0.942)	(0.7967)	(2.0563)		(0.942)	(0.7967)	(2.0563)	
Ice Cream	-0.417***	-0.084	-0.052		-0.028	0.098	0.12	
	(0.1556)	(0.1636)	(0.5189)		(0.1642)	(0.1771)	(0.5543)	
Regular Soda	-9.56	-2.138	8.378		0.583	-0.706	2.836	
	(92.2295)	(36.1001)	(16.252)		(6.3367)	(19.1253)	(4.2764)	
Diet Soda	0.869***	0.694***	0.619	✓	0.373	0.694***	3.188***	✓
	(0.2922)	(0.2099)	(0.9497)		(0.254)	(0.2099)	(1.0077)	
Frozen Pizza	0.338*	0.387*	0.662	✓	-0.081	-0.016	-0.426	
	(0.193)	(0.2034)	(0.6381)		(0.1952)	(0.1831)	(0.5704)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income.

Table W19: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Virtue Goods, Over 65 Sample

	Low Income				High Income			
Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Dry Beans	-1.991	0.553	1.103		-1.991	0.553	1.103	
	(12.0002)	(0.577)	(1.0508)		(12.0002)	(0.577)	(1.0508)	
Rice	1.038	-1.058**	-2.365		-1.188	0.678	0.722	
	(0.8666)	(0.4917)	(2.1139)		(0.7619)	(0.4724)	(2.4089)	
Fresh Salad	-0.157	0.148	0.864		0.174	0.529*	-1.276**	✓
	(0.1521)	(0.2814)	(0.5359)		(0.2)	(0.2786)	(0.5479)	
Frozen Vegetables	0.2	0.022	0.731		0.648***	-0.561***	0.708*	✓
	(0.1403)	(0.1527)	(0.4461)		(0.1339)	(0.1752)	(0.4183)	
Eggs	-0.022	-0.195	0.233		0.116	0.142	0.115	
	(0.1945)	(0.1834)	(0.3305)		(0.1675)	(0.1558)	(0.344)	
Tea Bags	0.126	0.178	2.054		0.039	0.218	-1.105	
	(0.3738)	(0.3299)	(1.5127)		(0.4299)	(0.3484)	(1.4439)	
Milk	-0.093	0.164	0.482		-0.269**	0.146	-0.479	
	(0.1154)	(0.1045)	(0.473)		(0.1212)	(0.1087)	(0.4993)	
Yogurt	6.093	-	-1.986*		6.093	-	-1.986*	
	(8.2942)		(1.0634)		(8.2942)		(1.0634)	
Hot Cereal	0.344	0.023	-2.419***		0.151	0.244	1.343	
	(0.2228)	(0.2269)	(0.8364)		(0.2597)	(0.2749)	(0.8966)	
Bottled Water	0.124	0.026	1.204***	✓	0.124	0.026	1.204***	✓
	(0.0965)	(0.1096)	(0.2961)		(0.0965)	(0.1096)	(0.2961)	
Canned Vegetables	-0.203**	0.242**	-0.368	✓	0.408***	-0.032	-0.147	✓
	(0.1021)	(0.1121)	(0.4174)		(0.0967)	(0.1232)	(0.4375)	
Dry Pasta	0.811**	-0.329	-0.718	✓	0.535*	0.495*	0.158	✓
	(0.3815)	(0.2647)	(0.8614)		(0.2735)	(0.2825)	(0.7568)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income.

Table W20: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Vice Goods, All Ages Aggregated

	Low Income				High Income			
Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Chocolate Candy	-0.1	0.13	0.331		0.011	0.116	0.266	
	(0.0681)	(0.0854)	(0.2871)		(0.0747)	(0.1188)	(0.3572)	
Non Chocolate Candy	0.157**	-0.206**	0.355	✓	-0.016	0.062	1.01***	✓
	(0.0766)	(0.0898)	(0.2983)		(0.0728)	(0.0948)	(0.318)	
Cookies	-0.003	0.044	0.331		0.007	-0.138	-1.084***	
	(0.0982)	(0.1257)	(0.4096)		(0.0798)	(0.1194)	(0.3551)	
Donuts	-0.157	0.081	1.66**	✓	-0.507*	0.225	2.407***	✓
	(0.2587)	(0.1664)	(0.6478)		(0.2613)	(0.1816)	(0.782)	
Frozen Novelties	0.123*	-0.038	-0.03	✓	-0.075	-0.407***	-0.752***	
	(0.0643)	(0.0621)	(0.2497)		(0.0586)	(0.0548)	(0.2251)	
Dessert Cakes	-0.091	-0.074	2.064***	✓	-0.201	-0.221	0.609	
	(0.1326)	(0.1346)	(0.5596)		(0.1243)	(0.1475)	(0.4965)	
Potato Chips	0.126	0.138	0.058		0.053	0.019	-0.912***	
	(0.0966)	(0.1063)	(0.3327)		(0.0861)	(0.1114)	(0.305)	
Pudding	0.613	-0.915**	0.423		0.613	-0.915**	0.423	
	(0.4758)	(0.3953)	(0.9476)		(0.4758)	(0.3953)	(0.9476)	
Ice Cream	-0.092	-0.014	0.29		-0.194***	0.083	-0.215	
	(0.0699)	(0.0691)	(0.2399)		(0.0687)	(0.0691)	(0.2301)	
Regular Soda	1.976	-1.227	17.385***	✓	-0.297	1.119	9.558	
	(3.6732)	(4.5998)	(3.141)		(3.684)	(3.1445)	(11.6889)	
Diet Soda	1.525***	0.166	1.418*	✓	0.387*	0.587*	0.132	✓
	(0.3041)	(0.2841)	(0.8153)		(0.2333)	(0.3021)	(0.9047)	
Frozen Pizza	0.314***	0.145	0.976***	✓	0.093	-0.013	0.114	
	(0.1094)	(0.1145)	(0.337)		(0.0881)	(0.0878)	(0.2941)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income. For the Pudding category, the high income interactions were not identified and so were not included in the model.

Table W21: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Virtue Goods, All Ages Aggregated

	Low Income				High Income			
Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Dry Beans	0.83	1.304**	1.911*	✓	0.83	0.441	0.914	
	(1.6284)	(0.6109)	(1.1075)		(1.6284)	(0.6495)	(1.3382)	
Rice	0.43	-0.16	-0.212		-0.256	0.191	-0.116	
	(0.4291)	(0.2507)	(1.0767)		(0.3407)	(0.2079)	(0.9814)	
Fresh Salad	0.044	0.128	-0.095		0.048	0.325***	-0.451***	✓
	(0.0662)	(0.0979)	(0.2073)		(0.0576)	(0.0783)	(0.1711)	
Frozen Vegetables	0.107	0.048	0.468*	✓	0.201***	-0.105	-0.204	✓
	(0.0807)	(0.0917)	(0.2665)		(0.0658)	(0.0803)	(0.2129)	
Eggs	-0.073	-0.152	0.281		-0.051	-0.032	-0.15	
	(0.1108)	(0.1021)	(0.1991)		(0.0886)	(0.078)	(0.164)	
Tea Bags	-0.018	-0.002	1.742**	✓	-0.062	-0.101	0.369	
	(0.1982)	(0.1647)	(0.7333)		(0.1688)	(0.1377)	(0.612)	
Milk	0.046	0.139	-0.193		-0.088	0.024	-0.053	
	(0.1071)	(0.1089)	(0.4353)		(0.0916)	(0.0941)	(0.3936)	
Yogurt	3.3***	-	-1.269***	✓	3.3***	-	-1.269***	✓
	(0.7181)		(0.4726)		(0.7181)		(0.4726)	
Hot Cereal	-0.058	0.019	-1.213**		0.201	0.167	1.796***	✓
	(0.1528)	(0.1492)	(0.553)		(0.1434)	(0.1392)	(0.5047)	
Bottled Water	0.015	0.037	0.255*	✓	0.015	0.037	0.255*	✓
	(0.0426)	(0.0478)	(0.1493)		(0.0426)	(0.0478)	(0.1493)	
Canned Vegetables	-0.309***	0.211***	0.051	✓	0.174***	0.028	-0.105	✓
	(0.0639)	(0.0711)	(0.268)		(0.0523)	(0.0625)	(0.2214)	
Dry Pasta	0.193	-0.303**	0.087		0.568***	0.112	-0.169	✓
	(0.1396)	(0.132)	(0.4558)		(0.1346)	(0.1346)	(0.3766)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income. For the Pudding category, the high income interactions were not identified and so were not included in the model.

Table W22: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Vice Goods, No Three-Way Interactions

Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Chocolate Candy	-0.022	0.175**	0.037	✓
	(0.0658)	(0.0874)	(0.2949)	
Non Chocolate Candy	0.072**	0.053*	0.274***	✓
	(0.0294)	(0.0281)	(0.0999)	
Cookies	0.057	-0.273**	-0.759**	
	(0.076)	(0.1136)	(0.3219)	
Donuts	-0.366	0.131	1.726**	✓
	(0.2494)	(0.1648)	(0.687)	
Frozen Novelties	-0.143**	-0.265***	-0.77***	
	(0.0576)	(0.0547)	(0.2209)	
Dessert Cakes	-0.167	-0.034	1.262***	✓
	(0.1162)	(0.1265)	(0.4475)	
Potato Chips	0.046	0.121	-0.545**	
	(0.0756)	(0.0916)	(0.2659)	
Pudding	-0.576	-0.417	-0.914	
	(4.35)	(1.3016)	(9.0235)	
Ice Cream	-0.172**	0.181**	-0.146	✓
	(0.0842)	(0.0836)	(0.2987)	
Regular Soda	-12.402	-10.209	10.579***	✓
	(17.096)	(17.2773)	(4.0888)	
Diet Soda	1.205***	-0.141	0.155	✓
	(0.3117)	(0.3845)	(1.1162)	
Frozen Pizza	0.2**	0.085	0.578**	✓
	(0.0873)	(0.088)	(0.2743)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income. For the Pudding category, the high income interactions were not identified and so were not included in the model.

Table W23: Estimated Interactions Between Obesity, Income, and Promotional Variables in the Consideration Probability for Virtue Goods, No Three-Way Interactions

Category	Obese × Feature	Obese × Display	Obese × Deal	Any Positive
Dry Beans	-	1.665	2.02	
		(1.3354)	(1.6587)	
Rice	0.136	0.154	-0.078	
	(0.3746)	(0.2295)	(1.0123)	
Fresh Salad	-0.009	0.203	0.324	
	(0.0838)	(0.1313)	(0.2489)	
Frozen Vegetables	0.039	0.158**	-0.453**	✓
	(0.0666)	(0.0789)	(0.2143)	
Eggs	-0.174*	-0.118	-0.004	
	(0.0991)	(0.088)	(0.1598)	
Tea Bags	-0.127	-0.183	1.336**	✓
	(0.1705)	(0.1412)	(0.6022)	
Milk	0.149	-0.123	-0.157	
	(0.0965)	(0.0972)	(0.3937)	
Yogurt	1.739***	-	-0.731	✓
	(0.5591)		(0.5241)	
Hot Cereal	-0.076	0.066	1.045**	✓
	(0.1419)	(0.1359)	(0.4877)	
Bottled Water	-0.042	0.059	-0.043	
	(0.0536)	(0.0596)	(0.194)	
Canned Vegetables	-0.114**	0.096	-0.01	
	(0.0552)	(0.0609)	(0.2195)	
Dry Pasta	0.353***	-0.174	-0.102	✓
	(0.1207)	(0.1205)	(0.3734)	

Notes: Standard errors are in parentheses. * = 10%, ** = 5%, *** = 1%. H.Inc is an indicator that is 1 if the individual is above median income. For the Pudding category, the high income interactions were not identified and so were not included in the model.