

OBESITY AND SELF-CONTROL: EVIDENCE FROM FOOD PURCHASE DATA*

Ying Bao[†]
University of Toronto

Matthew Osborne[‡]
University of Toronto

Emily Wang[§]
University of Massachusetts Amherst

Edward C. Jaenicke[¶]
Penn State University

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Abstract

In this paper, we examine the relationship between obesity and food purchase behavior using a novel and unique dataset that links individual-level scanner data on food purchases to survey data containing questions about an individual's obesity status. We find that obese individuals have higher purchase shares of unhealthy goods, are more likely to purchase products offered in checkout lanes that exploit consumer temptation, and are significantly more sensitive to price changes in product categories that are both unhealthy and tempting. We find no differences in price sensitivity across obesity levels in comparable product categories that would not be considered tempting. Moreover, we find that the relationship between price sensitivity and BMI is significantly smaller for individuals who have recently lost weight. Our empirical results are consistent with the model of self-control developed by Gul and Pesendorfer (2001) and Bénabou and Pycia (2002). We do not find systematic support for the idea that more obese individuals are more myopic, in contrast to earlier research. We also do not find systematic evidence that obesity is correlated with worse information about the consequences of unhealthy eating.

Keywords: Obesity, self-control, health data, scanner data, marketing and health
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[†]Rotman School of Management, 105 St George St, Toronto, ON, Canada M5S 3E6. Email: ying.bao14@rotman.utoronto.ca.

[‡]Corresponding Author. University of Toronto, Institute for Management and Innovation and Rotman School of Management, 3359 Mississauga Road, Suite 2200, Mississauga, ON, Canada L5L 1C6. Email: matthew.osborne@rotman.utoronto.ca

[§]University of Massachusetts Amherst, Department of Resource Economics, 80 Campus Center Way, Amherst, MA 01003. Email: emilywang@resecon.umass.edu.

[¶]Penn State University, 208C Armbsy University Park, PA 1682. Email: tjaenicke@psu.edu.

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.

The analysis, findings, and conclusions expressed in this paper also should not be attributed to Information Resources, Inc. (IRI). This research was conducted in collaboration with USDA under a Third Party Agreement with IRI.

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1 Introduction

The weight of an average American male adult today is just under 200 lbs. This is a drastic increase from the average of 168 lbs in the 1960s (Fryar et al., 2012). Unfortunately, this statistic no longer comes as a surprise to most people. As the percentage of obese men rose from 3.2% in 1975 to 10.8% in 2014 and that of obese women from 6.4% to 14.9% in the same period across 186 countries (NCD Risk Factor Collaboration, 2016), fighting obesity and its associated chronic illnesses have become a priority worldwide. The change in obesity rates has been even more alarming in the U.S., increasing from around 30% in 2000 to 40% in 2016, according to the latest update from the Centers for Disease Control and Prevention. This has led to increased medical expenses and increased health insurance premiums (Bhattacharya and Sood, 2011), amounting to \$190.2 billion (Cawley and Meyerhoefer, 2012), as well as productivity losses in the labor market (Fletcher, 2011).

Obesity is a major health problem. It is now the second leading cause of death in the U.S. (Mokdad et al., 2000). Understanding its causes is key to creating effective policy solutions. Researchers across many fields have investigated potential causes of obesity along multiple dimensions. These include how socio-economic factors drive diet differences (Pickett et al., 2005; Bronnenberg et al., 2012); whether race and immigration status influence weight outcomes (Garca-Pérez, 2016; Hales et al., 2017); if technological innovation and price decreases have inadvertently increased obesity rates (Cutler et al., 2003; Dubois et al., 2014); and whether food deserts have been a cause of the obesity epidemic (Allcott et al., 2018; Abeykoon et al., 2017). While this issue is extensively studied, researchers have not yet reached a consensus on the leading causes of the current obesity epidemic. Weight increases are a result of an imbalance between calories consumed and calories expended. As Cutler et al. (2003) points out, the average calories expended has not changed significantly since 1980, but the average calories consumed have risen markedly. This fact suggests that an important avenue for research is to examine how food purchase correlates with obesity.

A key challenge in examining this relationship empirically rests in the absence of observational data linking consumer's food purchase behavior to his/her health outcomes¹. In this paper, we make use of a unique dataset to quantify the relationship between food purchase and obesity. Our data links a household-level panel of food purchases for the years 2010 through 2016 to an annual comprehensive survey on lifestyle and health conditions for all members of each household in the panel. The survey data asks individuals about their height and weight, allowing us to compute a measure of their Body Mass Index (BMI), which captures their obesity status. This provides an unique opportunity for us to explore how the

¹In a rare exception, Oster (2018) studies how individuals make diet decisions after being diagnosed with Type II diabetes. In our paper, we are not limited to individuals with Type II diabetes. Instead, we examine behaviors associated broadly with obesity.

demand for unhealthy food varies across BMI brackets.

We find that higher BMI individuals have higher expenditure shares of product categories that are unhealthy. Additionally, they are more likely to purchase products commonly offered at the checkout counter which are designed to tempt consumers, such as candy bars or magazines. We also find that for unhealthy categories, the share of purchases that occur on price promotion is higher for more obese individuals. In contrast, we do not find differences in these shares across BMI brackets for categories that are neutral or healthy. These results suggest that the demand for tempting and unhealthy food categories is different for obese individuals than for those who are not obese. To quantify the relationship between obesity and the demand for tempting foods, we estimate demand curves for four tempting product categories, allowing both the level and slope of demand to depend on an individual's BMI. We find that for such categories, obese individuals are significantly more price sensitive than individuals who are not obese. The magnitude of the difference in price sensitivity between obese and non-obese individuals for tempting goods is substantial. In particular, if the price of a tempting good increases, individuals reduce consumption by about 25%, relative to the total amount purchased. The reduction in purchase volume for an extremely obese person is about 17% to 40% more than an individual who is healthy. To demonstrate the economic significance of the differences in price sensitivities across BMI levels, we perform a simple exercise where we forecast the impact of a 10% price increase for all the tempting categories we study on the population distribution of BMI one year later. We find that such a price increase could result in a 0.75% drop in the yearly obesity rate. This effect is significant, since yearly obesity rates are rising by a similar percentage.²

A natural follow-up question is, what factors might moderate the relationship between BMI and price sensitivity in these tempting food categories? One intuitive candidate is information or perceptions, as individuals who understand the consequences of unhealthy eating may be less responsive to price changes for tempting goods. Our survey data also includes a number of questions that should be correlated with the amount of information the individual has about healthy eating, as well as questions that directly ask about individual's perception of her weight. We find that price sensitivity does not seem to be affected by these variables, suggesting that if a tempting product is discounted, perceptions or information are not enough to mitigate the effect of the discount on an obese individual's quantity demanded. Although information does not seem to have an effect, we do find evidence that actions taken in the past by individuals can moderate the relationship between BMI and price sensitivity: In particular, if an individual loses weight, her price sensitivity in tempting categories is

²En route to this calculation we estimate the relationship between weight and past consumption in these categories. The consumption of the tempting goods we analyze has a strong impact on weight: A person who reduced her yearly consumption of the unhealthy products we examine by half would lose about 35 pounds.

significantly reduced. Such individuals may be making efforts that are not captured in the survey to reduce consumption of unhealthy categories.

It is important to ask what underlying theoretical mechanisms could drive these findings. There is a long literature that relates obesity to behavioral biases. The majority rely either on experiments (Chabris et al. 2008; Sadoff et al. 2015; Richards and Hamilton 2012) or on surveys (Ikeda et al., 2010). In this paper, we provide evidence from field data that obesity is related to temptation and self-control. We show that our findings are consistent with a version of a dual-self model of self-control developed by Bénabou and Pycia (2002), which is in turn based on Gul and Pesendorfer (2001)'s model of costly self-control. In our formulation of this model, we show that for a tempting good, increasing the cost of exerting self-control increases demand for the good, and increases price sensitivity. Our empirical results are consistent with higher BMI individuals having higher self-control costs. Moreover, the fact that in our empirical work we find that if an individual loses weight her price sensitivity decreases for tempting goods suggests that individuals can exert effort to lower their self-control costs.

We also consider four alternative candidate explanations, but do not find strong evidence for them. One candidate alternative explanation for the empirical results above is that obese individuals are more price sensitive for other reasons, such as having lower income (Andrejeva et al., 2010). If this were true, obese individuals would be more price sensitive for other, non-tempting categories as well. We find no difference in price sensitivity across obesity levels in comparable product categories that would not be thought of as tempting, such as frozen vegetables, dry pasta, or packaged salads. We also interact price with income in our regressions, we do not find the interactions to be significant.

A second explanation is that obese individuals simply have different preferences: for example, they prefer unhealthy goods and are also more price sensitive in these categories due to having higher elasticities of substitution between unhealthy foods and other goods. We find this explanation less satisfying for two reasons. First, most commonly used demand specifications imply that as demand for a product increases, price sensitivity decreases, contrary to our results. Second, as we show above individuals who lose weight become less price sensitive. A preference-based theory would require preferences to change along with weight.

A third alternative behavioral explanation for obesity that has been explored in earlier work is that obese individuals are more myopic or present-biased (Komlos et al., 2004; Smith et al., 2005; Borghans and Golsteyn, 2006; Zhang and Rashad, 2008; Richards and Hamilton, 2012, and Courtemanche et al. 2014). Courtemanche et al. (2014) show theoretically that myopia can lead to a positive correlation between obesity and price sensitivity. Empirically, Courtemanche et al. (2014), as well as the other cited studies, rely on quantifying the corre-

lation between a proxy for the discount factor that is measured with a survey question and a measure of an individual's BMI. To test this theory, we turn to examining a different type of forward-looking behavior: stockpiling of storable goods. In a reduced-form theory testing context, Hendel and Nevo (2006) show that more forward-looking individuals will purchase a larger share of a storable good on price promotion, and will be more sensitive to inventory changes. However, we find empirically that higher BMI individuals do not differ in their deal sensitivities for storable goods generally, and at the specific food category level we do not find any systematic interaction between BMI and inventory sensitivity. As a result, we do not find evidence that more obese individuals are more myopic.³

A fourth possible explanation is information-based. It is possible that more obese individuals have a less comprehensive understanding of the impact of unhealthy eating on their future weight. If this explanation were true, the relationship between price sensitivity and obesity we measure would actually be driven by lack of information. To test this, we can appeal to the fact that we find no significant interactions between variables in the survey that capture information and price sensitivity. To be precise, we know if an individual is suffering from an obesity-related condition such as high cholesterol, heart problems or diabetes. Upon diagnosis of such a disease it is common practice for the individual's doctor would inform the patient about ways to curb obesity, such as healthy eating. The survey also asks whether an individual is concerned about his or her weight, or if the individual considers him or herself to suffer from obesity as a disease condition. With respect to the latter question, an individual who is obese but does not consider themselves a sufferer of obesity may lack information about his or her weight. None of these variables significantly affect price sensitivity. Our finding for a role of self-control above information is consistent with previous work by Oster (2018), who identifies households who may have been diagnosed with diabetes and hence informed about its long-term effects. She finds that households engage in significant but small calorie reductions following diagnosis, which further suggests that individual behaviors are difficult to alter.⁴

Turning to the policy implications of our work, it is known that in many health contexts people appear resistant to undertaking costly behaviors that are beneficial to health (Ogden et al., 2007). Some strategies that have been used or considered recently to approach the growing obesity problem are taxes on unhealthy foods (such as soda), information campaigns, and policies that remove unhealthy and tempting products (such as checkout candy) from

³We note that the results of Courtemanche et al., 2014 and prior work are not inconsistent with the theory of self-control we propose. It is well-known that myopia, as measured by a lower rate of time preference, can proxy for many different behavioral biases (Frederick et al., 2002).

⁴Uetake and Yang (2018) find in a recent study of weight-loss app users that individual calorie consumption responds to goals, and use a structural model to inform the design of calorie budget goals.

consumers' choice sets.⁵ The effectiveness of these different strategies will be a function of the types of behavioral biases that drive obesity. For example, our finding that self-control is an issue suggests that strategies which remove alternatives from the choice set (even if they are not chosen) will improve welfare. Our findings provide support for such regulations.⁶

As for policies have been implemented, our results provide some support for the use of taxes on unhealthy foods, because obese individuals are more sensitive to price changes in these categories. Such policies will be most effective for individuals who may be most helped by them. In practice, these taxes have been applied to soda or sugar-sweetened beverages, rather than food categories. Examples include the Berkeley, CA implemented a penny-per-ounce tax on all sugar-sweetened beverages on January 1, 2015 - the first of its kind; Philadelphia, PA approved a 1.5-cents-per-ounce tax on all soda (regular and diet) that became effective on January 1, 2017, and more recently, Seattle approved a 1.75-cents-per-ounce tax on sugar-sweetened beverages, which passed the city council vote on June 5th, 2017. No consensus has been reached on whether taxation of sugary drinks is effective in decreasing obesity (Wang, 2015; Wang et al., 2017; Taylor et al., 2016; Bollinger and Sexton, 2018, and Seiler et al. 2019). Some studies (Falbe et al., 2015; Cawley and Frisvold, 2017; and Silver et al., 2017) show that despite limited pass-through of the tax onto the products, consumption shows both statistically significant and economically meaningful decreases. Others (Rojas and Wang, 2017; Bollinger and Sexton, 2018, and Seiler et al. 2019) find limited evidence of any actual consumption change. Our empirical findings suggest that an alternative avenue for such taxes could be to target tempting foods, rather than carbonated drinks, since obese individuals are significantly more price sensitive than the non-obese for such goods. Evidence on whether education and information campaigns affect obesity is similarly mixed (Hornik, 2002; Randolph and Viswanath, 2004; and Elbel et al., 2009). One explanation for the limited success of such strategies is that they do not actually inform consumers, for example, about the long-term health effects of obesity. An alternative is that information is not enough to overcome issues related to self-control. The fact that our empirical results do not suggest a systematic link between information and obesity supports this second explanation.

In addition to documenting novel relationships between food purchase and obesity, our paper contributes to a small but growing empirical literature about self-control. In particular, our work generalizes the findings of an earlier experimental study by Toussaert

⁵The U.K. has recently proposed regulation to ban the sale of candy at grocery store checkout counters (<https://www.telegraph.co.uk/politics/2018/06/01/supermarket-guilt-lanes-two-for-one-junk-food-offers-will-banned/>).

⁶If advertising tempts individuals to purchase unhealthy goods by adding them to the choice set, then our theory also supports interventions that limit such advertising. We note that recently, Dubois et al. (2018) studies the effect of banning advertising of potato chips, and finds that any potential improvement gain with advertising ban may be offset by lowered prices and substitution to other junk foods on the part of the consumer. Even so, it is possible that such bans could be effective if they cover a broad set of tempting categories.

(2018) to field data. In particular, the experiment conducted in Toussaert (2018) suggests that a significant subsample of the population finds it difficult to manage their weight, and is aware of their self-control problems, supporting the theory of Gul and Pesendorfer (2001). Recent complementary work by Cherchye et al. (2017) provides evidence for self-control in food purchases by focusing on a different behavioral dimension, which is the within individual purchase share of healthy foods. Their paper shows that this share sharply increases on Jan 1st, and declines thereafter, which is consistent with a two-self model of self-control where the bargaining power of an individual's healthy self decreases over time.

We structure the remainder of the paper as follows. Section 2 describes our data and how we construct our sample. In Section 3, we document how the food purchase behavior of individuals is correlated with BMI, with a focus on empirical evidence that could be consistent with self-control problems. In Section 4, we provide additional analysis related to the economic significance of our empirical results. In Section 5, we explore the plausibility of different theoretical explanations in light of our empirical findings. And Section 6 concludes.

2 Data and Sample Selection

Our analysis makes use of three datasets: the IRI Homescan data, a survey linked to the Homescan data called Medprofiler, and Nielsen's store level price and quantity data. The IRI Homescan panel is analogous to the Nielsen Homescan panel that has been used in much past empirical work in industrial organization and marketing, and tracks individual purchases of grocery products over time. The Medprofiler survey is a large-scale survey that is 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. The Medprofiler data that was available to us covers the years 2010 through 2016. About one third of Homescan households complete the Medprofiler survey: The number of households in the Homescan panel, and those who are in the Medprofiler data, are shown in the first two columns of Table 1.

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 their purchase behavior. The Homescan data does not identify which member of the household is shopping in a given trip, so we can only match shopping trips to household members in one person households. Even though our sample is limited to one person households, as can be seen in the third column of Table 1, we still retain about eight to ten thousand households every year. When we construct our sample of 1 person households we exclude households who never make purchases

Table 1: Number of Households

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
2016	63,150	15,375	41,163	9,470

in the five 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.

In Appendix Tables A1 through A7, we document how the distributions of several observable demographic variables in our sample of one person households compares to that of the entire Medprofiler sample. In particular, both samples are similar in terms of ethnicity, Hispanic origin and education.⁷ The samples differ somewhat in age and gender composition. In particular, over 70% of one person households are female while around 50% of individuals in all households in the Medprofiler dataset are 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.

A comparison of the distribution of BMI, one of our main variables of interest, between the entire 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. Individuals are typically classified into one of five BMI brackets, which are shown in the first column of the table. The second shows the BMI cutoffs used to assign an individual to a particular bracket. In this table, both the Medprofiler and the one person sample exclude individuals who are under the age of 20 because the typical BMI bracket designations do not apply to individuals under that age. We exclude individuals under this age for all analysis in this paper. There are two important points to take away from this table: First, the distributions of BMI brackets are similar for both the Medprofiler and the one person household sample. Second, the BMI distribution presented in the table is very similar the population distribution of BMI in the United States during this period

⁷In 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.

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

BMI Bracket	BMI Ranges	Medprofiler Percent household-years	1 Person Medprofiler Percent household-years
Underweight	< 18.5	1.79	1.71
Healthy	18.5 – 24.9	28.39	27.61
Overweight	25 – 29.9	33.64	32.16
Obese	30 – 39.9	28.44	29.36
Extremely Obese	≥ 40	7.74	9.16

(Center for Disease Control, 2015). This latter point is notable, because although individual weight is self-reported, the fact that BMI as measured in the survey mimics the nationwide distribution of BMI suggests that there are not systematic biases in how individuals report their weight. Appendix Figures A1 and A2 show the distributions of weight in pounds, as well as BMI, for individuals over 20 years old for both samples. These graphs also make it clear that the BMI distributions are similar for the one person and entire Medprofiler samples.

In addition to height and weight questions, the Medprofiler survey asks a number of questions about how individuals perceive their weight, what disease conditions they suffer from and how they are treating them, including how they are treating their obesity. We tabulate the answers to these questions across different BMI brackets for one person households in Table 3, as well Appendix Table A8. Table 3 shows how the answers to three relevant questions about weight perceptions varies across different BMI brackets. In the first question, shown in the top panel, respondents were asked how concerned they were about their weight. As one might expect, more obese individuals tend to more concerned about their weight. The second question asks how individuals perceive their weight. Although many obese and extremely obese individuals recognize they are overweight, over 50% of obese individuals described themselves as slightly overweight, suggesting that some individuals have biased perceptions about their weight. The third panel of the Table 3 addressed the question of whether obese individuals are treating their condition. It is interesting that many overweight to obese individuals identify themselves non-sufferers of obesity (in other words, they do not recognize it as a disease) and very few obese or extremely obese individuals treat their condition. In addition to asking how individuals treat obesity, the Medprofiler survey has a similar set of questions about many other health conditions, ranging from acne to yeast infections. We provide cross-tabulations between four obesity-related diseases (high cholesterol, type 2 diabetes, heart attack, or other heart problems) and an individual's BMI bracket in Appendix Table A8. As expected, more obese individuals are more likely to suffer

from these diseases.

Tabulations of the answers to additional questions about health perceptions, and habits related to eating and exercise, are shown in Appendix Tables A9 through A12. The first panel of Appendix Table A9 shows more obese individuals generally feel they could do more to be healthy. The second panel suggests that most obese people see themselves as less healthy than their peers, however there are significant exceptions: Around 30% of individuals in the obese BMI bracket believe they are much healthier than most people of the same age. The third panels of Appendix Tables A9 and A10 address an individual's attitude towards exercise and exercise habits. As individuals get more obese, they place less importance on exercise. Turning to eating habits, it can be seen in the first two panels of Table A10 that more obese individuals state that they eat more desserts and snacks, and more fast food. Interestingly, there seems to be little variation across BMI brackets in how likely people say they are to read nutritional labels (fourth panel, Appendix Table A9). The Medprofiler survey also includes separate questions asking if an individual is on a low-calorie diet, a low carb diet, a low fat diet or a low sugar diet. Appendix Table A11 shows the percentage of individuals who say they are at least one of these diets, by BMI bracket. The more obese individuals become, the more likely they are to claim they are on a diet.⁸ Appendix Table A12 shows a cross-tabulation of our diet variable with the weight concern question. If an individual is concerned about his/her weight, he or she is more likely to claim to be on a diet. Interestingly, about 40% of individuals who claim that they are very concerned about their weight are not on any diet. In Appendix Table A13, we tabulate the fraction of individuals who ever state they are on a diet (column 1), that they exercise most days (column 2), and both (column 3), by whether the individual's BMI bracket is the same or greater at the end of the sample, or whether they individual's BMI bracket drops. The table suggests that individuals who lose weight are more likely to go on diets or exercise, suggesting that weight loss arises as a result of the exertion of effort.

In the empirical analysis for this paper, we further restrict our sample to individuals who are below 65 years old. We do this for a number of reasons. First, the BMI calculation may not be a good indicator of health for the elderly (Diehr et al., 2008). Second, an individual's lifestyle may change significantly after the age of 65, when most people in the United States retire.⁹ Retired individuals may exhibit substantially different behavior than those who are working. Third, our data oversamples individuals above the age of 65, and including these individuals may skew our results if their behavior is substantially different from the general population. Excluding the elderly reduces our sample size by 29%.

⁸We produced similar tables for each different diet type, but found similar patterns.

⁹About 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>.

Table 3: Answers to Questions Related to Weight

Weight Concern					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Very Concerned	15.27	10.43	21.23	46.89	71.12
Somewhat Concerned	32.85	45.94	65.25	49.55	26.92
Not at All	51.88	43.63	13.52	3.55	1.95
Weight Description					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Slightly Underweight	66.16	8.40	0.81	0.55	0.15
About Right	25.68	69.46	18.34	1.97	0.36
Slightly Overweight	6.64	21.88	77.52	54.21	9.67
Very Overweight	1.52	0.25	3.33	43.26	89.82
How are you treating obesity					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Rx Only	0.08	0.08	0.27	1.04	2.27
OTC Only	0.24	0.29	1.38	5.12	7.64
Dual	0.16	0.11	0.18	0.79	1.70
Suffer, do no treat	1.20	0.40	3.90	27.81	54.42
Non-sufferer	98.32	99.12	94.28	65.24	33.97

3 Obesity, Food Purchases, and Price Sensitivity

3.1 General Patterns: Obesity and Food Purchase

As a first step to understanding how food purchase relates to obesity, in Table 4 we compute the expenditure shares of different food categories for different BMI brackets. The top panel, labeled “Broad Category Definition”, shows the expenditure shares for a number of broadly defined categories that encompass all grocery purchases.¹⁰ The line “Magnet Data” shows the expenditure share for IRI’s magnet products, which do not have standard UPC codes. These products include fresh fruits and vegetables, fresh meat, and bakery goods. It is notable that obese individuals spend proportionately more on categories that could be considered unhealthy, such as frozen foods, deli products, and packaged meats. The second panel of the table shows the shares of a narrower set of categories. Consistent with our findings in broader category definitions, more obese individuals spend proportionately more of their monthly grocery expenditures on diet soda, ice cream, baked desserts, salty snacks and chocolate candy, while they spend less on healthier goods such as fruits and vegetables (fresh or frozen), packaged salads, pasta, cereals, or juice. Interestingly, more obese individuals are also spending less on regular sodas but more on diet sodas. It is possible that since the negative health effects of soda have been heavily publicized, more

¹⁰The category definitions we use correspond to IRI’s department codes.

Table 4: Monthly spending shares, by product category and household BMI

Broad Category Definition					
Category	Underweight	Healthy	Overweight	Obese	Extreme Obese
Dry Grocery	43.5076	41.0185	40.2315	40.6613	40.6289
Frozen Foods	12.6688	12.4393	12.9567	13.3778	13.7362
Dairy	7.6054	8.9240	8.9570	8.9742	9.5708
Deli	5.1328	6.0050	7.0477	7.6760	9.2846
Packaged Meat	2.8464	2.7881	3.3414	3.5089	4.1268
Fresh Produce	4.7636	6.6096	5.8653	5.3520	4.8065
Alcohol	4.0170	5.8797	5.5022	3.5206	1.9958
Magnet Data	19.4583	16.3358	16.0983	16.9292	15.8504
Narrow Category Definition					
Category	Underweight	Healthy	Overweight	Obese	Extreme Obese
Vegetables	1.7277	2.2278	1.9297	1.7070	1.5141
Fruits	2.3284	3.0432	2.5498	2.4143	2.2200
Frozen Vegetables	0.8711	0.7309	0.6274	0.6433	0.6200
Salad	0.3752	0.7644	0.7589	0.7362	0.7309
Pasta	0.2364	0.2617	0.2574	0.2372	0.2366
Cereal	1.9464	1.7744	1.5077	1.3669	1.3682
Regular Soda	1.7492	1.5847	1.7328	1.6539	1.4204
Diet Soda	2.4237	1.7401	1.6960	1.8384	2.4437
Ice Cream	1.0073	0.8157	0.9561	0.9418	1.0622
Desserts	1.7140	1.5414	1.7051	1.7781	1.8965
Snacks	2.1240	2.1520	2.2638	2.3905	2.6553
Chocolate	1.9786	1.9931	2.0280	2.2316	2.4024
Cake	0.1808	0.1598	0.1783	0.1886	0.1957
Juice	1.8612	1.7388	1.7309	1.6257	1.2788
Other	79.4760	79.4719	80.0778	80.2465	79.9551

Notes: This table shows average monthly shares of food expenditures for single-person households. We restrict the sample in this table to individuals who are in IRI's magnet households. Categories in the first panel correspond to IRI's department codes, while those in the second are narrower product categories. The other category in the second panel is an aggregate of all uncategorized grocery expenditures.

obese individuals will switch to diet sodas in order to prevent additional weight gain.

Many of the product categories that have higher purchase shares for more obese individuals (such as ice cream or chocolate candy) could be considered to be tempting. To provide some further evidence that obese individuals seem to be more attracted to tempting products, in Table 5 we regress a dummy variable for whether an individual purchases a product that is offered at the checkout counter on the individual's BMI bracket. We examine two different product categories: chocolate bars in sizes that are offered at checkouts, and magazines that are often sold at checkout counters such as celebrity gossip magazines or National Enquirer. Prior research suggests that products are offered at the checkout in order

Table 5: Regression of purchase indicator on BMI bracket: Checkout products

	Chocolate Bars		Magazines	
Regressor	(1)	(2)	(1)	(2)
Constant	0.021979*** (0.000811)	- -	0.001829*** (0.000222)	- -
Overweight	0.001940* (0.001074)	0.001988* (0.001062)	-0.000113 (0.000284)	-0.000029 (0.000311)
Obese	0.006655*** (0.001115)	0.005529*** (0.001075)	0.000901** (0.000435)	0.000954** (0.000443)
Extreme Obese	0.011499*** (0.001579)	0.008949*** (0.001541)	0.000812* (0.000471)	0.000906** (0.000449)
HH Controls	No	Yes	No	Yes

Notes: The dependent variable in this regression is an indicator for whether a purchase occurs in a category. The chocolate bars category is restricted to chocolate bars between 1 and 4.5 ounces, from major national brands. Magazines identifies a purchase of one of the following magazines: “ABC Soaps in Depth”, “CBS Soaps in Depth”, “Globe”, “In Touch”, “Life and Style Weekly”, “National Enquirer”, “National Examiner”, “OK!”, “People”, “Soap Opera Digest”, “Star”, “Us Weekly” or “Vogue”. Specification (1) includes no controls, while (2) includes the following individual level controls: income, employment, occupation, ethnicity, Hispanic origin, gender, and age dummy variables. The number of observations is 3,378,394. Standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

to take advantage of consumers’ self control issues (Cohen and Babey, 2012). It is especially notable that more obese individuals are more prone to purchasing checkout counter-related magazines, even though these products are non-food products. In Table 5, specification 1 is a regression with no other controls, while specification 2 includes a rich set of household controls. We do not find significant effects of obesity in a regression with individual fixed effects. We note that in these regressions, because BMI is very persistent over time (the within individual correlation of BMI from year to year is about 90%), the impact of BMI on checkout purchase will be identified from cross-sectional, rather than within individual, variation. We also do not include prices in these regressions as prices for checkout products do not seem to vary much.

3.2 Obesity and Sensitivity to Deals and Prices

In the previous subsection we found that more obese individuals are more prone to purchasing product categories that are tempting and unhealthy, such as ice cream or baked desserts. This finding suggests that the category-level demand curves for obese individuals may be different than non-obese individuals. Understanding this type of variation in demand could be particularly useful for informing policy. For example, if a policymaker were to consider

taxing these categories, it would be useful to know if obese individuals are relatively more price sensitive. If so, it would suggest the policy would be most effective for the individuals who would be most helped by it.

We begin by investigating whether obesity is correlated with price sensitivity across a broad range of product categories. In Table 6, we regress a dummy variable for whether a particular product in a trip is purchased on deal or not on characteristics of the product category and individual. In the table, specification (1) includes no extra controls, specification (2) includes a large set of individual controls, and specification (3) includes individual fixed effects. We classify product categories as healthy or unhealthy ourselves, and as storable or perishable following Bronnenberg et al. (2008). The overall fraction of goods bought on deal is very slightly higher for higher BMI individuals (but this effect is not always significant). However, there is some evidence of a positive interaction between BMI and unhealthy categories being purchased on deal, suggesting that higher BMI individuals are more price sensitive in these categories.

We include a categorization for storability because individuals may purchase more of a product on deal if the good can be stockpiled. We feel it is insightful to consider storable goods separately because stockpiling is forward-looking behavior. Hendel and Nevo (2006) develop a series of reduced-form tests for stockpiling based on a theoretical model of purchase in a storable category, where the null hypothesis in their model is that individuals are myopic and do not stockpile. One of these tests is that for individuals who are more forward-looking, the fraction of a storable good that such individuals purchase on deal should be higher. Intuitively, we find that the fraction of storable goods bought on deal is higher than non-storable goods, which is consistent with forward-looking behavior. However, for storable goods, there is no correlation between BMI and deal sensitivity, suggesting that more obese individuals are not behaving in a more or less forward-looking way than the non-obese when they stockpile. Appendix Tables A14 and A15 show a similar set of regressions, except the BMI variable is replaced with an indicator for whether an individual is obese or extremely obese, or indicators for specific BMI brackets. Our findings are robust to these different specifications.

The above analysis provides some suggestive evidence that individuals who are more obese are more sensitive to price changes in unhealthy categories. However, the exercise has some drawbacks. First, the dependent variable is only a measure of whether a product is on promotion or not; it would also be useful to know whether obese individuals are more sensitive to price changes in general. A second drawback to the prior exercise is that it relies on accepted, rather than offered, prices: if unhealthy products are put on deal more often in stores where higher BMI individuals shop, then one would expect to see a higher correlation between purchases made on deal and BMI for unhealthy products for this reason, rather than

Table 6: Regression of Probability of Buying on Deal on Characteristics (BMI)

Regressor	(1)	(2)	(3)
Unhealthy Category	-0.0064 (0.0071)	0.0075 (0.0070)	0.0317*** (0.0049)
Storable Category	0.1485*** (0.0062)	0.1511*** (0.0060)	0.1319*** (0.0038)
BMI	0.0003* (0.0002)	0.0003** (0.0002)	2.549e-05 (6.220e-05)
Unhealthy \times BMI	0.0005** (0.0002)	0.0004** (0.0002)	5.614e-06 (0.0001)
Unhealthy \times Storable	-0.0354*** (0.0088)	-0.0421*** (0.0086)	-0.0586*** (0.0058)
Storable \times BMI	-0.0001 (0.0002)	-9.615e-05 (0.0002)	6.067e-05 (0.0001)
Unhealthy \times Storable \times BMI	-0.0002 (0.0003)	-0.0002 (0.0003)	-1.162e-05 (0.0002)
Constant	0.2083*** (0.0049)	-	0.2171*** (0.0018)

Notes: An observation in this regression is a purchase event of a particular product (UPC). Unhealthy categories are defined as bakery desserts, cookies, ice cream, salty snacks, regular soda, and candy. Neutral/healthy categories are fresh fruits and vegetables, yogurt, milk, eggs, bread, frozen vegetables, cereals, pasta, and diet soda. We define the following categories as storable: ice cream, salty snacks, packaged cookies, candy, frozen vegetables, cereal, pasta, and soda. Specification (1) includes no additional controls, while (2) includes income, employment, occupation, ethnicity, hispanic origin, gender, and age dummy variables. Specification (3) includes household fixed effects. The number of observations is 6,181,783. Standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

as a result of underlying individual differences. To address these issues, we will quantify the impact of price response across BMI levels at the category level, using prices observed in the store. We will examine 8 specific categories: 4 different categories that individuals likely perceive as being tempting, and 4 comparable categories which are not likely to be perceived as tempting. Our 4 tempting categories are ice cream, baked desserts, chocolate candies, and salty snacks, while the non-tempting categories we choose are frozen vegetables, pasta, cereal, and packaged salads. The categories we denote as tempting are high-fat or high-sugar categories that are heavily advertised relative to the non-tempting categories. Moreover, advertisements and branding for these products tend to emphasize how tasty the product is (Oakes, 2006; Hoegg and Alba, 2007). Moreover, past research has suggested that foods that are high in fat, sugar or salt tend to be addictive and therefore individuals likely have to exert self-control to avoid consuming them (Avena et al., 2008; Avena et al., 2012). One possible criticism of our category selections is that the cereal category contains products that are heavily advertised and are high in sugar, but we categorize it as not tempting. We note, however, that our study focuses on the purchase behavior of adults, and most cereal advertising is directed to children (Harris et al., 2010; Berning et al., 2014). Moreover, advertising for breakfast cereal brands aimed at adults tends to emphasize the healthy quality of the cereal (Berning et al., 2014).

In Figure 1, we provide plots of nonparametric estimates of demand for the tempting and non-tempting product categories conditional on obesity status. Our measure of the category level price is computed as the weighted average of the price per ounce of all UPCs in each category for each week and store. The weights in the averaging correspond to the share of units sold of each UPC available in the store in a given week. We estimate demand using household-level trip data, where each observation is a store visit. To estimate demand flexibly, for each category we bin the product's price per ounce into deciles, and for each decile we regress a dummy variable for whether an individual makes a purchase in a category or not on an indicator for whether the individual is obese or not, and a rich set of fixed effects.¹¹ For each category, the solid curve, labeled "non-obese", plots out the estimated purchase probability at the average of the fixed effects, while the dashed curve, labeled "obese", plots the same predicted probability, with the coefficient on the obesity dummy added in. The dotted lines show 95% confidence bounds around the estimated effect of obesity on demand. The curves suggest three things: first, for tempting goods, obese individuals have higher demand. Second, for tempting goods, the slopes of the demand curves for obese individuals are greater than non-obese, suggesting obese individuals have higher demand elasticities. Third, for non-tempting good there are not statistically significant differences between obese and non-obese individuals.

¹¹The fixed effects capture age, income, occupation, ethnicity, education, county code, gender and hispanic origin.

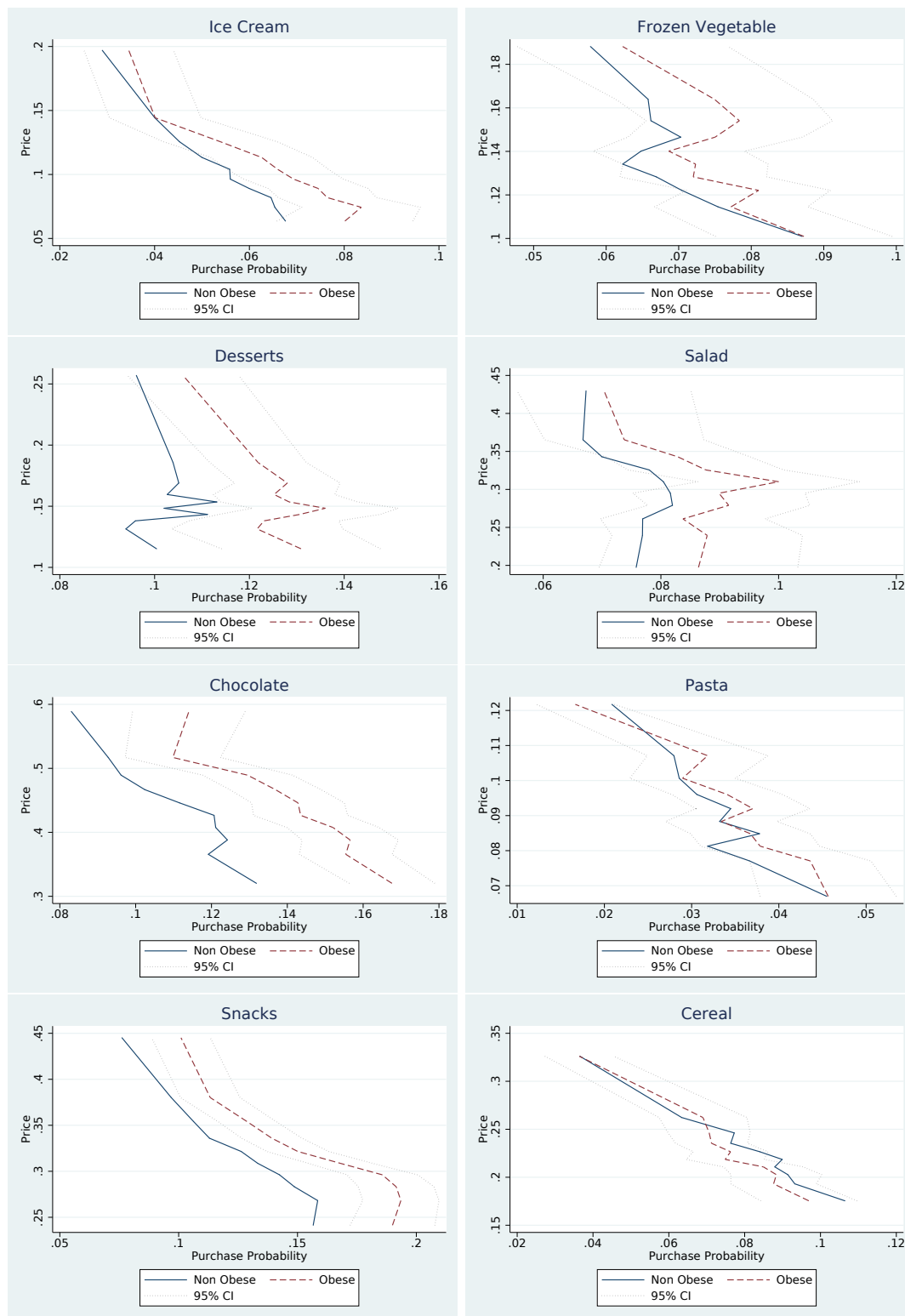


Figure 1: Nonparametric Estimates of Demand Curves for Eight Product Categories (Left Column: Tempting Products, Right Column: Non-tempting Products)

3.3 Regression Analysis of Price Sensitivity

In this section we turn to regression analyses of the demand for tempting and non-tempting categories, conditional on BMI. The regression approach allows us to easily investigate the exact functional form of this relationship, as well as to quantify whether the interaction depends on additional factors. For example, an individual's perception of their weight may affect price sensitivity, in addition to the individual's actual weight.

Our regression specifications are based on equation (1) below:

$$y_{ijt} = \alpha_{ij} + \beta_{1j}BMI_{it} + \beta_{2j}Inv_{ijt} + \beta_{3j}Inv_{ijt} \times BMI_{it} + \beta_{4j} \log(p_{ijt}) + \beta_{5j} \log(p_{ijt}) \times BMI_{it} + \epsilon_{ijt}. \quad (1)$$

The dependent variable in this regression is a dummy variable for whether an individual indexed by i purchases a UPC in a particular category indexed by j during a shopping trip indexed by t . BMI_{it} measures the individual's BMI at the time of trip t , and Inv_{ijt} is a measure of category-level inventory.¹² As was the case with the construction of demand curves in the previous subsection, the category level price, p_{ijt} , is measured as the weighted average of the prices of all UPCs in category j that are offered in the store where the individual shops during trip t .¹³ Prices are measured in price per ounce, the weights in the averaging correspond to the share of units sold of each UPC available in the store in a given week.

Our regression results are shown in Table 7. Specification (1) corresponds to the equation (1), while Specification (2) includes price in levels, as well as a control for especially low prices that appear to be deals. The deal variable is the share-weighted average across UPCs of a dummy variable that indicates whether a product appears to be on deal in a given week. We note that the Nielsen store data does not contain an indicator for whether a product is on promotion, so we have to create this dummy variable ourselves. To do this, for each UPC and store we compute the quarterly modal price of the UPC, and identify a price as a deal if it is 5% or more below the minimum.¹⁴ This procedure follows Hendel and Nevo (2006); we inspected the price series of some popular products and found that the algorithm seemed to identify temporarily low prices.

¹²To measure inventory, we assume a constant daily consumption rate within a category. We compute the consumption rate as the total quantity, in ounces, that the individual purchases over the time she is observed, and divide by the total number of days over which we observe purchases. Inventory at the beginning of day t is measured as total quantity purchased prior to that day minus total consumption. An individual's inventory at the beginning of the sample will be absorbed by their fixed effect.

¹³In the store data, prices are measured at the weekly level.

¹⁴If there are multiple modes, we take the maximum mode.

Table 7: Regression of Purchase Indicator on Price and BMI, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0014*	0.0008**	-0.0021**	0.0013***	0.0003	-0.0023***	-0.0022**	0.0024**
	(0.0007)	(0.0004)	(0.0010)	(0.0005)	(0.0006)	(0.0009)	(0.0010)	(0.0010)
Inventory	-0.0746***	-0.0741***	-0.0680	-0.0678	-0.1776***	-0.1799***	-0.1881***	-0.1874***
	(0.0196)	(0.0196)	(0.0463)	(0.0464)	(0.0435)	(0.0425)	(0.0482)	(0.0481)
BMI \times Inventory	0.0014**	0.0013**	-0.0007	-0.0007	0.0025*	0.0025*	0.0018	0.0018
	(0.0006)	(0.0006)	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
log (Price)	-0.0312***	-	0.0304*	-	-0.0697***	-	-0.0954***	-
	(0.0094)		(0.0155)		(0.0192)		(0.0238)	
log (Price) \times BMI	-0.0008***	-	-0.0014***	-	0.0002	-	-0.0019**	-
	(0.0003)		(0.0005)		(0.0007)		(0.0008)	
Price	-	-0.2465***	-	0.1048*	-	-0.1457***	-	-0.2555***
		(0.0728)		(0.0612)		(0.0487)		(0.0764)
Deal	-	0.0147	-	0.0212	-	0.0227	-	0.0009
		(0.0117)		(0.0136)		(0.0187)		(0.0170)
Price \times BMI	-	-0.0048**	-	-0.0046**	-	0.0035**	-	-0.0069***
		(0.0024)		(0.0021)		(0.0017)		(0.0025)
Deal \times BMI	-	0.0006	-	-0.0003	-	0.0024***	-	-0.0007
		(0.0004)		(0.0005)		(0.0006)		(0.0006)
Constant	-0.0247	0.0668***	0.1540***	0.0784***	0.0636***	0.1787***	0.0351	0.2269***
	(0.0214)	(0.0111)	(0.0296)	(0.0138)	(0.0179)	(0.0246)	(0.0290)	(0.0296)
<i>N</i>	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table 8: Regression of Purchase Indicator on Price and BMI, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0029*	-0.0008	0.0009	0.0006	0.0015**	0.0004	0.0004	0.0003
	(0.0015)	(0.0009)	(0.0009)	(0.0004)	(0.0008)	(0.0006)	(0.0007)	(0.0006)
Inventory	-0.0206	-0.0236	0.0378	0.0380	0.0772*	0.0770*	-0.0124	-0.0134
	(0.0411)	(0.0411)	(0.0616)	(0.0619)	(0.0465)	(0.0466)	(0.0484)	(0.0483)
BMI \times Inventory	-0.0025*	-0.0025*	-0.0053**	-0.0053**	-0.0049***	-0.0049***		
	(0.0014)	(0.0014)	(0.0021)	(0.0021)	(0.0014)	(0.0014)	(0.0021)	(0.0021)
log (Price)	-0.0513**	-	-0.0392***	-	-0.1087***	-	-0.0496***	-
	(0.0235)		(0.0114)		(0.0161)		(0.0171)	
log (Price) \times BMI	0.0012	-	0.0002	-	0.0006	-	0.0002	-
	(0.0008)		(0.0004)		(0.0005)		(0.0006)	
Price	-	-0.2020	-	-0.2011	-	-0.3721***	-	-0.1475**
		(0.1866)		(0.1219)		(0.0586)		(0.0583)
Deal	-	0.0591***	-	0.0238***	-	0.0211	-	0.0260**
		(0.0152)		(0.0063)		(0.0156)		(0.0132)
Price \times BMI	-	0.0096	-	-0.0012	-	0.0023	-	-0.0002
		(0.0060)		(0.0039)		(0.0018)		(0.0019)
Deal \times BMI	-	-0.0000	-	-0.0003	-	-0.0007	-	-0.0001
		(0.0005)		(0.0002)		(0.0005)		(0.0004)
Constant	-0.0412	0.0697**	-0.0707***	0.0337**	-0.0966***	0.1416***	0.0156	0.1108***
	(0.0471)	(0.0287)	(0.0274)	(0.0133)	(0.0241)	(0.0185)	(0.0219)	(0.0198)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Our main coefficient of interest is the interaction between price and BMI, β_{5j} . Focusing on the first column of Table 7, it is notable that this interaction is negative, indicating that higher BMI individuals are more sensitive to price changes in the ice cream category. We find similar results in the baked desserts and salty snacks categories. The results from Specification 2 show that higher BMI individuals are more price sensitive in these three categories when price is measured in levels, as well. For these categories, there is no interaction between BMI and deal sensitivity. In the chocolate category, there are significant positive coefficients on the interactions between price and BMI, as well as deal and BMI, suggesting that higher BMI individuals are both more sensitive to deals, and less sensitive to price changes. We note that if a deal occurs, the impact of a deal on the purchase probability of an obese individual should swamp the impact of a lower price. The reason for this is that prices are measured in dollars per ounce, and the average price per ounce for chocolate is about 0.4, so the impact of a price cut on choice probabilities is quite small.

Table 8 shows a similar set of regressions for the neutral categories. We chose non-tempting categories that we felt would have similar characteristics to the goods in the tempting categories. For example, frozen vegetables and ice cream are similar in terms of prices, storability, package sizes, and share of grocery budget spent; the main differences between the categories are that one contains tempting goods and the other contains non-tempting goods. Similarly, bakery desserts and packaged salads are both perishable goods, while chocolate candies and salty snacks are both storable, tempting goods. Pasta and cereal are both storable, non-tempting products. Our regression results for these categories show that price sensitivity does not vary with BMI. Overall, our findings suggest that more obese individuals are more price sensitive in tempting categories, but they are not more price sensitive overall.

The results presented above relate to purchase incidence rather than quantity purchased. We ran additional specifications in Appendix Tables A22 and A23 where the dependent variable is quantity purchased (measured in ounces), given a purchase occurs, but do not find a statistically significant effect of BMI or of the interaction between price and BMI. This latter result suggests that the avenue through which higher price sensitivity in higher BMI individuals manifests itself is that of purchase incidence rather than quantity. For example, more obese individuals will be more likely than non-obese individuals to purchase a package of chocolate if it is on sale, but will not be more likely than non-obese individuals to buy multiple packages.

The results above suggest a correlation between price sensitivity and an individual's actual BMI. An individual's behavior may also be affected by their perception of their weight. For example, individuals who are concerned about their weight may be less sensitive to price changes in tempting products categories since they are trying to avoid consuming them. In

our data, there are a number of variables that may be informative about an individual's perceptions. One is the set of variables that directly ask individuals about their obesity status (Table 3). A set of indirect questions are those asking about obesity-related diseases. An obese individual who has been diagnosed with one of these diseases is more likely to have been informed about the consequences of unhealthy eating by his or her health care provider.

To address these questions, we run the regression in equation (1) with an additional set of interactions between BMI and price. Appendix Tables A26 and A27 show the results of regressions where we include interactions between a dummy variable for whether an individual states he or she is very concerned about her weight and the price, as well as the price and BMI interaction. Similarly, we define a weight perception dummy variable to be 1 if an individual is obese or extremely obese and he or she describes him or herself as slightly underweight, about right, or slightly overweight (Table 3). In Appendix Tables A30 and A31 we show the results of regressions where we include interactions this weight perception dummy variable and the price, as well as the price and BMI interaction. In Table 3 we find that there are many obese or extremely obese individuals who recognise that suffer from obesity as a disease condition. In Appendix Tables A28 and A29, we show the results of regressions where we include interactions between a dummy variable for such individuals, as well as the price and BMI interaction. Finally, we also define a dummy variable for whether an individual suffers from one of the four obesity-related diseases identified in Appendix Table A8. In Appendix Tables A24 and A25 we show the results of regressions that includes an additional interaction between price, BMI and whether an individual has an obesity-related disease. For weight concern, and diagnosis with an obesity related disease, we do not find any significant interactions between these variables and price sensitivity. These results suggest that perceptions on their own do not seem to affect price sensitivity.¹⁵ Additionally, we do not find statistically significant interactions between BMI, price sensitivity and any of the dummy variables just described. The coefficients of the interactions between BMI and price are still significant and negative. This result suggests that for more obese individuals, perceptions do not affect price sensitivity.

¹⁵Note that the other two dummy variables, weight perceptions for obese people and treatment of obesity, are defined to be 1 only for obese individuals.

Table 9: Regression of Purchase Indicator on Price, BMI, and Indicator for Weight Loss, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Inventory	-0.3154 (0.2288)	-0.3184 (0.2323)	-0.3631* (0.2006)	-0.3859* (0.1973)	-0.8917*** (0.1887)	-0.8857*** (0.1936)	-0.7709*** (0.2106)	-0.7916*** (0.2131)
BMI \times Inventory	0.0030 (0.0080)	0.0031 (0.0082)	-0.0042 (0.0059)	-0.0033 (0.0058)	0.0142** (0.0063)	0.0141** (0.0065)	0.0002 (0.0057)	0.0008 (0.0058)
log (Price)	-0.0107 (0.0162)	-	0.0586** (0.0232)	-	-0.0394 (0.0390)	-	-0.0872** (0.0409)	-
log (Price) \times BMI	-0.0019*** (0.0005)	-	-0.0026*** (0.0008)	-	-0.0013 (0.0013)	-	-0.0028** (0.0014)	-
log (Price) \times BMI \times Lostweight	0.0014* (0.0008)	-	0.0002 (0.0008)	-	0.0011 (0.0017)	-	0.0043*** (0.0015)	-
Price	-	-0.2732* (0.1419)	-	-0.0473 (0.1352)	-	-0.1490* (0.0846)	-	-0.3414*** (0.1283)
Deal	-	0.0067 (0.0248)	-	-0.0310 (0.0279)	-	-0.0280 (0.0306)	-	0.0012 (0.0319)
Price \times BMI	-	-0.0074 (0.0045)	-	-0.0000 (0.0048)	-	0.0016 (0.0029)	-	-0.0057 (0.0043)
Price \times BMI \times Lostweight	-	0.0129** (0.0060)	-	0.0014 (0.0031)	-	0.0007 (0.0041)	-	0.0138*** (0.0045)
Deal \times BMI	-	0.0010 (0.0008)	-	0.0014 (0.0009)	-	0.0028*** (0.0010)	-	-0.0004 (0.0011)
Deal \times BMI \times Lostweight	-	0.0003 (0.0013)	-	-0.0016** (0.0008)	-	-0.0004 (0.0012)	-	-0.0007 (0.0013)
Constant	-0.0745*** (0.0130)	0.1103*** (0.0056)	0.0904*** (0.0139)	0.1326*** (0.0059)	0.0516*** (0.0090)	0.1407*** (0.0136)	-0.0349*** (0.0131)	0.3149*** (0.0138)
	61665	61665	61065	61065	72893	72893	74798	74798

Notes: An observation in this regression an individual shopping trip occurring between Aug 1st and Feb 28th. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. Lostweight is 1 if an individual's BMI bracket in the last year he/she is observed is lower than in the initial year. These regressions are performed only for the last year an individual is observed in the data. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

So far, our results suggest that across individuals, there is a positive correlation between BMI and price sensitivity for tempting goods. An important and related question is whether an individual's price sensitivity changes when their weight changes. To investigate this question, we identify individuals who lose a significant amount of weight over the course of the sample period.¹⁶ In Table 9 we run a slightly different specification from (1) where we include an interaction between price, BMI, and a dummy for such weight loss. Since we condition on an individual having lost weight, we only run the regression for the final year of the sample.¹⁷ In the regression, we find evidence in three of the four product categories that such individuals do have lower demand elasticities. In particular, we can see a significant positive interaction between price, BMI and having lost weight in the ice cream and snacks categories, and a negative significant interaction between deal exposure, BMI and having lost weight in the dessert category. We note that significance of these interactions is less robust than the interactions in our main regressions, which likely due to the smaller sample size. We also ran a similar regression where we interacted a dummy variable for weight gain with price sensitivity and BMI, but did not find any significant interaction.

3.4 Robustness Exercises

In this section we show our finding that price sensitivity increases with BMI for tempting categories is robust to variable definitions, functional form, and the inclusion of additional controls. The regression results presented in Tables 7 and 8 restrict the sample to transactions that occur between Oct 1st and Dec 31st, in a 1 month window around the November survey. We choose a window close to the survey because the individual's measured BMI will be most accurate at that time. In Appendix Tables A16 and A17, we examine a wider window of 7 months. In the regressions in Appendix Tables A18 and A19, we replace the BMI variable with an indicator for whether an individual is in the obese or extremely obese BMI bracket, and find similar results, although in the snacks category, the price interactions become insignificant (in this particular specification, the price interactions are significant with a rich set of individual characteristics - it is only with fixed effects we lose significance). With respect to functional form, we also re-ran our regressions using a fixed-effects logit model, and found similar results.

In addition to the robustness exercises presented above, we have also run specifications where we include interactions of additional variables with price. We find that the coefficient of the BMI and price interaction is not affected by including additional interactions between income and price, or age and price, suggesting that the BMI-price interaction is not

¹⁶We define weight loss as significant if an individual drops one BMI bracket over the course of the sample.

¹⁷We run the regression using a seven month time window around the November survey, rather than the three month window in Tables 7 and 8, due to the significantly smaller sample size.

a proxy for higher price sensitivity of lower-income or younger individuals.¹⁸ We also ran a specification that included an interaction for whether an individual regularly eats fast-food and price. This exercise allows us to investigate another possible avenue by which BMI and price sensitivity could be related, which is that individuals who are more price sensitive for tempting goods may be so because they live in areas where substitutes, such as fast food restaurants, are more prevalent. Again, we find that fast-food eating has no effect on the BMI-price interaction.

Last, we have also investigated in the ice cream category whether price sensitivity varies with BMI differently for products that are low-fat or low-calorie. We find that if we exclude such products, our qualitative findings are unchanged. We do not find systematic differences in price sensitivities across BMI brackets for low-fat or low-calorie ice creams. It is possible that an effect is difficult to estimate for these products because they are a small share of overall purchase in the category, or that people do not view them as tempting because the low-fat or low-calorie features are typically made very salient on the product packaging.

4 Economic Significance

In this section we demonstrate that the difference in price sensitivity across BMI levels is economically significant. In Table 10, the first set of entries in each table cell present the predicted effect of a 10% price increase in each category on category-level volume consumed, across different BMI brackets. To make a prediction about volume, we run the regression specification in equation (1) using volume purchased (including 0) as the dependent variable. The estimated parameters, presented in Appendix Table A32, are qualitatively similar to the results presented in Table 7. The second set of entries in Table 10 show the average trip-level volume purchased across each BMI bracket. Two patterns are clear: first, individuals are price sensitive because for most categories the 10% price increase reduces consumption by about 25%. Second, the reduction in volume is substantially greater for more obese individuals. For example, for ice cream we find that extremely obese individuals reduce their consumption by about 40% more than healthy individuals.

To put the numbers in Table 10 in perspective, we forecast how much weight an individual would lose if he or she were to reduce consumption by the amount predicted. To make this forecast, we regress an individual's weight, in pounds, measured in the November survey on the logarithm of an individual's consumption of each category (measured in ounces) for the prior 12 months, controlling for household fixed effects.¹⁹ The regression re-

¹⁸We include a dummy for whether an individual's income is below the lowest third, and whether an individual is younger than 40. Neither of these interactions is significant.

¹⁹We use as our independent variables logarithm of one plus volume so that the independent variables are defined if volume is zero. The average volume purchased is large (on the order of hundreds of ounces), so the transformation

Table 10: Effect of 10% Price Increase on Purchase Volume

Bmi Bracket	Ice Cream	Dessert	Chocolate	Snacks
Underweight	-0.3326, 2.2484	0.0145, 1.1863	-0.2896, 0.9951	-0.2401, 1.1123
Healthy	-0.3652, 1.5805	-0.0054, 1.0378	-0.3017, 0.8226	-0.2557, 1.1683
Overweight	-0.3942, 1.9855	-0.0230, 1.2442	-0.3124, 0.9217	-0.2695, 1.3225
Obese	-0.4335, 1.9702	-0.0470, 1.3546	-0.3269, 1.0747	-0.2883, 1.4878
Extreme Obese	-0.5065, 2.4800	-0.0914, 1.6538	-0.3540, 1.3091	-0.3232, 1.8797

Notes: First number is the predicted change in volume purchased from a 10% price increase, while the second shows the overall average volume purchased per trip in the category.

sults, presented in Table 11, suggest that three of the four tempting categories lead to weight gain (ice cream, desserts and salty snacks), while only one of the non-tempting categories (pasta) does. It is notable that there is not a statistically significance impact of chocolate candy on weight gain, but this may be due to the fact that the volume purchased of this category is much lower than the other tempting categories, by 30 to 50%. The regression coefficients suggest that the impact of increases in consumption of unhealthy products on weight is substantial. For example, a 10 percent increase in the consumption of salty snacks over the course of a year leads to a weight gain of more than 3 pounds.

Next, we take every individual in the data, and compute the change in weight that would result at the end of the first year they enter the data if their consumption were to drop by the amount we predict in Table 10, using the regression results from Table 11. Table 12 presents the change in population distribution over a year resulting from such a reduction in consumption. The changes are significant, as they would result in a reduction of the fraction of individuals who are obese by about 0.75%, which is close to the yearly growth rate of 0.9 in obesity.²⁰ In order to better illustrate the effect of price increase, we compute the fraction of individuals in each BMI bracket who drop one bracket in Table 13. Interestingly the largest change is for overweight individuals, but we see substantial decreases across all brackets.

We interpret the exercise above as an illustration of the economic significance of our main empirical findings. Another possible interpretation of the exercise is that a 10% price increase due to a tax would reduce the fraction of obese individuals by 0.75%. Indeed, a 10% price per ounce tax was one of the first soda tax proposed (Brownell and Frieden, 2009) and remains a popular option debated by many US jurisdictions. We caution that such an interpretation of our exercise sidesteps a number of potentially important complication. In particular, in response to a price increase of these tempting categories, individuals may

of adding one to volume should not be problematic.

²⁰For US adults only. The number is calculated based on the average annual obesity growth rate from 1999 to 2016 reported by the *The State of Obesity*.

Table 11: Regression of Weight on Logarithm of Past Category Purchase Volume

Category	Estimate
Ice Cream	0.123640*** (0.047124)
Dessert	0.173294*** (0.066093)
Chocolate	0.012854 (0.068770)
Snacks	0.387893*** (0.084233)
Frozen Vegetables	-0.010079 (0.052024)
Pasta	0.157696*** (0.053484)
Cereal	-0.139806** (0.064654)
Salad	-0.047764 (0.066076)
Other	-0.555110*** (0.129256)
<i>N</i>	38,848

Notes: An observation in this regression is a year-individual pair. The dependent variable measures the individual's weight in pounds in November of year t . Category volume is the log of 1 + total volume, in ounces, purchased between November of year t and October of year $t - 1$, inclusive. Regression includes individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table 12: Effect of 10% Price Increase on Population Distribution of BMI, after 1 year

Bmi Bracket	Beginning of Year BMI	End of Year BMI
Underweight	1.82	1.93
Healthy	27.22	27.95
Overweight	31.30	31.08
Obese	29.72	29.25
Extreme Obese	9.94	9.79

Table 13: Percentage of Individuals who Drop one BMI Bracket after a 10% Price Increase

Bmi Bracket	Percent who Drop One Bracket
Healthy	0.40
Overweight	2.66
Obese	2.08
Extreme Obese	1.55

substitute to other unhealthy goods. A complete analysis of the effect of such a tax would require us to estimate a category-level demand model that would allow elasticities of substitution to depend on individual characteristics, including obesity. Such an exercise is beyond the scope of this paper. In the presence of such substitution effects, our measured effect of the policy is likely an upper bound. Nevertheless, our exercise suggests that if substitution effects are small, then levying such a tax on tempting categories could potentially be an effective approach to curbing growth in obesity.

5 Theoretical Explanations

In this section we describe a number of candidate theories that relate obesity to purchase behavior, and discuss how well they can rationalize our empirical results. Recall that we document three broad sets of findings: First, that obese individuals have higher demand for tempting and unhealthy goods; second, that obese individuals are more sensitive to price changes in these categories than non-obese individuals; and third, if an individual loses weight, she becomes less sensitive to price changes in tempting categories. Three explanations that have received a significant amount of prior attention are self-control, myopia, or lack of information (i.e., misunderstanding the impact of consumption on future weight). Two other explanations that we consider are that individuals are fully rational but obesity is simply correlated with higher preferences for tempting goods, or obesity is correlated with price sensitivity for other reasons. Overall, our empirical results are consistent with a dual-self theory of self-control. We do not find evidence that our findings can be explained by obese individuals being more myopic than non-obese. We also do not find systematic evidence that differentials in lack of information across BMI brackets is a driver. Finally, in general correlations between obesity and preferences or other drivers of price sensitivity do not adequately rationalize our findings.

5.1 Self-Control

We consider a model of self-control that builds on earlier work by Gul and Pesendorfer (2001), and Bénabou and Pycia (2002). In our model, an individual allocates income, y , between a tempting focal category, x , and a numeraire good, z . We assume that the decision to purchase x is binary, i.e., $x \in \{0, 1\}$. We denote the price of x as p , and normalize the price of the numeraire good to 1. We assume that the individual's purchase decision is determined as an equilibrium outcome of a game that is played between two selves, following Bénabou and Pycia (2002). At the point of purchase, one of the selves is chosen to make a decision, and each self solves a different utility maximization problem at that point. One self is denoted as the planner, and if that self is selected to make a purchase decision it solves the following utility maximization problem:

$$\begin{aligned} \max_{x \in \{0,1\}, z \geq 0} \quad & u(x, z) + kv(x), \\ \text{s.t.} \quad & z + px \leq y. \end{aligned} \tag{2}$$

The planner's utility from consumption is $u(x, z)$. We assume that utility function u is continuous in both arguments, and increasing in z . In Gul and Pesendorfer (2001)'s terminology, $u(x, z)$ is called the commitment utility, and corresponds to what a rational actor would maximize. The consumer problem in equation (2) differs from a standard utility maximization problem with the addition of the term $kv(x)$, which is called the *temptation utility*. This term captures the impact of the individual's urges. We assume that v is increasing in x , and the parameter $k > 0$ controls the strength of an individual's temptation. Following Gul and Pesendorfer (2001), we assume that $u(0, y) + kv(0) > u(1, y - p) + kv(1)$, so the planner will not purchase the tempting good if she is chosen to make a decision.

The other self is called the doer, and she solves the following problem upon being granted the opportunity to make a decision:

$$\begin{aligned} \max_{x \in \{0,1\}, z \geq 0} \quad & kv(x), \\ \text{s.t.} \quad & z + px \leq y. \end{aligned} \tag{3}$$

Because we assume v is increasing, the doer always chooses to purchase the tempting good.

Bénabou and Pycia (2002) assume that prior to a decision occurring, the planner

and doer play a costly lobbying game to determine who gets to make a decision, following Thaler and Shefrin (1981). One interpretation of this game is that the planner and doer lobby the brain's motor control system, and the winner is selected with a probability that is proportional to the amount of resources invested into winning the game. If the planner invests r_P , and the doer invests r_D , then the winner is chosen with probability $\pi_i = r_i/(r_D + r_P)$, $i \in \{P, D\}$. Each self chooses resources to maximize ex-ante expected utility, which for the planner is

$$\pi_P[u(0, y) + kv(0)] + (1 - \pi_P)[u(1, y - p) + kv(1)] - r_P,$$

and for the doer is

$$\pi_D[kv(1)] + (1 - \pi_D)[kv(0)] - r_D.$$

If we denote the equilibrium resource allocations as r_D^* and r_P^* , and the resulting probabilities as π_D^* and π_P^* , the probability that the doer makes the purchase decision and the purchase occurs is

$$Pr(x = 1) = \pi_D^* = \frac{k(v(1) - v(0))}{u(0, y) - u(1, y - p)}. \quad (4)$$

Note that the purchase probability is increasing in k . Moreover, there is an important interaction between temptation and price sensitivity:

$$\frac{\partial^2 Pr(x = 1)}{\partial k \partial p} = -\frac{v(1) - v(0)}{(u(0, y) - u(1, y - p))^2} \frac{\partial u(1, y - p)}{\partial z} < 0. \quad (5)$$

Increasing temptation utility will also increase an individual's price sensitivity (i.e., her purchase probability will be more responsive to price changes). The intuition here is that if an individual is never tempted (i.e. $k = 0$), she does not buy the tempting good. However, if temptation increases a small amount (i.e. k becomes positive), then her purchase probability must rise, and therefore her price sensitivity must also increase in magnitude.

The term $k(v(1) - v(0))$ can also be interpreted as a utility cost of exerting self-control, which is incurred if an individual resists the temptation to buy the tempting good. To see this, note that if the tempting good is in the individual's choice set, her expected utility prior to purchase is $u(0, y) - k(v(1) - v(0))$, while if the good is not, her ex-ante expected utility is $u(0, y)$. The preferences generated by these utility functions correspond to the Gul and Pesendorfer (2001) ex-ante preferences: If an individual has costly self-control, she would prefer to avoid having the tempting good in her choice set. In our formulation, k is a parameter that measures how costly self-control is for an individuals: individuals with

higher values of k face greater temptation. A difference between the Gul and Pesendorfer (2001) and the Bénabou and Pycia (2002) model is that in Gul and Pesendorfer (2001)'s formulation, there is no game between selves at the point a decision is made, and ex-post preferences are the same as ex-ante preferences. As a result, individuals never succumb to temptation in that model.

We relate our empirical results to three testable implications of this simple theory. First, individuals who are more likely to succumb to temptation should be more likely to purchase tempting goods. In Table 4, we document that purchase shares for tempting goods are positively correlated with obesity, and in Figure 1, the demand curves for tempting goods are generally higher for obese individuals. Additionally, more obese individuals are more likely to purchase goods offered at the checkout counter (Table 5), including even non-food products. Second, individuals with higher self-control costs should be more sensitive to price changes in tempting categories than individuals who we believe may be less likely to succumb to temptation. We find support for this in our regression analyses in Table 7, where the interactions between BMI and price are highly significant and negative for three of four tempting goods, while the interaction between deal and BMI is positive and significant for the fourth. The third implication relates to within individual behavior: individuals who start to exert effort to reduce their weight (i.e., by reducing their self-control cost captured by k) should become less sensitive to price changes for tempting categories. We find support for this hypothesis in our analysis where we interact weight loss with price sensitivity and BMI (Table 9). There we document that individuals who lose weight become significantly less price sensitive. This latter analysis provides a very direct link between price sensitivity and self-control.

5.2 Myopia

Some past research has documented a possible link between myopia and obesity. Recently, Courtemanche et al. (2014) provide suggestive evidence that individuals who are more obese have lower discount factors (or are more present-biased). They estimate individual-specific geometric and hyperbolic discount factors using survey questions from the National Longitudinal Survey of Youth (NLSY) that ask individuals how much they would be willing to trade money in the future for money in the present, and show that these estimates are correlated with another survey question that asks about an individual's BMI. They also provide evidence, using aggregate price data, that an individual's BMI is more strongly correlated with prices conditional on the individual having a lower discount factor. In addition, they show that these findings are consistent with a theoretical model based on O'Donoghue and Rabin (1999) and DellaVigna and Malmendier (2004), where individuals consider the impact

of current consumption on future weight, but more obese individuals may be myopic and underweight this effect. Individuals with lower discount factors are also more price sensitive in that model, as they do not take into account the impact of future consumption on their weight. We note that Courtemanche et al. (2014)'s measure of the discount factor could proxy for self-control costs, rather than myopia (the idea that the discount factor may capture other behavioral biases has also been put forth in Frederick et al. (2002)). When answering the NLSY survey question related to intertemporal tradeoffs of money, individuals with greater self-control problems will prefer the option of receiving money today. As a result, even if individuals all have similar underlying discount factors, individuals with higher self-control costs will appear more myopic.

One implicit implication from Courtemanche et al. (2014) is that if higher BMI individuals have lower discount factors, the purchase patterns of obese individuals across a broad range of food categories should suggest they behave more myopically than the non-obese. One particular type of purchase behavior that is a function of how forward-looking individuals are is consumer stockpiling behavior: Forward-looking individuals should stockpile in response to price promotions for storable goods. Recall that Hendel and Nevo (2006) show that as individuals get more forward-looking, the fraction of purchases of storable goods that occur on deal should increase. Our analysis around the results presented in Table 6 suggests that overall individuals do behave in a forward-looking way, as they are more deal-sensitive in storable categories. However, obese individuals are no more or less likely to stockpile than non-obese individuals, suggesting they do not systematically differ in terms of their discount factor.

Hendel and Nevo (2006) also argue that as individuals get more forward-looking, their purchase amount will become more sensitive to inventory. Their theory suggests that purchase likelihoods should decrease in inventory. In a reduced-form exercise, Hendel and Nevo (2006) test for stockpiling behavior by regressing purchase quantity on an inventory measure that is similar to what we in equation (1). In Appendix Tables A20 and A21, we run the regression from equation (1) with volume as the dependent variable. Note that in this regression we include an interaction between BMI and the inventory proxy, so we can directly measure whether higher BMI individuals are more or less sensitive to inventory changes. We find that for non-tempting storable goods such as pasta or cereal, the interaction between BMI and inventory is either insignificant or negative, suggesting obese individuals may be slightly more responsive to inventory changes. For the tempting goods, none of the inventory and BMI interactions are significant. Overall, there does not appear to be a systematic relationship between inventory sensitivity and BMI.

To summarize, our results do not provide systematic evidence that higher BMI individuals have lower discount factors. We note that Courtemanche et al. (2014)'s analysis assumes

that discount factors are not context-specific: in other words, individuals trade present and future money in the same way they trade present and future utility from food consumption. Our conclusion that discount factors do not vary with BMI based on the results in Table 6 does not rely on this assumption, because it is only performed in the context of all food purchase. A possible criticism of our analysis of storable goods in the aggregate would be that high BMI individuals could act in a more myopic way only when considering the purchase of tempting goods.²¹ Our analysis of the interaction between BMI and inventory sensitivity based on the results in Appendix Table A20 addresses this concern, because this analysis is performed at the category level. These results do not provide evidence that higher BMI individuals are less inventory sensitive, even when focusing solely on tempting categories.

5.3 Information

Another possible explanation for our finding that higher BMI individuals are more price sensitive for tempting goods is that obese individuals underestimate the impact of consumption of these goods on their future weight due to having worse information. To assess the feasibility of this explanation, we appeal to our analysis where we run the regression in equation (1) with additional interactions between BMI, price, and dummy variables reflecting weight perceptions, weight concerns, and whether the individual suffers from an obesity-related disease. All these latter variables will proxy for the amount of information an individual has about the effects of unhealthy eating.

Intuitively, individuals who are more concerned about their weight should be more likely to seek out information about how to mitigate obesity. Such individuals should appear less price sensitive than unconcerned individuals. Individuals who perceive their weight condition to be better than it is should exhibit greater price sensitivity than those who do not, since they seem to have incorrect perceptions of their weight. Individuals who are diagnosed with an obesity-related disease should have been informed by their doctor about lifestyle changes aimed at mitigating the disease (i.e., physical activity, healthy eating, etc), and if better information had an effect one would expect the estimated coefficient of the interaction between price and having the condition to be positive. Similarly, individuals who recognize that obesity is a disease condition should be less price sensitive. Recall that we run a number of auxiliary regressions where we interact dummy variables for these information-related proxies with price, as well as price and BMI (see Section 3.3, and Appendix Tables A24 through A31), and we find that none of the coefficients of these interactions are significant. Taken together, the insignificance of the coefficients of the interactions related to information

²¹Some past research has found evidence that in different decision-making domains, individuals may discount future returns differently. For example, Richards and Green (2015) show that individuals are more myopic when considering utility from environmental goods than from financial goods.

about obesity indicate that information does not seem to be having a strong effect on the price sensitivity for tempting goods. We emphasize that even when we control for these additional effects, the interactions between BMI and prices or deals still suggest that higher BMI individuals are more price sensitive. We also investigated whether individuals with better information appeared to purchase smaller quantities conditional on purchase, since such individuals might be more likely to limit consumption. We did not find any systematic evidence for such a relationship.

5.4 Other Explanations

In this section we explore two additional candidate explanations for our empirical findings. The first candidate theory behind the behavior of obese individuals is that these individuals do (not) suffer from self-control issues, but their preferences are such that they prefer unhealthy goods and are also more price sensitive. For example, using the notation introduced in Section 5.1, one could consider a standard discrete choice model where an individual's utility from consumption of the tempting good, $x \in \{0, 1\}$, and the numeraire good, $z \geq 0$, is $u(x, z, w) + \varepsilon_{xit}$. Here we define w to be an individual's BMI, ε_{xit} to be an i.i.d. choice-specific error, and assume that $u(1, z, w) - u(0, z, w)$ is increasing in w , so that higher BMI individuals have a stronger preference for x . In general, one would expect increases in preference for x to make individuals *less* price sensitive, rather than more price sensitive. Nevertheless, it is possible to construct preferences where increases in preference for x also increase price sensitivity.²² However, we believe our results in Table 9 make an explanation that exclusively relies on preference differences less plausible. This table shows that for a given level of obesity, individuals who have lost weight are less price sensitive, suggesting a direct relationship between price sensitivity and self-control that cannot be explained by a simple contemporaneous correlation between preference and weight. In order for preferences to explain this result, it would have to be the case that an individual's preference for a tempting category decreased at the same time that weight changed.

A second possible alternative explanation of our finding that higher BMI individuals have more elastic demand than low BMI individuals is that higher BMI individuals are more price sensitive for reasons that are not attributable to behavioral biases: For example, the marginal utility of income could be higher for these individuals because they are lower

²²The cross-partial derivative of the choice probability with respect to BMI and price will be a sum of two terms that may have different signs. The sign of one term depends on the sign of the derivative of density of the error term. Theory does not provide guidance on the properties of the error distribution. The other term depends on the sign of the cross-partial derivative u_{wz} . If increasing BMI also increases utility for the numeraire good (i.e., $u_{wz} > 0$) in addition to increasing preference for x , it can be the case that higher BMI individuals would both be more likely to purchase x and be more price sensitive. However, most standard formulations of discrete choice models assume utility is quasilinear in the focal category and the numeraire (i.e., $u_{wz} = 0$).

income or for other, unobservable reasons.²³ However, if this were true, we would find that higher BMI individuals were more price sensitive in non-tempting categories as well. Our empirical findings do not support this. Additionally, we have run auxiliary regressions in the tempting categories where we have interacted price with other demographic characteristics that could be correlated with price sensitivity (such as having low income or being younger). Even with these additional controls, we find that the interaction between BMI and price is negative and highly significant.

6 Conclusion

Little is known about how food purchase correlates with obesity, yet understanding this relationship is fundamental to understanding how to address rising obesity rates. In particular, although increased consumption of unhealthy food may play a role, alternative explanations have been offered. For example, one explanation is that a rising proportion of jobs involve sedentary, rather than physical work. Another is that over the long-term, the prices of all foods have fallen, leading to increasing consumption and as a consequence, higher obesity rates (for example, see Lakdawalla and Philipson (2009)). Neither of these explanations involve increases in consumption of unhealthy food, specifically. In this paper, we use a novel dataset to better understand the relationship between food category purchase and obesity. We find that more obese individuals do have higher consumption of food categories that would be considered unhealthy. Moreover, we find that more obese individuals are more prone to purchasing products that are designed to exploit self-control, even for non-food goods. Finally, we document that obesity is positively related to increased price sensitivity for categories that one would consider tempting, but not for comparable non-tempting categories. These findings suggest that regulations which are aimed at decreasing unhealthy food consumption, such as taxes or advertising bans, have potential to be effective.

Taken together, our findings can be rationalized by some behavioral theories, but not others. In particular, a dual-self theory of self-control similar to Bénabou and Pycia (2002) provides an explanation that matches our findings well, and are theoretically appealing. It is intuitive that some food categories involve self-control costs, while others do not. We note that the fact that within individual losses in weight seem to be related to decreases in price sensitivity is consistent with individuals deciding to exert self-control. When we analyse stockpiling behavior, we do not find evidence that higher BMI individuals act in a more myopic way, even when we consider purchase behavior at the category level.

Turning to future directions, our finding that obese individuals are more price elastic in

²³In our model, we could parameterize this by multiplying the price by a price coefficient α , which is higher for higher BMI individuals.

tempting categories suggests that taxes on these products could be an effective policy remedy. In the past, tax policy has primarily targeted sugary drinks, with mixed success. Our analysis of category-level spending shares suggests that obese individuals seem to be spending less on sugary sodas than non-obese individuals, which may explain why the effectiveness of such taxes has been limited. An unanswered question is, which products should be taxed, and by how much? In order to answer this question, it would be necessary to estimate both own and cross-elasticities of demand at the category level, across different obesity levels. Such an exercise would require the estimation of a larger scale demand system. Our findings may also shed light on the role of food consumption in the increase in obesity rates. It has already been shown that food prices in general have been decreasing over time (Lakdawalla and Philipson, 2009), but if the prices of tempting goods have decreased proportionately more, then that will exacerbate the rise in obesity. A larger scale study examining how prices for such products have changed over the long-term could shed more light on this question.

References

- Abeykoon, A. H., Engler-Stringer, R., and Muhajarine, N. (2017). Health-related outcomes of new grocery store interventions: a systematic review. *Public Health Nutrition*, 20(12):2236-2248.
- Allcott, H., Lockwood, B. B., and Taubinsky, D. (2018). Regressive sin taxes, with an application to the optimal soda tax. Working Paper.
- Andreyeva, T., Long, M., and Brownell, K. (2010). The impact of food prices on consumption: A systematic review of research on the price elasticity of demand for food. *American Journal of Public Health*, 100(2):216–222.
- Avena, N., Bocarsly, M., and Hoebel, B. (2012). Animal models of sugar and fat bingeing: Relationship to food addiction and increased body weight. *Psychiatric Disorders. Methods in Molecular Biology*, 829:351–365.
- Avena, N., Rada, P., and Hoebel, B. (2008). Evidence for sugar addiction: Behavioral and neurochemical effects of intermittent, excessive sugar intake. *Neuroscience & Biobehavioral Reviews*, 32:20–39.
- Bénabou, R. and Pycia, M. (2002). Dynamic inconsistency and self-control: a planner-doer interpretation. *Economics Letters*, 77(3):419 – 424.
- Berning, J., Huang, R., and Rabinowitz, A. (2014). An evaluation of government and industry proposed restrictions on television advertising of breakfast cereals to children. *Journal of Consumer Policy*, 37(4):507–525.
- Bhattacharya, J. and Sood, N. (2011). Who pays for obesity? *Journal of Economic Perspectives*, 25(1):139–58.
- Bollinger, B. and Sexton, S. (2018). Local excise taxes, sticky prices, and spillovers: Evidence from berkeley’s soda tax. Working paper.
- Borghans, L. and Golsteyn, B. (2006). Time discounting and the body mass index: evidence from the netherlands. *Economics and Human Biology*, 4:29–61.
- Bronnenberg, B. J., Dubé, J.-P. H., and Gentzkow, M. (2012). The evolution of brand preferences: Evidence from consumer migration. *American Economic Review*, 102(6):2472–2508.
- Bronnenberg, B. J., Kruger, M. W., and Mela, C. F. (2008). Database paper-the iri marketing data set. *Marketing Science*, 27(4):745–748.
- Brownell, K. D. and Frieden, T. (2009). Ounces of prevention - the public policy case for taxes on sugared beverages. *The New England Journal of Medicine*, 360:1805–1808.
- Cawley, J. and Frisvold, D. (2017). The pass-through of taxes on sugar-sweetened beverages to retail prices: The case of berkeley, california. *Journal of Policy Analysis and Management*, 36:303-326.

- Cawley, J. and Meyerhoefer, C. (2012). The medical care costs of obesity: an instrumental variables approach. *Journal of Health Economics*, 31:219–230.
- Center for Disease Control (2015). Adult obesity facts. Technical report, Center for Disease Control.
- Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., and Taubinsky, D. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of Risk and Uncertainty*, 37.
- Cherchye, L., Rock, B. D., Griffith, R., O’Connell, M., Smith, K., and Vermeulen, F. (2017). A new year, a new you? heterogeneity and self-control in food purchases. Working Paper.
- Cohen, D. A. and Babey, S. H. (2012). Candy at the cash register - a risk factor for obesity and chronic disease. *New England Journal of Medicine*, 367(15):1381–1383. PMID: 23050524.
- Courtemanche, C., Heutel, G., and McAlvanah, P. (2014). Impatience, incentives and obesity. *The Economic Journal*, 125:1–31.
- Cutler, D., Glaeser, E., and Shapiro, J. (2003). Why have americans become more obese? Working Paper 9446, National Bureau of Economic Research.
- DellaVigna, S. and Malmendier, U. (2004). Contract design and self-control: Theory and evidence. *Quarterly Journal of Economics*, 119:353–402.
- Diehr, P., OMeara, E., Fitzpatrick, A., Newman, A., Kuller, L., and Burke, G. (2008). Weight, mortality, years of healthy life, an active life expectancy in older adults. *Journal of the American Geriatrics Society*, 56:76–83.
- Dubois, P., Griffith, R., and Nevo, A. (2014). Do prices and attributes explain international differences in food purchases? *American Economic Review*, 104(3):832–67.
- Dubois, P., Griffith, R., and O’Connell, M. (2018). The effects of banning advertising in junk food markets. *The Review of Economic Studies*, 85(1):396–436.
- Elbel, B., Kersh, R., Brescholl, V., and Dixon, L. (2009). Calorie labeling and good choices: a first look at the effects on low-income people in new york city. *Health Affairs*, 28:1110–1121.
- Falbe, J., Thompson, H., Becker, C., Rojas, N., McCulloch, C., and Madsen, K. (2015). Impact of the berkeley excise tax on sugar-sweetened beverage consumption. *American Journal of Public Health*, 106:1865–1871.
- Fletcher, J. (2011). Soda taxes and substitution effects: will obesity be affected? *Choices*, 26.
- Frederick, S., Loewenstein, G., and O’Donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, 40:351–401.

- Fryar, C., Carroll, M., and Ogden, C. (2012). Prevalence of overweight, obesity, and extreme obesity among adults: United states, trends 19601962 through 20092010. *Centers for Disease Control and Prevention*.
- Garca-Pérez, M. (2016). Converging to american: Healthy immigrant effect in children of immigrants. *American Economic Review*, 106(5):461–66.
- Gul, F. and Pesendorfer, W. (2001). Temptation and self-control. *Econometrica*, 69:1403–1435.
- Hales, C., Carroll, M., Fryar, C., and Ogden, C. (2017). Prevalence of obesity among adults and youth: United states, 20152016. *Centers for Disease Control and Prevention, NCHS Data Brief*, 288.
- Harris, J., Schwartz, M., and Brownell, K. (2010). Fast food facts: Evaluating fast food nutrition and marketing to youth. *New Haven, CT: Rudd Center for Food Policy and Obesity*.
- Hendel, I. and Nevo, A. (2006). Sales and consumer inventory. *The RAND Journal of Economics*, 37:543–561.
- Hoegg, J. and Alba, J. (2007). Taste perception: more than meets the tongue. *Journal of Consumer Research*.
- Hornik, R. (2002). *Public Health Communications: Making Sense of Contradictory Evidence*. Erlbaum.
- Ikeda, S., Kang, M.-I., and Ohtake, F. (2010). Hyperbolic discounting, the sign effect, and the body mass index. *Journal of Health Economics*, 29(2):268 – 284.
- Komlos, J., Smith, P., and Bogin, B. (2004). Obesity and the rate of time preference: is there a connection? *Journal of Biosocial Science*, 36:209–219.
- Lakdawalla, D. and Philipson, T. (2009). The growth of obesity and technological change. *Economics & Human Biology*, 7(3):283 – 293.
- Mokdad, A., Marks, J., Stroup, D., and Gerberding, J. (2000). Actual causes of death in the united states. *The Journal of the American Medical Association*, 291:1238–1245.
- NCD Risk Factor Collaboration (2016). Trends in adult body-mass index in 200 countries from 1975 to 2014: A pooled analysis of 1698 population-based measurement studies with 19.2 million participants. *Lancet*, 387:13771396.
- Oakes, M. (2006). Filling yet fattening: stereotypical beliefs about the weight gain potential and satiation of foods. *Appetite*.
- O’Donoghue, T. and Rabin, M. (1999). Doing it now or later. *American Economic Review*, 89(1):103–124.
- Ogden, C., Carroll, M., McDowell, M., and Fleal, K. (2007). Obesity among adults in the united states no statistically significant chance since 2003-2004. *NCHS Data Brief*, 1:1–8.

- Oster, E. (2018). Diabetes and diet: Behavioral response and the value of health. *American Economic Journal: Applied Economics*, 10:308–348.
- Pickett, K. E., Kelly, S., Brunner, E., Lobstein, T., and Wilkinson, R. G. (2005). Wider income gaps, wider waistbands? an ecological study of obesity and income inequality. *Journal of Epidemiology & Community Health*, 59(8):670–674.
- Randolph, W. and Viswanath, K. (2004). Lessons learned from public health mass media campaigns: marketing health in crowded media world. *Annual Review of Public Health*, 25:419–437.
- Richards, T. J. and Green, G. P. (2015). Environmental choices and hyperbolic discounting: An experimental analysis. *Environmental and Resource Economics*, 62(1):83–103.
- Richards, T. J. and Hamilton, S. F. (2012). Obesity and hyperbolic discounting: An experimental analysis. *Journal of Agricultural and Resource Economics*, 37(2):181–198.
- Rojas, C. and Wang, E. (2017). Do taxes for soda and sugary drinks work? scanner data evidence from berkeley and washington. *Mimeo*.
- Sadoff, S., Samek, A., and Sprenger, C. (2015). Dynamic inconsistency in food choice: Experimental evidence from a food desert. Working Paper <http://dx.doi.org/10.2139/ssrn.2572821>.
- Seiler, S., Tuchman, A., and Yao, S. (2019). The impact of soda taxes: Pass-through, tax avoidance, and nutritional effects. Working paper.
- Silver, L., Ng, S. W., Ryan-Ibarra, S., Taillie, L. S., Induni, M., Miles, D., Poti, J., and Popkin, B. (2017). Changes in prices, sales, consumer spending, and beverage consumption one year after a tax on sugar-sweetened beverages in berkeley, california, us: a before-and-after study. *PLOS Medicine*.
- Smith, P., Bogin, B., and Bishai, D. (2005). Are time preference and body mass index associated? evidence from the national longitudinal survey of youth. *Economics and Human Biology*, 3:259–270.
- Taylor, R., Kaplan, S., Villas-Boas, S., and Jung, K. (2016). Soda wars: Effect of a soda tax election on soda purchases. Working Paper.
- Thaler, R. and Shefrin, H. (1981). An economic theory of self-control. *Journal of Political Economy*, 89(2):392–406.
- Toussaert, S. (2018). Eliciting temptation and self-control through menu choices: a lab experiment. *Econometrica*, 86:859–889.
- Uetake, K. and Yang, N. (2018). Harnessing the small victories: Goal design strategies for a mobile calorie and weight loss tracking application. *Working Paper*.
- Wang, E., Rojas, C., and Colantuoni, F. (2017). Heterogeneous behavior, obesity, and storability in the demand for soft drinks. *American Journal of Agricultural Economics*, 99(1):18–33.

- Wang, E. Y. (2015). The impact of soda taxes on consumer welfare: implications of storability and taste heterogeneity. *The RAND Journal of Economics*, 46(2):409–441.
- Zhang, L. and Rashad, I. (2008). Obesity and time preference: the health consequences of discounting the future. *Journal of Biosocial Science*, 40:97–113.

Table A1: 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 A2: 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

A Appendix Tables

Table A3: 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 A4: 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 A5: 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 A6: 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 A7: 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

Table A8: Obesity-Related Diseases

Heart Attack					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Rx Only	1.12	1.16	1.77	2.24	2.04
OTC Only	0.24	0.28	0.39	0.31	0.36
Dual	0.32	0.42	0.42	0.55	0.64
Suffer, do no treat	0.24	0.15	0.19	0.28	0.25
Non-sufferer	98.08	97.99	97.23	96.62	96.70
Heart Problems					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Rx Only	5.52	6.31	7.59	8.78	9.71
OTC Only	0.72	0.61	0.65	0.53	0.55
Dual	1.52	1.06	1.45	1.78	1.82
Suffer, do no treat	1.04	0.62	0.63	0.89	1.01
Non-sufferer	91.21	91.40	89.68	88.02	86.90
High Cholesterol					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Rx Only	12.63	17.90	28.30	33.68	35.82
OTC Only	3.36	3.00	3.29	2.86	2.19
Dual	1.52	2.13	3.20	3.60	3.67
Suffer, do no treat	3.92	3.55	4.43	4.56	4.15
Non-sufferer	78.58	73.42	60.79	55.30	54.17
Type 2 diabetes					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Rx Only	1.68	3.08	7.21	14.88	24.64
OTC Only	0.24	0.29	0.46	0.50	0.51
Dual	0.32	0.35	1.07	2.13	2.85
Suffer, do no treat	0.48	0.57	0.95	1.48	1.60
Non-sufferer	97.28	95.71	90.31	81.02	70.41

Table A9: Answers to Health-Related Questions

I don't feel I'm doing enough to stay healthy					
	Underweight	Healthy	Overweight	Obese	Extreme Obese
Agree	22.28	18.84	25.25	39.49	54.95
Neutral	31.80	30.91	34.90	35.08	28.71
Disagree	45.92	50.25	39.85	25.43	16.34
I'm much healthier than most people my age					
	Underweight	Healthy	Overweight	Obese	Extreme Obese
Agree	49.70	59.84	50.82	32.29	14.20
Neutral	36.29	32.86	38.92	46.02	40.67
Disagree	14.01	7.30	10.26	21.70	45.13
Exercise is an important part of my life					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Agree	52.40	57.49	46.69	32.76	21.05
Neutral	29.92	29.56	35.25	39.27	36.04
Disagree	17.68	12.95	18.06	27.98	42.91
I often read nutritional labels on food					
	Underweight	Healthy	Overweight	Obese	Extreme Obese
Agree	69.10	70.01	66.81	65.54	63.18
Neutral	16.92	17.15	18.45	18.85	19.88
Disagree	14.61	12.84	14.74	15.61	16.94

Table A10: Eating/Exercise Habits

How Often Do you Eat Dessert/Indulgent Snacks					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Most Days	23.60	20.49	18.58	19.55	19.27
Some Days	45.68	50.49	54.22	55.04	56.35
Rarely/Never	30.72	29.02	27.20	25.41	24.38
How Often Do you Eat Fast Food					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Most Days	2.64	2.02	2.51	3.73	6.13
Some Days	28.56	28.99	36.23	42.60	48.49
Rarely/Never	68.80	68.99	61.26	53.67	45.38
Exercise/Active for at least 20 minutes per day					
	Underweight	Healthy	Overweight	Obese	Extremely Obese
Most Days	48.32	50.22	39.27	26.96	15.92
Some Days	29.60	32.91	38.49	40.22	35.61
Rarely/Never	22.08	16.87	22.24	32.83	48.47

Table A11: Are you on a low calorie/carb/fat/sugar diet?

	Underweight	Healthy	Overweight	Obese	Extremely Obese
No	65.79	61.20	55.01	48.78	44.19
Yes	34.21	38.80	44.99	51.22	55.81

Table A12: Is Respondent on a Diet Given Weight Concern?

	Concern Level		
	Very Concerned	Somewhat Concerned	Not at All
No	39.51	56.91	70.06
Yes	60.49	43.09	29.94

Table A13: Diet/Exercise Given Weight Loss

	Diet	Exercise	Both
BMI Bracket Same/Increase	62.0	53.9	36.8
BMI Bracket Decrease	71.9	60.3	45.5

Table A14: Regression of Probability of Buying on Deal on Characteristics (Obese Dummy)

Regressor	(1)	(2)	(3)
Unhealthy Category	0.0005 (0.0056)	0.0130** (0.0054)	0.0326*** (0.0038)
Storable Category	0.1501*** (0.0049)	0.1528*** (0.0047)	0.1338*** (0.0031)
Obese	-0.0047 (0.0058)	0.0018 (0.0057)	0.0029 (0.0027)
Unhealthy \times Obese	0.0198** (0.0084)	0.0155* (0.0082)	-0.0020 (0.0054)
Unhealthy \times Storable	-0.0375*** (0.0069)	-0.0441*** (0.0067)	-0.0589*** (0.0046)
Storable \times Obese	-0.0115 (0.0072)	-0.0112 (0.0070)	-0.0008 (0.0045)
Unhealthy \times Storable \times Obese	-0.0114 (0.0104)	-0.0091 (0.0101)	0.0001 (0.0065)
Constant	0.2167*** (0.0038)	-	0.2167*** (0.0013)

Notes: An observation in this regression is a purchase event of a particular product (UPC). The dummy variable obese is 1 if an individual's BMI bracket is obese or extremely obese. Unhealthy categories are defined as bakery desserts, cookies, ice cream, salty snacks, regular soda, and candy. Neutral/healthy categories are fresh fruits and vegetables, yogurt, milk, eggs, bread, frozen vegetables, cereals, pasta, and diet soda. We define the following categories as storable: ice cream, salty snacks, packaged cookies, candy, frozen vegetables, cereal, pasta, and soda. Specification (1) includes no additional controls, while (2) includes income, employment, occupation, ethnicity, hispanic origin, gender, and age dummy variables. Specification (3) includes household fixed effects. Standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A15: Regression of Probability of Buying on Deal on Characteristics (BMI Bracket)

Regressor	(1)	(2)	(3)
Unhealthy Category	0.0012 (0.0076)	0.0138* (0.0072)	0.0301*** (0.0053)
Storable Category	0.1500*** (0.0059)	0.1527*** (0.0057)	0.1309*** (0.0038)
Overweight	-0.0134** (0.0065)	-0.0100 (0.0063)	-2.952e-05 (0.0025)
Obese	-0.0158** (0.0069)	-0.0075 (0.0068)	0.0017 (0.0027)
Extreme Obese	-0.0108 (0.0096)	0.0015 (0.0095)	0.0019 (0.0037)
Unhealthy \times Overweight	0.0027 (0.0096)	0.0014 (0.0093)	0.0035 (0.0068)
Unhealthy \times Obese	0.0203** (0.0103)	0.0159 (0.0099)	0.0021 (0.0068)
Unhealthy \times Extreme Obese	0.0157 (0.0129)	0.0112 (0.0125)	-0.0040 (0.0085)
Unhealthy \times Storable	-0.0299*** (0.0091)	-0.0368*** (0.0087)	-0.0471*** (0.0060)
Storable \times Overweight	0.0014 (0.0080)	0.0006 (0.0079)	0.0067 (0.0052)
Storable \times Obese	-0.0091 (0.0084)	-0.0093 (0.0082)	0.0035 (0.0052)
Storable \times Extreme Obese	-0.0175 (0.0113)	-0.0169 (0.0110)	-0.0003 (0.0072)
Unhealthy \times Storable \times Overweight	-0.0103 (0.0120)	-0.0092 (0.0116)	-0.0192** (0.0082)
Unhealthy \times Storable \times Obese	-0.0238* (0.0126)	-0.0202* (0.0122)	-0.0144* (0.0081)
Unhealthy \times Storable \times Extreme Obese	-0.0067 (0.0163)	-0.0057 (0.0158)	-0.0044 (0.0099)
Constant	0.2265*** (0.0049)	-	0.2204*** (0.0016)

Notes: An observation in this regression is a purchase event of a particular product (UPC). Unhealthy categories are defined as bakery desserts, cookies, ice cream, salty snacks, regular soda, and candy. Neutral/healthy categories are fresh fruits and vegetables, yogurt, milk, eggs, bread, frozen vegetables, cereals, pasta, and diet soda. We define the following categories as storable: ice cream, salty snacks, packaged cookies, candy, frozen vegetables, cereal, pasta, and soda. Specification (1) includes no additional controls, while (2) includes income, employment, occupation, ethnicity, hispanic origin, gender, and age dummy variables. Specification (3) includes household fixed effects. Standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A16: Regression of Purchase Indicator on Price and BMI, Tempting Categories (7 month window)

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0006 (0.0004)	0.0005** (0.0002)	-0.0009 (0.0006)	0.0007*** (0.0002)	0.0005 (0.0003)	-0.0007 (0.0005)	-0.0008 (0.0005)	0.0009* (0.0005)
Inventory	-0.0613*** (0.0138)	-0.0611*** (0.0137)	-0.1030*** (0.0301)	-0.1030*** (0.0301)	-0.1194*** (0.0244)	-0.1186*** (0.0242)	-0.1698*** (0.0323)	-0.1688*** (0.0322)
BMI \times Inventory	0.0008** (0.0004)	0.0008** (0.0004)	0.0000 (0.0009)	0.0000 (0.0009)	0.0009 (0.0008)	0.0008 (0.0008)	0.0010 (0.0010)	0.0010 (0.0010)
log (Price)	-0.0458*** (0.0059)	-	0.0104 (0.0088)	-	-0.0769*** (0.0110)	-	-0.1205*** (0.0126)	-
log (Price) \times BMI	-0.0004** (0.0002)	-	-0.0007** (0.0003)	-	0.0000 (0.0004)	-	-0.0007* (0.0004)	-
Price	-	-0.3335*** (0.0456)	-	0.0263 (0.0342)	-	-0.1417*** (0.0262)	-	-0.3489*** (0.0402)
Deal	-	0.0175** (0.0068)	-	0.0085 (0.0067)	-	0.0382*** (0.0095)	-	-0.0053 (0.0085)
Price \times BMI	-	-0.0028* (0.0014)	-	-0.0018 (0.0012)	-	0.0017* (0.0009)	-	-0.0026* (0.0014)
Deal \times BMI	-	0.0006** (0.0002)	-	0.0001 (0.0002)	-	0.0012*** (0.0003)	-	-0.0003 (0.0003)
Constant	-0.0537*** (0.0132)	0.0797*** (0.0064)	0.1227*** (0.0167)	0.0977*** (0.0061)	0.0386*** (0.0095)	0.1526*** (0.0131)	0.0063 (0.0146)	0.2594*** (0.0147)
<i>N</i>	370973	370973	332594	332594	414226	414226	406944	406944

Notes: An observation in this regression an individual shopping trip occurring between Aug 1st and Feb 28th of the following year. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A17: Regression of Purchase Indicator on Price and BMI, Non-Tempting Categories (7 month window)

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0001 (0.0008)	-0.0002 (0.0005)	0.0000 (0.0005)	-0.0004 (0.0003)	0.0007* (0.0004)	-0.0004 (0.0003)	0.0002 (0.0004)	-0.0002 (0.0004)
Inventory	-0.0404 (0.0351)	-0.0416 (0.0350)	-0.0058 (0.0600)	-0.0055 (0.0601)	0.0349 (0.0516)	0.0348 (0.0518)	-0.0274 (0.0420)	-0.0274 (0.0419)
BMI \times Inventory	-0.0019* (0.0011)	-0.0019* (0.0011)	-0.0043** (0.0019)	-0.0043** (0.0019)	-0.0036*** (0.0013)	-0.0036*** (0.0013)	-0.0018 (0.0017)	-0.0018 (0.0017)
log (Price)	-0.0135 (0.0131)	-	-0.0287*** (0.0061)	-	-0.1080*** (0.0088)	-	-0.0600*** (0.0103)	-
log (Price) \times BMI	-0.0000 (0.0004)	-	0.0000 (0.0002)	-	0.0005* (0.0003)	-	0.0003 (0.0003)	-
Price	-	0.0243 (0.0988)	-	-0.3202*** (0.0762)	-	-0.3673*** (0.0323)	-	-0.1669*** (0.0347)
Deal	-	0.0498*** (0.0088)	-	0.0129*** (0.0037)	-	0.0057 (0.0090)	-	0.0384*** (0.0082)
Price \times BMI	-	0.0007 (0.0031)	-	0.0032 (0.0025)	-	0.0018* (0.0010)	-	0.0002 (0.0011)
Deal \times BMI	-	0.0001 (0.0003)	-	0.0001 (0.0001)	-	-0.0001 (0.0003)	-	-0.0003 (0.0003)
Constant	0.0489* (0.0261)	0.0567*** (0.0148)	-0.0310** (0.0146)	0.0626*** (0.0076)	-0.0751*** (0.0132)	0.1677*** (0.0094)	0.0194 (0.0128)	0.1285*** (0.0115)
N	294390	294390	337230	337230	393820	393820	279557	279557

Notes: An observation in this regression an individual shopping trip occurring between Aug 1st and Feb 28th of the following year. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A18: Regression of Purchase Indicator on Price and Obese Dummy, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Obese	-0.0282** (0.0123)	0.0112 (0.0072)	-0.0450*** (0.0158)	0.0103 (0.0080)	-0.0117 (0.0102)	-0.0227 (0.0159)	-0.0266* (0.0157)	0.0186 (0.0161)
Inventory	-0.0412*** (0.0066)	-0.0410*** (0.0066)	-0.0778*** (0.0187)	-0.0777*** (0.0187)	-0.1116*** (0.0153)	-0.1131*** (0.0153)	-0.1630*** (0.0152)	-0.1625*** (0.0151)
Obese \times Inventory	0.0204* (0.0105)	0.0205** (0.0104)	-0.0241 (0.0275)	-0.0242 (0.0275)	0.0223 (0.0229)	0.0237 (0.0227)	0.0641*** (0.0231)	0.0635*** (0.0231)
log (Price)	-0.0495*** (0.0036)	-	-0.0018 (0.0050)	-	-0.0594*** (0.0064)	-	-0.1434*** (0.0083)	-
log (Price) \times Obese	-0.0132** (0.0054)	-	-0.0229*** (0.0080)	-	-0.0117 (0.0111)	-	-0.0193 (0.0131)	-
Price	-	-0.3524*** (0.0284)	-	0.0000 (0.0219)	-	-0.0533*** (0.0165)	-	-0.4329*** (0.0269)
Deal	-	0.0305*** (0.0042)	-	0.0153*** (0.0041)	-	0.0783*** (0.0069)	-	-0.0166*** (0.0055)
Price \times Obese	-	-0.0899** (0.0423)	-	-0.0779** (0.0328)	-	0.0171 (0.0293)	-	-0.0659 (0.0422)
Deal \times Obese	-	0.0016 (0.0068)	-	-0.0058 (0.0069)	-	0.0346*** (0.0109)	-	-0.0054 (0.0089)
Constant	-0.0536*** (0.0080)	0.0847*** (0.0044)	0.1114*** (0.0094)	0.1124*** (0.0043)	0.0764*** (0.0058)	0.1215*** (0.0088)	-0.0206** (0.0096)	0.2890*** (0.0101)
<i>N</i>	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Obese is a dummy variable if an individual is in the obese or extremely obese BMI bracket. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A19: Regression of Purchase Indicator on Price and Obese Dummy, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Obese	0.0360 (0.0237)	-0.0112 (0.0142)	0.0080 (0.0134)	0.0064 (0.0063)	0.0249** (0.0121)	0.0010 (0.0092)	0.0069 (0.0135)	0.0082 (0.0135)
Inventory	-0.0822*** (0.0154)	-0.0829*** (0.0154)	-0.0808*** (0.0257)	-0.0807*** (0.0258)	-0.0366* (0.0212)	-0.0366* (0.0212)	-0.0680*** (0.0127)	-0.0684*** (0.0127)
Obese \times Inventory	-0.0309 (0.0208)	-0.0306 (0.0209)	-0.0759** (0.0311)	-0.0758** (0.0311)	-0.0576** (0.0255)	-0.0576** (0.0255)	-0.0046 (0.0349)	-0.0041 (0.0349)
log (Price)	-0.0217*** (0.0076)	-	-0.0338*** (0.0038)	-	-0.0949*** (0.0054)	-	-0.0452*** (0.0067)	-
log (Price) \times Obese	0.0146 (0.0116)	-	0.0016 (0.0056)	-	0.0129 (0.0080)	-	0.0049 (0.0104)	-
Price	-	0.0280 (0.0606)	-	-0.2285*** (0.0400)	-	-0.3197*** (0.0198)	-	-0.1491*** (0.0241)
Deal	-	0.0572*** (0.0053)	-	0.0165*** (0.0021)	-	0.0030 (0.0052)	-	0.0246*** (0.0047)
Price \times Obese	-	0.1313 (0.0925)	-	-0.0194 (0.0582)	-	0.0377 (0.0286)	-	-0.0141 (0.0390)
Deal \times Obese	-	0.0018 (0.0083)	-	-0.0011 (0.0034)	-	-0.0095 (0.0080)	-	-0.0078 (0.0075)
Constant	0.0300* (0.0154)	0.0520*** (0.0090)	-0.0474*** (0.0091)	0.0492*** (0.0041)	-0.0611*** (0.0082)	0.1523*** (0.0059)	0.0253*** (0.0082)	0.1171*** (0.0083)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Obese is a dummy variable if an individual is in the obese or extremely obese BMI bracket. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A20: Regression of Quantity Purchased on Price and BMI, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.1096** (0.0535)	0.0504** (0.0255)	-0.0598** (0.0246)	0.0290*** (0.0111)	-0.0072 (0.0198)	-0.0045 (0.0274)	-0.0382* (0.0199)	0.0306 (0.0216)
Inventory	-2.6107 (2.6473)	-2.5715 (2.6418)	-5.3553* (3.1803)	-5.3517* (3.1831)	-8.1331*** (2.2681)	-8.1765*** (2.2533)	-4.0221*** (1.4595)	-4.0141*** (1.4585)
BMI \times Inventory	0.0232 (0.0752)	0.0226 (0.0749)	0.0884 (0.0913)	0.0883 (0.0914)	0.1033 (0.0688)	0.1042 (0.0681)	0.0289 (0.0447)	0.0287 (0.0446)
log (Price)	-2.3179*** (0.6884)	-	0.7596** (0.3847)	-	-2.5224*** (0.6400)	-	-1.9189*** (0.5211)	-
log (Price) \times BMI	-0.0594*** (0.0230)	-	-0.0362*** (0.0128)	-	-0.0220 (0.0220)	-	-0.0284* (0.0169)	-
Price	-	-17.0968*** (4.9526)	-	2.8662** (1.3826)	-	-4.8817*** (1.5892)	-	-5.1222*** (1.6498)
Deal	-	1.4117 (0.9366)	-	0.5460* (0.3274)	-	0.2390 (0.5253)	-	-0.0109 (0.3701)
Price \times BMI	-	-0.3594** (0.1652)	-	-0.1303*** (0.0467)	-	-0.0065 (0.0557)	-	-0.1052** (0.0525)
Deal \times BMI	-	0.0364 (0.0321)	-	-0.0098 (0.0109)	-	0.0484*** (0.0179)	-	-0.0079 (0.0121)
Constant	-2.4254 (1.5967)	4.1203*** (0.7714)	3.3403*** (0.7518)	1.4050*** (0.3219)	-0.0716 (0.5780)	4.1319*** (0.7814)	0.2091 (0.6073)	4.0711*** (0.6814)
N	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st where a purchase occurs in the given category. The dependent variable is total quantity purchased within the category, measured in ounces. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A21: Regression of Quantity Purchased on Price and BMI, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0966 (0.0738)	-0.0099 (0.0440)	0.0969** (0.0442)	-0.0139 (0.0174)	0.0532 (0.0429)	0.0147 (0.0212)	0.0025 (0.0152)	-0.0009 (0.0133)
Inventory	-2.2741 (2.5246)	-2.3938 (2.5322)	3.4340 (3.4895)	3.4381 (3.4920)	14.9693* (9.0329)	14.9820* (9.0419)	0.6131 (1.9379)	0.5972 (1.9356)
BMI \times Inventory	-0.1130 (0.0863)	-0.1095 (0.0866)	-0.2574*** (0.0944)	-0.2572*** (0.0946)	-0.5704* (0.3103)	-0.5708* (0.3106)	-0.0779 (0.0786)	-0.0774 (0.0785)
log (Price)	-2.1432** (1.0569)	-	-2.4850*** (0.6184)	-	-3.3269*** (0.8147)	-	-0.8206** (0.3300)	-
log (Price) \times BMI	0.0349 (0.0371)	-	0.0370** (0.0187)	-	0.0167 (0.0245)	-	0.0008 (0.0121)	-
Price	-	-8.4569 (7.9103)	-	-16.9587*** (5.2717)	-	-10.8957*** (2.4915)	-	-2.6274** (1.1370)
Deal	-	2.2412*** (0.6772)	-	0.8825*** (0.2412)	-	0.5420 (0.6187)	-	0.0948 (0.2588)
Price \times BMI	-	0.2807 (0.2832)	-	0.2666 (0.1650)	-	0.0647 (0.0760)	-	-0.0032 (0.0409)
Deal \times BMI	-	0.0002 (0.0229)	-	-0.0062 (0.0079)	-	-0.0028 (0.0193)	-	0.0104 (0.0085)
Constant	-2.3979 (2.1084)	2.3150* (1.2221)	-5.1848*** (1.4671)	2.0290*** (0.5464)	-3.5072** (1.4176)	3.7220*** (0.6539)	0.1576 (0.4194)	1.9155*** (0.3858)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st where a purchase occurs in the given category. The dependent variable is total quantity purchased within the category, measured in ounces. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A22: Regression of Quantity Purchased (Given Purchase) on Price and BMI, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.3804 (0.8588)	-0.0754 (0.2939)	-0.1902 (0.1321)	0.0728 (0.0699)	0.0865 (0.0968)	0.2195 (0.1369)	0.0263 (0.0925)	0.0715 (0.0873)
Inventory	8.4075 (8.8119)	8.7288 (8.8415)	-2.9473 (4.5661)	-3.0286 (4.6216)	-14.1037* (7.7025)	-14.3272* (7.7108)	-4.4414 (4.3948)	-4.3633 (4.3622)
BMI \times Inventory	-0.1348 (0.2279)	-0.1448 (0.2284)	0.0531 (0.1524)	0.0556 (0.1544)	0.1714 (0.2162)	0.1773 (0.2160)	0.0596 (0.1399)	0.0573 (0.1388)
log (Price)	-13.4491 (11.6182)	-	2.2888 (2.2062)	-	-11.5058*** (3.2351)	-	-3.7069 (2.3023)	-
log (Price) \times BMI	-0.1078 (0.3449)	-	-0.0886 (0.0697)	-	-0.0142 (0.1033)	-	0.0175 (0.0756)	-
Price	-	-86.6237 (87.3962)	-	15.4374* (9.0394)	-	-21.2966** (8.3792)	-	-5.7251 (7.4056)
Deal	-	5.3231 (8.6061)	-	1.7400 (2.0428)	-	4.6761* (2.7522)	-	2.0617 (1.5639)
Price \times BMI	-	-0.8324 (2.7090)	-	-0.5657* (0.2930)	-	-0.1736 (0.2718)	-	-0.1387 (0.2416)
Deal \times BMI	-	0.0718 (0.2650)	-	-0.0553 (0.0647)	-	-0.1343 (0.0893)	-	-0.0652 (0.0511)
Constant	32.2403 (28.6915)	70.1191*** (9.8610)	23.6773*** (4.1861)	16.7018*** (2.1454)	5.7479* (3.0453)	23.1658*** (4.1520)	11.0590*** (2.8063)	16.4929*** (2.6968)
<i>N</i>	13019	13019	22307	22307	31500	31500	33615	33615

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st where a purchase occurs in the given category. The dependent variable is total quantity purchased within the category, measured in ounces. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A23: Regression of Quantity Purchased (Given Purchase) on Price and BMI, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.4121 (0.5092)	0.7913** (0.3380)	2.5165* (1.3135)	-1.0694** (0.5416)	-0.1948 (0.5016)	-0.0786 (0.3216)	0.0051 (0.0969)	-0.1482 (0.0983)
Inventory	-3.1386 (6.8336)	-3.4939 (6.9288)	-5.9924 (9.9552)	-5.9593 (9.9771)	64.3630* (35.2490)	64.5767* (35.3238)	2.3146 (4.5800)	2.3944 (4.5965)
BMI \times Inventory	-0.1003 (0.2651)	-0.0910 (0.2678)	0.0561 (0.4243)	0.0481 (0.4255)	-2.1629* (1.2979)	-2.1715* (1.3002)	-0.0687 (0.1743)	-0.0722 (0.1751)
log (Price)	1.3606 (8.1013)	-	-44.7609** (17.7573)	-	-3.6998 (10.7068)	-	-4.6694** (2.3444)	-
log (Price) \times BMI	-0.3468 (0.2569)	-	1.0622** (0.5313)	-	-0.0938 (0.3255)	-	0.0421 (0.0763)	-
Price	-	53.3552 (62.9907)	-	-3.9e+02** (177.8305)	-	-12.4790 (39.7805)	-	-16.9071** (8.4027)
Deal	-	10.1204* (5.6783)	-	4.7427 (6.0956)	-	-0.0136 (6.5965)	-	-1.9843 (1.9513)
Price \times BMI	-	-3.2163 (1.9982)	-	11.0840* (5.6720)	-	-0.1454 (1.2750)	-	0.2262 (0.2869)
Deal \times BMI	-	-0.1904 (0.1808)	-	0.0307 (0.1977)	-	0.1369 (0.2097)	-	0.0891 (0.0631)
Constant	28.5410* (16.0607)	15.0759 (10.4470)	-78.7386* (43.7524)	63.0805*** (16.8359)	23.2656 (16.4763)	31.7762*** (9.5901)	10.3835*** (2.9118)	21.9482*** (2.8825)
<i>N</i>	12924	12924	6767	6767	18935	18935	13396	13396

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st where a purchase occurs in the given category. The dependent variable is total quantity purchased within the category, measured in ounces. Price is measured in dollars per ounce, and inventory in ounces/1000. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A24: Regression of Purchase Indicator on Price, BMI, and Obesity-Related Disease, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0012*	0.0007*	-0.0020**	0.0012**	0.0003	-0.0022**	-0.0019**	0.0022**
	(0.0007)	(0.0004)	(0.0010)	(0.0005)	(0.0006)	(0.0009)	(0.0010)	(0.0010)
Inventory	-0.0747***	-0.0745***	-0.0679	-0.0693	-0.1772***	-0.1790***	-0.1887***	-0.1878***
	(0.0196)	(0.0196)	(0.0463)	(0.0464)	(0.0435)	(0.0427)	(0.0480)	(0.0480)
BMI \times Inventory	0.0014**	0.0014**	-0.0007	-0.0006	0.0025*	0.0025*	0.0018	0.0018
	(0.0006)	(0.0006)	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
log (Price)	-0.0305***	-	0.0295*	-	-0.0683***	-	-0.0958***	-
	(0.0095)		(0.0161)		(0.0193)		(0.0247)	
log (Price) \times BMI	-0.0008**	-	-0.0013**	-	0.0001	-	-0.0016*	-
	(0.0003)		(0.0006)		(0.0007)		(0.0008)	
Price	-	-0.2325***	-	0.0453	-	-0.1738***	-	-0.2664***
		(0.0796)		(0.0653)		(0.0511)		(0.0772)
Deal	-	0.0152	-	0.0382**	-	0.0442*	-	0.0120
		(0.0143)		(0.0171)		(0.0226)		(0.0208)
Price \times BMI	-	-0.0046*	-	-0.0022	-	0.0042**	-	-0.0058**
		(0.0026)		(0.0024)		(0.0018)		(0.0025)
Deal \times BMI	-	0.0006	-	-0.0009	-	0.0016**	-	-0.0012*
		(0.0005)		(0.0006)		(0.0008)		(0.0007)
Disease Condition	-0.0131	-	-0.0019	-	0.0011	-	-0.0291**	-
	(0.0133)		(0.0160)		(0.0101)		(0.0146)	
Disease Condition \times log (Price)	-0.0057	-	0.0007	-	-0.0012	-	-0.0207	-
	(0.0067)		(0.0115)		(0.0152)		(0.0173)	
Disease Condition \times log (Price) \times BMI	0.0000	-	-0.0001	-	0.0002	-	-0.0001	-
	(0.0001)		(0.0003)		(0.0004)		(0.0004)	
Disease Condition \times Price	-	0.0063	-	0.0050	-	-0.0116	-	0.0132
		(0.0072)		(0.0082)		(0.0155)		(0.0156)
Disease Condition \times Price \times BMI	-	-0.0764	-	0.1155	-	0.0807**	-	-0.0305
		(0.0977)		(0.0887)		(0.0409)		(0.0611)
Disease Condition \times Deal	-	0.0008	-	-0.0046*	-	-0.0021**	-	-0.0010
		(0.0027)		(0.0027)		(0.0010)		(0.0016)
Disease Condition \times Deal \times BMI	-	-0.0060	-	-0.0353	-	-0.0502*	-	-0.0178
		(0.0203)		(0.0283)		(0.0296)		(0.0294)
Constant	-0.0232	0.0000	0.1539***	0.0013	0.0639***	0.0018*	0.0364	0.0009
	(0.0216)	(0.0007)	(0.0296)	(0.0009)	(0.0179)	(0.0009)	(0.0291)	(0.0010)
<i>N</i>	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Disease is 1 if an individual answers that she is a sufferer or treats any of the four diseases in Table A8. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A25: Regression of Purchase Indicator on Price, BMI, and Disease, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0028*	-0.0006	0.0007	0.0006	0.0014*	0.0003	0.0004	0.0003
	(0.0015)	(0.0009)	(0.0009)	(0.0004)	(0.0008)	(0.0006)	(0.0007)	(0.0007)
Inventory	-0.0200	-0.0227	0.0376	0.0379	0.0785*	0.0782*	-0.0122	-0.0134
	(0.0411)	(0.0411)	(0.0616)	(0.0619)	(0.0463)	(0.0464)	(0.0483)	(0.0482)
BMI \times Inventory	-0.0026*	-0.0025*	-0.0053**	-0.0053**	-0.0050***	-0.0049***	-0.0022	-0.0021
	(0.0014)	(0.0014)	(0.0021)	(0.0021)	(0.0014)	(0.0014)	(0.0021)	(0.0021)
log (Price)	-0.0478**	-	-0.0390***	-	-0.1151***	-	-0.0508***	-
	(0.0236)		(0.0114)		(0.0163)		(0.0176)	
log (Price) \times BMI	0.0011	-	0.0001	-	0.0008	-	0.0003	-
	(0.0008)		(0.0004)		(0.0005)		(0.0006)	
Price	-	-0.2218	-	-0.2244*	-	-0.3493***	-	-0.1300**
		(0.1899)		(0.1284)		(0.0617)		(0.0576)
Deal	-	0.0521***	-	0.0257***	-	0.0289	-	0.0164
		(0.0187)		(0.0082)		(0.0190)		(0.0167)
Price \times BMI	-	0.0095	-	-0.0004	-	0.0015	-	-0.0007
		(0.0061)		(0.0042)		(0.0019)		(0.0020)
Deal \times BMI	-	0.0001	-	-0.0003	-	-0.0009	-	0.0001
		(0.0007)		(0.0003)		(0.0006)		(0.0006)
Disease Condition	-0.0009	-	0.0112	-	0.0118	-	0.0081	-
	(0.0248)		(0.0139)		(0.0119)		(0.0138)	
Disease Condition \times log (Price)	-0.0053	-	0.0045	-	0.0203*	-	0.0016	-
	(0.0135)		(0.0063)		(0.0108)		(0.0126)	
Disease Condition \times log (Price) \times BMI	0.0002	-	0.0000	-	-0.0006***	-	-0.0001	-
	(0.0002)		(0.0001)		(0.0002)		(0.0003)	
Disease Condition \times Price	-	-0.0150	-	0.0009	-	0.0095	-	0.0118
		(0.0142)		(0.0064)		(0.0090)		(0.0132)
Disease Condition \times Price \times BMI	-	0.1316	-	0.0683	-	-0.0554	-	-0.0607
		(0.1340)		(0.1013)		(0.0575)		(0.0576)
Disease Condition \times Deal	-	-0.0021	-	-0.0021	-	0.0018	-	0.0016
		(0.0030)		(0.0027)		(0.0017)		(0.0014)
Disease Condition \times Deal \times BMI	-	0.0232	-	-0.0078	-	-0.0261	-	0.0255
		(0.0277)		(0.0124)		(0.0268)		(0.0258)
Constant	-0.0385	-0.0006	-0.0702**	0.0001	-0.0981***	0.0006	0.0122	-0.0007
	(0.0471)	(0.0009)	(0.0273)	(0.0004)	(0.0242)	(0.0008)	(0.0217)	(0.0008)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Disease is 1 if an individual answers that she is a sufferer or treats any of the four diseases in Table A8. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A26: Regression of Purchase Indicator on Price, BMI, and Weight Concern, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0017** (0.0008)	-0.0017** (0.0008)	-0.0020* (0.0011)	-0.0021* (0.0011)	0.0003 (0.0007)	0.0004 (0.0007)	-0.0028*** (0.0010)	-0.0031*** (0.0010)
Inventory	-0.0682*** (0.0214)	-0.0677*** (0.0212)	-0.0619 (0.0475)	-0.0614 (0.0475)	-0.1590*** (0.0441)	-0.1640*** (0.0437)	-0.1839*** (0.0541)	-0.1821*** (0.0537)
BMI \times Inventory	0.0014** (0.0006)	0.0014** (0.0006)	-0.0007 (0.0015)	-0.0007 (0.0015)	0.0016 (0.0015)	0.0018 (0.0015)	0.0019 (0.0017)	0.0018 (0.0017)
log (Price)	-0.0268*** (0.0103)	-	0.0328** (0.0162)	-	-0.0650*** (0.0202)	-	-0.0917*** (0.0253)	-
log (Price) \times BMI	-0.0011*** (0.0004)	-	-0.0015*** (0.0006)	-	0.0000 (0.0007)	-	-0.0022** (0.0009)	-
Price	-	-0.0209* (0.0116)	-	0.0364** (0.0163)	-	-0.0599*** (0.0227)	-	-0.0913*** (0.0297)
Deal	-	0.0271 (0.0195)	-	0.0229 (0.0177)	-	0.0175 (0.0251)	-	0.0044 (0.0259)
Price \times BMI	-	-0.0011*** (0.0004)	-	-0.0016*** (0.0006)	-	0.0014* (0.0008)	-	-0.0027*** (0.0010)
Deal \times BMI	-	0.0002 (0.0007)	-	-0.0003 (0.0006)	-	0.0026*** (0.0009)	-	-0.0010 (0.0009)
Concern	0.0083 (0.0122)	-	-0.0018 (0.0170)	-	0.0022 (0.0107)	-	0.0257* (0.0155)	-
Concern \times log (Price)	-0.0002 (0.0065)	-	-0.0076 (0.0111)	-	-0.0040 (0.0162)	-	0.0300 (0.0197)	-
Concern \times log (Price) \times BMI	0.0002 (0.0001)	-	0.0002 (0.0002)	-	0.0001 (0.0004)	-	-0.0003 (0.0005)	-
Concern \times Price	-	0.0076 (0.0121)	-	-0.0018 (0.0170)	-	0.0001 (0.0106)	-	0.0278* (0.0160)
Concern \times Price \times BMI	-	-0.0062 (0.0095)	-	-0.0078 (0.0115)	-	-0.0002 (0.0248)	-	0.0310 (0.0266)
Concern \times Deal	-	0.0003 (0.0003)	-	0.0002 (0.0002)	-	-0.0001 (0.0007)	-	-0.0002 (0.0008)
Concern \times Deal \times BMI	-	-0.0319 (0.0323)	-	-0.0010 (0.0311)	-	0.0150 (0.0452)	-	-0.0031 (0.0419)
Constant	-0.0209 (0.0224)	0.0009 (0.0011)	0.1531*** (0.0305)	-0.0000 (0.0010)	0.0631*** (0.0185)	-0.0004 (0.0014)	0.0426 (0.0292)	0.0003 (0.0014)
<i>N</i>	219384	219384	200852	200852	249506	249506	246548	246548

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Concern is 1 if an individual answers that he/she is very concerned about his/her weight on the Medprofiler survey. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A27: Regression of Purchase Indicator on Price, BMI, and Weight Concern, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0021 (0.0016)	0.0028* (0.0017)	0.0006 (0.0010)	0.0004 (0.0010)	0.0013 (0.0008)	0.0014* (0.0008)	0.0004 (0.0008)	0.0004 (0.0007)
Inventory	-0.0104 (0.0430)	-0.0128 (0.0431)	0.0451 (0.0828)	0.0446 (0.0830)	0.0089 (0.0453)	0.0085 (0.0453)	0.0264 (0.0500)	0.0259 (0.0502)
BMI \times Inventory	-0.0029** (0.0014)	-0.0029** (0.0014)	-0.0059** (0.0026)	-0.0059** (0.0027)	-0.0030** (0.0015)	-0.0030** (0.0015)	-0.0027 (0.0022)	-0.0027 (0.0022)
log (Price)	-0.0452* (0.0240)	- (0.0240)	-0.0384*** (0.0120)	- (0.0120)	-0.1071*** (0.0164)	- (0.0164)	-0.0468*** (0.0179)	- (0.0179)
log (Price) \times BMI	0.0008 (0.0008)	-	0.0001 (0.0004)	-	0.0005 (0.0005)	-	0.0001 (0.0006)	-
Price	-	-0.0245 (0.0258)	-	-0.0241** (0.0122)	-	-0.1037*** (0.0177)	-	-0.0365** (0.0186)
Deal	-	0.0546** (0.0212)	-	0.0147 (0.0090)	-	0.0157 (0.0227)	-	0.0273 (0.0179)
Price \times BMI	-	0.0011 (0.0009)	-	0.0001 (0.0004)	-	0.0004 (0.0006)	-	0.0001 (0.0006)
Deal \times BMI	-	0.0001 (0.0008)	-	0.0001 (0.0003)	-	-0.0006 (0.0008)	-	-0.0001 (0.0006)
Concern	0.0342 (0.0229)	-	0.0062 (0.0156)	-	0.0029 (0.0122)	-	0.0080 (0.0133)	-
Concern \times log (Price)	0.0161 (0.0122)	-	0.0060 (0.0070)	-	0.0004 (0.0109)	-	-0.0093 (0.0135)	-
Concern \times log (Price) \times BMI	-0.0000 (0.0002)	-	-0.0001 (0.0001)	-	0.0001 (0.0002)	-	0.0003 (0.0003)	-
Concern \times Price	-	0.0338 (0.0235)	-	0.0022 (0.0160)	-	0.0026 (0.0122)	-	0.0079 (0.0132)
Concern \times Price \times BMI	-	0.0196 (0.0136)	-	0.0061 (0.0074)	-	0.0039 (0.0139)	-	-0.0091 (0.0163)
Concern \times Deal	-	-0.0001 (0.0002)	-	-0.0002* (0.0001)	-	-0.0000 (0.0003)	-	0.0002 (0.0004)
Concern \times Deal \times BMI	-	0.0285 (0.0339)	-	0.0117 (0.0138)	-	0.0138 (0.0321)	-	0.0012 (0.0295)
Constant	-0.0294 (0.0475)	-0.0006 (0.0011)	-0.0648** (0.0287)	-0.0005 (0.0004)	-0.0925*** (0.0242)	-0.0004 (0.0010)	0.0140 (0.0226)	-0.0000 (0.0009)
<i>N</i>	177696	177696	204487	204487	238622	238622	165163	165163

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Concern is 1 if an individual answers that he/she is very concerned about his/her weight on the Medprofiler survey. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A28: Regression of Purchase Indicator on Price, BMI, and Recognition of Obesity as a Disease, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0013*	0.0008**	-0.0018	0.0012**	0.0006	-0.0025***	-0.0024**	0.0023**
	(0.0008)	(0.0004)	(0.0011)	(0.0005)	(0.0007)	(0.0009)	(0.0011)	(0.0011)
Inventory	-0.0746***	-0.0740***	-0.0669	-0.0658	-0.1770***	-0.1794***	-0.1878***	-0.1872***
	(0.0197)	(0.0196)	(0.0465)	(0.0465)	(0.0436)	(0.0427)	(0.0475)	(0.0475)
BMI \times Inventory	0.0014**	0.0013**	-0.0007	-0.0008	0.0024*	0.0025*	0.0018	0.0018
	(0.0006)	(0.0006)	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
log (Price)	-0.0318***	-	0.0262	-	-0.0742***	-	-0.0914***	-
	(0.0100)		(0.0169)		(0.0202)		(0.0271)	
log (Price) \times BMI	-0.0008**	-	-0.0012**	-	0.0005	-	-0.0021**	-
	(0.0004)		(0.0006)		(0.0007)		(0.0010)	
Price	-	-0.2832***	-	0.0958	-	-0.1581***	-	-0.2609***
		(0.0772)		(0.0688)		(0.0506)		(0.0818)
Deal	-	0.0328**	-	0.0393**	-	0.0153	-	-0.0068
		(0.0130)		(0.0159)		(0.0214)		(0.0209)
Price \times BMI	-	-0.0034	-	-0.0042	-	0.0041**	-	-0.0067**
		(0.0027)		(0.0026)		(0.0018)		(0.0029)
Deal \times BMI	-	-0.0002	-	-0.0010*	-	0.0027***	-	-0.0003
		(0.0005)		(0.0006)		(0.0007)		(0.0007)
Obese Disease	-0.0027	-	-0.0054	-	-0.0157	-	0.0064	-
	(0.0151)		(0.0213)		(0.0138)		(0.0206)	
Obese Disease \times log (Price)	-0.0001	-	-0.0009	-	-0.0257	-	-0.0022	-
	(0.0079)		(0.0145)		(0.0204)		(0.0258)	
Obese Disease \times log (Price) \times BMI	-0.0000	-	-0.0001	-	0.0003	-	0.0002	-
	(0.0002)		(0.0003)		(0.0004)		(0.0006)	
Obese Disease \times Price	-	-0.0043	-	0.0076	-	0.0108	-	0.0044
		(0.0087)		(0.0093)		(0.0204)		(0.0219)
Obese Disease \times Price \times BMI	-	0.1345	-	-0.0538	-	-0.0292	-	0.0361
		(0.1378)		(0.1001)		(0.0580)		(0.1037)
Obese Disease \times Deal	-	-0.0041	-	0.0009	-	-0.0000	-	-0.0010
		(0.0035)		(0.0026)		(0.0012)		(0.0022)
Obese Disease \times Deal \times BMI	-	-0.0437	-	-0.0459	-	0.0279	-	-0.0016
		(0.0281)		(0.0422)		(0.0411)		(0.0423)
Constant	-0.0257	0.0016**	0.1486***	0.0016	0.0573***	-0.0008	0.0377	-0.0002
	(0.0220)	(0.0008)	(0.0322)	(0.0012)	(0.0184)	(0.0011)	(0.0311)	(0.0012)
<i>N</i>	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Obese Disease is 1 if an individual answers she is a sufferer or is treating obesity on the Medprofiler question tabulated in the third panel of Table 3. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A29: Regression of Purchase Indicator on Price, BMI, and Recognition of Obesity as a Disease, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0021 (0.0017)	-0.0005 (0.0010)	0.0013 (0.0010)	0.0002 (0.0005)	0.0017** (0.0009)	0.0003 (0.0007)	0.0002 (0.0008)	0.0004 (0.0007)
Inventory	-0.0217 (0.0411)	-0.0246 (0.0411)	0.0377 (0.0616)	0.0380 (0.0619)	0.0773* (0.0466)	0.0772* (0.0467)	-0.0121 (0.0481)	-0.0132 (0.0480)
BMI \times Inventory	-0.0025* (0.0014)	-0.0024* (0.0014)	-0.0053** (0.0021)	-0.0053** (0.0021)	-0.0049*** (0.0014)	-0.0049*** (0.0014)	-0.0022 (0.0021)	-0.0021 (0.0021)
log (Price)	-0.0447* (0.0254)	- (0.0254)	-0.0428*** (0.0122)	- (0.0122)	-0.1077*** (0.0174)	- (0.0174)	-0.0430** (0.0180)	- (0.0180)
log (Price) \times BMI	0.0009 (0.0009)	- (0.0009)	0.0004 (0.0004)	- (0.0004)	0.0006 (0.0006)	- (0.0006)	-0.0001 (0.0006)	- (0.0006)
Price	- (0.2009)	-0.1308 (0.2009)	- (0.2009)	-0.2809** (0.1362)	- (0.1362)	-0.4112*** (0.0661)	- (0.0661)	-0.1459** (0.0610)
Deal	- (0.0189)	0.0590*** (0.0189)	- (0.0189)	0.0209*** (0.0079)	- (0.0079)	0.0221 (0.0192)	- (0.0192)	0.0167 (0.0157)
Price \times BMI	- (0.0068)	0.0066 (0.0068)	- (0.0068)	0.0024 (0.0047)	- (0.0047)	0.0037* (0.0022)	- (0.0022)	-0.0003 (0.0021)
Deal \times BMI	- (0.0007)	-0.0000 (0.0007)	- (0.0007)	-0.0001 (0.0003)	- (0.0003)	-0.0007 (0.0007)	- (0.0007)	0.0002 (0.0006)
Obese Disease	0.0255 (0.0282)	- (0.0282)	-0.0123 (0.0175)	- (0.0175)	-0.0086 (0.0152)	- (0.0152)	0.0074 (0.0149)	- (0.0149)
Obese Disease \times log (Price)	0.0257* (0.0151)	- (0.0151)	-0.0035 (0.0083)	- (0.0083)	-0.0171 (0.0128)	- (0.0128)	-0.0028 (0.0150)	- (0.0150)
Obese Disease \times log (Price) \times BMI	-0.0003* (0.0002)	- (0.0002)	-0.0000 (0.0001)	- (0.0001)	0.0004* (0.0002)	- (0.0002)	0.0003 (0.0003)	- (0.0003)
Obese Disease \times Price	- (0.0164)	-0.0151 (0.0164)	- (0.0164)	0.0128 (0.0079)	- (0.0079)	0.0009 (0.0107)	- (0.0107)	-0.0052 (0.0150)
Obese Disease \times Price \times BMI	- (0.1573)	-0.0278 (0.1573)	- (0.1573)	-0.1575 (0.1130)	- (0.1130)	0.1328* (0.0779)	- (0.0779)	0.0220 (0.0712)
Obese Disease \times Deal	- (0.0032)	0.0032 (0.0032)	- (0.0032)	0.0008 (0.0028)	- (0.0028)	-0.0040* (0.0020)	- (0.0020)	-0.0004 (0.0016)
Obese Disease \times Deal \times BMI	- (0.0395)	-0.0122 (0.0395)	- (0.0395)	0.0020 (0.0193)	- (0.0193)	-0.0282 (0.0366)	- (0.0366)	0.0289 (0.0350)
Constant	-0.0228 (0.0508)	0.0003 (0.0011)	-0.0784*** (0.0295)	-0.0001 (0.0005)	-0.1004*** (0.0256)	0.0006 (0.0010)	0.0201 (0.0225)	-0.0010 (0.0009)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Obese Disease is 1 if an individual answers she is a sufferer or is treating obesity on the Medprofiler question tabulated in the third panel of Table 3. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A30: Regression of Purchase Indicator on Price, BMI, and Weight Perception, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.0013*	0.0007**	-0.0020*	0.0013**	0.0003	-0.0023***	-0.0020**	0.0026***
	(0.0007)	(0.0004)	(0.0010)	(0.0005)	(0.0006)	(0.0009)	(0.0010)	(0.0010)
Inventory	-0.0746***	-0.0742***	-0.0683	-0.0685	-0.1784***	-0.1801***	-0.1870***	-0.1861***
	(0.0197)	(0.0196)	(0.0464)	(0.0464)	(0.0434)	(0.0424)	(0.0482)	(0.0481)
BMI \times Inventory	0.0013**	0.0013**	-0.0007	-0.0007	0.0025*	0.0025*	0.0018	0.0018
	(0.0006)	(0.0006)	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
log (Price)	-0.0307***	-	0.0302*	-	-0.0689***	-	-0.0935***	-
	(0.0094)		(0.0157)		(0.0192)		(0.0240)	
log (Price) \times BMI	-0.0008***	-	-0.0014**	-	0.0002	-	-0.0019**	-
	(0.0003)		(0.0005)		(0.0007)		(0.0008)	
Price	-	-0.2469***	-	0.1090*	-	-0.1427***	-	-0.2554***
		(0.0740)		(0.0630)		(0.0491)		(0.0768)
Deal	-	0.0134	-	0.0173	-	0.0163	-	0.0014
		(0.0121)		(0.0141)		(0.0195)		(0.0174)
Price \times BMI	-	-0.0048*	-	-0.0048**	-	0.0033*	-	-0.0070***
		(0.0025)		(0.0023)		(0.0017)		(0.0026)
Deal \times BMI	-	0.0007*	-	-0.0001	-	0.0026***	-	-0.0008
		(0.0004)		(0.0005)		(0.0007)		(0.0006)
Weight Perception	0.0056	-	-0.0064	-	-0.0056	-	-0.0068	-
	(0.0135)		(0.0190)		(0.0123)		(0.0180)	
Weight Perception \times log (Price)	-0.0041	-	-0.0002	-	-0.0082	-	-0.0385	-
	(0.0075)		(0.0156)		(0.0228)		(0.0259)	
Weight Perception \times log (Price) \times BMI	0.0002	-	-0.0000	-	0.0004	-	0.0012*	-
	(0.0001)		(0.0004)		(0.0006)		(0.0006)	
Weight Perception \times Price	-	0.0079	-	-0.0048	-	-0.0135	-	-0.0190
		(0.0078)		(0.0092)		(0.0185)		(0.0198)
Weight Perception \times Price \times BMI	-	0.0135	-	-0.1072	-	-0.0666	-	0.0837
		(0.1250)		(0.1370)		(0.0573)		(0.1094)
Weight Perception \times Deal	-	-0.0004	-	0.0033	-	0.0023	-	-0.0018
		(0.0037)		(0.0039)		(0.0014)		(0.0029)
Weight Perception \times Deal \times BMI	-	-0.0102	-	0.0734	-	0.0879	-	0.0342
		(0.0338)		(0.0716)		(0.0547)		(0.0684)
Constant	-0.0261	-0.0001	0.1539***	-0.0025	0.0634***	-0.0027	0.0298	-0.0006
	(0.0214)	(0.0010)	(0.0302)	(0.0021)	(0.0182)	(0.0016)	(0.0292)	(0.0020)
<i>N</i>	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression is an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Weight Perception is 1 if an individual is obese and answers he/she is slightly overweight or less on Table 3. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A31: Regression of Purchase Indicator on Price, BMI, and Weight Perception, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0032** (0.0016)	-0.0007 (0.0009)	0.0007 (0.0009)	0.0006 (0.0004)	0.0013* (0.0008)	0.0004 (0.0006)	0.0005 (0.0007)	0.0002 (0.0006)
Inventory	-0.0197 (0.0411)	-0.0224 (0.0411)	0.0375 (0.0616)	0.0378 (0.0619)	0.0772* (0.0465)	0.0769 (0.0466)	-0.0126 (0.0482)	-0.0138 (0.0483)
BMI \times Inventory	-0.0026* (0.0014)	-0.0025* (0.0014)	-0.0053** (0.0021)	-0.0053** (0.0021)	-0.0049*** (0.0014)	-0.0049*** (0.0014)	-0.0021 (0.0021)	-0.0021 (0.0021)
log (Price)	-0.0527** (0.0236)	- (0.0114)	-0.0387*** (0.0114)	- (0.0161)	-0.1065*** (0.0161)	- (0.0169)	-0.0506*** (0.0169)	- (0.0021)
log (Price) \times BMI	0.0013* (0.0008)	-	0.0002 (0.0004)	-	0.0005 (0.0005)	-	0.0003 (0.0005)	-
Price	-	-0.2240 (0.1872)	-	-0.1841 (0.1224)	-	-0.3684*** (0.0589)	-	-0.1518*** (0.0581)
Deal	-	0.0619*** (0.0155)	-	0.0242*** (0.0065)	-	0.0210 (0.0159)	-	0.0265** (0.0134)
Price \times BMI	-	0.0105* (0.0061)	-	-0.0021 (0.0040)	-	0.0019 (0.0018)	-	0.0001 (0.0019)
Deal \times BMI	-	-0.0002 (0.0005)	-	-0.0003 (0.0002)	-	-0.0007 (0.0005)	-	-0.0001 (0.0005)
Weight Perception	-0.0226 (0.0288)	-	0.0125 (0.0161)	-	0.0232 (0.0142)	-	-0.0058 (0.0153)	-
Weight Perception \times log (Price)	-0.0233 (0.0171)	-	0.0123 (0.0082)	-	0.0191 (0.0144)	-	0.0011 (0.0172)	-
Weight Perception \times log (Price) \times BMI	0.0004 (0.0003)	-	-0.0002 (0.0001)	-	-0.0001 (0.0003)	-	-0.0002 (0.0004)	-
Weight Perception \times Price	-	-0.0003 (0.0174)	-	-0.0055 (0.0074)	-	-0.0063 (0.0104)	-	0.0134 (0.0168)
Weight Perception \times Price \times BMI	-	0.3030 (0.2149)	-	-0.1021 (0.1497)	-	0.0831 (0.1050)	-	-0.0091 (0.0940)
Weight Perception \times Deal	-	-0.0099* (0.0054)	-	0.0049 (0.0040)	-	-0.0012 (0.0030)	-	-0.0008 (0.0024)
Weight Perception \times Deal \times BMI	-	-0.0343 (0.0706)	-	0.0006 (0.0266)	-	-0.0561 (0.0538)	-	-0.0203 (0.0548)
Constant	-0.0477 (0.0474)	0.0014 (0.0021)	-0.0665** (0.0275)	0.0001 (0.0008)	-0.0929*** (0.0242)	0.0013 (0.0016)	0.0158 (0.0219)	0.0004 (0.0016)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dummy variable Weight Perception is 1 if an individual is obese and answers he/she is slightly overweight or less on Table 3. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A32: Linear Regression of Volume on Price, Obese, Tempting Categories

Regressor	Ice Cream		Desserts		Chocolate		Snacks	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	-0.1096** (0.0535)	0.0504** (0.0255)	-0.0598** (0.0246)	0.0290*** (0.0111)	-0.0072 (0.0198)	-0.0045 (0.0274)	-0.0382* (0.0199)	0.0306 (0.0216)
Inventory	-2.6107 (2.6473)	-2.5715 (2.6418)	-5.3553* (3.1803)	-5.3517* (3.1831)	-8.1331*** (2.2681)	-8.1765*** (2.2533)	-4.0221*** (1.4595)	-4.0141*** (1.4585)
BMI \times Inventory	0.0232 (0.0752)	0.0226 (0.0749)	0.0884 (0.0913)	0.0883 (0.0914)	0.1033 (0.0688)	0.1042 (0.0681)	0.0289 (0.0447)	0.0287 (0.0446)
log (Price)	-2.3179*** (0.6884)	-	0.7596** (0.3847)	-	-2.5224*** (0.6400)	-	-1.9189*** (0.5211)	-
log (Price) \times BMI	-0.0594*** (0.0230)	-	-0.0362*** (0.0128)	-	-0.0220 (0.0220)	-	-0.0284* (0.0169)	-
Price	-	-17.0968*** (4.9526)	-	2.8662** (1.3826)	-	-4.8817*** (1.5892)	-	-5.1222*** (1.6498)
Deal	-	1.4117 (0.9366)	-	0.5460* (0.3274)	-	0.2390 (0.5253)	-	-0.0109 (0.3701)
Price \times BMI	-	-0.3594** (0.1652)	-	-0.1303*** (0.0467)	-	-0.0065 (0.0557)	-	-0.1052** (0.0525)
Deal \times BMI	-	0.0364 (0.0321)	-	-0.0098 (0.0109)	-	0.0484*** (0.0179)	-	-0.0079 (0.0121)
Constant	-2.4254 (1.5967)	4.1203*** (0.7714)	3.3403*** (0.7518)	1.4050*** (0.3219)	-0.0716 (0.5780)	4.1319*** (0.7814)	0.2091 (0.6073)	4.0711*** (0.6814)
<i>N</i>	225890	225890	200854	200854	252583	252583	246532	246532

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dependent variable measures the quantity consumers purchase include no purchase. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

Table A33: Linear Regression of Volume on Price, Obese, Non-Tempting Categories

Regressor	Fr. Vegetables		Pasta		Cereal		Salad	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
BMI	0.0966 (0.0738)	-0.0099 (0.0440)	0.0969** (0.0442)	-0.0139 (0.0174)	0.0532 (0.0429)	0.0147 (0.0212)	0.0025 (0.0152)	-0.0009 (0.0133)
Inventory	-2.2741 (2.5246)	-2.3938 (2.5322)	3.4340 (3.4895)	3.4381 (3.4920)	14.9693* (9.0329)	14.9820* (9.0419)	0.6131 (1.9379)	0.5972 (1.9356)
BMI \times Inventory	-0.1130 (0.0863)	-0.1095 (0.0866)	-0.2574*** (0.0944)	-0.2572*** (0.0946)	-0.5704* (0.3103)	-0.5708* (0.3106)	-0.0779 (0.0786)	-0.0774 (0.0785)
log (Price)	-2.1432** (1.0569)	-	-2.4850*** (0.6184)	-	-3.3269*** (0.8147)	-	-0.8206** (0.3300)	-
log (Price) \times BMI	0.0349 (0.0371)	-	0.0370** (0.0187)	-	0.0167 (0.0245)	-	0.0008 (0.0121)	-
Price	-	-8.4569 (7.9103)	-	-16.9587*** (5.2717)	-	-10.8957*** (2.4915)	-	-2.6274** (1.1370)
Deal	-	2.2412*** (0.6772)	-	0.8825*** (0.2412)	-	0.5420 (0.6187)	-	0.0948 (0.2588)
Price \times BMI	-	0.2807 (0.2832)	-	0.2666 (0.1650)	-	0.0647 (0.0760)	-	-0.0032 (0.0409)
Deal \times BMI	-	0.0002 (0.0229)	-	-0.0062 (0.0079)	-	-0.0028 (0.0193)	-	0.0104 (0.0085)
Constant	-2.3979 (2.1084)	2.3150* (1.2221)	-5.1848*** (1.4671)	2.0290*** (0.5464)	-3.5072** (1.4176)	3.7220*** (0.6539)	0.1576 (0.4194)	1.9155*** (0.3858)
<i>N</i>	177699	177699	204477	204477	238619	238619	169700	169700

Notes: An observation in this regression an individual shopping trip occurring between Oct 1st and Dec 31st. The dependent variable is an indicator for purchase within a category. Price is measured in dollars per ounce, and inventory in ounces/1000. The dependent variable measures the quantity consumers purchase include no purchase. All regressions include individual fixed effects, and standard errors are clustered at the individual level. *, **, and *** indicate at the 10%, 5%, and 1% levels, respectively.

B Appendix Figures

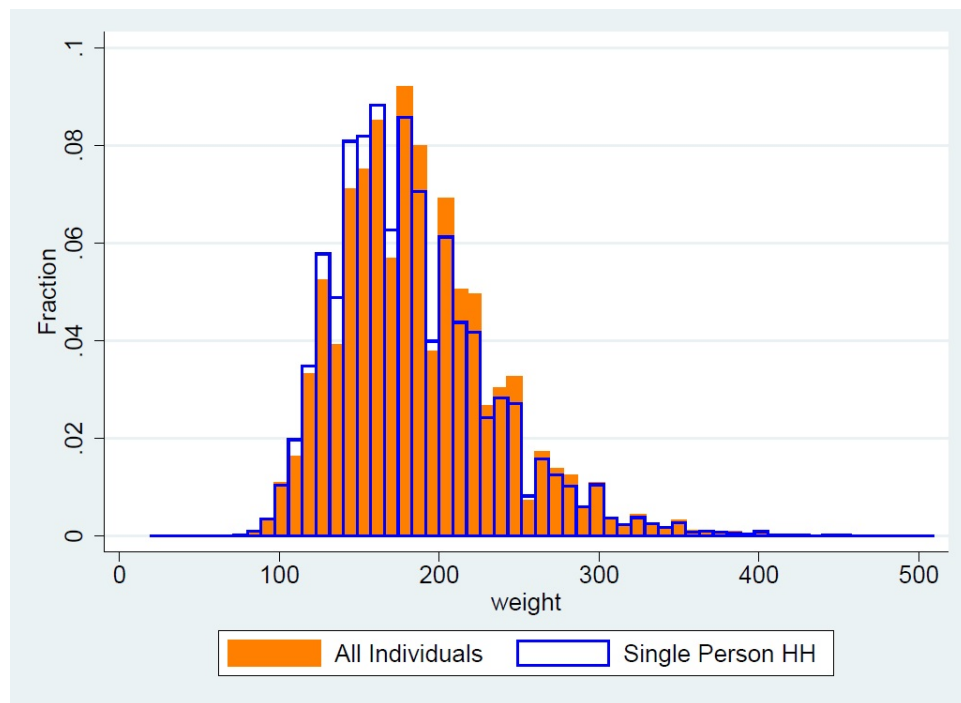


Figure A1: Weight distribution of individuals over 20 years old

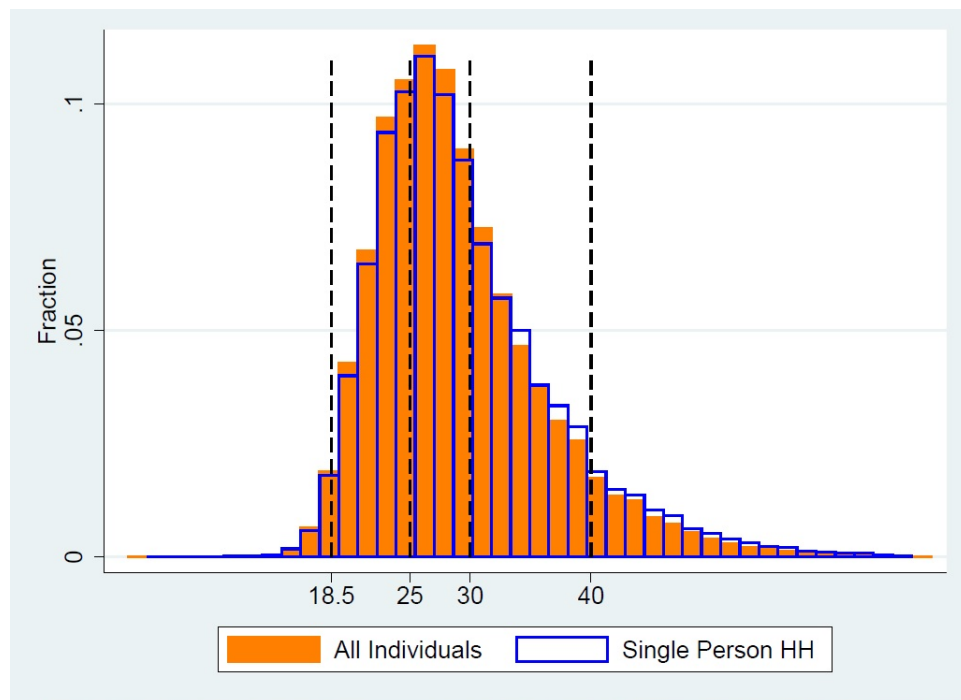


Figure A2: BMI distribution of individuals over 20 years old. Dotted lines indicate BMI bracket cutoffs.