CONSUMER FOOD PREFERENCES: THREE ESSAYS ON LABELING, ANTI-OBESITY POLICIES AND SOCIAL PRESENCE

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CONSUMER FOOD PREFERENCES: THREE ESSAYS ON LABELING, ANTI-OBESITY POLICIES AND SOCIAL PRESENCE

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This dissertation is comprised of three independent research essays focused around consumer food preferences in the U.S. The first essay, entitled "Taxes, Subsidies, and Advertising Efficacy in Changing Eating Behavior: An Experimental Study", examines whether unhealthy foods taxes, healthy foods subsidies, anti-obesity advertising, and healthy foods advertising have an impact on changing consumers' choices of lunch items and the nutrient content of their choices for a selected meal. The analysis relies on a lab experiment with 258 adult non-student participants. A difference-in-difference regression model was used to determine the efficacy of the various policy treatments. The results indicate that the unhealthy foods tax, healthy foods advertising, and unhealthy foods tax combined with anti-obesity advertising significantly reduced the content of some nutrients of concern, such as calories, calories from fat, carbohydrates, and cholesterol in meal selections. The essay is concluded with a discussion of the policy implications of these findings and venues for future research.

The second essay, "Noisy Information Signals and Credence Attribute Labeling", examines consumers' reaction to information about various food

ingredients. This research paper uses a model based on the theoretical framework of Johnson and Myatt (2006) to measure the impact of "Contains" food labels with and without additional negative information about the labeled ingredients. Credence attribute labeling is modeled as a noisy information signal. For the most concerned consumers, a "Contains" label absent additional information serves as a noisy warning signal and increases uncertainty, leading them to overestimate the riskiness of consuming the labeled product. The provision of additional (even negative) information reduces the noise in the information signal, thereby mitigating the large negative signaling effect of the label.

Finally, the third essay moves away from examining the impact of information, and considers the effect of social effects on consumer food choices. The "Social Presence and Shopping Behavior: Evidence from Video Data" paper uses a unique combined dataset of video surveillance and sales data from a small boutique wine store to study the effect of social presence on shopping behavior. By exploiting quasi-experimental exogenous variation of other shoppers coming in or leaving the store, the effect of the change in the level of social presence on customers' shopping behavior is estimated. In particular, the results indicate that people are significantly more likely to buy when the level of social presence is lower, with some customers increasing their total spending, and others buying cheaper wines. The essay concludes with a discussion on the importance of social characteristics of the environment in the consumer decision-making process.

BIOGRAPHICAL SKETCH

Nadezhda Andreevna Streletskaya received her B.A. in international economics from the Moscow State Institute of International Relations (MGIMO-University), Russia in 2011. Her current research interests are in the fields of behavioral and experimental economics, consumer preferences, labeling, nutrition and marketing.

To my parents, Andrey and Natalia, who have always believed in me.

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CHAPTER 1. Introduction

1.1 Background

Food consumption is an indelible part of human life. The way food is consumed around the world has been shifting dramatically in the past hundred years, with dietary patterns changing around the world and in the U.S. (Popkin, 2006). As ultra-processed food[1] is becoming dominant in both developed and developing countries (Monteiro et al., 2013), worries about food labeling, safety and obesity are becoming more prominent among both governments and individual consumers.

As processed foods become a bigger part of the diet, their widespread presence is fueling a consumer movement calling for stricter and more detailed food labeling regulations (Liaukonyte et al. 2013). Given the overall low consumer knowledge about various specific ingredients (e.g. Hallman et al., 2003), stricter labeling might actually unintentionally reduce consumer choice (Sexton, 2012) and act as a noisy quality signal, with some consumers changing their evaluation of the product simply based on the fact that an ingredient of the food is labeled. As more U.S. states move to implement stricter labeling, research on various types of information and their impact on heterogeneous consumers' choices becomes particularly pertinent.

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[1] Defined as attractive, hyper-palatable, cheap, ready-to-consume food products that are characteristically energy-dense, fatty, sugary or salty and generally obesogenic (Monteiro et al. 2013)

On the other hand, with obesity-associated health costs in 2010 in the U.S. identified at over $150 billion per year, calls for anti-obesity policies are heard more and more often. As empirical evidence remains mixed on the efficacy of various anti-obesity policies, providing policy-makers with information on the relative impact of proposed policies in an experimental setting could be used to narrow down the candidates for effective anti-obesity campaigns in the field.

Finally, food consumption and purchasing remains a social activity, at least to some extent (Reisch et al., 2013). While it is known that consumers often engage in status signaling through consumption of various durable goods, such behavior in food is not well known. Some consumer studies (e.g. Dubois et al., 2012) indicate consumers believe their food choice reveals information about their social standing and preferences to others; however, the extent to which these considerations guide their choices is not well examined.

1.2 Dissertation objectives

The main objectives of this dissertation are to investigate in detail how exogenously provided information, in form of labeling and advertising, fiscal incentives, such as taxes and subsidies, and social characteristics of the environment affect consumer food choice and willingness to pay for various products. To that effect two economics lab experiments with non-student participants were designed, focusing on labeling for various ingredient and production processes consumers are

currently concerned about and the effect of anti-obesity policies currently proposed or under design.

While experimental data allows for a better degree of control over the observed characteristics and a better identification, it's generalizability to the field is somewhat limited, due to the atypical environment and absence of potentially important factors present in real life settings (Levitt and List, 2007). This is of particular concern when examining the impact of social characteristics of the shopping environment on consumer choices.

Due to the reason above, data from a functioning boutique wine store is used to investigate the impact of social presence on consumer choices. The use of video surveillance allows to collect data usually unavailable to economist through secondary sources; in particular, information on customers coming in the store and leaving without a purchase allows for a more precise modeling and estimation of consumer behavior.

The specific objectives of this dissertation can be summarized as follows:

1. To estimate the impact of healthy foods subsidy, unhealthy food taxes, antiobesity and healthy food tax (and several combinations of thereof) on the total nutrient and caloric content and density of selected lunch meals;
2. To estimate the impact of ingredient labeling, allowing for endogeneity between labeling and consumer preferences, on consumer willingness to pay for various

food items in presence or absence of additional (secondary to the label) negative information about the labeled ingredient;

3. To estimate the effect that presence of other shoppers has on consumer shopping behavior, particularly on propensity to buy, total spending and purchased bottle price;

and, finally,

4. To propose and test behavioral explanations for the effect of social presence on shopping behavior.

These objectives are going to be discussed in depth in each of the respective essay chapters, the outline for which is detailed below.

1.3 Dissertation Outline

The rest of the dissertation is arranged as follows. Chapter 2 introduces the first essay, titled "Taxes, Subsidies, and Advertising Efficacy in Changing Eating Behavior: An Experimental Study". The chapter examines the impact of various fiscal and informational anti-obesity policies on consumer choices of lunch items in an experimental setting. The essay relies on a difference-in-difference design, and provides interesting insights on potential unintended consequences of anti-obesity policies, such as reduction in fiber content and the potential for synergies between different anti-obesity policies.

Chapter 3 expands on the potential effects of information provision when consumers have heterogeneous prior beliefs, in the essay "Noisy Information Signals

and Credence Attribute Labeling". Using the example of different food ingredient labels and secondary negative information about such ingredients, the paper attempts to identify the signaling component of labels. In most theoretical and empirical economic models on food labeling, consumer preferences for labeled food products are assumed to be exogenous to the presence of labels. However, it is possible that the label itself (and not the information on the label) is interpreted as a noisy warning signal. The chapter uses data from an economics lab experiment to identify some of the structural effects of both labels and secondary information.

Finally, Chapter 4 moves from investigating the impact of various types of information to examining the effect the presence of other shoppers has on wine consumer choices. The essay "Social Presence and Shopping Behavior: Evidence from Video Data" uses a unique field data-set from a small wine store, and relies on a natural quasi-experimental sert up to identify the changes in shopping behavior as the level of social presence in the store changes. As results of the paper suggest that social presence indeed has an effect on propensity to buy, total spending and wine price, guilt reciprcity behavior and status signaling are suggested and evaluated as potential explanations for the observed behavior.

REFERENCES

Dubois, D., Rucker, D.D. and A.D. Galinsky. 2012. Super size me: product size as a signal of status. *Journal of Consumer Research*, 38(6):1047–1062.

Hallman, W. K., Hebden, W.C., Aquino, H.L., Cuite, C.L., and Lang, J.T. 2003. Public *Perceptions of Genetically Modified Foods: A National Study of American Knowledge and Opinion.* New Brunswick, NJ: Food Policy Institute, Cook College, Rutgers - The State University of New Jersey.

Levitt, S. D., and J. A. List. 2007. Viewpoint: On the Generalizability of Lab Behaviour to the Field. *Canadian Journal of Economics/Revue canadienne d'économique* 40: 347-70.

Liaukonyte J, Streletskaya NA, Kaiser HM, Rickard BJ. 2013. Consumer response to "contains" and "free of" labeling: Evidence from lab experiments. *Applied Economic Perspectives and Policy,* 35 (3): 476-507.

Lillis, M. 2010. CDC: Skyrocketing Obesity Translates into Enormous Health Costs. *The Hill,* http://thehill.com/blogs/healthwatch/state-issues/112455-cdc-skyrocketing-obesitytranslates-into-enormous-health-costs.

Monteiro, C.A., Moubarac, J.C., Cannon, G., Ng, S.W. and Popkin, B., 2013. Ultra-processed products are becoming dominant in the global food system. *Obesity reviews*, *14*(S2): 21-28

Popkin, B.M., 2006. Global nutrition dynamics: the world is shifting rapidly toward a diet linked with noncommunicable diseases. *The American Journal of Clinical Nutrition*, *84*(2): 289-298.

Reisch, L., Eberle, U. and Lorek, S., 2013. Sustainable food consumption: an overview of contemporary issues and policies. *Sustainability: Science, Practice, & Policy*, *9*(2).

Sexton, S. 2012. How California's GMO Labeling Law Could Limit Your Food Choices and Hurt the Poor." In *Freakonomics: the hidden side of everything.*

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CHAPTER 2. Taxes, Subsidies, and Advertising Efficacy in Changing Eating Behavior: An Experimental Study

2.1 Introduction

Obesity is a tremendous social problem in the United States with over 34% of the current population categorized as obese and over 67% classified as overweight (WHO, 2011). Obesity, which has become substantially more prevalent in the past two decades, is linked to significant health problems including diabetes, cancer and heart disease, which collectively have increased health care costs an estimated $150 billion per year (Lillis, 2010). Establishing healthy eating patterns is essential for improving health and for reducing risk of chronic disease (ARS, 2010b).

The high incidence of obesity in the U.S. has been blamed on a host of factors such as relatively low prices per calorie for high fat and sweetened foods, insufficient exercise, lack of parental oversight of children's eating habits, substantial marketing campaigns by the fast food industry, agricultural subsidies that have promoted production of high fat and/or sugary foods at the expense of fruits and vegetables, and other environmental and economics factors (Liaukonyte et al. 2012). Although there are many anti-obesity policies such as calorie information on menus, bans on junk food in schools, restrictions on sugary and salty food marketing to children, and limits on size of soda sold in municipalities, the focus of the research reported here is

on four broad-based fiscal and advertising policy tools: taxes on unhealthy foods, subsidies on healthy foods, anti-obesity advertising, and healthy (fruit and vegetable) food advertising.

The economic literature on the efficacy of taxes and subsidies has generally showed that such fiscal tools have little impact on changing behavior. For example, Chouinard et al. (2007), Powell and Chaloupka (2009), and Kuchler et al. (2005) find that a tax on unhealthy foods has minimal impact since the estimated price response is relatively inelastic. On the other hand, a recent study by Andreyeva et al. (2011) concludes that a penny per ounce excise tax on sugar-sweetened non-diet beverages reduces consumption of such beverages between 6% and 26.7% with the greatest impact on carbonated soft drinks. Hence, the empirical evidence is somewhat mixed on the efficacy of taxes and subsidies in nudging healthier eating.

While these and other studies are useful, they have relied upon the use of secondary observational price and quantity data with natural variation not due to taxes or subsidies. Edwards (2011) discusses the absence of randomized controlled trials (RCT) in the literature and the difficulties in measuring treatments and outcomes. These studies also assume the tax and price elasticity of demand are the same, but the tax elasticity is generally more inelastic (Zheng et al. 2012). An alternative to these methods is a laboratory experiment where experimental participants are randomized into treatment groups and their behavior directly observed.

Healthy food and anti-obesity advertising campaigns are less commonly used policies for mitigating obesity and are infrequently studied. According to Emery et al. (2007), research has generally shown that campaigns with health-related messages have small-to-moderate effects on attitudes, beliefs, and behaviors related to the primary message. The limited research on these policies has indicated that healthy food advertising has a small, but statistically significant effect on increasing consumption of fruits and vegetables (Liaukonyte et al. 2012; Pollard et al. 2008). Anti-obesity advertising, which use emotive and scary messages targeted primarily to overweight people, is mostly state-sponsored, with the nationwide CDC Verb campaign being the only anti-obesity media campaigns at the national level. To our knowledge, there have been no economic studies conducted on the efficacy of anti-obesity advertising.

The purpose of the research summarized here is to examine whether unhealthy foods taxes, healthy foods subsidies, anti-obesity advertising, and healthy foods advertising have an impact on changing consumer choices of lunch items and nutrient content and nutrient and energy density of the selected meal. The analysis is based on an economic experiment conducted with 258 adult, non-student subjects, each of whom were randomly placed into a control group or one of six treatments: (1) 20% unhealthy foods excise tax; (2) 20% healthy foods excise subsidy; (3) anti-obesity advertising; (4) healthy (fruit and vegetable) advertising; (5) 20% unhealthy foods excise tax with anti-obesity advertising; (6) 20% healthy food excise subsidy with

healthy foods advertising. A difference-in-difference regression model is used to determine the efficacy of the various policy treatments. The results indicate that the unhealthy foods tax, healthy foods advertising, and unhealthy foods tax combined with anti-obesity advertising significantly reduced content of some nutrients of concern in meal selections.

2.2 Background and Previous Literature

The rise in obesity and overweight levels is generally acknowledged to have started in the 1970s and 1980s in high-income countries, and since then has spread through most countries of the world (Swinburn et al. 2011; Kelly et al. 2008). The majority of Americans now are overweight or obese, with the rates roughly tripling in the last 20 years (Sturm, 2007). In 1993 obesity was the second leading cause of premature death after smoking (Rashad et al. 2006).

There is evidence of a shift in the population weight distribution with disproportionate increases in high weight groups (Sturm, 2007). Epidemiologists believe that the occurrence of severe obesity is affected by behavioral changes in the general population, and policies targeted at reducing overall weight gain through changing behavior will also help contain morbid obesity (Sturm, 2007).

Food taxes are one of the most often discussed policies against obesity, and have been in use in some European countries for some years. Hungary now levies a health-oriented tax on an even broader set of products containing high amounts of salt, sugar, fat, along with all soft drinks and liquors (Cheney, 2011; Cain, 2011), and

France has introduced a soda tax of one euro penny per liter of sugar-sweetened beverages, leaving diet varieties of soda drinks exempt. (Spiegel Online, 2011).

While some countries are implementing these policies, the question of their efficacy remains largely unanswered, and there is some opposition to the overall idea of taxing unhealthy food (Gandel, 2011) citing the low impact and regressive nature of such tax policies.

Brownell et al. (2009) argue that current tax rates on sugar sweetened beverages are too low to impact consumption (e.g., 33 American states have a mean sales tax rate of 5.2%). They propose an excise tax of one cent per ounce of the sugar-sweetened beverage, which would increase the price of a 20-ounce beverage by 15-20%, and cause a minimum reduction of 10% in calorie consumption from sweetened beverages. Andreyeva et al. (2011) focused on both the public health impact and potential governmental revenues for a one cent per ounce excise tax on sugar-sweetened beverages, and estimate this tax measure could generate $79 billion over 2010-2015, and a maximum of a 24% reduction in consumption of sugar-sweetened beverages. However, a reduction in soda consumption does not necessarily imply reduced total calorie consumption, and most of these studies ignore the possibility of caloric substitution.

Subsidies are also commonly proposed as a possible anti-obesity policy tool, with some limited evidence of its effect on obesity. Horgen and Brownell (2002) studied the effect of price changes in the form of health food subsidies and health

messages in a delicatessen-style restaurant over a 14-week period, and find that price decreases are more efficient at increasing consumption of healthy foods, while health messages can have controversial effect on healthy food items sales, possibly making the items seem less tasty.

Advertising is another frequently proposed type of anti-obesity policy, aiming to change viewers' behavior through provision of specific health information or encouragement of healthier dietary patterns. Currently food is commonly advertised on television, and is the most frequently advertised product category on children's television programming (Batada et al. 2008). Children exposed to such advertising choose the featured food products at significantly higher rates than unexposed children (Borzekowski and Robinson, 2001; Young, 2003). Boynton-Jarrett et.al (2003) investigated survey data over a 19-month period from 1995 to 1997 and found that television viewing was inversely associated with intake of healthy foods, such as fruits and vegetables, among adolescents. Their study also demonstrated that commercial advertisements broadcasted during children's television programming promoted food-consumption patterns that contradict the national dietary recommendations.

Some studies directly investigated the effect of food advertising to adults. Tucker and Friedman (1989) and Tucker and Bagwell (1991) measured the relation between time spent watching television per week and obesity in 4,771 adult females and 6,138 employed adult males. The prevalence of obesity among males and females

who reported three to four hours of television viewing per day was almost twice as high as among those who watched less than an hour of television a day, and the prevalence of obesity among those who reported over four hours of television per day was more than twice as high.

Other studies focused on governmental healthy food advertising programs, such as the West Australia's Go for 2&5® campaign. The campaign significantly increased consumption of vegetables and knowledge about recommended servings of specific food groups (Pollard et al. 2008). Liaukonyte et al. (2012) used data from economic experiments to investigate consumers' reaction to various types of broad-based advertising for fruits and vegetables, and find a significant increase in WTP for these food groups, and via a simulation model conclude it will lead to an average decrease in caloric consumption. However, no study examines advertising implemented in tandem with taxes or subsidies in a common framework and the potential for a multiplicative impact from pairing these policy tools. Current literature is rich on the effects of food tax and subsidies on consumer demand, but rarely, if ever, examines changes in the overall diet. Fiscal policies aimed at improving diet and health outcomes may be less effective when 'spillovers' are present. For example, a decrease in soda consumption of an individual due to a soda tax might be offset by a selection of a chocolate cookie; the net effect on calorie consumption is ambiguous. By providing a comprehensive menu, we are able to directly observe the changes in the dietary choices of the participants. We examine the compound effect of fiscal

policies and various advertising on food consumption through directly observing changes in the menu choices. The structure of the experiment is described below.

2.3 Methodology and Experiment Design

Table 2.1. Items and respective prices in control and treatments

Item	Price in dollars		
	Control, no price change[1]	Healthy subsidy[2]	Unhealthy tax[3]
Diet Pepsi	2.00	1.60	2.00
Pepsi	2.00	2.00	2.40
Gatorade Low Calorie	2.33	1.86	2.33
Mountain Dew	2.00	2.00	2.40
Unsweetened Iced Tea	2.15	1.72	2.15
Original Iced Tea	2.15	2.15	2.59
Tropicana Lemonade	2.00	2.00	2.40
Bottled water	1.95	1.56	1.95
Green salad	7.03	5.62	7.03
Green salad with tuna	7.03	5.62	7.03
Veggie Cup with Hummus or Light Ranch	4.32	3.46	4.32
Cheese pizza	4.32	4.32	5.18
Pepperoni pizza	4.86	4.86	5.83
Local bacon cheeseburger	6.27	6.27	7.52
Lean turkey whole grain sandwich	6.16	4.93	6.16
Macaroni and cheese	3.78	3.78	4.53
Doritos nachos cheese chips	1.29	1.29	1.55
Fresh apple	1.00	0.80	1.00
Fresh Banana	1.00	0.80	1.00
Fresh orange	1.00	0.80	1.00
Chocolate chip cookies	1.83	1.83	2.20
Brownie bar	1.61	1.61	1.94

(1) Control, healthy food advertising, anti-obesity advertising
(2) Subsidy, subsidy and healthy food advertising
(3) Tax, tax and anti-obesity advertising

A total of 258 adult non-student subjects participated in the economic experiment. Subjects were paid $15 cash, plus a $10 voucher that could be spent exclusively on food items selected from a lunch menu, which we provided. The menu

featured items from a local cafeteria in four main categories: appetizers, main dishes, desserts, and drinks, with relatively healthy and unhealthy items presented in all categories (the complete list of items and their prices is provided in table 2.1). During the experiment subjects completed a series of these menus interspersed with television show excerpts with a particular type of advertising, depending on the treatment.

At the beginning of the experiment, subjects were asked to select lunch items from each of a series of lunch menus, which would be presented to them in the course of the experiment, and that they could use their $10 endowment to pay for their lunch selections. The participants were told that one of the completed menus was randomly drawn before the start of the experiment, and that the choice of lunch food items on this particular menu would become binding for them. If they spent less than their $10 endowment on the selected lunch food items on the drawn menu, they did not receive the excess in cash, and if they selected items that totaled over $10, they could use their $15 cash participation payment in addition to the $10 endowment to pay for the selected items. For the control and all six treatments, subjects were instructed to complete the first menu, and prices on the first menu were the same across all treatments. After the first menu was completed, the control group was shown a mix of excerpts from "Portlandia", a comedy series on the Independent Film Channel, and the opening ceremony for the Emmy Awards 2010 without any advertisements (see the full list of videos used in Appendix, A2), and then presented

with another menu, identical to the first one. A description of the six treatments' structure is provided below:

I. *Unhealthy foods tax treatment.* After completing the control menu, subjects watched a mix of excerpts from "Portlandia" and the opening ceremony for Emmy Awards 2010, and were then given a second menu where the prices for the unhealthy items were increased by 20% in comparison to the prices for the same items on the first control menu. Prices for healthy items were the same as the control treatment. The menu carried the following note on the top: "Some menu prices are subject to an unhealthy foods tax under the U.S. Health Promotion Policy".

II. *Healthy foods subsidy treatment.* After completing the control menu and watching a mix of excerpts from "Portlandia" and the opening ceremony for Emmy Awards 2010, subjects were given a second menu where the prices for healthy items were decreased by 20% in comparison to the control menu. Prices for the unhealthy items were the same as the control. The menu carried the following note on the top: "Some food prices are subject to a healthy foods subsidy under the U.S. Health Promotion Policy".

III. *Healthy foods advertising treatment.* After completing the control menu, subjects viewed the same television show excerpts as participants in the other treatments interspersed with healthy food advertising, which featured three minutes of advertisements, such as social advertising from Singapore and

Australia, and private advertising of American agri-businesses, encouraging increased consumption of vegetables and fruits (the list of TV-show excerpts and advertisements used in each treatment is provided in Appendix A1). Then the subjects were asked to fill out a second menu that had identical prices as the first control menu.

IV. *Anti-obesity advertising treatment.* This treatment is the same as the healthy food advertising treatment, except rather than healthy food advertisements this treatment featured three minutes of different social anti-obesity advertisements from several American States (more information about the clips used is provided in appendix, A1).

V. *Tax and anti-obesity advertising treatment.* This treatment represents a combination of the tax and anti-obesity advertising treatments. The subjects in this treatment were presented first with the control menu, and then were shown a mix of TV-show excerpts interspersed with anti-obesity advertisements followed by the unhealthy tax menu (20% increase in prices for unhealthy items and the following note on the top: "Some menu prices are subject to an unhealthy foods tax under the U.S. Health Promotion Policy"). More information about the clips used is provided in appendix, A1.

VI. *Healthy subsidy and healthy foods advertising treatment.* Similarly to the tax and anti-obesity advertising treatment, this treatment is a combination of the

control menu, followed by television show excerpts mixed with anti-obesity clips, and a final healthy subsidy menu, where the prices for the healthy items were decreased and the following note was displayed: "Some food prices are subject to a healthy foods subsidy under the U.S. Health Promotion Policy".

In the control and all six treatments the menus were presented to subjects on their computer screen, and the subjects were asked to put the number of servings they wanted to have for lunch next to the description of the desired item. The total cost of all selected items was reflected at the bottom of the menu, and in cases where it exceeded $10, the subjects received a pop-up message reminding them that they would need to pay the excess from their $15 participation payment, or change their selection of the items. The list of all items offered on the menus is provided in table 2.1, along with the price of these items on the second menu in the control and treatment groups.

Each session of the experiment began with an explanation of how the computerized menus work. After both menus were completed, participants filled out a computerized questionnaire, revealing their attitudes towards organic food, their health habits, and some demographic information. The complete list of all the questions asked in the computerized survey is presented in appendix, A2.

2.4 Data and Estimation

The data used to estimate the treatment effects were obtained by summing the nutrients for all items selected on each menu for all participants. Most of the nutritional information used for that was obtained from Food-A-Pedia, a USDA nutritional information database accessible online at https://www.supertracker.usda.gov/foodapedia.aspx; the exception was the nutritional information on beverages, which was either obtained from the manufacturer's official website (http://www.pepsicobeveragefacts.com/) or the nutritional label on the bottle, when no nutritional information was provided online by the manufacturer of the beverage. The total value of the meal selected on each menu by major nutrients, such as calories, calories from fat, cholesterol, sodium and others, along with the weight of the meal in grams, is the final result of the data conversion.

The experimental design provides pre- and post-treatment observations on every participant in both control and treatments groups and enables a true difference-in-difference approach to estimating treatment effects.

We estimate two very similar models, one focusing on the changes in the total content of selected nutrients after the treatment, and the other estimating the changes in the energy and nutrient density per gram of the meal. An example of the data structure is provided in the appendix (table A3). As the difference-in-difference approach is used in the estimation, the dependent variables are the difference in

nutrients or nutrient and energy density between the second and the first menu: a negative (positive) value implies a decrease (increase) in the nutrient content or density of the items selected in the first menu compared to those selected in the second menu while zero indicates nutrient content of the selections in the two menus did not change.

The basic equation for analyzing treatment effects is

$$\Delta Y_i = \beta_0 + \sum_{j=1}^{6} \beta_j TREAT_j + \beta_7 X_i + \varepsilon_i,$$

where ΔY_i is the difference in content or density of nutrient Y from menu 1 to menu 2 for individual i, $TREAT_j$ is a series of treatment dummies from 1 to 6, X_i is a vector of socio-demographic and other characteristics of individual i, and β_7 is a vector of estimated coefficients of Xi. In this study we focus on several basic nutrients, chosen according to the Dietary Guidelines to Americans, 2010 and Dietary Guidelines Advisory Committee Report, 2010 (ARS, 2010a, 2010b). The following nutrient and calorie content and density information was examined for each individual: total calorie content, empty calorie content, calories from fat, added sugars, cholesterol, protein, carbohydrates, fiber and sodium contents.

Due to the fact that the content of different nutrients is correlated for each individual, multiple single equation OLS regressions are statistically inefficient, and thus we employ the seemingly unrelated regression (SUR) estimation for all nine dependent variables, and the independent variables.

2.5 Nutritional information

In our study we focus our attention on nine nutrients, evaluating the change in their content separately, and below we provide some background information that helps evaluate the estimated changes in nutrient content.

2.5.1 Calories

The over-consumption of total calories coupled with very low physical activity and too much sedentary time are often identified as the main reasons behind the current obesity epidemic in the U.S. (ARS, 2010b). Recent estimates of the energy gap between energy consumed and energy expended range from 100 to 400 extra calories per day (Bouchard, 2008; Butte and Christiansen, 2007; Wang et al. 2006). One of the possible reasons for such a big gap is the systematic underestimation of energy intake, especially by overweight and obese people, up to 14-21% of the actual caloric content (Karelis et al. 2010). The relevant dietary recommendation is the reduction of total caloric intake to match the individual energy needs (ARS, 2010a).

2.5.2 Empty calories, calories from fat, added sugars

Empty calories are defined by USDA's Food-a-Pedia as "calories from food components such as added sugars and solid fats that provide little nutritional value", and are a combined measure of calories from such sources. Added sugars are sugars and syrups, among them the high fructose corn syrup (HFCS), which are added to foods or beverages during processing or preparation. Naturally occurring sugars, such as those in fruits, are not part of the added sugars, and are not included in the empty

calorie content. Solid fats come from many animal foods and can be made from vegetable oils through the process of hydrogenation, and are abundant in foods like butter, animal fats, and margarine, among others. Fats contribute nine calories per gram. Americans currently consume around 35 percent of their total calories from foods high in solid fats and added sugars, with 365 calories per day of added sugars and 433 calories per day of solid fat for an average child (NCI, 2011). According to the currently recommendations, only 5 to 15 percent of total calories should come from solid fats and added sugars (ARS, 2010b). The content of calories from total fat was also considered separately, as was the content of added sugars.

2.5.3 Cholesterol

Intakes of dietary fatty acids and cholesterol are major determinants of cardiovascular disease (CVD) and type 2 diabetes (T2D), two major causes of morbidity and mortality in Americans. Consumption of dietary cholesterol should be limited to less than 300 milligrams per day, and 200 milligrams per day for people with or at high risk for CVD or T2D (ARS, 2010a).

2.5.4 Protein

Proteins provide essential amino acids, which human bodies cannot produce on their own, and are a calorie source, contributing four calories per gram. Protein is a nutrient neither under-consumed or over-consumed by the general public, typically providing about 15 percent of total calories (NCI, 2011); however, lower calorie diets require higher proportion of protein (ARS, 2010b). Vegetarian and vegan eating patterns do

not necessarily lead to inadequate protein consumption, though such an outcome is possible.

2.5.5 Carbohydrates

Carbohydrates consist of sugars, starches, and fibers, and provide four calories per gram. Sugars and starches provide glucose, the main energy source for the brain, central nervous system, and red blood cells; however, in case of calorie over-consumption, it is converted to body fat. Sedentary people, including most Americans, should decrease consumption of energy-dense carbohydrates, especially refined, sugar-dense sources, to balance energy needs (ARS, 2010b).

2.5.6 Fiber

The current intake of dietary fiber is inadequate in most adults and children in the U.S, with less than 3% to 6% of the population consuming the recommended daily amount or greater (ARS, 2010c). Diets high in fiber have been linked to reduced risk of coronary heart disease, diabetes, colon cancer, obesity, and other chronic diseases, and foods high in dietary fiber generally are more satiating than low fiber foods, important when limiting calorie consumption to encourage weight-loss.

2.5.7 Sodium

Americans currently consume excessively high amounts of sodium, with 97 percent of the population consuming daily levels associated with higher health risks. Nearly a third (32%) of adult Americans already have hypertension, and roughly

another third are pre-hypertensive (Wang and Wang, 2004; Cutler et al. 2008), and some studies show that a reduced intake of sodium can have a significant negative effect on blood pressure in both hypertensive and healthy people (He and MacGregor, 2004). In 2005, the recommended daily sodium intake was not higher than 2,300 milligrams for the general adult population and even less for certain population groups and people with or at risk of hypertension.

2.6 Results

Table 2.2 presents the mean and standard deviation of the change in total caloric consumption and the demographic characteristics across treatments. Overall, 73.3% of all participants were female and 74% were Caucasian, which is very close to the existing statistics on primary grocery and food shoppers (FMI, 2006). In our sample, over 70% of participants were over 31 years old, with almost 35.9% having an income level of $40,000 to $80,000, 22.9% - income level of $80,000 to $120,000, while 22.5% had a family income of less than $40,000 a year.

Table 2.2. Descriptive Statistics (Means and St. Dev.) of Selected Variables by Treatment

	Treatment							
	All	Control	Unhealthy food tax	Healthy food subsidy	Anti-obesity ads	Healthy food ads	Tax and anti-obesity ads	Subsidy and healthy ads
Average change in calories	-33.245 (249.495)	48.882 (288.844)	-152.088 (264.289)	64.897 (211.559)	-44.162 (162.672)	-85.477 (257.367)	-147.333 (201.968)	91.324 (233.831)
Average change in beverage weight	-2.701 (283.566)	-73.559 (280.417)	-31.529 (287.180)	9.744 (285.284)	38.378 (233.447)	0 (258.976)	-12.861 (304.825	45.265 (339.711)
Average change in solid foods weight	25.902 (121.839)	35.588 (97.475)	-43.914 (97.967)	88.669 (133.983)	1.141 (100.078)	3.768 (133.56)	4.633 (100.658)	92.141 (121.628)
# of items ordered, menu 2	2.915 (0.904)	2.941 (0.547)	2.382 (0.652)	3.385 (1.067)	2.757 (0.863)	2.727 (0.899)	2.806 (0.577)	3.412 (1.104)
Female	0.733 (0.443)	0.559 (0.504)	0.735 (0.448)	0.769 (0.427)	0.865 (0.347)	0.773 (0.424)	0.750 (0.439)	0.647 (0.485)
Age less 20	0.016 (0.124)	0.059 (0.239)	0 (0)	0 (0)	0 (0)	0 (0)	0.028 (0.167)	0.029 (0.171)
Age 21-30	0.275 (0.447)	0.618 (0.493)	0.294 (0.462)	0.154 (0.366)	0.270 (0.450)	0.182 (0.390)	0.083 (0.280)	0.382 (0.493)
Age 31-40	0.174 (0.380)	0.088 (0.288)	0.176 (0.387)	0.128 (0.339)	0.162 (0.374)	0.250 (0.438)	0.222 (0.422)	0.176 (0.387)
Age 41-50	0.256 (0.437)	0.059 (0.239)	0.265 (0.448)	0.359 (0.486)	0.270 (0.450)	0.273 (0.451)	0.333 (0.478)	0.206 (0.410)
Age over 50	0.279 (0.449)	0.176 (0.387)	0.265 (0.448)	0.359 (0.486)	0.297 (0.463)	0.295 (0.462)	0.333 (0.478)	0.206 (0.410)
Married	0.477 (0.500)	0.235 (0.430)	0.471 (0.507)	0.410 (0.498)	0.514 (0.507)	0.523 (0.505)	0.667 (0.478)	0.500 (0.506)
Children	0.527 (0.500)	0.176 (0.387)	0.529 (0.507)	0.641 (0.485)	0.649 (0.484)	0.591 (0.497)	0.639 (0.487)	0.412 (0.499)
Caucasian	0.744 (0.437)	0.529 (0.507)	0.765 (0.431)	0.846 (0.366)	0.757 (0.435)	0.795 (0.408)	0.750 (0.439)	0.735 (0.448)

Table 2.2 (Continued)

African American	0.031	0.088	0.059	0	0	0.045	0.028	0
	(0.174)	(0.288)	(0.239)	(0)	(0)	(0.211)	(0.167)	(0)
Asian	0.159	0.324	0.118	0.077	0.216	0.068	0.167	0.176
	(0.366)	(0.475)	(0.327)	(0.270)	(0.417)	(0.255)	(0.378)	(0.387)
Hispanic	0.027	0.059	0.029	0	0.027	0.045	0	0.029
	(0.163)	(0.239)	(0.171)	(0)	(0.164)	(0.211)	(0)	(0.171)
Smoke	0.047	0.059	0.088	0.051	0.054	0.045	0	0.029
	(0.211)	(0.239)	(0.288)	(0.223)	(0.229)	(0.211)	(0)	(0.171)
Alcohol	0.783	0.735	0.824	0.795	0.784	0.818	0.722	0.794
	(0.413)	(0.448)	(0.387)	(0.409)	(0.417)	(0.390)	(0.454)	(0.410)
Income less than $40,000	0.225	0.382	0.265	0.205	0.216	0.227	0.083	0.206
	(0.418)	(0.493)	(0.448)	(0.409)	(0.417)	(0.424)	(0.280)	(0.410)
Income $40,001-$80,000	0.349	0.265	0.353	0.410	0.513	0.386	0.250	0.235
	(0.478)	(0.448)	(0.485)	(0.498)	(0.507)	(0.493)	(0.439)	(0.431)
Income $80,001-$120,000	0.229	0.147	0.265	0.282	0.081	0.273	0.361	0.176
	(0.421)	(0.359)	(0.448(	(0.456)	(0.277)	(0.451)	(0.487)	(0.327)
Only high school	0.120	0.147	0.118	0.250	0.135	0.091	0.111	0.029
	(0.326)	(0.359)	(0.327)	(0.409)	(0.347)	(0.291)	(0.319)	(0.171)
Undergraduate degree	0.337	0.471	0.353	0.308	0.270	0.409	0.139	0.412
	(0.474)	(0.507)	(0.485)	(0.468)	(0.450)	(0.497)	(0.351)	(0.500)
Graduate degree	0.399	0.353	0.353	0.359	0.351	0.472	0.639	0.500
	(0.491)	(0.485)	(0.485)	(0.486)	(0.484)	(0.451)	(0.487)	(0.508)
Slightly overweight, overweight or obese	0.438	0.265	0.529	0.513	0.432	0.500	0.500	0.294
	(0.497)	(0.448)	(0.507)	(0.506)	(0.502)	(0.506)	(0.507)	(0.462)
# of subjects	258	34	34	39	37	44	36	34

Most of the participants were non-smokers (95.3%), who at least occasionally consumed alcohol (78.3%). It is interesting to note that, on average, most people chose meals with higher calorie content on the second menu in the control group and even more so in both treatments with price subsidies on healthy foods items. On the other hand, the mean change in calorie content for participants in the unhealthy food tax treatment, anti-obesity ads, healthy foods ads and the tax and anti-obesity ads was negative, with the tax and the tax and anti-obesity ads treatments having the biggest reduction of calorie content, 152 calories and 147 calories respectively.

2.6.1 Estimation of changes in total nutrient content

The estimation results from the SUR model[2] on total nutrient content for all participants are presented in table 2.3. First looking at the change in calorie content of the meal, the unhealthy foods tax treatment, healthy foods advertising treatment, and the tax and anti-obesity advertising treatment all had negative and statistically significant effects on calorie content. The combination of the unhealthy foods tax

[2] The SUR model was also estimated without the demographic and socioeconomic control variables and very similar results were found in terms of the impacts of the treatment variables, the results are provided in table 2.4.

Table 2.3. Estimation results, total energy and nutrient content, demographic control

Variables	Calories	Empty calories	Calories from fat	Cholesterol (mg)	Added Sugar (g)
R-squared	0.2534	0.1531	0.2300	0.2432	0.1553
Unhealthy food tax treatment	-194.324***	-51.790	-90.319***	-20.092**	-3.330
	(58.385)	(33.413)	(34.043)	(8.738)	(5.412)
Healthy food subsidy treatment	4.489	-0.883	-24.770	0.556	2.363
	(58.460)	(33.455)	(34.086)	(8.749)	(5.419)
Anti-obesity advertising treatment	-69.569	6.761	-31.744	-7.329	7.993
	(57.912)	(33.142)	(33.767)	(8.667)	(5.368)
Healthy food advertising treatment	-130.950**	-25.501	-78.802**	-23.081***	5.334
	(56.235)	(32.182)	(32.789)	(8.416)	(5.213)
Tax and anti-obesity advertising treatment	-222.950***	-67.228*	-116.756***	-23.399***	-2.211
	(60.208)	(34.456)	(35.106)	(9.011)	(5.581)
Healthy subsidy and healthy advertising treatment	37.631	5.551	-9.203	2.833	4.952
	(56.332)	(32.23725)	(32.84538)	(8.431)	(5.221)

	Protein (g)	Carbohydrates (g)	Fiber (g)	Sodium (mg)
R-squared	0.2353	0.1972	0.2115	0.1887
Unhealthy food tax treatment	-6.477**	-25.761***	-2.121***	-127.847
	(2.833)	(9.186)	(0.614)	(121.117)
Healthy food subsidy treatment	1.009	2.956	0.520	47.153
	(2.836)	(9.197)	(0.615)	(121.273)
Anti-obesity advertising treatment	-5.249*	-2.041	-0.909	-178.930
	(2.810)	(9.111)	(0.609)	(120.135)
Healthy food advertising treatment	-7.244***	-8.283	-0.653	-185.535
	(2.728)	(8.847)	(0.591)	(116.657)
Tax and anti-obesity advertising treatment	-5.272*	-26.857***	-1.637***	-167.815
	(2.921)	(9.472)	(0.633)	(124.898)
Healthy subsidy and healthy advertising treatment	3.841	3.068	0.498	184.354
	(2.733)	(8.862)	(0.592)	(116.857)

Table 2.3(Continued)

# Observations	258
Socio-economic dummies	gender, age, race, marital status, children, income level, educational level
Other dummies	alcohol and smoking habits, self-assessed weight status, preferences over organic food, rating of the shown excerpts, rating of the menu choices

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4. Estimation results, total energy and nutrient content, no demographic control

Variables

	Calories	Empty calories	Calories from fat	Cholesterol (mg)	Added Sugar (g)
R-squared	0.1379	0.0481	0.0685	0.0865	0.0252
Unhealthy food tax treatment	-200.971***	-69.971**	-88.412***	-19.853**	-5.985
	(56.076)	(31.695)	(33.373)	(8.559)	(5.242)
Healthy food subsidy treatment	16.015	-10.370	-13.385	5.337	0.733
	(54.249)	(30.662)	(32.286)	(8.280)	(5.071)
Anti-obesity advertising treatment	-93.045*	-24.359	-39.162	-6.457	1.815
	(54.928)	(31.046)	(32.690)	(8.384)	(5.135)
Healthy food advertising treatment	-134.356**	-43.611	-71.386**	-20.584**	1.811
	(56.235)	(29.840)	(31.420)	(8.0582)	(4.935)
Tax and anti-obesity advertising treatment	-196.216***	-85.588***	-93.750***	-15.943*	-7.182
	(55.292)	(31.252)	(32.907)	(8.440)	(5.169)
Healthy subsidy and healthy advertising treatment	42.441	-13.088 (31.695)	0.263	6.588	0.750
	(56.076)		(33.373)	(8.559)	(5.242)

	Protein (g)	Carbohydrates (g)	Fiber (g)	Sodium (mg)
R-squared	0.1229	0.0933	0.1170	0.0825
Unhealthy food tax treatment	-6.941**	-25.897***	-1.647***	-215.059*
	(2.714)	(8.768)	(0.589)	(114.833)
Healthy food subsidy treatment	2.106	3.512	1.063*	20.051
	(2.625)	(8.482)	(0.570)	(111.091)
Anti-obesity advertising treatment	-4.366	-8.018	-0.419	-192.990*
	(2.658)	(8.588)	(0.577)	(112.481)
Healthy food advertising treatment	-7.085***	-9.652	-0.091	-258.024**
	(2.555)	(8.254)	(0.555)	(108.111)
Tax and anti-obesity advertising treatment	-2.815	-26.734***	-0.806	-156.678
	(2.676)	(8.645)	(0.581)	(113.226)
Healthy subsidy and healthy advertising treatment	4.735*	2.824	1.059*	160.912 (114.833)
	(2.714)	(8.768)	(0.589)	

Table 2.4(Continued)

# Observations	258
Socio-economic dummies	none
Other dummies	none

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

with anti-obesity advertising had the largest impact on reducing calories consumed. Subjects in this treatment consumed 223 fewer calories than the control group, which represents a reduction of 31.3% in total lunch calories (all percentage change estimates cited in the text are based on the comparison to second menu selection of the control group, the average value for those are presented in table 2.5). The unhealthy food tax by itself had the next largest negative effect on calories. Subjects in this treatment consumed 194 (or 27.2%) fewer calories relative to the control group. Healthy food advertising also reduced calories consumed, but had the smallest impact of the three statistically significant treatments. Subjects in this treatment consumed 131 fewer calories, which represents an 18.4% reduction compared to the control.

Table 2.5. Average energy and nutrient content and density, control group, second menu

Variables

	Calories	Empty calories	Calories from fat	Cholesterol (mg)
Total content	712.853	184.059	203.824	72.206
	(258.601)	(164.273)	(161.619)	(33.898)
Density[1]	1.134	0.256	0.320748041	0.103
	(0.590)	(0.214)	(0.275)	(0.042)

	Protein (g)	Carbohydrates (g)	Fiber (g)	Sodium (mg)
Total content	34.324	85.059	5.471	1242.529
	(10.840)	(38.347)	(2.178)	(470.055)
Density[1]	0.053	0.117	0.0084	1.834
	(0.025)	(0.031)	(0.0040)	(0.690)

	Added Sugar (g)
Total content	20.191
	(24.520)
Density[1]	0.025
	(0.028)

(1) Density per gram for calories, empty calories, calories from fat, and per calorie for other nutrients

A test of statistical significance among these three treatments indicated that all three treatments were significantly different from each other with the combined tax–anti-obesity advertising treatment having the largest impact followed by the tax and then the healthy food advertising treatments. The healthy food subsidy, anti-obesity advertising, and combined healthy food subsidy and healthy food advertising treatments were all statistically insignificant.

The change in empty calorie content can improve our understanding of the change in the actual nutritional value of the meal beyond total calories. While the direction of the estimated treatment effects remained the same as for calories, only the tax and anti-obesity advertising treatment had a significant impact at a 10% significance level, with a 67-calorie reduction, or 36.4% reduction compared to the second menu selection in the control group.

Another similar measure is the content of calories from fat, which is often considered to be an indication of less healthy foods; however, most of the current literature suggests limiting consumption of solid fats, which are high in saturated and trans fats (NCI, 2011; ARS, 2010b). Three treatments had significant negative effects on fat-derived calories in a meal, with the tax and anti-obesity advertising treatment again having the strongest effect of almost 117 calories, or 57.4% reduction compared to the control group, closely followed by the unhealthy foods tax treatment, which reduced fat by 90 calories (44.1% reduction), and healthy foods advertising treatment, which reduced fat by 79 calories (38.7% less than the control group).

Cholesterol content, consistent with the results on calories, was significantly reduced in the same three treatments, but this time the healthy foods advertising and the tax and anti-obesity advertising both yielded significant and similar results, leading to a decline in cholesterol content of 23 and 23.4 mg respectively, which is 31.9% and 32.4% less than in the control group. The unhealthy foods tax treatment following closely behind with an estimated negative impact of 20 mg., or 27.8% in cholesterol compared to the second menu of the control group.

Several treatments had a significant negative impact on protein content, with the healthy foods advertising treatment having the strongest effect of 7.2 grams, followed by the tax treatment with a decrease of 6.5 grams, the tax and anti-obesity advertising, with a reduction of 5.3 grams, and the anti-obesity advertising treatments, with 5.2 less grams of protein than in the control. Compared to the protein content of the second menu selection in the control group, participants in the healthy advertising treatment consumed 20.1% less protein, subjects in the tax treatment consumed 19% less protein, and those in the tax and anti-obesity advertising and the anti-obesity advertising treatments selected meals with 15.5% and 15.2% less protein respectively.

The unhealthy foods tax and the tax and anti-obesity advertising treatment were the only treatments to have a significant effect on carbohydrate content, leading to similar reductions of 26 and 27 grams respectively, or 30.5% and 31.8% less than in the control group. Both of the treatments also had a significant negative impact on the fiber content of the meal (2 g. and 1.6 g., or 36.4% and 29.1% less fiber than the

control group), while the healthy advertising treatments did not have a significant impact on fiber content.

Neither the added sugar nor the sodium content changed significantly in any of the treatments.

2.6.2 Estimation of changes in nutrient and energy density of the meal

Though reduction of total calorie intake is one of the most important steps to reduce obesity prevalence (ARS, 2010b), the energy and nutrient density of foods consumed also plays an important role in managing one's weight. The 2010 Dietary Guidelines for Americans (ARS, 2010a) encourages low calorie density eating patterns, citing improved weight loss and weight maintenance, while promoting foods higher in nutrient density. Additionally, some research suggests that the negative health effects of high energy density are independent of the macronutrient composition of the diet (Kant and Graubard, 2005; Mendoza et al. 2007). Nutrient dense diets, on the other hand, are associated with healthier dietary patterns (ARS, 2010b) and may lessen the feeling of hunger, leading to weight loss and improved health over time (Fuhrman et al. 2010). In this light, it is necessary to consider the changes in both energy and nutrient density along with the changes in total calorie and nutrient content to provide a more complete picture of the possible policy impact on obesity. We define energy density as calories per gram for the entire meal (including beverages), calculated by dividing the total calories of the meal by the total meal weight. There are different scoring systems and metrics available for measuring

nutrient density, however there is currently no one commonly accepted measure. We chose to define nutrient density as the average content of selected nutrient per calorie content of the meal following some of the current nutrition literature (Drewnowski, 2009). While more sophisticated methods might be needed to identify the nutrient density score for individual foods, our definition allows for easy and consistent evaluation of change in nutrient density from menu one to menu two. We include beverages in our density measures, as drinks on our menus are significant sources of calories, empty calories, sodium, added sugars and carbohydrates. We provide information on average changes in weight from both beverages and solid foods per treatment in table 2.2.

The estimation results from the SUR model on nutrient and energy density of the meal per gram for all participants are presented in table 2.6. Most treatments, with the exclusion of the healthy subsidy and healthy advertising treatment, significantly reduced the overall energy density the meal. The healthy food subsidy and the healthy food advertising treatment both significantly reduced the energy density by approximately 42 and 43 calories per one hundred grams, or 37% and 38% compared to the energy density in the second menu of the control group, respectively. The anti-obesity advertising and the tax and anti-obesity advertising treatments reduced energy density by 45 and 44 calories per one hundred grams, or 40% and 39% compared to the second menu in the control group. The lowest significant reduction in energy density was associated with the unhealthy food tax, which reduced energy density by

Table 2.6. Estimation results, energy density per gram and nutrient density per calorie, SUR model, demographic controls

Variables	Calories	Empty calories	Calories from fat	Cholesterol (mg)	Added Sugar (g)
R-squared	0.1587	0.1339	0.1729	0.1708	0.1762
Unhealthy food tax treatment	-0.349*	-0.051	-0.192**	-0.0031	0.0070
	(0.186)	(0.066)	(0.090)	(0.0129)	(0.0079)
Healthy food subsidy treatment	-0.422**	-0.101	-0.185**	0.0001	0.0017
	(0.1846432)	(0.065)	(0.089)	(0.0128)	(0.0079)
Anti-obesity advertising treatment	-0.453**	-0.018	-0.148*	-0.0001	0.0138*
	(0.186)	(0.066)	(0.089)	(0.0134)	(0.0079)
Healthy food advertising treatment	-0.429**	-0.099	-0.205**	-0.0170	0.0153**
	(0.179)	(0.064)	(0.086)	(0.0125)	(0.0077)
Tax and anti-obesity advertising treatment	-0.439**	-0.101	-0.203**	0.0016	-0.0035
	(0.193)	(0.069)	(0.093)	(0.0134)	(0.0046)
Healthy subsidy and healthy advertising treatment	0.0036	0.039	0.034	0.013	0.0121
	(0.179)	(0.063)	(0.086)	(0.0124)	(0.0076)

	Protein (g)	Carbohydrates (g)	Fiber (g)	Sodium (mg)
R-squared	0.1463	0.1572	0.1418	0.1460
Unhealthy food tax treatment	-0.0017	-0.0102	-0.0025	0.320
	(0.0069)	(0.0135)	(0.0020)	(0.295)
Healthy food subsidy treatment	-0.0031	0.0113	0.0018	-0.206
	(0.0068)	(0.0114)	(0.0020)	(0.292)
Anti-obesity advertising treatment	-0.0062	0.0045	-0.0007	-0.181
	(0.0069)	(0.0135)	(0.0020)	(0.294)
Healthy food advertising treatment	-0.0039	0.0209	0.0018	-0.135
	(0.0069)	(0.0130)	(0.0019)	(0.284)
Tax and anti-obesity advertising treatment	0.0096	-0.0056	0.0001	0.302
	(0.0071)	(0.0140)	(0.0021)	(0.305)
Healthy subsidy and healthy advertising treatment	0.0072	-0.0043	-0.0019	0.0083
	(0.0066)	(0.0129)	(0.0020)	(0.305)

Table 2.6 Continued	
# Observations	258
Socio-economic dummies	gender, age, race, marital status, children, income level, educational level
Other dummies	alcohol and smoking habits, self-assessed weight status, preferences over organic food, rating of the shown excerpts, rating of the menu choices

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

35 calories per one hundred grams, or 31% compared to the second menu selection in the control group, significant at a 10% level.

The changes in calories from fat density are similar to those in the overall energy density. The unhealthy food tax and the tax and anti-obesity advertising treatments led to a 19 and 20 calories per hundred gram reduction in energy density, which is a 59% and 63% reduction in density compared to the second menu in the control group. The calories from fat density were also significantly and negatively affected by both the healthy food subsidy treatment and the healthy food advertising treatment, decreasing by approximately 19 and 20 calories, respectively, per one hundred grams, or 59% and 63% reductions compared to the control. The anti-obesity advertising treatment had the smallest negative effect of 15 calories per one hundred grams, a reduction of 47% compared to the control, significant at a 10% level.

The empty calories density per gram of the meal was not significantly impacted by any of the treatments.

Most of the nutrient densities were not significantly affected by any of the treatments. The only exception is the added sugar density, which increased by 1.4 and 1.5 in the anti-obesity and the healthy foods advertising treatments respectively.

2.7 Discussion

The unhealthy foods tax treatment and the unhealthy foods tax and anti-obesity advertising treatments had the strongest impact on nutrient content of the meal, with more nutrient categories affected by these treatments than by any of the others.

The unhealthy foods tax, which participants experienced as a 20% excise tax, led to several desirable changes in nutritional composition of the meal, with calories, calories from fat and cholesterol reduced. While the total content of fiber and protein was significantly reduced by both treatments, we observed no significant change in these nutrients' densities. This suggests no negative impact on the dietary composition of the diet.

The unhealthy foods tax combined with anti-obesity advertising had an even stronger significant effect on total calories, calorie density, calories from fat and cholesterol. Moreover, this treatment was the only one to significantly reduce the empty calorie content of the meal, which implies a significant reduction in calories from added sugars or solid fats. Similar to the unhealthy tax alone, this treatment negatively affected the total content of protein and carbohydrates in the meal, as well as fiber, while the respective nutrient densities remained unchanged.

The treatment having the next strongest impact on a range of different nutrients is the healthy food advertising treatment. With a negative and significant impact (though in some cases relatively smaller than those of the treatments discussed above) on total calories, calories from fat, cholesterol and protein content, this

treatment does not have a significant impact on total carbohydrates and fiber content, making it the least controversial treatment in terms of the overall change of in the nutritional composition of the meal.

Among the nine nutrients selected for this analysis, the total content of two, added sugars and sodium, – was not significantly impacted by any of the treatments. Current research suggests that obesity is caused by a diet high in added sugars and fats, and low in fiber (ARS, 2010b; Du et al. 2010; Tucker and Thomas, 2009), so the lack of change in the added sugar content and negative change in fiber content are worrisome and possibly represent adverse unintended effects for some of the proposed policies. Lustig et al. 2012, argue that while obesity is a metabolic dysfunction, associated with such chronic diseases as the heart disease, cancer, diabetes and hypertension, it is often not the cause of these illnesses. The authors believe that the focus should be on added sugars, which are currently just part of the "empty calories" USDA classification. With consumption of sugar tripling worldwide in the past 50 years, and a growing body of research suggesting toxicity, adverse effects of sugar on health, and potential for sugar dependency, the authors suggest taxation and healthy food subsidization among other interventions to curb sugar consumption. However, our study indicates that neither the unhealthy foods 20% excise tax, nor healthy foods 20% excise subsidy, nor the other often-proposed policies directly affect added sugars consumption. Moreover, added sugar density increased in the healthy food advertising treatment and the anti-obesity advertising

treatment. One reason for this lack of effect can be participants' generally low knowledge about added sugars content and its adverse effects on health (Variyam et al. 2001). Consumption of dietary salt is similarly not only linked to hypertension, but also associated with a number of negative effects on the cardiovascular system, such as higher possibility of strokes and more severe cardiac failure, along with other negative effects on bone and calcium metabolism in the body (de Wardener and MacGregor, 2002).

Among all six treatment considered, neither of the two including a healthy food 20% excise subsidy were effective. While some researchers suggest the use of healthy food subsidies as a viable anti-obesity measure (Horgen and Brownell, 2002), others find these fiscal policies to have low or insignificant effects on obesity (Powell and Chaloupka, 2009). Horgen and Brownell (2002) estimate moderate to strong increases in sales of "healthy items" subject to a 10% to 25% subsidy; however, they focus on item sales, and due to limitations in the data availability, their field study did not consider the possibility that customers are buying other less healthy items to go along with the promoted healthy items.

Our results suggest that neither the nutrient content, nor the nutrient and energy densities of the meal were significantly impacted by the two treatments with subsidy. In line with the possible income effects of subsidies (in all treatments with subsidy the price for some items were reduced 20%, and the budget was effectively increased), we observe that the average number of items ordered on the second menu

(see table 2.2) is higher and significantly different at the 5% significance level from the control group for both the healthy food subsidy and the healthy food subsidy and healthy advertising treatments.

It is worth noting that while healthy food advertising when used on its own is one of the most effective treatments, its effect becomes insignificant when combined with a healthy food subsidy. One of the possible explanations is that the income effect plays a stronger role in defining participants' behavior than the positively framed messages of the healthy food advertising, leading to an increased number of items chosen in one meal. We observe participants ordering an average of 3.41 ordered items on the second menu of this treatment compared to 2.92 items on the second menu for the control group. In the healthy foods advertising treatment the average number of ordered items was very close to that of the control group – 2.8 items. This suggests that under the effect of subsidy, participants bought more items overall, instead of only switching towards subsidized items.

The healthy food advertising treatment had a strong effect on nutrient content of the selected meals, but anti-obesity advertising on its own did not have the same effect. Some research suggests that negatively-framed advertising messages that are aimed at changing peoples' behavior can have the unintended consequence of inducing resistance and reducing the probability of self-change, especially when advertising is emotive, as well as framed and perceived as a health threat (Brown, 2001; Brown and Locker, 2009). The use of the so called "fear appeals", emotive

messages with information on possible health risks aimed at scaring the message's recipients into changing their behavior to a healthier one, is generally not recommended in health promotion campaigns (Ruiter et al. 2001). Our results are in line with this literature, as the anti-obesity advertising treatment, which included three minutes of emotive negatively framed anti-obesity advertising, had little effect on nutrient content, especially compared with the healthy foods advertising treatment.

However, when combined with an unhealthy food tax, anti-obesity advertising had the strongest effect of all in total calorie and calories from fat reduction. Moreover, it was the only treatment to have a significant negative impact on the empty calorie content; this phenomenon may be driven by behavioral responses. The additional economic incentive of the 20% excise tax may have steered participants to more rational reactions, while the anti-obesity ads on their own may have evoked defensive emotional reactions from the participants, limiting the extent of the behavioral change (Sherman et al. 2000; Liberman and Chaiken, 1992). When combined, these two policies might have had several secondary effects.

First, some evidence indicates that the lack of easy to follow guidelines and possible damage to one's self-image might be primary reasons behind resistance to health promotion messages (Ruiter et al. 2001). The tax in the treatment identified unhealthy food items, making it easier to avoid them and make a judgment in relation to the healthiness of the item.

Second, according to some research, highly relevant negative information often leads to defensive systematic processing of the message, probably because the person in the risk group, for whom the provided information would be very relevant, anticipates some damage to her self-image (Sherman et al. 2000; Liberman and Chaiken, 1992). Personally relevant health messages that trigger defensive message processing leave people unconvinced of the need to change. Anti-obesity ads are specifically tailored so that viewers recognize they are in the risk group and change their behavior, probably triggering the defensive processing of the anti-obesity message (Ruiter et al. 2001). However, the presence of tax gives a different motivation to change the lunch selection (higher prices), one that does not necessarily require recognizing oneself as an unhealthy eater and may therefore limit the potential for biased and defensive processing of the negative information. Additionally, some evidence suggests that actual precautionary action suggested in the health promotion campaigns is more likely to occur in presence of both clear instructions and fear appeals, in line with the observed outcomes in this study (fear appeals, precautionary messages and possible behavioral reactions are discussed in detail in Ruiter et al. 2001).

2.8 Concluding Remarks and Policy Implications

The main objective of our research was to obtain a better understanding of the likely impact of some proposed anti-obesity policies on nutrient consumption patterns in order to identify the most effective strategies for improving current dietary patterns

and reducing obesity. Using experimental methods, we estimated the effects of six anti-obesity policies on nutrient composition and density of selected meals, measured across nine different nutrients or nutrient groups. We find some policies, such as unhealthy foods tax and unhealthy food tax in combination with anti-obesity advertising, are very effective in reducing some of the target nutrients (including calories and calories from fat or cholesterol). All treatments that included healthy food subsidies did not have any significant effect on the nutrient composition of the meal selected by our participants, most likely due to income effects of the 20% excise subsidy – the average number of ordered items in treatments with subsidy was around 3.4 in both treatments, compared to 2.9 on the second menu in the control treatment.

Our paper adds to the existing literature by simultaneously examining the effect of six often-proposed policies and studying their effect on nutrient consumption. Most previous studies either modeled demand effects through available food price elasticity estimates, as in case of fruit and vegetable advertising effects on consumption and obesity (Liaukonyte et al. 2012), food taxes and subsidies effects (Kuchler et al. 2005; Chouinard et al. 2007; Andreyeva et al. 2011), or observed changes in the number of sold items under specific healthy food subsidies (Horgen and Brownell, 2002). Our study observes the actual change in the nutrient composition of the whole meal, estimating effects not only on calorie or added sugar consumption, but also other nutrients such as fat, empty calories (saturated fats and added sugar), cholesterol, sodium, protein, carbohydrates and protein.

Our study contributes to the ongoing policy debate by allowing direct comparison of such anti-obesity policies as taxes on unhealthy foods, subsidies on healthy foods, anti-obesity advertising and healthy foods advertising, and two combinations of those: simultaneous application of tax and anti-obesity advertising, or subsidy and healthy foods advertising. One major result of our study is the possible negative effect on the overall diet composition of such policies as unhealthy food tax or the unhealthy food tax together with anti-obesity advertising; the second major finding is the lack of change in the content of such nutrients as added sugars or sodium. Another interesting implication of our study is that when economic measures, such as tax and subsidy, were combined with anti-obesity and healthy foods advertising, respectively, their effect was not a simple combination of these policies' effects. For example, anti-obesity advertising on its own is not effective in changing people's behavior, in line with the existing literature on the effect of fear appeals in health promotion campaigns; however, the resistance and denial of the anti-obesity advertising messages can be mitigated through use of unhealthy food tax, providing additional reasons for behavioral change and appealing to people's rationality. Working in synergy, tax and anti-obesity advertising have the strongest effect on total calories, empty calories and many other nutrients. On the other hand, healthy food advertising is one of the most effective policies on its own; but when combined with subsidy, the effect of the healthy food advertising is negated by the strong income effect of the subsidy. Our results imply that policy makers should be mindful of the

possible interaction effects of the proposed measures, and more research is needed to explore these possible effects.

Our study highlights the need for detailed examination of possible unexpected effects and synergistic outcomes of different anti-obesity policies. While our research provides some information on the actual change in the nutrient content of the meal under different policies, further research should examine long-term effects of such policies and ideally observe nutrient change across all meals in a day for an extended period of time. Our estimates should be interpreted as the upper bound of the possible policy effects, both because the effect is likely to wear off over time as people become more used to the proposed policies, and because the experimental setting limits outside influences such as advertising with conflicting messages. One should also remember that our research conclusions are based on experimental data obtained in a laboratory, and not in the field. As noted by Levitt and List (2007), laboratory results are not always supported in the field; however, they often serve as a good indication of the relative effects of the proposed measures. Overall, to our knowledge, these results provide the first comparison of anti-obesity policies' effects on nutrient content of a meal; however, these results should be interpreted with caution due to the experimental nature of our data.

REFERENCES

Abend, L. 2011. Beating Butter: Denmark Imposes the World's First Fat Tax. *Time*, http://www.time.com/time/world/article/0,8599,2096185-1,00.html. Accessed on Nov. 06, 2012

Agricultural Research Service (ARS). 2010a. Dietary Guidelines for Americans, 2010. *United States Department of Agriculture, United States Department of Health and Human Services.*

———. 2010b. Report of the Dietary Guidelines Advisory Committee on the Dietary Guidelines for Americans, 2010. To the Secretary of Agriculture and the Secretary of Health and Human Services. *United States Department of Agriculture, United States Department of Health and Human Services.*

———. 2010c. Dietary Fiber (G): Usual Intakes from Food and Water, 2003-2006, Compared to Adequate Intakes. *Food Surveys Research Group, ARS, USDA*. Part of the What We Eat in America, NHANES 2003-2006.

American Heart Association (AHA), Samuel S. Gidding, Barbara A. Dennison, Leann L. Birch, Stephen R. Daniels, Matthew W. Gilman, Alice H. Lichtenstein, Karyl Thomas Rattay, Julia Steinberger, Nicolas Stettler, and L. V. Horn. 2006. Dietary Recommendations for Children and Adolescents: A Guide for Practitioners. *Pediatrics* 117 (2): 544-59.

Andreyeva, T., F. J. Chaloupka, and K. D. Brownell. 2011. Estimating the Potential of Taxes on Sugar-Sweetened Beverages to Reduce Consumption and Generate Revenue. *Preventive Medicine* 52 (6): 413-16.

Batada, A., M. D. Seitz, M. G. Wootan, and M. Story. 2008. Nine out of 10 Food Advertisements Shown During Saturday Morning Children's Television Programming Are for Foods High in Fat, Sodium, or Added Sugars, or Low in Nutrients. *Journal of the American Dietetic Association* 108 (4): 673-78.

Borzekowski, D. L. G., and T. N. Robinson. 2001. The 30-Second Effect: An Experiment Revealing the Impact of Television Commercials on Food Preferences of Preschoolers. *Journal of the American Diabetes Association* 101 (1): 42-46.

Bouchard, C. 2008. The Magnitude of the Energy Imbalance in Obesity Is Generally Underestimated. *International Journal of Obesity* 32: 879-80.

Boynton-Jarrett, R., T. N. Thomas, K. E. Peterson, J. Wiecha, A. M.Sobol, and S. L. Gortmaker. 2003. Impact of Television Viewing Patterns on Fruit and Vegetable Consumption among Adolescents. *Pediatrics* 112 (6): 1321-26.

Brown, S., and E. Locker. 2009. Defensive Responses to an Emotive Anti-Alcohol Message. *Psychology & Health* 24 (5): 517-28.

Brown, S. L. 2001. Emotive Health Advertising and Message Resistance. *Australian Psychologist* 36 (3): 193-99.

Brownell, K. D., T. Farley, W. C. Willett, B. M. Popkin, F. J. Chaloupka, J. W. Thompson, and D. S. Ludwig. 2009. The Public Health and Economic Benefits of Taxing Sugar-Sweetened Beverages. *New England Journal of Medicine* 361 (16): 1599-605.

Butte, N. F., and E. Christiansen. 2007. Energy Imbalance Underlying the Development of Childhood Obesity. *Obesity* 15 (12): 3056-66.

Cain, P. 2011. Hungary for A "Fat Tax". *Global Post*, http://www.globalpost.com/dispatch/news/regions/europe/110620/hungary-fat-tax-junk-food. Accessed on Nov. 06, 2012.

Cheney, C. 2011. Battling the Couch Potatoes: Hungary Introduces 'Fat Tax'. *Spiegel Online*, http://www.spiegel.de/international/europe/battling-the-couch-potatoes-hungary-introduces-fat-tax-a-783862.html. Accessed on Nov. 06, 2012.

Chouinard, H. H., D. E. Davis, J. T. LaFrance, and J. M. Perloff. 2007. Fat Taxes: Big Money for Small Change. *Forum for Health Economics & Policy* 10 (2).

Cutler, J. A., P. D. Sorlie, M. Wolz, T. Thom, L. E. Fields, and E. J. Roccella. 2008. Trends in Hypertension Prevalence, Awareness, Treatment, and Control Rates in United States Adults between 1988-1994 and 1999-2004. *Hypertension* 52 (5): 818-27.

Drewnowski, A. 2009. Defining Nutrient Density: Development and Validation of the Nutrient Rich Foods Index. *Journal of the American College of Nutrition* 28 (4): 421S-26S.

Du, H., A. D. van der, H. C. Boshuizen, N. G. Forouhi, N. J. Wareham, J. Halkjaer, A. Tjonneland, K. Overvad, M. U. Jakobsen, H. Boeing, B. Buijsse, G. Masala, D. Palli, T. I. Sorensen, W. H. Saris, and E. J. Feskens. 2010. Dietary Fiber and Subsequent Changes in Body Weight and Waist Circumference in European Men and Women. *American Journal Clinical Nutrition* 91 (2): 329-36.

Edwards, R. D. 2011. Commentary: Soda Taxes, Obesity, and the Shifty Behavior of Consumers. *Preventive Medicine* 52 (6): 417-18.

Emery, S. L., G. Szczypka, L. M. Powell, and F. J. Chaloupka. 2007. Public Health Obesity-Related TV Advertising: Lessons Learned from Tobacco. *American Journal of Preventive Medicine* 33 (4, Supplement): S257-S63.

Food Marketing Institute (FMI). 2006. U.S. Grocery Store Shopper Trends. Arlington, VA.

Fuhrman, J., B. Sarter, D. Glaser, and S. Acocella. 2010. Changing Perceptions of Hunger on a High Nutrient Density Diet. *Nutrition Journal* 9 (1): 51.

Gandel, S. 2011. Denmark Levies First-Ever Fat Tax, Should the Us? *Time*, http://business.time.com/11/10/05/denmark-levies-first-ever-fat-tax-should-the-u-s/. Accessed on Nov. 06, 2012.

He, J., and G. A. MacGregor. 2004. Effect of Longer-Term Modest Salt Reduction on Blood Pressure. *Cochrane Database of Systematic Reviews* (1): Art. No.: CD004937.

Horgen, K. B., and K. D. Brownell. 2002. Comparison of Price Change and Health Message Interventions in Promoting Healthy Food Choices. *Health Psychology* 21 (5): 505-12.

Horn, L. V., and AHA. 1997. For the Nutrition Committee. Fiber, Lipids, and Coronary Heart Disease: A Statement for Healthcare Professionals from the Nutrition Committee. American Heart Association. *Circulation* 95: 2701-04.

Kant, A. K., and B. I. Graubard. 2005. Energy Density of Diets Reported by American Adults: Association with Food Group Intake, Nutrient Intake, and Body Weight. *International Journal of Obesity and Related Metabolic Disorders* 29 (8): 950-56.

Karelis, A. D., M. E. Lavoie, J. Fontaine, V. Messier, I. Strychar, R. Rabasa-Lhoret, and E. Doucet. 2010. Anthropometric, Metabolic, Dietary and Psychosocial Profiles of Underreporters of Energy Intake: A Doubly Labeled Water Study among Overweight/Obese Postmenopausal Women - a Montreal Ottawa New Emerging Team Study. *European Journal of Clinical Nutrition* 64 (1): 68-74.

Kelly, T., W. Yang, C. S. Chen, K. Reynolds, and J. He. 2008. Global Burden of Obesity in 2005 and Projections to 2030. *International Journal of Obesity* 32 (9): 1431-37.

Kuchler, F., A. Tegene, and J. M. Harris. 2005. Taxing Snacking Foods: Manipulating Diet Quality or Financing Information Programs? *Review of Agricultural Economics* 27: 4-20.

Levitt, S. D., and J. A. List. 2007. Viewpoint: On the Generalizability of Lab Behavior to the Field. *Canadian Journal of Economics/Revue canadienne d'économique* 40: 347-70.
Lewis, M. K., and A. J. Hill. 1998. Food Advertising on British Children's Television: A Content Analysis and Experimental Study with Nine-Year Olds. *International Journal of Obesity* 22 (3): 206-14.

Liaukonyte, J., B. J. Rickard, H. M. Kaiser, A. M. Okrent, and T. J. Richards. 2012. Economic and Health Effects of Fruit and Vegetable Advertising: Evidence from Lab Experiments. *Food Policy* 37 (5): 543-53.

Liberman, A., and S. Chaiken. 1992. Defensive Processing of Personally Relevant Health Messages. *Personality and Social Psychology Bulletin* 18 (6): 669-79.

Lillis, M. 2010. CDC: Skyrocketing Obesity Translates into Enormous Health Costs. *The Hill,* http://thehill.com/blogs/healthwatch/state-issues/112455-cdc-skyrocketing-obesitytranslates-into-enormous-health-costs. Accessed on March 14, 2013.

Lustig, R. H., L. A. Schmidt, and C. D. Brindis. 2012. Public Health: The Toxic Truth About Sugar. *Nature* 482 (7383): 27-29.

Mendoza, J. A., A. Drewnowski, and D. A. Christakis. 2007. Dietary Energy Density Is Associated with Obesity and the Metabolic Syndrome in U.S. Adults. *Diabetes Care* 30 (4): 974-979.

National Cancer Institute (NCI). 2011. Sources of Selected Nutrients among the U.S. Population, 2005-06. Risk Factor Monitoring and Methods Branch Website. Applied Research Program. *National Cancer Institute.* http://riskfactor.cancer.gov/diet/foodsources/. Accessed on March 14, 2013.

Pollard, C. M., M. R. Miller, A. M. Daly, K. E. Crouchley, K. J. O'Donoghue, A. J. Lang, and C. W. Binns. 2008. Increasing Fruit and Vegetable Consumption: Success of the Western Australia Go for 2&5® Campaign. *Public Health Nutrition* 11 (3): 314-20.

Powell, L. M., and F. J. Chaloupka. 2009. Food Prices and Obesity: Evidence and Policy Implications for Taxes and Subsidies. *Milbank Quarterly* 87 (1): 229-57.

Rashad, I., M. Grossman, and S.-Y. Chou. 2006. The Super Size of America: An Economic Estimation of Body Mass Index and Obesity in Adults. *Eastern Economic Journal* 32 (1): 133-48.

Ruiter, R. A. C., C. Abraham, and G. Kok. 2001. Scary Warnings and Rational Precautions: A Review of the Psychology of Fear Appeals. *Psychology & Health* 16 (6): 613-30.

Sherman, D. A. K., L. D. Nelson, and C. M. Steele. 2000. Do Messages About Health Risks Threaten the Self? Increasing the Acceptance of Threatening Health Messages Via Self-Affirmation. *Personality and Social Psychology Bulletin* 26 (9): 1046-58.

Spiegel Online. 2011. French "Cola Tax" Approved: Paris Vows to Fight Deficit and Obesity, http://www.spiegel.de/international/europe/french-cola-tax-approved-paris-vows-to-fight-deficit-and-obesity-a-806194.html. *Spiegel Online*. Accessed on Nov. 06, 2012.

Sturm, R. 2007. Increases in Morbid Obesity in the USA: 2000-2005. *Public Health* 121 (7): 492-96.

Swinburn, B. A., G. Sacks, K. D. Hall, K. McPherson, D. T. Finegood, M. L. Moodie, and S. L. Gortmaker. 2011. The Global Obesity Pandemic: Shaped by Global Drivers and Local Environments. *The Lancet* 378 (9793): 804-14.

Tucker, L. A., and M. Bagwell. 1991. Television Viewing and Obesity in Adult Females. *American Journal of Public Health* 81 (7): 908-11.

Tucker, L. A., and G. M. Friedman. 1989. Television Viewing and Obesity in Adult Males. *American Journal of Public Health* 79 (4): 516-8.

Tucker, L. A., and K. S. Thomas. 2009. Increasing Total Fiber Intake Reduces Risk of Weight and Fat Gains in Women. *Journal of Nutrition* 139 (3): 576-81.

Variyam, J. N., Y. Shim, and J. Blaylock. 2001. Consumer Misperceptions of Diet Quality. *Journal of Nutrition Education* 33 (6): 314-21.

Wang, Y., and Q. J. Wang. 2004. The Prevalence of Prehypertension and Hypertension among U.S. Adults According to the New Joint National Committee Guidelines: New Challenges of the Old Problem. *Archives of Internal Medicine* 164: 2126-34.

Wang, Y. C., S. L. Gortmaker, A. M. Sobol, and K. M. Kuntz. 2006. Estimating the Energy Gap among U.S. Children: A Counterfactual Approach. *Pediatrics* 118 (1721-33).

de Wardener, H. E., and G. A. MacGregor. 2002. Harmful Effects of Dietary Salt in Addition to Hypertension. *Journal of Human Hypertension* 16 (4): 213-23.

World Health Organization (WHO). 2011. NCD Indicators. *WHO Global Infobase* https://apps.who.int/infobase/Indicators.aspx.

Young, B. 2003. Advertising and Food Choice in Children: A Review of the Literature. Report prepared for the *Food Advertising Unit*, August 2003.

Zheng, Y., E. W. McLaughlin, and H. M. Kaiser. 2012. Salience and Taxation: Salience Effect Versus Information Effect. *Applied Economics Letters* 20 (5): 508-10.

APPENDIX 2.A. Supplemental information on experimental design

Additional information about the questionnaire and advertising and video material used in the experiment is provided in Appendix 2.A.

Table 2A.1. TV-excerpts and advertisements used in the experiment.

Excerpt name	Description	Used in
Portlandia. Excerpt 1.	"Portlandia: House Sitter." Season 1, Episode 4.	All treatments
Portlandia. Excerpt 2.	"Portlandia: Battlestar Galactica." Season 2, Episode 2.	All treatments
Emmy Awards 2010.	Opening Ceremony for the 62nd Primetime Emmy Awards.	All treatments
Healthy food advertising, 1.	"Eat more fruits and vegetables." Brought to you by Produce for Better Health & Syngenta.	Healthy food advertising treatment; subsidy and healthy food advertising
Healthy food advertising, 2.	"Eat 2 fruit + 2 veggies every day for good health!" Health Promotion Board, Tote Board, Singapore	Healthy food advertising treatment; subsidy and healthy food advertising
Healthy advertising, 3, 4 and 5.	"Eat More", "Looking Good", "Mummy, I'm hungry". The Department of Health and Ageing, Australia. Go for 2&5 campaign.	Healthy food advertising treatment; subsidy and healthy food advertising
Healthy food advertising, 6.	"Emma's Healthy Snack". Fresh Food, Kids, Woolworths, Australia (http://freshfoodkids.com.au)	Healthy food advertising treatment; subsidy and healthy food advertising
Anti-obesity advertising, 1.	"What Did You Eat Today?", Obesity P.S.A. (http://www.obesity.org)	Anti-obesity advertising treatment; tax and anti-obesity advertising
Anti-obesity advertising, 2.	"This is Joe". CDC (Center for Disease Control and Prevention). Safer Healthier Life.	Anti-obesity advertising treatment; tax and anti-obesity advertising
Anti-obesity advertising, 3.	"Don't Drink Yourself Fat", NYC Health.	Anti-obesity advertising treatment; tax and anti-obesity advertising
Anti-obesity advertising, 4.	"Fat Lane". Produced for Participant Productions in support of the marketing campaign of the film "Fast Food Nation".	Anti-obesity advertising treatment; tax and anti-obesity advertising
Anti-obesity advertising, 5.	"Cost of Obesity Pinwheel" by the Stone Agency, for Blue Cross and Blue Shield of North Carolina.	Anti-obesity advertising treatment; tax and anti-obesity advertising

Table 2A.2. Socio-Demographic Questions and Answer Option List

#	Question	Answer Options/Description
1	What is your gender?	male female
2	What is your age?	20 or less 21-30 31-40 41-50 51 or more
3	What is the highest level of education you have achieved?	High School Undergraduate degree Associate degree Graduate degree or higher
4	How would you describe yourself?	Drop-down list: Caucasian African American Asian/Asian American Hispanic Native American Other
5	What is your family household income?	Less than $40,000 $40,001-$80,000 $80,001-$120,000 $120,001-$160,000 Over 160,000 Decline to answer
6	What is your marital status?	single married other
7	How many children do you have?	no one two three four more than four
8	Do you smoke?	yes no
9	Do you drink alcoholic beverages?	yes no
10	How would you describe your health condition?	underweight normal weight slightly overweight overweight obese
11	Do you often buy organic products?	yes no
12	On a scale of 1-5, please rate your preferences on the television segments and advertisements you have just watched. (1 - dissatisfied and 5 - very satisfied):	TV show, Menu variety, Price are rated from 1 to 5.

A3. Data structure example

Id	Δ Calories	Δ Empty calories	Δ Calories from fat	Δ Choles-terol	Δ Added sugar	Δ Protein	Δ Carbo-hydrate	Δ Fiber	Δ Sodium	Demographics	Treatment dummies
						…					
5	-36	-37	-54	-7	-8	-1	6	2	-78	See A2, appendix	Tax treatment
						…					
180	21	0	-27	0	0	0	14	0	-155	See A2, appendix	Healthy food ads
						…					

CHAPTER 3. Noisy Information Signals and Credence Attribute Labeling

3.1 Introduction

One of the most widely discussed issues in the food industry today is whether labels should be required for certain types of product ingredients or production methods.[3] Most of such debated ingredients are classified as "credence attributes".[4] Unlike search and experience attributes, it is impractical or nearly impossible for the typical consumer to verify claimed credence attributes (Darby and Karni, 1974). For example, consumers are unlikely to be able to verify whether organic milk was actually produced under the conditions implied by the term "organic" or whether an item actually contains genetically modified ingredients (GMOs). Therefore, credence attributes have to be communicated to consumers via a credible third party (e.g., government mandated nutrition labels) or voluntarily by the producer of a product (e.g., label highlighting that a product contains or is free of a certain ingredient that could not be independently determined by a consumer) (Hotz and Xiao, 2013; Brouhle and Khanna, 2007; Karstens and Belz, 2006).

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[3] At the time of the manuscript submission, 29 U.S. states have proposed bills to require genetically modified organism (GMO) labeling. Maine, Connecticut and Vermont have just recently passed laws to require GMO labeling.

[4] Attributes of consumer goods can be divided into three broad categories: search, experience, and credence attributes. Search attributes can be determined by inspection prior to purchase, whereas experience attributes refer to those qualities that are impossible to determine prior to purchase, but can be ascertained by the consumer after the purchase (Nelson, 1974).

There is a wide range in consumers' reactions to food labeling. Some consumers are suspicious about the health (human and animal) and environmental effects of biotechnology and other production methods, and are apprehensive of foods containing genetically modified organisms (GMOs), products produced with antibiotics, irradiation, or containing ingredients perceived to be unhealthy (Lusk et al., 2005; Liaukonyte et al., 2013; Fox et al., 2002). These concerns are fueling a movement that calls for stricter food labeling requirements, and provision of often-negative information about such ingredients. At the same time, the level of consumer knowledge about such production methods remains quite low: only 30% of Americans know that foods produced through biotechnology are available in supermarkets, and only one-quarter of Americans believe they have ever eaten food containing GMO ingredients (Hallman et al., 2003; Consumer Perceptions of Food Technology Survey, 2012). Moreover, the information that is available about these production processes and ingredients, presented from a variety of sources, is often conflicting (Huffman et al., 2004; Rousu et al., 2007) and alarmist (Sexton, 2012), causing uncertainty, confusion, and concern. Hence, while there clearly is a segment of U.S. consumers that are quite indifferent about food ingredients and production practices, there is also a large cohort of consumers that can be categorized as unaware about the existence, misinformed, and/or concerned about some credence attributes and ingredients.

Labeling negatively perceived credence characteristics can potentially send a signal to uninformed consumers that they should avoid or be worried about the safety of the product. For example, a consumer could be reluctant to consume products that are labeled to contain GMO ingredients, not because of the objectively definable inherent risks of such ingredients, but simply because the label itself sends a warning signal about the product (Lusk and Rozan, 2008). A lack of information about products containing GMO ingredients, and what specific risks they entail, may lead to the perception that the consumption of such products is much riskier than it actually is. In most theoretical and empirical economic models on food labeling (e.g., Crespi and Marette, 2003; Fulton and Giannakas, 2004; Hu et. al. etc.), consumer preferences for labeled food products are assumed to be exogenous to the presence of labels. However, if the label in itself (and not the information in the label) is interpreted by a consumer as a noisy warning signal, then the exogeneity assumption about the consumer preferences with respect to labels no longer holds. Few papers focused on examining the endogeneity assumption. Specifically, Artuso, 2003 examines optimal product regulation in the case of endogenous consumer product acceptance through a theoretical model, and argues that labeling is only welfare improving when accompanied by measures to assure consumers of safety of labeled products. Using survey data, Lusk and Rozan 2008 estimate that consumer beliefs about safety of GM foods are impacted by introduction of mandatory labeling policies; however

Constanigro and Lusk, 2014 find little evidence of the signaling effect from exposure to labels.

In this paper we study the impact of credence attribute labeling on consumer uncertainty and, consequently, on demand. We explicitly endogenize the preferences for labeled characteristics and allow them to be affected by the mere existence of the label. The label serves as a noisy information signal. Consumers' level of uncertainty is influenced by the quality of information provided: the noisier the information signal, the more uncertain is the consumer's preferences for the product. To our knowledge, this paper is the first attempt to separately identify shift and rotation effects associated with food labeling that is motivated and grounded in a theory of consumer behavior and preference heterogeneity.

We develop a model based on the theoretical framework of Johnson and Myatt (2006) and estimate it with data collected from a food labeling experiment. The experiment examines the impact of the label "Contains X" with and without additional negative information about X (where "X" is a credence attribute that is viewed by at least some consumers as negative). Based on the attitudes revealed in a food preference and shopping habits questionnaire, we categorize consumers into "concerned" and "indifferent" groups (reflecting how concerned these individuals are about certain production methods and their attitudes towards organic and health foods). We identify how labels and additional information in our experiment either allow these consumer groups to better align product characteristics with their

preferences, or simply alert consumers to the existence of the universally liked or disliked product or product characteristics.

Additionally, we are able to expand our model to examine the signaling nature of labeling and tie in the concepts of information noise and uncertainty to explain a seemingly counterintuitive phenomenon – the idea that willingness to pay for a product might increase when, in addition to a "Contains X" label, negative information is provided about the nature of a disliked credence attribute. The differential effects of information on consumer mean valuation and dispersion are directly linked to both information noise, and product idiosyncrasy, which depends on the (noisy) information provided to consumers about the existence of credence attributes. We use the theoretical insights on consumer reaction to ambiguity and the nature of labeling in our experiment to separately identify the effects of uncertainty and product idiosyncrasy on both the mean WTP and the dispersion of consumer valuations.

Our results suggest that WTP is negatively impacted by labels with the phrase "Contains X" both with and without additional negative information regarding credence attribute X. The concerned consumer group has the largest decrease in WTP in the label with no additional negative information treatment (relative to the control group, which received no labels and no additional information). On the other hand, the indifferent consumers react more negatively to the treatment that provides additional negative information alongside the label. We estimate the parameters

representing the shifts and rotations of demand in each scenario. We show that these estimates provide insight regarding how consumers' priors are affected by information supplied in a particular treatment. We also show that the different uncertainty levels are driving the differences in mean WTP and dispersion. Additionally, and perhaps most importantly, we are able to provide empirical and theoretical evidence that for the most concerned consumers, the "Contains X" label without any additional information serves as a noisy warning signal leading them to perceive that the consumption of labeled products is riskier than it actually is. Interestingly, this significant negative signaling effect of the label for the concerned consumers is largely mitigated by additional information, which ultimately reduces the noise in the information signal.

The rest of the paper is organized as follows. First, we briefly discuss the core concepts of the theoretical model used in the paper and the features of our experimental design, which allow us to separately identify the relative levels of the key parameters of interest for the "indifferent" and "concerned" consumers. Next, we present the experimental design of the study and the econometric model used to obtain our empirical results. Following that, we provide details on the available data and present our primary estimation results. Finally, we disentangle the effects of the two parameters, providing deeper insights into consumers' reaction to information and discuss the implications of our results.

3.2 Theoretical framework

3.2.1 Shifts and Rotations of Demand

Johnson and Myatt (2006) provide a basis for studying demand curve transformations that stem not only from changes in the mean consumer valuation, but also from changes in the dispersion of valuations, which rotate the demand curve[5].

The core intuition of the theoretical model is as follows. Information about product attributes that are universally attractive to all consumers leads to the outward shift of demand. We expect to observe an inward shift of the demand curve, since we are presenting negative information and revealing the existence of a negatively perceived credence attribute. Rotations of the demand curve, on the other hand, occur due information that highlights the actual attributes of the product and allows consumers to find out whether those attributes are consistent with their preferences. As more and better quality information about specific attributes is presented, some consumers are turned-off by the product, while others' demand increases because they value the highlighted attributes. As a result, such information increases the dispersion of consumers' WTP, thereby rotating the demand curve clockwise.

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[5] Two prior studies have applied Johnson and Myatt (2006) theoretical model to estimate shifts and rotations of demand. Rickard et al. (2011) use this framework to estimate the effects of commodity-specific and broad-based advertising, and Richards and Nganje (2013) apply the framework to study the welfare effects of food safety recalls. However, no studies estimated this model in food labeling setting; and more importantly, to our knowledge, no studies were able to estimate the expanded version of the model that includes product idiosyncrasy and information noise. The latter is a significant contribution of our paper.

Thus, revealed credence attributes by means of "Contain X" labels and additional information about the labeled ingredients are evaluated by consumers based on their priors, and simultaneously can play the role of rotating the demand curve, by realizing the match of the attributes with their inherent preferences, and shifting it inwards, by alerting consumers about the existence of a generally disliked credence attribute.

More formally, we assume that there is a unit mass of consumers, each willing to pay up to θ for one unit of a particular product. θ is drawn from the distribution $F_s(\theta)$, is twice continuously differentiable in both s and θ, with support on a $(\underline{\theta}_s, \overline{\theta}_s)$ interval, where $s \in \mathrm{S} = [s_l, s_h]$ indexes a family of distributions. Thus, s governs the shape of the valuation distributions, and an increase in s represents a spread in the density of θ, which leads to a clockwise rotation of $F_s(\theta)$ around some point $\breve{\theta}$. The effect of such spread in valuations on the distribution of market demand can be expressed through the inverse demand curve $P_s(q) = F_s(1-p)$, where q is the proportion of consumers willing to purchase the product at price p, and is given by $q = 1 - {F_s}^{-1}(p)$. In this framework, the effect of a change in s is similar to that of the changes in the actual distribution of valuations, and rotates the inverse demand curve. If the demand q is below some pivotal point $\breve{q}$, then $\frac{\partial P_s(q)}{\partial s} > 0$: an increase in the spread of valuations causes a rise in the market price, and vice versa. In other words, if q is below the pivotal point $\breve{q}$, greater dispersion in valuations causes the

valuation of the marginal consumer, and hence the market price, to rise; if q is above $\breve{q}$, greater dispersion in valuations causes the market price to fall.

Graphically, the changes in the cumulative distribution (CDF) function and corresponding demand functions representing changes in valuation dispersion and means are presented in Figure 3.1. Specifically, panel (a) illustrates the counter-clockwise CDF rotation, which then leads to counter-clockwise demand rotation represented in panel (c). Both sets of these rotations are associated with a decreased dispersion in WTP among consumers. Panels (b) and (d) in Figure 3.1 illustrate scenarios where both shift and rotation effects happen simultaneously. In the theoretical scenarios demonstrated in panels (b) and (d), demand and CDF shift to the left and rotate clockwise, representing a situation where mean valuations decrease, while the standard deviation (dispersion) of valuations increases.

Next, we derive an empirical model of information signals in the context of credence attribute labeling. We specify an econometric model to estimate the impact of explicit credence attribute labeling and additional information in order to discern when an information signal has more of a universal reduction in demand effect, and when it increases the dispersion of valuations. Our model allows this signal to be evaluated differently by different consumer types, and it also allows for simultaneous occurrence of both of those effects.

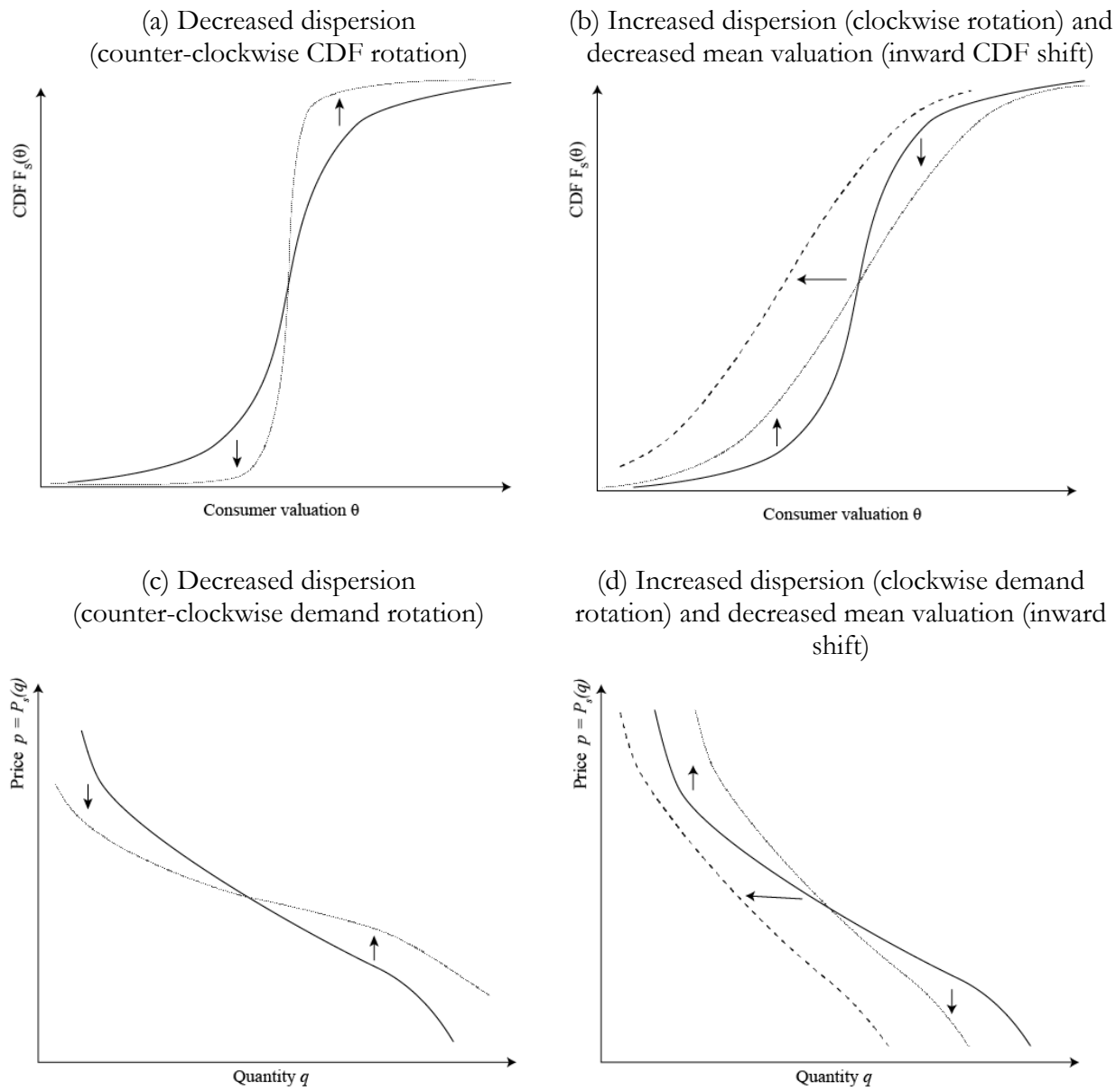

Figure 3.1. Theoretical illustration of CDF rotations and shifts

3.2.2 Uncertainty, Product Idiosyncrasy, and Information Signals.

The theoretical model outlined in the previous section provides insights into how the shape of demand curve changes in response to varying degrees of

information. While these comparative statics by themselves contribute to our understanding of how labels and secondary information might impact demand, in this section we provide a more in depth analysis of the underlying micro-foundations consistent with such consumer behavior. We expand the theoretical framework presented in Section 3.2.1, by introducing two key parameters: 1) ρ^2, the degree of product idiosyncrasy and 2) ξ^2, the information signal noise.

3.2.3 Degree of product idiosyncrasy

Suppose the prior distribution of Bayesian consumers' true monetary utility for a product satisfies $\omega \sim N(\mu, \rho^2)$, where ρ^2 is the dispersion of true consumer payoffs and can be thought of as the degree of heterogeneity or idiosyncrasy of preferences across product attributes. For example, small ρ^2 implies that all consumers value all characteristics similarly, and high ρ^2 represents highly variable valuations implying that consumer preferences for that product are highly polarized: some people like the product a lot, while others absolutely hate it. Similar to Johnson and Myatt (2006), we also assume that such valuation distribution can be influenced by additional external information signals. In other words, after receiving an information signal about the product or its attribute, a consumer updates her prior. For example, revealing that a product contains GMO ingredients might allow the consumer to better match product attributes to her preferences; if consumers have heterogeneous preferences for GMO ingredients, the idiosyncrasy of the product will increase, but if all

consumers value (or dislike) these ingredients similarly, idiosyncrasy will fall. Therefore, in our setting additional information may increase or decrease ρ^2 depending on whether the additional information signal introduces the existence of universally disliked attribute (decrease in ρ^2, demand rotates counter-clockwise, CDF becomes steeper), or an attribute consumers have heterogeneous preferences over (increase in ρ^2, demand rotates clockwise, CDF becomes flatter).

3.2.4 Information noise and uncertainty

Furthermore, conditional on true unknown valuation ω, the information signal is assumed to be noisy and follows the distribution $x \sim N\ (\omega, \xi^2)$, where ξ^2 can be interpreted as an approximation of noise in the information signal. We can also think about ξ^2 as the level of uncertainty about the product quality that arises due to the information provided: the more (as perceived subjectively) unbiased and informative the information is, the less noise it contains, leaving consumer in a less uncertain state about her own preferences for the product. For example, when a consumer is provided with a noisy information signal, which she has little factual prior knowledge, her ability to evaluate its validity and implications is low; thus, the level of uncertainty is higher than when no such noisy information is provided. In general, a noisier information signal will increase uncertainty.

3.2.5 Characterization of CDF as a function of ρ^2 and ξ^2

Given the information signal *x*, a Bayesian consumer updates her beliefs to obtain posterior beliefs over ω. Then, with λ being a risk aversion level, consumer's willingness to pay for the product will be the certainty equivalent:[6]:

$$\theta(x) = \frac{1}{1+\rho^2/\xi^2}\left[\mu - \frac{\lambda\rho^2}{2}\right] + \frac{\rho^2/\xi^2}{1+\rho^2/\xi^2}x$$

To characterize the CDF of valuations, we consider the distribution of $WTP(x)$ as a function of these parameters. If realized information signals follow the distribution $x \sim N\ (\mu, \rho^2 + \xi^2)$, and if consumer valuations are linear in *x*, then they satisfy (see the Appendix 3.B for more details):

$$WTP \sim N\left(\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}, \frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}\right)$$

As a result, the CDF and inverse demand curve are indexed by both precision signals: ρ^2 and $\frac{1}{\xi^2}$. Below we discuss the comparative statics with respect to these two parameters.

<u>Mean (Shifts of CDF).</u> Keeping λ constant[7], the mean valuation, $\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}$, is dependent on two parameters: ρ^2 and ξ^2. For a fixed ρ^2, the mean valuation is

[6] See Appendix 3.B for more detailed derivation of these mathematical relationships.

decreasing in ξ^2: a noisier information signal that raises more concern and uncertainty lowers mean WTP (higher risk premium from uncertainty). For a fixed ξ^2, the mean valuation is also decreasing in ρ^2: increasing the product idiosyncrasy reduces the mean WTP. If a product is not universally liked, the purchase becomes more of a gamble.

<u>Standard deviation (Rotations of CDF)</u>. Standard deviation, $\sqrt{\frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}}$, is increasing in ρ^2: the valuation distribution is higher when the product design is more idiosyncratic (higher ρ^2), but decreasing in ξ^2 – if information is noisier, the valuation dispersion falls. When the information signal is less noisy, or as the degree of product idiosyncrasy due to the provided information increases, consumers are better able to match ideal product attributes to their own preferences. In such cases, some consumers like a product more because of the new information while other consumers like it less. The higher the noise of the information signal – the more difficult it is for the consumer to identify and evaluate the actual product attributes and the more difficult it is for the consumer to evaluate and place a value on the actual product.

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[7] Note, that λ being constant across all treatments is a reasonable assumption, as it is an inherent risk aversion parameter that is constant for the same group of people across treatments. This, however, does not limit us to have different λs (risk aversion levels) for concerned and indifferent consumers.

3.3 Econometric model of demand shifts and rotations

We use the theoretical model presented in Section 3.2 to motivate and derive an econometric model of the impact of information signal in credence attribute labeling setting on consumer choice. We assume a random utility model for consumer utility of the general form: $U_{ij} = V_{ij} + \varepsilon_{ij}$, for product *j* for consumer *i*, where ε_{ij} is the independent and identically distributed error term and V_{ij} is a deterministic utility, which in turn is a function of product attributes, demographic attributes of the decision maker, and the information provided about the product (Anderson et al. 1992). Rickard et al. (2011) show that willingness to pay by consumer *i* is an additive function of choice and chooser attributes. Specifically, we write the deterministic part of this utility function as:

$$V_{ijm} = \sum_k \beta_k x_{jk} + \sum_n \delta_n z_{in} + \sum_m \gamma_{im} I_m + \varsigma_{ijm} \qquad (3.1)$$

here *i* indexes individual consumers, *j* – products, and *m* – information treatments. x_{jk} are the observable and known attributes for all consumers for product *j* and z_{in} are the observable demographic characteristics of consumer *i*. ς_{ijm} is an independent and identically distributed error term. Lastly, and most importantly, γ_{im} is the individual-specific impact of information about the credence attribute on indirect utility. This information, I_m, differs by treatment (I_m={*no label* + *no information; label* + *no information; label* + *information*}).

Further, as outlined in our theoretical model in Section 3.2, we allow information to have both a direct (shift) and an indirect (rotational) effect. Rotations

of demand associated with universally unappealing information and its effect on consumer valuation are modeled through changes in WTP dispersion, while shifts of the demand curve resulting from information heterogeneously evaluated by different consumer types are represented by changes in the mean valuation. As information specific to the treatments is the only signal affecting the universally and heterogeneously evaluated information mix in our experiment from treatment to treatment, we model γ_{im} recognizing that the information effect will be different across the consumers and depend, among other things, on their prior beliefs, and the noise of the information signal, i.e., how concerned they are with the additional information provided and how uncertain they are given the information available to them:

$$\gamma_{im} = \overline{\gamma_m} + \sigma_m \tau_{im} + I_j \; ; \; \tau_{im} \sim N(0,1) \qquad (3.2)$$

We can interpret $\overline{\gamma_m}$ as the common direct effect (shift) due to provided information, and σ_m as the indirect effect (rotation) caused by changes in the dispersion of valuations, under information level I_m . τ_{im} captures unobserved individual heterogeneity (Berry, 1994) and can be interpreted as an unobserved variability in the prior and posterior beliefs relating to credence attributes. Lastly, I_j controls for item-specific information type. Combining equations (3.1) and (3.2) provides an estimable model of the impact of credence attribute labeling on the willingness to pay under each type of information provision. We estimate several specifications of this random coefficients model and present and discuss the results in Section 3.5. Next, we

describe the data gathered during an economic experiment that is used to test the implications of the outlined model.

3.4 Experiment design and data

A total of 169 adult, non-student subjects participated in the economic experiment. Subjects were paid $25 for participating, and they could use part of the cash payment to bid on several food items that were presented in a series of auctions.

Subjects were randomly assigned to one of the three information treatments: T0: Control (No Label + No information); T1: Label "Contains X" + No information; and T2: Label "Contains X" + negatively-framed information about credence attribute X. Negatively-framed information in the T2 treatment summarized the views of the critics of the credence attributes. The list of labeled credence attributes, and the information presented about them, is provided in the Appendix 3.A, Table 3A.1. The first column indicates the credence attribute revealed in the "Contains X + No Info" treatment (T1) and "Contains X + Info" treatment (T2), the second column – the auctioned item, and the last column lists the negative information that was provided alongside the label in "Contains X + Info" (T2) treatment. The credence attributes considered include genetically modified ingredients (granola bar), ingredients that have been exposed to growth hormones (mozzarella string cheese), irradiated ingredients (granola trail mix with dried fruit and nuts), ingredients that have been exposed to antibiotics (beef jerky), high fructose corn syrup (oatmeal cookies), partially hydrogenated oils (oven baked potatoes) and artificial

color Red No. 40 (gummy bears). In our econometric specification we control for the attribute type to estimate common, generalizable effects of labeling credence attributes and providing secondary information.

Each session of the experiment began with an explanation of how the auctions and the bidding process worked. To guarantee that subjects understood the mechanism of the auctions, a practice round was included where each subject submitted a bid for a board game. After the practice round, seven rounds of bidding for seven different food items took place. In the beginning of each round the food item that subjects were bidding on was displayed to them. Since we were auctioning items commonly sold in grocery stores, we removed brand logos to eliminate any brand-image effects. We replicated the nutrition and ingredient list information from the actual labels and presented this brand-free label along with treatment-specific information to the participants on the projector slide and on their individual computer screens.

The Becker Degroot Marschak (1964) (BDM) auction was used to elicit subjects WTP for the seven items. In the experiment, we expected that subjects would have a range of valuations for the various products, and the BDM is an ideal elicitation method because subjects do not bid against each other, but rather submit a sealed bid for each product and then have the chance to "win" a randomly selected food product if their bid exceeded a randomly drawn price (Becker, Degroot and Marschak, 1964). Once all bids were submitted in a session, we randomly chose a

market price for one randomly selected food item (from a distribution around the retail price of the auctioned item); in cases where a subject's bid was equal to or exceeded the market price, we sold the selected food product to the subject for the randomly chosen market price. Subjects were told at the beginning of the experiment that only one product was randomly picked to be sold at the end of all the auctions and therefore they would only buy one item at most in the auctions. This was done to avoid having subjects bid lower on selected products due to budget constraint considerations.

After all seven item auctions were completed, participants filled out a computerized questionnaire revealing their attitudes towards food, nutrition knowledge, and some demographic information. Answers on this questionnaire were later used to identify participants as consumers who are either "concerned" or "indifferent" about the labeled ingredients. The complete list of all the questions asked in the computerized survey is presented in Appendix 3.A, table 3A.2.

3.5 Estimation and results

3.5.1 Descriptive Statistics

In our empirical estimation we distinguish between two types of identifiable demographic groups: (1) consumers concerned about food production processes and ingredients, who often pay a premium to avoid them (n=80), and (2) consumers indifferent about these food attributes, who do not regularly or ever shop at health

food stores or buy organic products (n=89)[8]. The socio-economic characteristics of the sample are similar across both groups and three treatments. The key demographic information for the subjects in our sample is very similar to data on primary food shoppers in the U.S. (Food Marketing Institute 2006).

Table 3.1 presents descriptive statistics for the concerned and indifferent consumer groups. The mean WTP varies quite significantly from one treatment and group to the other, with the control treatment consistently having the highest average bid. It is interesting to note that the relative average WTP in the "label + no negative information" and "label + negative information" is very different for the concerned and indifferent groups: for the concerned group, the "label + no negative information" treatment has the lowest mean bid, while the indifferent consumers on average bid the lowest in the "label + negative information" treatment.

Similar patterns emerge in the graphical representation of the cumulative distribution functions of WTP and the corresponding demand schedules. Figure 3.2 plots the cumulative distributions of valuations of these two consumer types across the three experiment treatments, while Figure 3.3 plots corresponding demand schedules.

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[8] This is a self-revealed distinction based on survey answers of the participants, specifically questions 14 and 15 (see table 3A.2 in Appendix 3.A). This approach leads to two groups with distinct observable reactions to the provided information. Other potential groupings were considered, including latent grouping, but did not exhibit such distinctly different reactions. This grouping approach and the model estimates associated with it also lead to important practical implications, which we elaborate upon in the last section.

Table 3.1. Descriptive Statistics of Demographic Variables by Group and Treatment

	Concerned:			Indifferent:		
	Control	No Info	Info	Control	No Info	Info
WTP	0.862	0.360	0.467	0.840	0.800	0.577
	(0.696)	(0.479)	(0.585)	(0.612)	(0.717)	(0.680)
Age	42.736	44.45	41.167	41.644	40.191	42.063
	(14.166)	(11.046)	(12.504)	(11.332)	(9.290)	(14.430)
Female	0.756	0.800	0.778	0.556	0.627	0.710
	(0.430)	(0.401)	(0.417)	(0.498)	(0.486)	(0.455)
Children	0.348	0.500	0.449	0.716	0.564	0.633
	(0.478)	(0.502)	(0.499)	(0.452)	(0.498)	(0.483)
Caucasian	0.726	0.800	0.838	0.842	0.627	0.755
	(0.447)	(0.401)	(0.369)	(0.365)	(0.486)	(0.431)
African American	0.030	0.050	0	0.032	0.064	0.024
	(0.171)	(0.219)	(0)	(0.175)	(0.245)	(0.155)
Asian	0.174	0.100	0.097	0.126	0.064	0.147
	(0.380)	(0.301)	(0.297)	(0.333)	(0.245)	(0.355)
Only High school	0	0	0	0	0	0.024
	(0)	(0)	(0)	(0)	(0)	(0.154)
Some college	0.134	0.100	0.157	0.063	0.245	0.147
	(0.342)	(0.301)	(0.365)	(0.244)	(0.432)	(0.355)
Associate's degree	0.070	0.200	0.098	0.248	0.318	0.098
	(0.255)	(0.401)	(0.297)	(0.433)	(0.468)	(0.298)
College degree	0.348	0.300	0.454	0.378	0.255	0.465
	(0.478)	(0.499)	(0.499)	(0.486)	(0.438)	(0.499)
Master's degree	0.313	0.350	0.259	0.248	0.055	0.171
	(0.465)	(0.479)	(0.439)	(0.433)	(0.228)	(0.377)
Income less $40,000	0.174	0.150	0.259	0.252	0.127	0.294
	(0.380)	(0.358)	(0.439)	(0.435)	(0.334)	(0.456)
Income $40,000-	0.478	0.600	0.356	0.374	0.500	0.437
	(0.501)	(0.492)	(0.480)	(0.485)	(0.502)	(0.497)
Healthy eaters	0.831	0.900	0.583	0.437	(0.318)	0.315
	(0.376)	(0.301)	(0.494)	(0.497)	(0.468)	(0.465)
Vegetarian or vegan	0.099	0.250	0.162	0.032	0	0.024
	(0.300)	(0.435)	(0.369)	(0.175)	(0)	(0.155)
Taken a nutrition	0.279	0.200	0.259	0.369	0.318	0.220
	(0.449)	(0.402)	(0.439)	(0.484)	(0.467)	(0.415)
Usually read nutrient	0.930	0.900	0.773	0.622	0.436	0.780
	(0.255)	(0.301)	(0.419)	(0.486)	(0.498)	(0.415)
Require disclosure of altered ingredients'	0.896	1.00	1.00	0.815	0.873	0.951
	(0.307)	(0)	(0)	(0.389)	(0.334)	(0.216)
# of bids	201	140	216	222	110	286

As is evident from these figures, these two consumer groups responded to the same information about credence attributes very differently. Concerned participants reacted to information presented in T1 ("label + no negative information") more negatively than to information provided in T2 ("label + negative information") as suggested by a larger leftward shift of valuation CDF and inward shift of the demand

curve. Indifferent consumers, on the other hand, reacted to information in T2 more negatively than to information in T1. We also note that patterns of change in CDF and demand slope and rotation are quite different for the two consumer types.

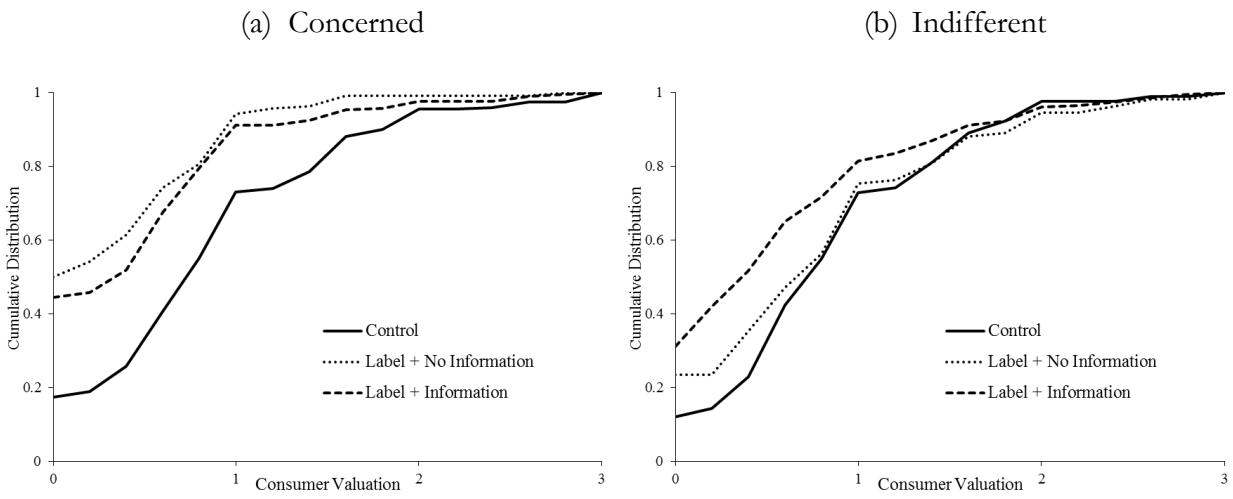

Figure 3.2. Cumulative Distributions of Consumer Valuations, Information Treatments

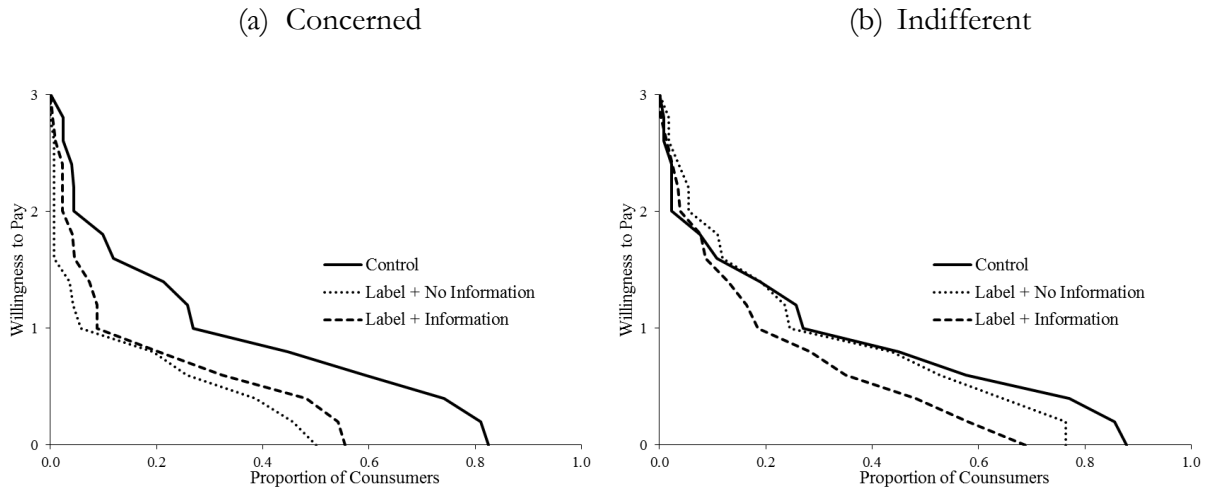

Figure 3.3. Overall Demand Changes across Information Treatment

3.5.2 CDF shifts and rotations

In this paper we focus on identifying the common, generalizable effects of labeling credence attributes and providing secondary information. To do so, we

include attribute fixed effects to control for systematic differences across the attributes and the information nature associated with our analyzed credence attributes.[9]

To identify the common element of shifts and rotations of CDF after controlling for other observable variables, we estimate combined equations (1) and (2) using simulated maximum likelihood with robust standard errors.[10] The results are presented separately for the segments of the sample defined as "concerned" and "indifferent." All of the reported specifications also include credence attribute fixed effects to control for the heterogeneity in the value and information type supplied with the auctioned items, as well as observed consumer socioeconomic controls. Thus, the estimated common demand shift and rotation effects are robust and directly attributable to information treatments.

We conduct a number of specification tests to determine whether the additional structure of our model due to unobserved preference heterogeneity is justified by the data and present ordinary least squares (OLS) estimates for comparison purposes. The likelihood ratio tests and log likelihood function of random coefficient vs. linear regression favor random coefficient model (LR=32.60, P

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[9] We have also investigated estimating individual, attribute-specific specifications. We generally found that they do not add much additional insight, since we already control for item fixed effects and most of the specifications and empirical CDFs exhibit similar estimates and patterns as the estimated common effects.

[10] Additionally, a random coefficient Tobit econometric specification was estimated, with similar results.

> chi2 = 0.000 for the "concerned" subsample and LR=127.44, P > chi2 = 0.000 for the "indifferent"). Additionally, t-tests of each individual shift and standard deviation parameters show that they are significantly different from zero at least at 5% level of significance. Consequently, we conclude that the random coefficient specification is superior to the constant parameter alternative. In what follows, we discuss the results of the random coefficient model summarized in the last 2 columns of Table 3.2.

Table 3.2. OLS and Random Coefficients Estimates

	OLS		Random Coefficient	
	Concerned	Indifferent	Concerned	Indifferent
	$\overline{\gamma_m}$: Mean Estimates (Shifts)			
T0: Control	0.858***	0.972***	0.874***	0.937***
	(0.150)	(0.160)	(0.196)	(0.237)
T1: Label + No Info	0.343**	0.898***	0.359**	0.859***
	(0.150)	(0.169)	(0.192)	(0.276)
T2: Label + Info	0.475***	0.705***	0.490***	0.665***
	(0.146)	(0.160)	(0.194)	(0.243)
	σ_m: Standard Dev. Estimates (Rotations)			
T0: Control	N.A.	N.A.	0.250***	0.293***
			(0.062)	(0.042)
T1: Label + No Info	N.A.	N.A.	0.173***	0.535***
			(0.076)	(0.065)
T2: Label + Info	N.A.	N.A.	0.307***	0.408***
			(0.060)	(0.043)
Credence Attribute Type F.E.	yes	yes	yes	yes
Demographic F.E.	yes	yes	yes	yes
Sigma	N.A.	N.A.	0.588**	0.556**
			(0.189)	(0.017)
Log-likelihood	**-546.67**	**-647.77**	**-530.37**	**-584.04**

Notes: Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Concerned consumers (Table 3.2, Column 3). Relative to the control treatment (T0), and controlling for the credence attribute type and consumer demographics, the "label + no negative information" treatment (T1) leads to a significant decrease in both the

mean valuation and dispersion for concerned consumers. The point estimate of the mean parameter decreases from 0.874 for the control treatment to 0.359 for the T1 treatment, and the estimate for the dispersion of valuations parameter decreases from 0.250 for the control to 0.173 for the T1. These relative changes of estimates imply that moving from T0 to T1, the empirical CDF shifts inwards and rotates counter-clockwise, which translates to the corresponding demand schedule becoming flatter and shifting to the left. In the "label + information" treatment (T2) the mean valuation also falls (point estimate 0.490), but less so than in the previous treatment, and the dispersion parameter increases relative to both control treatment and T1 (point estimate of the dispersion parameter is 0.307). These estimates imply that moving from T0 to T2, the empirical CDF shifts to the left (and to the right, relative to T1) and rotates clockwise, corresponding to demand shift to the left and rotating to become steeper.

We can infer that the effects of both knowledge about a universally disliked attribute – leading to the inward shift in the demand, – and heterogeneously evaluated information – rotations of the demand curve – are present within the treatments. Some information signal allows consumers to match their heterogeneous preferences towards the labeled attribute, and additional information signal in T2 does just that by providing negative information on both the production processes and possible consequences of consuming the labeled ingredient. These results also suggest that concerned consumers have strong prior beliefs about the credence attributes and they

are also the type of consumers who are willing to pay extra to avoid these credence attributes.

Indifferent consumers (Table 3.2, Column 4). Relative to the control treatment (T0), in the "label + no negative information" treatment (T1) the mean valuation falls slightly and the dispersion increases for indifferent consumers. The point estimate of the mean parameter decreases from 0.937 for the control treatment to 0.859 for the T1 treatment and the estimates for the dispersion of valuations increase from 0.293 for the control to 0.535 for the T1. These results imply that moving from T0 to T1, the empirical CDF for the concerned consumers shifts inwards and rotates clockwise, as the corresponding demand becomes steeper and shifts to the left. In the "label + information" treatment (T2) the mean valuation falls further (decreasing from 0.859 for T1 to 0.665 for T2), and the dispersion decreases relative to T1 (dispersion parameter decreases from 0.535 for T1 to 0.408 for T2). This suggests that moving from T1 to T2, the empirical CDF shifts leftwards and rotates counter-clockwise and the corresponding demand schedule becomes flatter and shifts to the left.

Similar to concerned consumers, the universally negatively evaluated nature of the label and additional information decreases mean WTP, shifting the demand inwards; however, in this case indifferent consumers don't have strong prior beliefs about the labeled ingredients – while most indifferent consumers dislike the labeled ingredient, the extent to which they dislike it is fairly heterogeneous across consumers. In this demographic group, label in T1 compared to T0 also plays the role of shifting

demand, providing consumers with enough information to update their valuation. In T2, all of the indifferent consumers are provided with the same negative additional information – the dispersion decreases relative to T1, implying that consumers assign label and additional information more to the demand shift role (as more information is provided about the credence attribute (T2), both the mean and the dispersion fall significantly). Thus, these results suggest that the indifferent group has significantly less strong initial beliefs about the credence attributes and they could be unaware of the widespread existence or the possible consequences and traits of these attributes. Finally, it is worthwhile to note that the drop in the mean WTP in both T1 and T2 is drastically bigger for the concerned group compared to the indifferent group. Overall, it confirms the self-revealed preferences of concerned consumers, who routinely pay an organic foods premium to avoid the labeled ingredients.

The distinctly different response of the concerned participants when compared with the indifferent group within our model implies they treat the same information signals differently based on their priors. While these mean and dispersion results help us identify changes in the shape of the demand functions, they do not provide us with concrete insights on what might be the underlying cause for such different reactions to the same information (beyond the fact that it is due to unobserved consumer heterogeneity). The next step in our analysis involves looking for deeper insights about the relative levels of uncertainty and product idiosyncrasy that would be consistent with the estimated shift and rotation parameters, $\overline{\gamma_m}$ and σ_m. Combining

the theoretical characterizations of CDFs discussed with our empirical results, we are able to identify relative levels of uncertainty associated with the information signal, ξ^2, and relative levels of product idiosyncrasy, ρ^2, across the three treatments and two consumer groups.

The experimental nature of our study allows us to trace the relative levels of ξ^2 while varying ρ^2 across experimental treatments. All auctioned items remain exactly the same across treatments, and their observable attributes objectively do not change. By definition, participants are not able to observe the credence attribute directly, therefore, we assume it is the explicit labeling of such an attribute that alerts the consumer to a change in the set of attributes of the product. Thus, ρ^2, the degree of product idiosyncrasy, changes only when consumers are made aware of a *new* attribute, which may or may not be universally disliked by them. Next, we describe how ξ^2 *and* ρ^2 change across three of our experiment treatments.

<u>T0: Control.</u> In the baseline control treatment we do not mention the existence of the credence attributes, i.e., there are no labels. Some consumers might still suspect that labeled ingredients exist or are part of the product content, which would affect their level of uncertainty since they lack actual information on whether the product has the credence attribute in question. The baseline degree of product differentiation and level of uncertainty faced by consumers in this treatment are ρ_0^2 and ξ_0^2, *respectively*.

<u>T1: Label + no information.</u> In this treatment, we introduce the existence of the credence attribute by providing a label "Contains X", alerting consumers to an

existence of a credence attribute, and therefore change the idiosyncrasy of product design to ρ_1^2. By providing any type of additional information about the products we are also altering ξ_1^2, the baseline noise of the information signal.

<u>T2: Label + negative information</u>. In this treatment we also reveal the existence of the same credence attribute as in the "label" treatment, so the degree of product differentiation stays the same as in the "label" treatment T1 (ρ_1^2). Given that the credence attribute is explicitly labeled in T1 and T2, the known product attributes in those two treatments are the same. However, here we also introduce additional information signal about the credence attribute, which is likely to change the perception of noisiness of the information signal level, ξ_2^2.

Table 3.3. Levels of ρ^2 and ξ^2 for the Concerned and Indifferent groups

	Concerned	**Indifferent**
ρ^2: Degree of Product Idiosyncrasy		
T0: control	ρ_{C0}^2	ρ_{I0}^2
T1: label + no information	ρ_{C1}^2	ρ_{I1}^2
T2: label + information	ρ_{C1}^2	ρ_{I1}^2
ξ^2: Uncertainty Level/Information Noise		
T0: control	ξ_{C0}^2	ξ_{I0}^2
T1: label + no information	ξ_{C1}^2	ξ_{I1}^2
T2: label + information	ξ_{C2}^2	ξ_{I2}^2

Table 3.3 summarizes the notation for different levels of ξ^2 and ρ^2 across the three different treatments and two different consumer groups: we distinguish between four different ρ^2 that define the degree of product idiosyncrasy, and six distinct ξ^2

that reflect the information noise associated with each of the experiment treatments[11]. This allows us to have different parameter values not only across treatments, but also across the "concerned" and "indifferent" consumer groups.

3.5.3 Relative Levels of Idiosyncrasy and Uncertainty: Results.

The two main results come from utilizing the observation that in both treatments T1 ("label + no negative information") and T2 ("label + negative information") consumers know about the existence of the credence attribute: ρ^2 is constant (though it might still have different levels for two different consumer groups). As shown in Table 3.2, and discussed before, an interesting pattern emerges when we compare treatments 1 and 2 across the two consumer groups: for the concerned consumers, the estimated mean and standard deviation increases when more information is provided, while for the indifferent group the exact opposite is the case. Since the product idiosyncrasy parameter stays constant across the two treatments, this implies that these relative changes are attributable to the noisiness of the information signals in those treatments. More specifically, we find that[12]:

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[11] Recall that the degree of product differentiation stays the same in the "*label + no information*" and "*label + information*" treatments (ρ_1^2), since both of them reveal the credence attribute. However, T2 introduces additional information about the credence attribute, which is likely to change the *perception* of noisiness of the information signal level, ξ_2^2.

[12] See the Appendix 3.B for mathematical proofs of these results.

1. $\xi^2_{C1} > \xi^2_{C2}$: for the **concerned** group, once the existence of the credence attribute is revealed (which is the case in both treatments 1 and 2), the uncertainty level associated with the information signal is lower in the treatment with more information provided (T2). In other words, for this group of consumers, a label alone without any information (T1) appears to be a highly noisy signal, which is associated with missing information deemed highly relevant by these consumers. Provision of additional information in this case provides relevant information to the consumer, who treats it as believable and useful. This is one of the most interesting results of our paper: more information (even though it is negative) softens some consumers' concerns about the meaning of a label. Another, more intuitive way to interpret this result, is to note that for the most concerned consumers "Contains X" label without any additional information serves as a noisy warning signal leading them to infer that the consumption of labeled products is riskier than it actually is. This large negative signaling effect of the label is mitigated by additional information, which ultimately reduces the noise in the information signal.

2. $\xi^2_{I1} < \xi^2_{I2}$: for the **indifferent** consumers, once they are made aware of the existence of the credence attribute, additional information about the credence attribute is interpreted as a noisy signal relative to the label alone. The indifferent group might not have strong priors about the possible implications of the labeled ingredient or production process, and the additional information provided with the treatment is treated as ambiguous. Similar to Fox and Weber (2002) in this case

uncertainty arises from the comparative ignorance context: the indifferent consumers are not sure how to evaluate the information provided, compared to how they evaluate the stand-alone label. In other words, when the indifferent group sees a label by itself, it has less impact on their WTP because their priors are such that they are not very concerned. However, if you shock them with both a label and negative information, it then reduces their WTP more drastically. In this case, additional negative information about the credence attribute raises uncertainty and reduces the WTP as well as the dispersion of bids.

3.6 Concluding remarks and policy implications

In light of continuing debate surrounding mandatory labeling policies, this paper addresses two main objectives. First, we explore whether and how label information changes the shape of demand for different types of consumers. Second, we examine how uncertainty perceptions and endogenous preferences for labeled credence attributes affect consumer demand.

We develop a theory-based econometric model to measure the impact of food labels with and without additional information on consumer demand. The preferences for labeled characteristics is modeled endogenously, and thus explicitly addresses concerns expressed in the literature that labels themselves might serve as warning signals about the safety of labeled products (Artuso, 2003; Lusk and Rozan, 2008; and Constanigro and Lusk, 2014). We find some empirical support for this assertion.

Specifically, we find that for concerned consumers, who also tend to be the most vocal supporters of such labeling policies, a "Contains" label absent additional secondary information serves as a noisy warning signal and increases uncertainty, leading this type of consumer to overestimate the riskiness of consuming the labeled product. The provision of additional (even negative) information reduces the noise in the information signal, thereby mitigating the negative signaling effect of the label. Additionally, we find that indifferent consumers do not have strong priors about the possible implications of the labeled ingredients or production processes, and additional negative information is treated as noisy. For this type of consumer, additional negative information about the credence attribute raises uncertainty and further reduces WTP compared to the label by itself.

The results of this study have direct and immediate implications for the food industry and policy makers who are currently considering requiring mandatory labeling of ingredients and/or production practices on food products. Our findings suggest that labeling initiatives in individual states and at the federal level could lead to a significant decrease in consumers' WTP for labeled items, depending on the composition of the consumer population and the methods of implementing the labeling requirements. An important consideration is that if labeling requirements are imposed, provision of even negative additional information (which is mostly provided to the interested public by consumer groups) can partially mitigate the demand-reducing effects of the label, but only if consumers in the market have pre-conceived

notions and beliefs about these ingredients. However, in markets where the majority of consumers are indifferent or pay little attention to the ingredients labeled, the provision of additional negative information would further decrease the WTP for such products.

REFERENCES

Anderson, S. P., A. de Palma, and Thisse, J.-F. 1992. *Discrete Choice Theory of Product Differentiation*. *Cambridge, MA:* MIT Press.

A. Artuso. 2003. Risk perceptions, endogenous demand, and regulation of agricultural biotechnology. *Food Policy* 28**:** 131–145

Becker, G. M., M. H. Degroot, and Marschak, J. 1964. Measuring Utility by a Single-Response Sequential Method. *Behavioral Science*: 226-232.

Berry, S. T. 1994. Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics* 25: 242-262.

Brouhle, K., and Khanna, K. 2007. Information and the Provision of Quality Differentiated Products". *Economic Inquiry* 45: 377-394.

Costanigro, M., and Lusk, J. L. 2014. The signaling effect of mandatory labels on genetically engineered food. *Food Policy* 49: 259-267.

Crespi, J. M., and Marette, S. ""Does Contain" Vs. "Does Not Contain": Does It Matter Which GMO Label Is Used?" *European Journal of Law and Economics* **16**(2003): 327-344.

Darby, M. R., and Karni, E. "Free Competition and the Optimal Amount of Fraud." *Journal of Law and Economics* **16**(1973): 67-88.

Food Marketing Institute (FMI). 2006. U.S. Grocery Store Shopper Trends." Arlington, VA.

Fox, C. R., and Weber, M. 2002. Ambiguity Aversion, Comparative Ignorance, and Decision Context. *Organizational Behavior and Human Decision Processes* 88: 476-498.

Fox, J., D. Hayes, and Shogren, J. 2002. Consumer Preferences for Food Irradiation: How Favorable and Unfavorable Descriptions Affect Preferences for Irradiated Pork in Experimental Auctions. *Journal of Risk and Uncertainty* 24: 75-95.

Fulton, M. and K. Giannakas. 2004. Inserting GM products into the food chain: the market and welfare effects of different labeling and regulatory regimes. *American Journal of Agricultural Economics* 86: 42–61

Hallman, W. K., Hebden, W.C., Aquino, H.L., Cuite, C.L., and Lang, J.T. 2003. *Public Perceptions of Genetically Modified Foods: A National Study of American Knowledge and Opinion*. New Brunswick, NJ. Food Policy Institute, Cook College, Rutgers - The State University of New Jersey.

Hotz, V. J., and Xiao, M. O. 2013. Strategic Information Disclosure: The Case of Multiattribute Products with Heterogeneous Consumers. *Economic Inquiry* 51: 865-881.

Hu, W., M. M. Veeman and W. L. Adamowicz. 2005. Labelling genetically modified food: heterogeneous consumer preferences and the value of information. *Canadian Journal of Agricultural Economics* 53: 83–102

Huffman, W. E., M. Rousu, J. F. Shogren, and Tegene, A. 2004. Consumer's Resistance to Genetically Modified Foods: The Role of Information in an Uncertain Environment. *Journal of Agricultural & Food Industrial Organization* 2: 1-15.

International Food Information Council. 2012. Consumer Perceptions of Food Technology Survey.

Johnson, J. P., and D. P. Myatt. 2006. On the Simple Economics of Advertising, Marketing, and Product Design. *The American Economic Review* **9**6: 756-784.

Karstens, B., and Belz, F.-M. 2006. Information Asymmetries, Labels and Trust in the German Food Market: A Critical Analysis Based on the Economics of Information. *International Journal of Advertising* 22: 189-211.

Liaukonyte, J., N. A. Streletskaya, H. M. Kaiser, and Rickard, B. J. Consumer Response To "Contains" And "Free Of" Labeling: Evidence from Lab Experiments. *Applied Economic Perspectives and Policy* 35: 476-507.

Lusk, J. L., M. Jamal, L. Kurlander, M. Roucan, and Taulman, L. "A Meta-Analysis of Genetically Modified Food Valuation Studies." *Journal of Agricultural and Resource Economics* **30**(2005): 28-44.

Lusk, J.L., and A. Rozan. 2008. Public policy and endogenous beliefs: the case of genetically modified food. *Journal of Agricultural and Resource Economics* 33: 270–289.

Richards, Timothy J., and William Nganje. 2014. Welfare Effects of Food Safety Recalls. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 62: 107-124.

Rickard, B. J., Liaukonyte, J., Kaiser, H. M., and Richards, T. J. 2011. Consumer response to commodity-specific and broad-based promotion programs for fruits and vegetables." *American Journal of Agricultural Economics* 93: 1312-1327.

Rousu, M., W. E. Huffman, J. F. Shogren, and Tegene, A. 2007. Effects and Value of Verifiable Information in a Controversial Market: Evidence from Lab Auctions of Genetically Modified Food. *Economic Inquiry* 45: 409-432.

Sexton, S. 2012. How California's GMO Labeling Law Could Limit Your Food Choices and Hurt the Poor. In *Freakonomics: the hidden side of everything*.

APPENDIX 3.A. Additional Information about Experiment Design

Table 3A. 1. Credence attributes in "Contains X" treatment and information supplied to subjects in "Contains + Information" treatment

Credence Attribute	Item	Additional Negative Information
Genetically modified ingredients	Chewy Granola Bar (with Chocolate Chips)	*GMOs can threaten plant biodiversity because nearby conventional crops are easily contaminated by the growing GMOs in the area. *Some research finds that genetically modified foods can distort natural digestive process and potentially lead to some food allergies. *One study shows that consumption of genetically modified soy can lead to liver problems.
Ingredients that have been exposed to growth hormones	Mozzarella String Cheese	*Growth hormones are used on dairy farms to increase a cow's milk production. *The use of growth hormones substantially increases health problems for cows and causes reproductive disorders in cows *Products containing growth hormones are banned in the European Union but not in the United States
Irradiated ingredients	Granola Trail Mix (with dried fruit and nuts)	*Irradiation exposes foods to radiant energy to prolong shelf life among other uses. *Some studies show that irradiated food can lose 5-80% of their vitamin content, and may damage natural enzymes making it harder to digest the irradiated foods. *Irradiated foods are banned in the EU, but they are not banned in the United States
Ingredients that have been exposed to antibiotics	Beef Jerky (with Natural Smoke Flavoring)	*Some scientific studies show that use of antibiotics will lead to human resistance to antibiotic drugs such as penicillin and bacitracin. *An estimated 14,000 Americans die every year from drug-resistant infections. *The use of non-therapeutic antibiotics is banned in the EU, but it is not banned in the United States
High fructose corn syrup	Soft Baked Oatmeal Chocolate Chip Cookies	*In the United States, HFCS is a processed corn syrup that has largely replaced table sugar as a sweetener in processed foods and beverages. *Studies show that extensive use of HFCS is more harmful to humans than regular sugar, contributing to weight gain by affecting normal appetite functions. *Some research shows that in some foods HFCS may be a source of mercury, a neurotoxin.
Partially hydrogenated oils	Oven Baked Potato Chips	*Partially hydrogenated oils contain trans fats which raise levels of bad cholesterol, and lower levels of good cholesterol leading to circulatory diseases including heart disease. *Food legislation in the United States and the European Union require labels to declare the trans fat content. *Trans fats are banned from foods sold in restaurants in New York City.
Artificial color Red No. 40	Gummy Bears	*Red No. 40 is an artificial coloring commonly used in gelatins, puddings, confections, and beverages. *Some research has suggested that artificial dye called Red No. 40, leads to behavioral changes in children diagnosed with ADHD. *Some companies started voluntarily withdrawing products with such artificial dyes.

Table 3A.2. Socio-Demographic Questions and Answer Option List

#	Question	Answer Options/Description
1	What is your gender?	male female
2	What is your age?	20 or less 21-30 31-40 41-50 51 or more
3	What is the highest level of education you have achieved?	High School Undergraduate degree Associate degree Graduate degree or higher
4	How would you describe yourself?	Drop-down list: Caucasian African American Asian/Asian American Hispanic Native American Other
5	What is your family household income?	Less than $40,000 $40,001-$80,000 $80,001-$120,000 $120,001-$160,000 Over 160,000 Decline to answer
6	What is your marital status?	single married other
7	How many children do you have?	no one two three four more than four
8	Do you smoke?	yes no
9	Do you drink alcoholic beverages?	yes no
10	How would you describe your health condition?	underweight normal weight slightly overweight overweight obese
11	Do you often buy organic products?	yes no
12	On a scale of 1-5, please rate your preferences on the television segments and advertisements you have just watched. (1 - dissatisfied and 5 - very satisfied):	TV show, Menu variety, Price are rated from 1 to 5.

APPENDIX 3.B. Information noise, product idiosyncrasy and distribution of WTP.

Suppose the prior distribution of Bayesian consumers' true monetary utility for a product satisfies $\omega \sim \mathrm{N}\,(\mu, \rho^2)$. Consumer updates her prior ω *given a noisy signal* $x|\omega \sim N\,(\omega, \xi^2)$. Her posterior becomes $\omega|x \sim N\left(\frac{\rho^2 x+\xi^2\mu}{\rho^2+\xi^2}, \frac{\rho^2\xi^2}{\rho^2+\xi^2}\right)$, or, multiplying both numerator and denominator by $\frac{1}{\xi^2}$, we get $\omega|x \sim N\left(\frac{(\rho^2/\xi^2)x+\mu}{1+\rho^2/\xi^2}, \frac{\rho^2}{1+\rho^2/\xi^2}\right)$.

Under assumed normality, consumer's WTP is certainty equivalent $E[\omega|x] - \lambda \mathrm{var}[\omega|x]/2$. Substituting in the mean and variance obtained above, we get WTP $\theta(x) = \frac{1}{1+\rho^2/\xi^2}\left[\mu - \frac{\lambda\rho^2}{2}\right] + \frac{\rho^2/\xi^2}{1+\rho^2/\xi^2}x$. This expression is a weighted average of the ex-ante certainty equivalent and the ex-post information signal realization. The weights depend on ρ^2, which approximates the heterogeneity in consumer preferences for a product, and ξ^2, the information noise, or the level of uncertainty that information signal triggers. As the realized information signal follows the distribution $x \sim N(\mu, \rho^2 + \xi^2)$ and consumer's valuations are linear in x, we obtain the distribution of consumer's WTP, θ.

$$WTP \sim N\left(\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}, \frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}\right)$$

Remember that θ is drawn from the distribution $F_s(\theta)$, twice continuously differentiable in both s and θ, with support on $(\underline{\theta}_s, \overline{\theta}_s)$ interval, where $s \in \mathrm{S} =$

$[s_l, s_h]$ indexes a family of distributions. The inverse demand is $P_s(q) = F_s(1-p)$, where q is the proportion of consumers willing to purchase the product at price p, and is given by $q = 1 - F_s^{-1}(p)$. $F(\bullet)$ is a continuous distribution with zero mean, unit variance and strictly positive density, and $\mathrm{P}(q) = \mathrm{F}^{-1}(1-q)$. $F_s[P_s(q)] = 1 - q \Leftrightarrow F_s\left[\frac{P_s(q)-\mu(s)}{\sigma(s)}\right] = 1 - q \Leftrightarrow P_s(q) = \mu(s) + \sigma(s)F^{-1}(1-z) = \mu(s) + \sigma(s)P(z)$.

For any choice of ρ^2 and ξ^2, the distribution remains within the normal family. Then, any changes in either ρ^2 or ξ^2, yield a variance-ordered family with a changing mean: $\mathrm{P}(q) = \left(\mu - \frac{\lambda\,\rho^2}{2(1+\rho^2/\,\xi^2)}\right) + \left(P(q)\sqrt{\frac{\rho^4/\,\xi^2}{1+\rho^2/\,\xi^2}}\right)$.

MATHEMATICAL PROOFS OF MAIN RESULTS

Table 3.B1. Means and dispersions as a function of model parameters

	Concerned		**Indifferent**	
	Mean	St. Dev.	Mean	St. Dev.
T0: control	(1C) $\mu_C - \frac{\lambda\rho_{C0}^2}{2(1+\rho_{C0}^2/\xi_{C0}^2)}$	(4C) $\sqrt{\frac{\rho_{C0}^4/\xi_{C0}^2}{1+\rho_{C0}^2/\xi_{C0}^2}}$	(1I) $\mu_I - \frac{\lambda\rho_{I0}^2}{2(1+\rho_{I0}^2/\xi_{I0}^2)}$	(4I) $\sqrt{\frac{\rho_{I0}^4/\xi_{I0}^2}{1+\rho_{I0}^2/\xi_{I0}^2}}$
T1: label + no information	(2C) $\mu_C - \frac{\lambda\rho_{C1}^2}{2(1+\rho_{C1}^2/\xi_{C1}^2)}$	(5C) $\sqrt{\frac{\rho_{C1}^4/\xi_{C1}^2}{1+\rho_{C1}^2/\xi_{C1}^2}}$	(2I) $\mu_I - \frac{\lambda\rho_{I1}^2}{2(1+\rho_{I1}^2/\xi_{C1}^2)}$	(5I) $\sqrt{\frac{\rho_{I1}^4/\xi_{C1}^2}{1+\rho_{C1}^2/\xi_{C1}^2}}$
T2: label + information	(3C) $\mu_C - \frac{\lambda\rho_{C1}^2}{2(1+\rho_{C1}^2/\xi_{C2}^2)}$	(6C) $\sqrt{\frac{\rho_{C1}^4/\xi_{C2}^2}{1+\rho_{C1}^2/\xi_{C2}^2}}$	(3I) $\mu_I - \frac{\lambda\rho_{I1}^2}{2(1+\rho_{I1}^2/\xi_{I2}^2)}$	(6I) $\sqrt{\frac{\rho_{I1}^4/\xi_{I2}^2}{1+\rho_{I1}^2/\xi_{I2}^2}}$

1. $\xi_{C1}^2 > \xi_{C2}^2$. Proof. Consider the comparison of estimated means and standard deviations for concerned group for treatments 1 and 2 in Table 3.3:

$$\begin{cases} \mu_C - \frac{\lambda\rho_{C1}^2}{2\left(1+\frac{\rho_{C1}^2}{\xi_{C2}^2}\right)} > \mu_C - \frac{\lambda\rho_{C1}^2}{2\left(1+\frac{\rho_{C1}^2}{\xi_{C1}^2}\right)} & (1) \\ \sqrt{\frac{\rho_{C1}^4/\xi_{C2}^2}{1+\rho_{C1}^2/\xi_{C2}^2}} > \sqrt{\frac{\rho_{C1}^4/\xi_{C1}^2}{1+\rho_{C1}^2/\xi_{C1}^2}} & (2) \end{cases}$$

Rearranging (1) we have $\frac{\lambda\rho_{C1}^4(\xi_{C1}^2-\xi_{C2}^2)}{2\xi_{C1}^2\xi_{C2}^2} > 0$. Since $\lambda > 0$, $\rho_{C1}^4 > 0$, $\xi_{C1}^2 > 0$, and $\xi_{C2}^2 > 0$, then it must be the case that $\xi_{C1}^2 > \xi_{C2}^2$. Rearranging (2) leads to $\sqrt{\frac{\rho_{C1}^4}{\rho_{C1}^2+\xi_{C2}^2}} < \sqrt{\frac{\rho_{C1}^4}{\rho_{C1}^2+\xi_{C1}^2}}$. For any given ρ_{C1}^4, and $\xi_{C1}^2 > \xi_{C2}^2$, this inequality also holds.

2. $\xi_{I1}^2 < \xi_{I2}^2$. Proof. Consider the comparison of estimated means and standard deviations for indifferent group for treatments 1 and 2 in Table 3.3:

$$\begin{cases} \mu_I - \frac{\lambda\rho_{I1}^2}{2\left(1+\frac{\rho_{I1}^2}{\xi_{I2}^2}\right)} < \mu_I - \frac{\lambda\rho_{I1}^2}{2\left(1+\frac{\rho_{I1}^2}{\xi_{I1}^2}\right)} & (1) \\ \sqrt{\frac{\rho_{I1}^4/\xi_{I2}^2}{1+\rho_{I1}^2/\xi_{I2}^2}} < \sqrt{\frac{\rho_{I1}^4/\xi_{I1}^2}{1+\rho_{I1}^2/\xi_{I1}^2}} & (2) \end{cases}$$

Rearranging (1) we have $\frac{\lambda\rho_{I1}^4(\xi_{I1}^2-\xi_{I2}^2)}{2\xi_{I1}^2\xi_{I2}^2} < 0$. Since $\lambda > 0$, $\rho_{I1}^4 > 0$, $\xi_{I1}^2 > 0$, and $\xi_{I2}^2 > 0$, then it must be the case that $\xi_{I1}^2 < \xi_{I2}^2$. Rearranging (2) leads to $\sqrt{\frac{\rho_{I1}^4}{\rho_{I1}^2+\xi_{I2}^2}} < \sqrt{\frac{\rho_{I1}^4}{\rho_{I1}^2+\xi_{I1}^2}}$. For any given ρ_{I1}^4, and $\xi_{I1}^2 < \xi_{I2}^2$, this inequality also holds.

CHAPTER 4. Social Presence and Shopping Behavior: Evidence from Video Data

4.1 Introduction

Even with the recent tremendous growth in e-commerce, consumers still purchase most products in the traditional retail shopping environment where they are surrounded by other shoppers and sales people. For example, in the second quarter of 2015, less than 7% of all retail sales occurred online in the U.S. (U.S. Department of Commerce, 2015). Hence, brick-and-mortar retail stores remain the place for the usual "shopping experience" complete with customer service and interactions with other customers (Hu and Jasper, 2006).

While the basic traditional theories of economic behavior treat consumer choices as being unaffected by the social nature of human interactions, a well-established body of behavioral economics and marketing research examines how consumer behavior might be impacted by social characteristics of the environment. In particular, this literature investigates the impact of social interactions with peers, family members or sales people on consumer purchasing behavior (see, for example, Becker and Murphy, 2000), and establishes that the concepts of reciprocity, social norms and conformism, altruism and other behavioral constructs are important in explaining consumer choices. These behavioral mechanisms are likely to be at work (though to a lesser degree) even in social settings with complete strangers (Gui and Sugden, 2005, provide a detailed discussion). To our knowledge, none of the existing

studies have investigated whether social presence of strangers affects consumer behavior[13], which is the main focus of this paper.

There are at least two plausible reasons why social presence might affect consumer choices: status signaling and guilt reciprocity. Status signaling implies that consumers' purchasing decisions, in part, are influenced by the status that they want to convey to others with their purchases. Consumers have been shown to engage in status signaling with a variety of goods, including environmentally friendly goods (Griskevicius et al., 2010, Johansson-Stenman and Martinsson, 2006) or, pertinently to this paper, food items (Dubois et al., 2012, Dimara and Skuras, 2005). Visibility is an important consideration in status signaling behavior and is likely to be affected by the number of people witnessing it. Status signaling is likely to be the strongest when other people are present, possibly leading consumers to either buy more expensive products, or to skip the purchase altogether to avoid a low-status signal. (Fremling and Posner, 1999).

Guilt reciprocity behavior, on the other hand, occurs when consumers experience a feeling of reciprocal responsibility towards the salesperson (Fehr and Gächter, 2000, Sugden, 1984, Rabin, 1993). Dahl et al. (2005) find that consumers tend to have complex reactions to even the most fleeting social interactions in the

[13] Dahl et al. (2001) looked at how consumers feel when buying embarrassing products such as condoms in the presence of others, but did not look specifically at how the change in social presence affected consumer behavior.

store and often feel guilty when they fail to fulfill the norm of reciprocity and make a purchase. The mechanism of responsibility diffusion (Darley and Latane, 1968, Forsyth et al., 2002) is likely to reduce the feeling of guilt in presence of more customers. The effect of higher level of social presence is commonly seen in tipping behavior, for example Freeman et al. (1975) and Lynn (2006) suggest that the primary reason why large dining parties leave smaller percentage tips is the diffusion of shared responsibility that each group member has for tipping the server.

This paper examines whether and how the presence of other people in stores impacts consumers' shopping behavior. Specifically, we use a unique dataset of video surveillance combined with sales data from a small boutique wine store to investigate the effect of change in the level of social presence on customer behavior. We observe the entrance and exit times as well as various actions of individual customers in a store and determine whether there was an exogenous change in a social presence during each consumer's shopping trip. As some customers might self-select to enter an empty or a full store, or might be anchored to the level of social presence at the time of entry, consumer preferences might be endogenous to social presence. The choice of other shoppers to enter or leave the store, however, is exogenous to the decision of any customer to enter the store. In other words, the exogenous change in social presence status essentially gives us random assignment into a control and treatment groups. Customers from the control group do not experience a change in the level of social presence: those who come into an empty store have no other customers enter

the store, while those who come into a full store do not end up shopping alone. Customers in the treatment group, on the other hand, experience a change in the level of social presence: those who enter an empty store have other shoppers come in, while customers who enter a full store end up shopping alone. Given the possible endogeneity concerns, we analyze consumers who enter the full and empty store separately. This two-by-two quasi-experimental design allows us to causally infer the effect of both a decrease and an increase in the level of social presence on shopping behavior. Furthermore, our unique data allows us to observe whether customers approached and investigated any wine on the central stand displaying only inexpensive wines, as well as whether consumers kept and purchased any of the wines that they picked up to consider. These coded actions provide rich data for analyzing status signaling and guilt reciprocity behaviors.

Our main finding is that people have a significantly lower propensity to buy anything when other shoppers are present. This is consistent with both status signaling and guilt reciprocity behaviors. We also find that social presence has a different impact on the price of purchased bottles and total spending based on whether the customer entered an empty or full store. Specifically, for the customers who enter a full store, a higher level of social presence leads to a significant increase in the mean price of purchased bottles. On the other hand, for consumers who enter an empty store, a higher level of social presence decreased total spending on bottles bought. We develop a theoretical model that accommodates status signaling as well as

guilt reciprocity behaviors and show that patterns observed in the data are consistent with our theoretical predictions.

This paper contributes to the behavioral economics and marketing literature by presenting robust empirical evidence that social characteristics of our environments affect our choices and should thus be taken into account when modeling consumer behavior. Specifically, this research contributes to the ongoing discussion on the social multiplier (Glaeser et al., 2003), a phenomenon of aggregate data not reflecting the relevant individual behavior and elasticities due to the presence of social interactions. Similarly, it highlights limitations of laboratory experiments that do not reflect realistic social environments. This is the first paper to our knowledge to present empirical field evidence of both behavior consistent with guilt reciprocity and status signaling. Finally, this paper provides insights about consumer behavior that are relevant for store managers.

We proceed with the paper by briefly summarizing the existing relevant research on status signaling and guilt reciprocity in section 4.2. We describe the data and provide descriptive statistics of interest in section 4.3. We develop a theoretical model and formulate relevant hypotheses in section 4.4. Section 4.5 discusses our estimation approach, and section 6 presents results. Finally, section 4.7 concludes.

4.2 Literature review

Two behavioral patterns most likely to influence consumer choices as the level

of social presence changes are: (i) status signaling and (ii) anticipatory guilt and reciprocity towards the salesperson. Below we summarize the current research on both status signaling and guilt and reciprocity, discuss other research relevant for evaluating the effects of social presence on consumer behavior, and identify some gaps in the existing literature.

4.2.1 Status Signaling

Status signaling is a widely recognized behavioral pattern, first identified by Veblen (1899) through the concept of conspicuous consumption, where concern for social status drives consumption aimed at signaling the individual's wealth. Since then, evidence for status signaling behavior has been identified in a variety of environments, including markets for durables, food and clothing retail items (Basmann et al., 1988), luxury goods (Han et al., 2010), and even environmental goods (Griskevicius et al., 2010). In addition to people engaging in status signaling behavior, it is now widely recognized that individuals often infer other people's social status and success from their possessions and signaling behavior (Richins, 1994, Burroughs et al., 1991).

Status signaling has important implications for many issues in economics, such as tax policy, growth models, environmental conservation, consumption and other areas (Corneo and Jeanne, 1997, Rege, 2008, Truyts, 2010, Kahneman et al., 1999, Brekke et al., 2003). The question of how strongly consumer behavior is actually affected by status signaling can inform the decision to model or ignore it. The extent

to which status signaling is observed remains a non-trivial issue as behaviors consistent with it could potentially be explained by other phenomena, and have different implications depending on how and who employs status signaling (e.g. Rucker and Galinsky, 2009, Brekke and Howarth, 2002).

Status signaling and conspicuous consumption are often used interchangeably, but status signaling need not be conspicuous. It has been identified in more short-term interactions or in purchases of food items (Dubois et al., 2012, Dimara and Skuras, 2005) that are much less conspicuous than durable goods. Finally, costly self-signaling can occur in the absence of any audience or observers (Johansson-Stenman and Martinsson, 2006).

In most cases status signaling manifests through consumption of higher priced items, or through higher than optimal consumption (Rege, 2008, Brekke and Howarth, 2002). The theory of status signaling (for an in-depth discussion see Fremling and Posner, 1999) suggests that its effects are not limited to the purchase of more expensive goods. Specifically, individuals might avoid making a purchase or any decision that would send a low status signal to others. For example, consider a customer shopping for a bottle of wine who considers the status signal any particular bottle would send, the cost of status signaling, and his original willingness-to-pay (WTP) for the bottle. This consumer may actually decide to forgo the purchase altogether if the desired social status signal is deemed too costly.

The data on people foregoing the purchase is often missing, which might lead to underestimation of the actual extent of social status signaling. Additionally, a lot of the existing research on status signaling relies on self-reported attitudes or plans, which do not necessarily reflect subsequent actions.

This paper exploits data on customers who don't buy anything to examine the propensity to buy, which allows for a more complete investigation of status signaling. Prices of wines bought and the total spending in the store supplement the data on the propensity to buy and are used in this paper to further examine consumer behavior in the store.

Wine in itself is a peculiar consumer product. Consumers tend to use such extrinsic cues as prices when evaluating quality of wines (Lockshin and Timothy Rhodus, 1993), and reputation for quality, as well as expert ratings, often have a stronger influence on price and consumer preferences that the actual quality and taste characteristics (Cardebat and Figuet, 2004). All in all, wine is a perfect product to examine the effect of status signaling, as it is commonly perceived as the preferred product of the affluent consumers (Bisson et al., 2002), and is commonly consumed by high-income consumers (Blaylock and Blisard, 1993), and is thus likely to be a product used in status signaling behavior.

4.2.2 Guilt and Reciprocity Paradigm

Guilt is a form of emotional distress that usually stems from the belief that one

has violated a personal or social norm (e.g. Lascu, 1991; Baumeisteretal., 1994).It is usually considered to be an adaptive function, acting as a behavioral interrupt and informing the consequent actions of the individual. The emotion of guilt in a consumption context has been linked to compulsive consumption and impulsive buying or returning of merchandise. More generally, guilt is often used in advertising or in motivating pro-social behavior, especially in the public goods domain (Renner et al., 2013).

Reciprocity is a social norm that encourages individuals to pay back what others provided, often by focusing on what the person needs, rather than by matching the initial actions (Cialdini, 1980, Clark, 1986, Fehr and Gächter, 2000, Rabin, 1993). Previous research has consistently shown that consumers value the social interactions with the salesperson (Hu and Jasper, 2006), and that consumers believe the act of purchase to be the expected normative outcome of an interaction with a salesperson. In this setting consumers violating the social reciprocal expectation of purchase will feel guilt, or anticipatory guilt when considering not buying anything. Using surveys administered after randomly assigned shopping tasks, Dahl et al., 2005 find that even short interactions with the salesperson lead to an increased experience of guilt when a purchase is not made, with participants planning to take that feeling into account during future visits to the store.

The above study has some limitations due to the self-reported nature of the

emotions and planned future actions, the fact that shopping tasks were assigned, and not self-selected, the extremely low cost of the purchases made ($2 spending limit for items such as snacks or school supplies) and the student sample used . This study, on the other hand, uses field data from all customers entering a wine store, with no limit on spending and no experimental compulsion to buy anything. Also, Dahl et al., 2005 do not control for the presence of other people in the store, which limits our understanding of how social presence affects guilt and reciprocity behavior.We use video data to identify the change in the level of social presence to address that shortcoming.

Presence of other shoppers may be an important consideration in any research that examines social norms due to responsibility diffusion. When other people are present, the pressure of maintaining any particular reciprocal norm is not focused on one individual, but rather on all people present (Darley and Latane, 1968). Therefore, the feeling of reciprocal responsibility diffuses proportionally to a group's size (Forsyth et al., 2002). The reciprocal responsibility is widely observed in tipping, which is a common economic activity motivated by mostly by social norms (Conlin et al., 2003), where the size of tip is significantly impacted by the number of people present, i.e., the larger the group size, the smaller the percentage tip (Freeman et al. (1975); see Lynn, 2006 for an extensive overview of tipping practices).

This leads us to expect responsibility diffusion to affect the extent to which

consumers feel guilt when they are not the only shoppers present, and thus are not the only people able to make the norm-driven purchase.

This paper addresses some of the shortcomings of the papers mentioned in this section. We expect both the guilt reciprocity and the status signaling to be present in our context, and in section 4 we develop a more formal model of consumer decision making.

4.3 Data and Descriptive Statistics

We use a combination of video surveillance data and sales data from a small boutique store specializing in small production estate-bottled wines and ciders for a period of 23 days in April-May 2014. The video data were collected using four different surveillance cameras covering the entire area of the store[14]. The surveillance video covered the whole area of the store, including the checkout counter, and provided the information on the time people entered and exited the store, and the various consumer actions at the store's displays and shelves. On the date and time stamps, present on all recorded files, seconds were used as the smallest unit of time. Seven research assistants were trained to code the surveillance data. A separate group

[14] Video surveillance in public is legal in New York State (the location of the studied boutique store) without explicit consent of people being observed as long as no audio data is recorded, and as long as the person surveyed does not have a reasonable expectation of privacy (Article 250, NY State Penal Law).

of research assistants were asked to code a random sample (20% of the total footage) to cross-check the reliability of the original coders. In total, we analyzed 184 hours of the recorded footage. Coders were instructed to watch all video files without fast-forwarding, and to record the entry and exit time of each customer, customer's gender, whether or not the salesperson provided any assistance during shopping, and for those customers, who did buy something, the time they checked out at the counter. Coders also noted the number of times the person picked any bottle for close examination from the shelf or display, and whether the customer ended up purchasing the bottle she picked up. Additionally, the number of times a consumer approached a table that exclusively featured bottles priced under $15 (with a sign prominently displaying the price range) was recorded.

The sales data, obtained directly from the store owners, included item descriptions, prices, quantities purchased, tax and discount amounts, final total cost and the time and date of the purchase. The timestamps from the sales data provided additional reference points for customers who made a purchase, and were used to match consumers in the video data to their expenditures. For customers who did not make a purchase, the number of bottles was coded as zero.

4.3.1 Quasi-experimental exogenous variation in number of people present in the store

A common and important challenge for studies investigating the effects of

social presence in the field is the problem of endogeneity. For example, a customer who is self aware might prefer to avoid any situation that leads him to, in his opinion, overspend, or to purchase unnecessary items. Similarly, consumers with specific preferences for the social aspects of shopping might prefer to come into a full or empty store. Finally, some consumers might be anchored to the social presence level in the store at the time of entry. This presents a serious endogeneity issue, since the preferences for social aspects of the shopping environment could potentially be correlated with the propensity to purchase anything and, for example, preferences for inexpensive or expensive wines. If customers do self-select the level of social presence at the time of entry, or become anchored to that level, then we can not compare the propensity to buy and the prices or total expenditures, of consumers who entered an empty or full store. On the other hand, for each customer, the decision of other people to come in or leave the store is exogenous to his or her own decision to come in.

We utilize this exogenous variation in the level of social presence in the study design. Using the time stamps for the entry and exit of customers in the sample, we classify consumers into four groups, with two customer groups that do not experience a change in the level of social presence during their visit to the store, and two groups that do. Based on this classification, we define a control and treatment group for customers who come into an empty store:

1. There are no other people in the store at any point while the customer is in the store. In other words, the customer comes into an empty store, and leaves a still empty store. This is the control group, with customers who do not experience a change in the level of social presence.
2. There are no other shoppers when the customer enters the store, but there are other shoppers present in the store when she leaves. This is the treatment group, in which consumers experience an increase in the level of social presence.

Similarly, the control and treatment groups are defined for customers who enter a full[15] store:

1. There are other shoppers in the store both at the time of entry and exit. This is the control group, where customers not experiencing a change in the level of social presence.
2. There are other people present when the customer enters the store, but no other customers when she leaves. This is the treatment group, with customers experiencing a decrease in the level of social presence.

[15] In this paper we use the word "full store" to denote a situation where there is at least one other customer present, other than the customer in question.

Figure 4.1 presents time frames for the four customer groups as outlined:

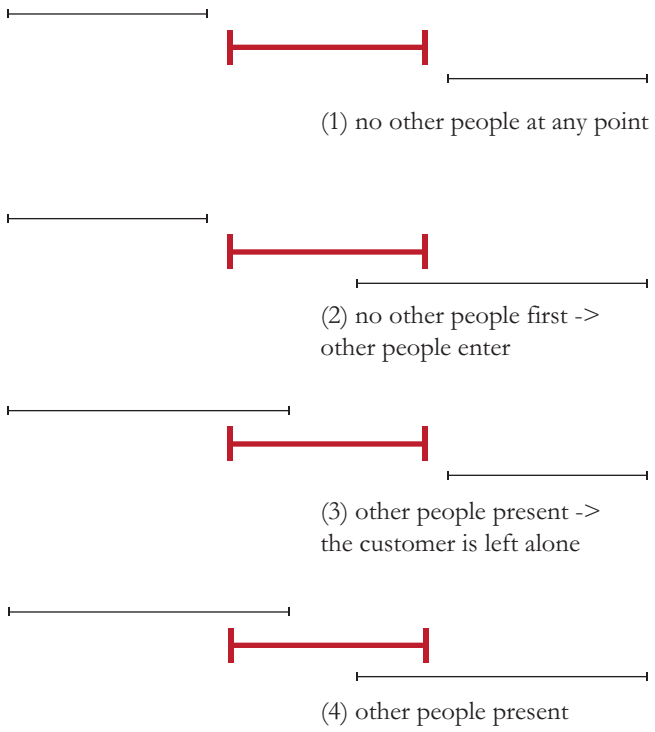

Figure 4.1 Customer categories based on social presence

We use this quasi-experimental exogenous variation to see how the change in the number of people present in the store affects customers' propensity to purchase as well as the price of their selected bottles. It is important to note that among customers who enter an empty store, we see the effect an increase in the level of social presence has on consumer choices, while the control and treatment groups for shoppers who come into a full store provide information on the effects of a decrease in the level of social presence. Using Kolmogorov-Smirnov tests, we compare the distributions of time of entry for consumers in the control and treatment groups for customers who enter a full or empty store, and find them not to be significantly

different from each other. This confirms that this change in social level presence can be treated as exogenous. The same test is used to compare the distribution of entry times between customers entering a full or an empty store in general, and they are also found to not be significantly different from each other.

4.3.2 Descriptive statistics

Over the course of the 23-day period, we observe 1,093 individual shoppers. Twice during the analyzed period the store held wine-tastings from 5 to 9 pm. We drop all observation of people shopping during the wine tasting, as the number of people in the store and the shop- ping behavior are likely to be influenced by the tasting and the promotional activities. After dropping these observations, a total of 982 individuals remain in our sample. Descriptive statistics for the whole sample and each of the four customer groups are presented in tables 4.1 and 4.2.

In the entire sample, 49% of customers make a purchase, most buying 1 or 2 bottles. The average price of the bottle is $18.66 (standard deviation of $12.11), and the cheapest bottle available in the store costs $6.80. The average visit is around 6 minutes, however, customers who buy anything on average spend significantly more time in the store.

Table 4.1. Descriptive statistics, full sample

Variables of interest:	
% of people buying	0.494 (0.500)
Average price of bottle, if bought	18.665 (12.132)
Average number of bottles, if bought	1.872 (1.641)
Total cost, if bought	34.271 (33.330)
% people assisted	0.338 (0.473)
Time spent in the store, minutes	6.061 (5.016)
Female	0.495 (0.500)
N	983

The proportion of female and male customers is about equal for all four customer groups, with the exception of the treatment group for customers who came into an empty store, which has more men, though the difference is not statistically significant compared to the other groups. Approximately 12% more customers receive manager's assistance when level of social presence is higher, a difference significant at the 5% level. This is reasonable as more people in the store makes it more difficult for a salesperson to help every customer.

Table 4.2. Descriptive statistics, four customer groups

Come in the store when it is:	Variables of interest:	*Leave the store when it is:* **empty**	*Leave the store when it is:* **full**
		Control	Treatment
empty	% of people buying	0.755 (0.431)	0.580 (497)
	Average price of bottle, if bought	19.516 (14.476)	17.185 (6.591)
	Average number of bottles, if bought	2.014 (1.811)	1.915 (1.365)
	Total cost, if bought	37.486 (38.046)	31.198 (20.830)
	% people assisted	0.433 (0.497)	0.407 (0.494)
	Time spent in the store, minutes	5.48 (5.29)	7.73 (8.88)
	Female	0.464 (0.500)	0.346 (0.479)
	N	196	81

		empty	**full**
		Treatment	Control
full	% of people buying	0.685 (0.467)	0.373 (0.484)
	Average price of bottle, if bought	18.507 (7.616)	18.461 (12.341)
	Average number of bottles, if bought	1.820 (1.365)	1.787 (1.644)
	Total cost, if bought	35.814 (36.564)	32.421 (31.200)
	% people assisted	0.416 (0.496)	0.2285 (0.452)
	Time spent in the store, minutes	7.24 (5.93)	5.86 (3.90)
	Female	0.438 (0.499)	0.533 (0.499)
	N	89	617

For the four customer groups, the most striking difference by far lies in the proportion of people making purchases: in general, a lower level of social presence increases the proportion of customers making a purchase. The mean prices of bottles bought varies approximately between $17.20 and $19.50 in the four customer groups, and figures 4.2 and 4.3 illustrate the mean price and total spending differences in more detail.

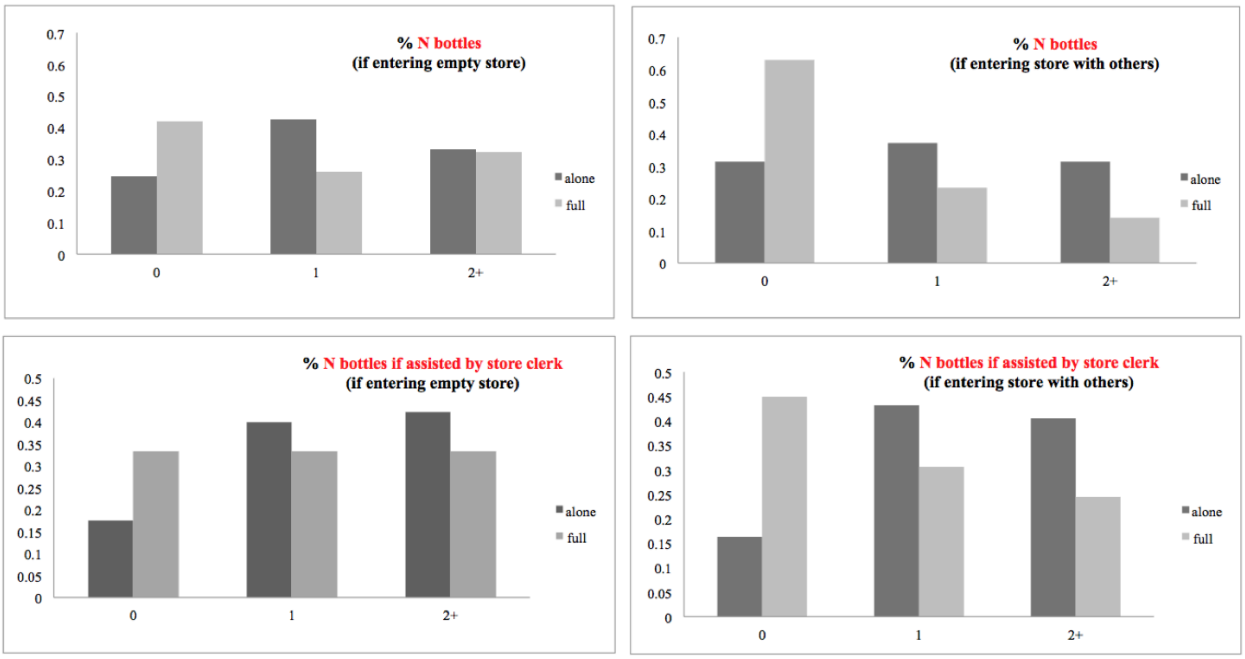

Figure 4.2. Number of bottles purchased

Higher level of social presence seems to have the same impact on the propensity to buy whether people entered the full or empty store. Customers in lower social presence level are approximately twice as likely to leave without buying anything for both customer groups. Over 60% of those who enter a full store do not make a purchase if always around other shoppers. A similar pattern of changes in propensity to buy is seen for the subset of people who receive some assistance from the sales

manager.

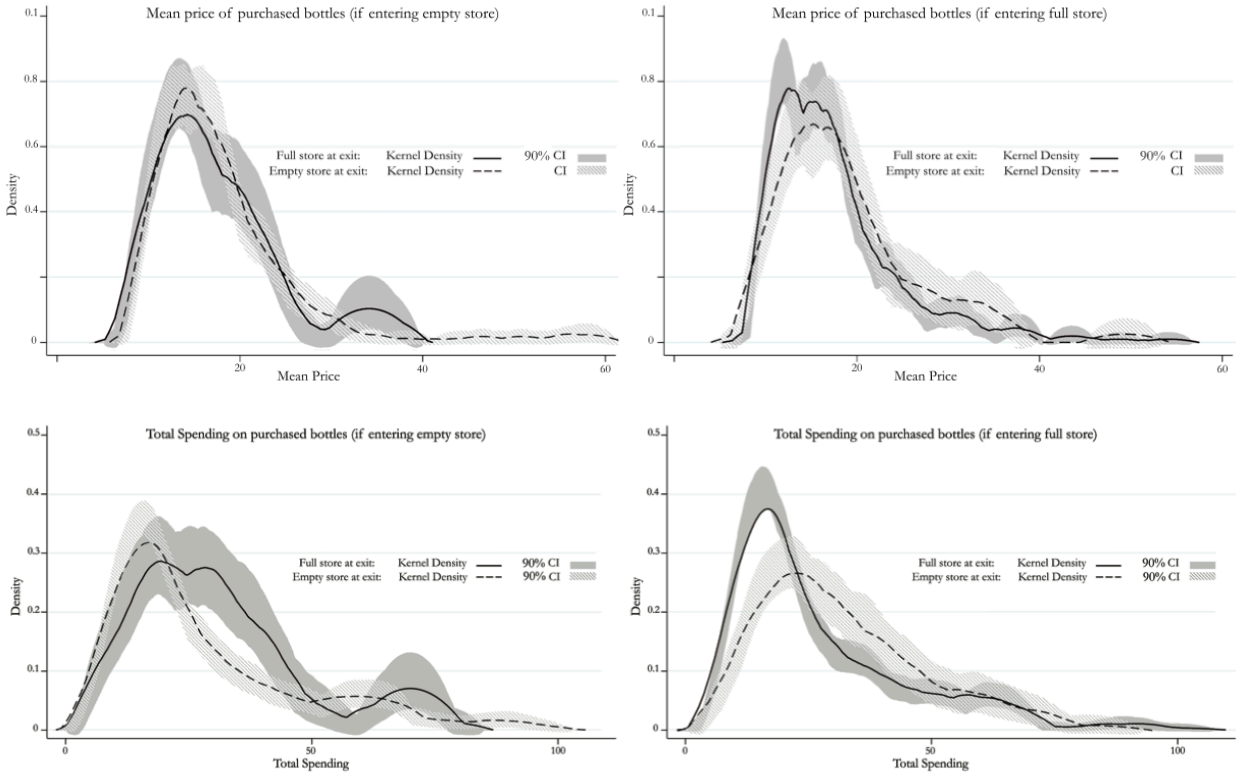

Figure 4.3. Mean price and total spending per group, kernel density and 95% confidence interval estimates

On the other hand, higher level of social presence has a different impact on customers who enter an empty store, and those who enter a full store. Figure 4.3 provides the estimated kernel densities with the corresponding 90% confidence intervals for both the mean price and total spending for the four customer groups. Lower social presence level leads to a more dispersed mean price distribution among people who entered an empty store, but to a less dispersed distribution for those who entered a full store. The differences in total spending in the store appear stronger and follow the same pattern as the changes in the mean price. It is important to note that these densities do not control for any fixed effects or differences between the four

groups.

This provides us with some preliminary evidence that the level of social presence has some correlation with the observed consumer behavior, and also that the presence level in the store at the time of entry is correlated with customer behavior as well. It is possible that people self-select to enter an empty or full store, or that social presence at the time of entry affects customer's behavior for the duration of the visit.

4.4 Theoretical Model and Hypotheses

In this section we develop a simple theoretical model that allows social presence to affect not only the propensity to buy, but also the average price and total expenditure at the store. We use the existing research (please see Rege, 2008, Truyts, 2010, Dahl et al., 2005, among others) on status signaling and guilt reciprocity behavior to guide the development of our model. We do not impose any restrictive assumptions on the model and let the data guide our estimation results. The theory model in this section can be used to deepen our understanding of the impact of other shoppers on one's behavior; however, given the complex nature of the relationship between social presence and purchasing decisions, the exact effects of guilt reciprocity and status signaling might be difficult to disentangle.

We modify a standard utility model to allow for both the signaling and the guilt reciprocity effects. The consumer's maximization problem, when deciding whether to purchase bottle *i* is in choosing whether to make the purchase given the price p_i and

other characteristics of the bottle and environment, or skip it. It can be formalized as follows:

$$\max[\ \underbrace{u(x_i, h)}_{consumption\ utility} + \underbrace{g(n, v)}_{signal\ multiplier}\ \underbrace{s(p_i)}_{signal\ utility} +$$

$$+ \underbrace{f(n)}_{reciprocity\ multiplier}\ \underbrace{R(h)}_{reciprocal\ utility} - p_i,\ 0]$$

where $u(x_i, h)$ is the customer's derived consumption utility for bottle *i* that depends on characteristics x_i of the bottle and help *h* received from the salesperson; $s(p_i)$ is the signaling utility of bottle *i*; given its price p; $g(n, v)$ is the modulator of the signaling effect, amplifying or decreasing the importance of signaling given the visibility of the signal v and the number of people present *n*; $R(h)$ is the reciprocity utility that depends on the level of assistance from the salesperson, *h*; and $f(n)$ regulates the effect of the reciprocity utility given the level of social presence (n) in the store.

Assuming $B = 1\ if\ max[V, 0] = V$, and $B = 0$ if $max[V, 0] = 0$, then probability of purchase $Prob(B = 1)$ increases as $[u(x_i, h) + g(n, v)s(p_i) + f(n)R(h) - p_i]$ increases. This allows us to interpret the changes in propensity to buy bottle *i* on average as a result of the changes in the level of social presence in the store.

The actual number of people present in the store might fluctuate during anyone's shopping trip. More people can come in at any time, a couple of customers

might leave and then new customers still could come in moments later. While those changes might have some effect on consumer behavior they would be very hard to identify because of their transient nature. Observing a categorical switch from being surrounded by other shoppers to being alone and vice versa allows us to cleanly identify the general effect of change in social presence but doesn't identify smaller marginal effect of one more person in the store[16]. Thus we observe two general levels of n on our sample for both customers who entered a full and an empty store, n_{lower} and n_{higher}. Among customers who enter an empty store, the control group has the lower level of social presence n_{lower}, while the treatment group has a higher level of social presence due to customers coming in n_{higher}. For customers who come into a full store, the control group has a higher level of social presence n_{higher}, and the treatment group has a lower level of social presence n_{lower}, as other customers leave. This is summarized in table 4.3.

With the general framework of customer utility defined, we proceed to discuss the individual components of interest.

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[16] We do estimate the model with the change between the maximum and the minimum number of present as the treatment variable and obtain similar results. However, we don't believe using these data on number of people present at various time points during a customer's visit to the store is justified, as multiple changes within the visit, sometimes of different directionality, occur.

Table 4.3. Discrete variation in the levels of social presence

		Group 1	Group 2
		Come in:	
		alone	**full**
leave:	**alone**	$n_{low\ 1}$	$n_{low\ 2}$
	full	$n_{high\ 1}$	$n_{high\ 2}$

4.4.1 Signaling Utility Component

To properly define the signaling component of customer utility, we need to allow for both positive and negative signaling utility. The utility of signaling is positive when the actual price of the bottle is equal or above the price customer believes will send a higher signal about her social status, given the bottle's characteristics. Assume each consumer has a bottle specific monetary-equivalent valuation for each bottle *i*, γ_i, that he believes will signal his social status perfectly. To signal a higher social status the price of the bottle needs to be $\gamma_i + \alpha_i$, where α_i would be the monetary valuation of the signaling above one's and could be equal to zero, when the customer just wants to signal his own social status (instead of signaling a higher one)[17]. The consumer signaling utility is the result of the comparison of $\gamma_i + \alpha_i$ with the price of the bottle p_i, which are weighted the two according to the consumer's signaling function. The

[17] This assumes status signaling is exhibited through spending more, not less money for the majority of shoppers, following the existing research on social signaling

signaling utility's absolute effect is amplified by the number of people (n) present in the store: the more people are around, the stronger the effect of signaling[18]:

$$\frac{\partial g(n,v)}{\partial n} > 0$$

Using discrete coding for the level of social presence, it can be expressed as

$$g(n_{higher}, v) - g(n_{lower}, v) > 0$$

Note, that it is consistent with our model to choose to send a negative signal and still maximize the utility. This might happen in the situations when the individual is placing a lot more weight on the price than on the status signaling component of the utility function. In addition to social presence affecting the extent of signaling, it is also modulated by the visibility of the purchase. The visibility of the purchase can be endogenously set by the customer - the customer can choose an item the price of which is more visible to other shoppers. In our model, higher visibility increases the magnitude of the signaling effect, which in turn can be both positive and negative:

$$\frac{\partial g(n,v)}{\partial v} > 0$$

[18] The above assumption follows existing research, but is not enforced in the estimation. It is only used to define the expected effect of the changes in social presence on consumer behavior.

4.4.2 Guilt Reciprocity Utility Component

Guilt reciprocity is also allowed to be impacted by the number of people present (n). The responsibility diffusion effect decreases the guilt reciprocity as the level of social presence is higher:

$$\frac{\partial f(n)}{n} < 0$$

As we look at discrete change in n, this is effectively equivalent to

$$f(n_{high}) - f(n_{low}) < 0$$

Following Dahl et al. 2005 results, the guilt reciprocity component depends on the level of assistance, *h*, received by the customer. Higher level of assistance increases guilt reciprocity behavior:

$$\frac{\partial R(h)}{h} > 0$$

In our dataset, the level of assistance is identified through a dummy variable equal to one when the salesperson provided any assistance before the purchase:

$$R(h = 1) - R(h = 0) > 0$$

Receiving help from the manager also impacts the search costs of the customer through consumption utility $u(x_i, h)$ - by making it easier or harder to identify the real characteristics of the wine. We allow it to be negative, in case some consumers are discomfited or confused by higher or lower levels of assistance. The effect of change in the level of assistance is ambiguous as *h* enters the maximization problem through both its impact on guilt, and the more traditional effect of assistance in limiting

search/cognitive costs. The guilt effects of assistance would be moderated by the number of people present, while the matching cognitive load effect of being assisted should not be affected by the number of people present in the store. This distinction allows us to test for the presence of guilt reciprocity in our data.

4.4.3 Propensity to Buy as a Function of Signal Visibility, and Manager's Assistance

In our model, the propensity to buy any given bottle depends on whether the customer believes the purchase of the bottle sends a positive or a negative signal, as described above.

When the signal is positive, the effect of an increase in the social presence on purchase probability is ambiguous, as social signaling effect would positively impact the propensity to buy, while the guilt reciprocity effect would decrease due to responsibility diffusion. When the signaling effect is dominant over the effect of guilt/reciprocity the probability of buying any given bottle increases, and vice versa.

A negative status signal will have an unambiguously negative effect on propensity to buy as the level of social presence increases:

$$\begin{array}{c}[u(x_i,h)+g(n_{high},v)s(p_i)+f(n_{high})R(h)-p_i]- \\ -[u(x_i,h)+g(n_{low},v)s(p_i)+f(n_{low})R(h)-p_i]\end{array} < 0$$

The overall effect of signaling would depend on the distributions of social signaling valuation for all customers, and distribution of prices p_i of wines available in

the store. On the one end of the extreme, if most bottles that customers can afford were considered to send a negative signal about their social status, we would expect customers to have a lower propensity to buy when surrounded by more people. This can be intuitively interpreted as people avoiding a negative signal by avoiding the purchase, or by responsibility diffusion preventing the customer from feeling guilty when no purchase is made. On the other side of the extreme, when most bottles of the desired social status are affordable, people will be more likely to buy the bottles and they might be of a higher price on average under the status signaling. Guilt reciprocity is still going to lead to a decreased propensity to buy in higher social presence environments.

Depending on whether the customer thinks a particular bottle or behavior sends a positive or negative signal, she can adjust the visibility of this signal. When a bottle sends a positive signal about one's social status, the customer would increase the visibility of the bottles price, and vice versa. In our study a centrally located table clearly labeled as "Wines under $10 and $15" serves as good proxy for how consumers might choose to modify the price visibility while shopping. Bottles available on that table are significantly cheaper than the wines bought elsewhere in the store. Approaching this table is a visible, and, likely can be interpreted as a negative status signal for most customers in the store.

Salesperson's assistance is another component that might have an ambiguous

effect on consumer behavior, as it enters both the consumption utility, and the guilt reciprocity utility. The sales clerk's assistance would increase the propensity to buy through an increase in guilt reciprocity when no one else is present. On the other hand, consumers might have differing preferences on the level of assistance in general. For some, assistance will minimize search costs and increase propensity to buy, for others assistance might have negative utility and do the opposite.

Finally, we assume $f(n)$ and of $g(n, v)$ to be different for people depending on their reference point or inherent preferences. In other words, we expect that either people who enter a store have inherently different preferences, or customers' behavior is primed and anchored by the level of social presence in the store at time of entry. All things equal, we might expect a customer who entered the store in presence of other people to be more aware of them, and thus more prone to status signaling, while people who stepped into the store that was empty except for the sales clerk would be more prone to exhibit guilt reciprocity behavior. We do not parameterize this expected difference in the behavior in our model, but rather expect to see some differences in the incidence and levels of signaling and guilt/reciprocity for the two groups depending on whether they self-selected to enter the full or empty store.

4.4.4 Hypotheses

Following the theoretical model detailed above and the existing research and data available from this study, the following hypotheses about the impact of social presence on consumer shopping and purchasing behavior emerge:

H1: Social presence affects consumer behavior through changes in the propensity to buy, bottle price, and total spending. The expected impacts will differ based on the relative strength of guilt reciprocity and status signaling effects.

We expect customers experiencing guilt reciprocity to have an increased propensity to buy items when alone with the salesperson (due to the responsibility diffusion effect). Under status signaling, on the other hand, in a higher level of social presence we might see an increase or a decrease in the propensity to buy, and an increase in price of items bought in the store. It is important to note that it is impossible to distinguish the effects of guilt and status signaling empirically just by looking at the propensity to purchase, as status signaling and guilt reciprocity effects would could coincide when most wines are easily affordable. Additionally, we expect that either people who enter a store have inherently different preferences or customers' behavior is primed and anchored by the level of social presence in the store at time of entry:

H2: The level of social presence at the time of entry affects customer behavior.

This could be true either because the level of social presence in the store at the time of entry is endogenous to consumer preferences, or because it anchors

customers to a particular state of social presence and primes them to pay more attention to (or to be more susceptible to) either guilt reciprocity or status signaling. Finally, a decrease in the level of social presence might have a different effect from an increase in it.

To provide a way to differentiate between status signaling and guilt reciprocity behavior, we develop supplemental hypotheses presented below.

Consumers engaged in status signaling are likely to choose to avoid visible signals, which might suggest their consideration of or preference for inexpensive wines:

H3: Customers modify the visibility of their signaling behavior when the level of social presence changes. If status signaling is a factor in purchasing behavior then, everything else constant, the number of approaches to the "Wines under $10 and $15" table will be lower when the level of social presence is higher. This would suggest an avoidance of sending a low-status signal.

Customers engaged in guilt reciprocity behavior are less likely to put down a bottle they expressed an interest in if the sales clerk assisted them. Intuitively, we would expect people to feel guiltier if they gave the clerk any indication that they were considering buying a bottle; that feeling would be exacerbated if they were assisted by the clerk and had a chance to build mutual rapport. This is particularly important as Dahl et al. (2005) suggest the guilt is stronger when consumers believe they could conceivably make the purchase.

H4: The effect of assistance is modified by the social presence level in case of guilt reciprocity behavior. In other words, under guilt reciprocity behavior, consumers shopping in a store with a lower level of social presence are more likely to keep a bottle they picked up to consider if receiving any assistance.

4.5 Estimation approach

In our data set, we observe both people making a purchase and deciding to not buy anything. This kind of observed behavior calls for a corner solution model to estimate the changes both at the intensive (mean price and total spending[19]) and extensive (propensity to buy) margins. We expect that some common unobserved factors affect both the purchase and the amount decisions, which is why we use the Exponential Type II Tobit (ET2T) model (Wooldridge, 2010) which allows for conditional correlation between the two stages. This model is very similar to the Heckman two-step approach (Heckit Heckman, 1979), but the dependent variable is log-transformed. We use data on consumers who left without buying anything to correct for the selection bias among customers who end up buying something and so are our only source of information on price and total spending. We specify the following model, estimated separately for customers who enter a full and an empty store:

[19] The model was estimated with the price of the most expensive bottle, to the same results.

$$\begin{cases} y_i = s_i \cdot w_i^* \\ w_i^* = \exp(\beta_0 + D\beta_D + x_{i1}'\beta_1 + u_i) \\ s_i = 1,\ if\ \delta_0 + D\delta_D + x_{i2}'\delta_2 > -v_i \end{cases}$$

where w^* is the observed continuous variable of interest (in this case, mean price or total spending), s is a binary indicator equal to one when a customer made a purchase, D is the treatment dummy variable equal to 1 when the level of social presence is higher, x1 is the vector of independent variables that affect the continuous variable of interest, and x2 is the set of independent variables that affects the probability of purchasing .

Correlation between s_i and $w_i{}^*$ is modeled through correlation between the error terms, where

$$(u, v) \sim N_2(0, \Sigma)$$

with

$$\Sigma = \begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}$$

The model above is estimated in two stages: first, a Probit model is used to estimate the probability of purchase, and then OLS is used to estimate the effect of social presence and other observed characteristics on the natural logarithm of the mean price and total cost for customers who made a purchase.

In the ET2T models x_1 and x_2 can contain the same set of variables, but generally the performance of a model improves with exclusion restrictions, making

the estimates more precise. The exclusion criteria that we utilize in this model are related to sales clerk assistance. We include a dummy variable for manager's assistance in the x_2; however we exclude this in x_1 and instead we include a dummy variable equal to one when the customer ends up buying a bottle recommended to her by the manager. Being assisted by the manager is likely to impact one's propensity to buy; however, the price is more likely to be affected if one follows the manager's advice.

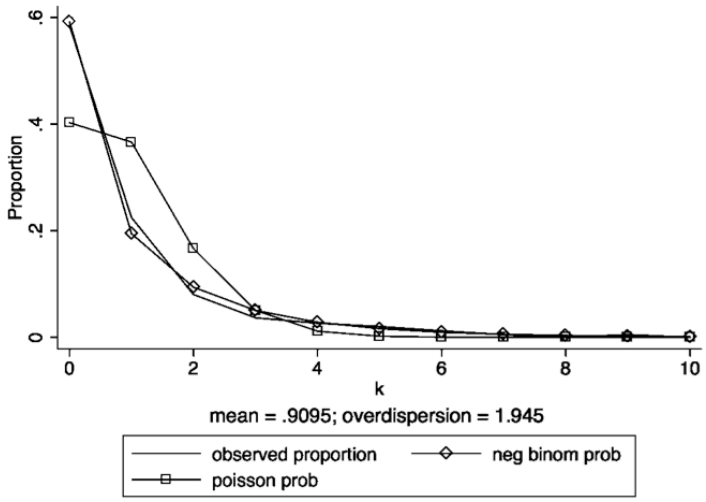

Figure 4.4. Number of approaches to "cheap" display table; Poisson and Negative Binomial Distribution

To investigate the third hypothesis, we use the information about the number of approaches a customer makes to the table display with inexpensive wine to estimate the effect of social presence on signal visibility. We adopt a negative binomial regression. This type of regression is specifically developed for dealing with count data, and fits the distribution of the dependent variable very well (see figure 4.4 for comparison between the actual distribution of count of approaches to the table, a Poisson and a negative binomial distribution). As a result, our model can be specified as:

$$\begin{cases} \text{Prob}(N = n_i|z_i) = \frac{\Gamma(\theta+n_1)}{\Gamma(n_i+1)\Gamma(\theta)} r_i^{n_i}(1-r_i)^{\theta} \\ \lambda_i = \exp(\gamma_0 + D\gamma_D + x_i\gamma_1 + \ln E_i + \varepsilon_i) \\ r_i = {}^{\lambda_i}/_{(\theta+\lambda_i)} \end{cases}$$

In the estimated equation, the dummy variable D=1 when the level of social presence is higher n_{high}, and x_i are the characteristics of the wine and the environment. The parameters are estimated by forming the log-likelihood conditional on ε_i and estimating using Maximum Likelihood.

The fourth hypothesis is estimated through a separate Probit model assessing the probability of keeping any bottle a customer picked up to consider.

All models are estimated separately for the two exogenous variation groups: people who come into an empty store, and people who come into a full store. As we are interested in the effect of the number of people present in the store, we are also forced to consider the effects of potential crowding. Being in a full or crowded room could affect consumer behavior through limiting easy access to wine displays, discourage purchases through a longer register line, and otherwise affect customers' behavior. Because of this we also run the above models for the less crowded sub-sample of observations, discussed in more detail in the Results section.

4.6 Results

Hypothesis 1: Social presence affects consumer behavior through changes in the propensity to buy, mean price, and total spending

To investigate this, we estimate the ET2T model for the two groups using the exogenous variation of other people exiting or entering the store. We compare people who enter a full store, and leave a full store, to people who enter a full store and leave an empty store. Similarly, for people who enter an empty store, we compare customers who spend their whole time in the store alone, to people who end up shopping with others. The estimation results for the main ET2T model for the two groups of interest are presented in table 4.4.

Table 4.4. Mean price and total cost, ET2T

	Second Stage (mean price and total cost)				First Stage (propensity to buy), margins	
	Come in empty store		*Come in full store*		*Come in empty*	*Come in full store*
dependent variable	ln(mean price)	ln(total cost)	ln(mean price)	ln(total cost)	Purchase = 1	Purchase = 1
Explanatory variables:						
T (more people)	-0.092	-0.249*	0.140~	0.147	-0.122**	-0.243***
	(0.085)	(0.135)	(0.088)	(0.140)	(0.059)	(0.051)
female	-0.106	-0.151	-0.053	-0.142*	0.090*	-0.002
	(0.069)	(0.104)	(0.049)	(0.079)	(0.058)	(0.034)
manager's assistance	-	-	-		0.083	0.215***
					(0.058)	(0.044)
manager's choice of bottle	0.109*	0.377***	0.107~	0.132	-	-
	(0.064)	(0.100)	(0.067)	(0.112)		
Controls:	day, time of day, female-assistance interaction, length of visit to the store					
Inverse mills (lambda)	-0.160	0.230	-0.380**	-0.471*		
	(0.304)	(0.472)	(0.158)	(0.256)		

The change in the shopping behavior with the change in social presence is observed for both groups. Moreover, the change is consistent across the two groups. If more people are present, customers were less likely to purchase anything. Among people who enter an empty store, those who continue without other shoppers present have a 12% higher probability of buying anything, significant at the 5% level. People who enter a full store are 24% less likely to buy anything when the level of social presence is higher.

Additionally, customers who enter an empty store spend approximately 22% less it total when the level of social presence is higher, significant at the 10% level. Among these customers the mean price of a bought bottle does not significantly change when more people are present. The opposite is true for customers who entered a full store. The mean price for these customers is 15% higher when more people are present (marginally significant at the 15% level); while the total spending on the bottles remained statistically the same.

As we are interested in the effects of social presence, we might be concerned about crowding affecting access to bottles. We ran the above model for people who have at most three other people present at any point during shopping, which leaves us with a sample of 536 customers. The results remain very similar, and we present them in table 4.5.

Table 4.5. Mean price and total cost, ET2T, 3 people maximum

	Second Stage (mean price and total cost)				First Stage (propensity to buy), margins	
	Come in empty store		*Come in full store*		*Come in empty*	*Come in full store*
dependent variable	ln(mean price)	ln(total cost)	ln(mean price)	ln(total cost)	Purchase = 1	Purchase = 1
Explanatory variables:						
T (more people)	-0.086 (0.088)	-0.331** (0.138)	0.243** (0.118)	0.116 (0.158)	-0.123** (0.061)	-0.224*** (0.056)
female	-0.108 (0.075)	-0.136 (0.104)	-0.056 (0.065)	-0.141* (0.090)	0.105* (0.058)	-0.039 (0.039)
manager's assistance	-	-	-	-	0.069 (0.059)	0.182*** (0.051)
manager's choice of bottle	0.107* (0.064)	0.410*** (0.100)	0.096 (0.082)	0.132 (0.112)	-	-
Controls:	day, time of day, female-assistance interaction, length of visit to the store					
Inverse mills (lambda)	-0.155 (0.306)	0.342 (0.479)	-0.508** (0.230)	-0.367 (0.323)		

If anything, the results are even stronger and more significant. Looking at this

subsample allows us to exclude the effects of the store being too crowded limiting access to the bottles or creating a long line at the checkout counter, for example. As the level of social presence is higher, the propensity to buy is lower by 12% for people who enter an empty store, or 22% for those who enter a full store. Social presence affects customer's behavior differently on the intensive margin depending on the state of the store at entry. When the level of social presence is higher, people entering a full store spend approximately 27% more on a single bottle, significant at a 5% level. People who enter the store alone, on the other hand, spend 28% less in total on wine purchased.

Both status signaling and guilt reciprocity can explain the changes in the propensity to buy. The differences in the pattern of change on the intensive margin (the mean price and total spending) is an interesting result indicating some differences in behavior between the groups, that might stem from the different behavioral mechanism guiding customers' behavior.

If the difference between the two groups purchasing behavior was just driven by inherent differences of the groups and self-selection, say, a preference for being surrounded by people, a higher level of social presence would be unlikely to have the same directional impact for both groups. In our sample both customers who enter a full or an empty store experience similar changes in the propensity to buy.

Following the results of table 4.4 and 4.5, we are able to reject the null in favor of H1.

Hypothesis 2: Social presence level at the time of entry affects customer's behavior

Table 4.6. Level of social presence at time of entry, ET2T

	Second Stage, All		*Second Stage, Uncrowded*		*First Stage, All*	*First Stage, Uncrowded*
dependent variable	ln(mean price)	ln(total cost)	ln(mean price)	ln(total cost)	Purchase = 1, margins	
Explanatory variables:						
T (more people)	0.178**	0.033	0.228**	0.048	-0.250***	-0.263***
	(0.075)	(0.110)	(0.107)	(0.140)	(0.032)	(0.033)
female	-0.088**	-0.164***	-0.10**	0.080	0.017	-0.006
	(0.040)	(0.059)	(0.049)	(0.118)	(0.106)	(0.042)
manager's assistance	-	-	-		0.205***	0.156***
					(0.034)	(0.038)
manager's choice of bottle	0.079	0.247***	0.744	0.545	-	-
	(0.051)	(0.082)	(0.060)	(0.147)		
Controls:	day, time of day, female-assistance interaction, length of visit to the store					
Inverse mills (lambda)	-0.425***	-0.318	-0.554***	-0.328*		
	(0.148)	(0.225)	(0.213)	(0.289)		

While we do see significantly different behavior reflected in the descriptive statistics for people and in the asymmetrical results of the main model presented in tables 5 and 6, we now explicitly check for it using a ET2T model for level of social presence at time of entry, where D is now a dummy variable equal to 1 when customer enters a full store. Assuming social presence at the time of entry or preferences for social presence indeed affects one's shopping behavior, we would expect to see the differences in the propensity to purchase, mean price, and total cost of items bought remain in the model controlling for the observable customer and shopping characteristics we have. This model is just to confirm there are any differences to suggest different behavior for people who enter a full or empty store. The results are presented in table 4.6.

We also see that the manager's assistance coefficients are significant in the first stage estimates. First, manager's help increases the probability of purchase for both groups. It is quite interesting to compare the estimated effects of change in social presence, estimated in H1, to the impacts of manager's assistance: they are approximately equal for those who entered an empty store, but the social presence effect is significantly different and stronger than the assistance effect for those who came into a full store.

Buying wine picked out or suggested by the manager, on average, increases the mean price of the bottle by around 12% significant at the 10% level for people who entered an empty store, and by 11% (marginally significant at the 15% level) for people who entered a full store. It also significantly (at the 10% level) increases total spending by 28% among people who entered an empty store.

Hypothesis 3: Consumers endogenously change the visibility of signaling as social presence changes

We expect to observe some other evidence for the signaling behavior than the change in propensity to buy. The store layout included a centrally placed table with two highly visible signs on it indicating the table carries the selection of more affordable wines under $15. Approaching this table would send a clear single about the customer looking for wines specifically under the $15 mark, which is significantly below the average price of bottle bought in the store (between $17 and $19 for different customer groups). Moreover, as all bottles presented on the table are also

available at other shelves in the store, the table is just a conveniently presented combination of cheaper wines, and avoiding it would not limit one's choice, but will make the information about the price range of the bottles you are buying less salient to other shoppers.

Table 4.7. Approaches to the "selection under $15" table, negative binomial regression

	Come in alone		Come in full store	
dependent variable	# of approaches to the "selection under $15" table		# of approaches to the "selection under $15" table	
	full sample	under 3 people present	full sample	under 3 people present
Explanatory variables:				
T (more people)	-0.063	0.073	-0.375**	-0.542***
	(0.266)	(0.271)	(0.171)	(0.187)
female	0.591*	0.590*	0.116	0.070
	(0.319)	(0.321)	(0.147)	(0.172)
manager's assistance	-0.512	-0.542	-0.261	-0.239
	(0.333)	(0.339)	(0.189)	(0.227)
Controls:	day, time of day, female-assistance interaction, length of visit to the store (exposure variable)			
Pseudo R2	0.0778	0.0810	0.0363	0.0434

For each customer, we count the number of time she approached the table, and estimate the effect of change in the level of social presence on number of times the table was approached, using the length of the shopping trip as the exposure variable[20]. We use the negative binomial distribution, with results presented in table 4.7, for both the full sample, and the less crowded subsample.

We find more evidence for the asymmetrical behavior between people who entered the store when it was empty versus when it was full. For customers who enter

[20] We ran a simple Poisson regression with very similar results, but slightly lower significance level. The negative binomial distribution is a better for the data – see figure 5. This is also supported by the goodness of fit test in the Poisson regression (the Lagrange multiplier test), and the likelihood ration test suggests the over-dispersion in the data makes Poisson regression not appropriate.

an empty store, higher level of social presence does not significantly impact the number of times they would approach the cheaper selection table. However, if the customers enter the store with other shoppers present, they approach the "cheap table" significantly fewer times when the level of social presence is higher. This holds for both the full and the less crowded subsample; moreover, the subsample's results are more significant and of a larger magnitude for customers who enter the full store. The pseudo R^2 is also higher for the subsample for both consumer groups, suggesting that removing observations from a more crowded store leads to a better fit of the model.

We reject the null for people who entered a full store, but are unable to reject for people who entered an empty store. In general, for people who entered a full store the pattern of behavior fits within the status-signaling framework. Specifically, we observe that people are less likely to buy anything, but the mean price of purchased bottles is higher, on average, when more people are present.

Hypothesis 4: The effects of sales clerk assistance depends on the social presence level under the effects of guilt reciprocity

Finally, we check for evidence of guilt reciprocity behavior by looking at how the number of bottles customers expressed interest in changes depending on the level of social presence in the store, along with the probability of buying any of these bottles. Previous research indicates that customers feel guiltier when they believe they have the choice to make a purchase, and when the level of interaction with the

salesperson is higher. Picking up a bottle is an indication of consumers considering a choice of whether to buy or not to buy a specific bottle. Controlling for the number of picks, we examine whether receiving assistance, having more people around and, most importantly, the interaction of those two variables of interest has any impact on consumer behavior. The effect of assistance on propensity to buy on its own is not enough to confirm the presence of guilt reciprocity behavior, as assistance can also reduce search costs. We run the above model for both the full and the less crowded sample, and present the results in table 4.8. As marginal effects of the interaction are not extremely useful for interpretation as interaction coefficient requires simultaneous changes in two variables, we just provide the coefficients estimates.

Table 4.8. Probability of keeping a picked up bottle

dependent variable	Come in alone		Come in full store	
	% of keeping a picked bottle			
	full sample	under 3 people present	full sample	under 3 people present
Explanatory variables:				
T (more people)	-0.264~	-0.291~	-0.540***	-0.474***
	(0.179)	(0.202)	(0.149)	(0.165)
manager's assistance	-0.088	-0.103	0.022	0.058
	(0.133)	(0.135)	(0.188)	(0.207)
T - assistance interaction	-0.497***	-0.557***	-0.188	-0.131
	(0.176)	(0.179)	(0.154)	(0.176)
female	-0.235*	-0.188~	0.015	-0.092
	(0.123)	(0.127)	(0.079)	(0.093)
Controls:	day, time of day, length of visit to the store, number of picks			
Pseudo R2	0.1615	0.1647	0.1061	0.1108

The interaction between the level of social presence and assistance from the salesperson is significant at the 1% level for people who enter an empty store, allowing for the separate effect of social presence and managers assistance. It is,

however, not significant for people who entered a full store. The results hold for both the full and the less crowded subsamples.

We reject the null for people who entered an empty store, but are unable to for shoppers who came into a full store. Overall, this suggests presence of guilt reciprocity behavior among customers who enter an empty store, but not a full one.

4.7 Discussion and Concluding Remarks

Using a series of models we estimate the impact of social presence on consumer behavior. Propensity to buy universally and significantly decreases when the level of social presence is higher. In terms of mean price of purchased bottles and of the total spending, customers behave differently based on whether they entered a full or an empty store: the former buy more expensive wines when the level of social presence is higher, and the latter spend less in total. These results, and all results presented in the paper, hold for both the full sample, which includes times when up to eleven people where present in the store at the same time, and for the less crowded sample, when at most three other customers where in the store at any time during one's shopping.

It is possible that the two groups were anchored to the social presence at the store at the time they enter: in this case, customers entering an empty store might be less aware of people coming in and mostly think about the presence of the manager, which would be more conducive for guilt reciprocity behavior rather than signaling.

On the other hand, customers entering a full store are from the onset surrounded by other shoppers, an environment that could potentially prime them for status signaling behavior.

We examine customers' shopping behavior in further detail by considering other support for both signaling and reciprocity behavior. We use the number of times a customer approaches the table of wines clearly labeled as "wines under $10 and $15" to consider whether customers approach it less frequently when more people are present in order to minimize the visibility of their interest in cheaper wines.

The fact that all bottles from this table are also available on the other shelves in the store and that the average price for all comparison groups is significantly above $15, made this wine display the perfect spot to examine how consumers modify the visibility of their signaling. We see customers who entered a full store approaching the table significantly fewer times when the level of social presence is higher. We do not find support for status signaling for customers who enter an empty store.

We proceed with examining the guilt reciprocity behavior by seeing how the probability of keeping any bottle the customer expressed an interest in changes with both the number of people present, and the level of assistance provided by the manager. Using the video surveillance data we record all instances of shoppers actually picking up any bottle, for example to examine the label or price more closely, and whether the customer ended up keeping the bottle or not. Controlling for the total number of times the customer picked something up, we see that people who enter an

empty store are significantly more likely to keep the bottle provided they received assistance from the sales clerk and there were no other shoppers present. This is independent of the direct impact of being assisted or surrounded by fewer people in the store. This result is consistent with responsibility diffusion lessening the feelings of guilt when more people are present, and the level of assistance playing a strong role in generating the original feelings of guilt. Interestingly, this result does not hold for people who entered a full store – their probability of keeping anything does not depend on the interaction of the number of people present and the level of assistance.

Together, the main results from the Exponential Type II model, on both the extensive and intensive margin, and the auxiliary analysis of other evidence for status signaling and guilt reciprocity suggest people who enter an empty store are more sensitive to the presence of the sales person and thus prone to guilt reciprocity behavior, while customers entering a full store are more prone to status signaling.

The intriguing asymmetry that we observe could be explained by customers with different preferences over social presence electing to enter either full or empty stores. This is not very likely, as it assumes customers know before entering whether the store is empty or full, and are able to base their decision to shop or not to shop based on this. Alternatively, customers could be primed by the presence of others in the store at the time of entry to be either more sensitive to their interactions with the salesperson or their signaling towards other customers. Given the importance of

reference points and priming for a variety of consumer behavior, that seems like a viable explanation.

This research is both useful for the practical purposes of store and retail managers, and for expanding our understanding of how social interactions or just visible presence of other people affects economic behavior. The latter contributes to the ongoing discussion on whether aggregate data can be used to make individual behavior inferences, especially when no information about the level of social presence is available, or whether individual behavior obtained in socially isolated environments such as economic lab experiments reliably translates into aggregate level inferences Glaeser et al., 2003).

Finally, while we do observe stark differences in consumer behavior depending on the level of social presence, the field nature of the data carries inherent complications as many influences are competing motivations are present among consumers at the same time. To further examine the behavioral mechanisms behind the effects of social presence on purchasing decisions, field data needs to be supplemented with controlled lab and field studies that could isolate the priming, status signaling, responsibility diffusion, and guilt reciprocity impacts on consumer behavior. This paper is the first to our knowledge to examine the effects of social presence on consumer behavior using quasi-experimental exogenous variation in the field and is just a step towards identifying the impacts. While we provide and examine the support for two behavioral mechanisms behind the impact of social presence, the

limitations of field data do not allow us to isolate those effects separately or to precisely estimate their relative impact. Those challenges provide ample room for further research on the issue.

REFERENCES

Robert L Basmann, David J Molina, and Daniel J Slottje. 1988. A note on measuring Veblen's theory of conspicuous consumption. *The Review of Economics and Statistics,* 70(3):531– 535.

Roy F Baumeister, Arlene M Stillwell, and Todd F Heatherton. 1994. Guilt: an interpersonal approach. *Psychological bulletin,* 115(2): 243.

Gary S. Becker and Kevin M. Murphy. 2000. *Social Economics : market behavior in a social environment.* The Belknap Press of Harvard University Press: Cambridge, Massachusetts, and London, England.

Linda F. Bisson, Andrew L. Waterhouse, Susan E. Ebeler, M. Andrew Walker, and James T. Lapsley. 2002. The present and future of the international wine industry. *Nature*, 418(6898): 696–699.

J. R. Blaylock and W. N. Blisard. 1993. Wine consumption by US men. *Applied Economics,* 25(5):645–651.

Kjell Arne Brekke and Richard B Howarth. 2002. *Status, growth and the environment: goods as symbols in applied welfare economics.* Edward Elgar Publishing, Cheltenham.

Kjell Arne Brekke, Richard B Howarth, and Karine Nyborg. 2003. Status-seeking and material affluence: evaluating the Hirsch hypothesis. Ecological Economics, 45(1):29–39.

W Jeffrey Burroughs, David R Drews, and William K Hallman. 1991. Predicting personality from personal possessions: A self-presentational analysis. *Journal of Social Behavior & Personality.*

Jean-Marie Cardebat and Jean-Marc Figuet. 2004. What explains Bordeaux wine prices? *Applied Economics Letters,* 11(5):293–296.
Robert B Cialdini. 1980. Full-cycle social psychology. *Applied Social Psychology Annual*, 1980.

Margaret S Clark. 1986. Evidence for the effectiveness of manipulations of communal and exchange relationships. *Personality and Social Psychology Bulletin*, 12(4):414–425.

Michael Conlin, Michael Lynn, and Ted O'Donoghue. 2003. The norm of restaurant tipping. *Journal of Economic Behavior & Organization*, 52(3):297–321.

Giacomo Corneo and Olivier Jeanne. 1997. Conspicuous consumption, snobbism and conformism. *Journal of Public Economics*, 66(1):55–71.

Darren W Dahl, Rajesh V Manchanda, and Jennifer J Argo. 2001. Embarrassment in consumer purchase: The roles of social presence and purchase familiarity. *Journal of Consumer Research*, 28(3):473–481.

Darren W Dahl, Heather Honea, and Rajesh V Manchanda. 2005. Three Rs of interpersonal consumer guilt: Relationship, Reciprocity, Reparation. *Journal of Consumer Psychology*, 15 (4):307–315.

John M Darley and Bibb Latane. 1968. Bystander intervention in emergencies: diffusion of responsibility. *Journal of Personality and Social Psychology*, 8(4p1):377.

Efthalia Dimara and Dimitris Skuras. 2005. Consumer demand for informative labeling of quality food and drink products: a European union case study. *Journal of Consumer Marketing*, 22(2):90–100.

David Dubois, Derek D Rucker, and Adam D Galinsky. 2012. Super size me: product size as a signal of status. *Journal of Consumer Research,* 38(6):1047–1062.

Ernst Fehr and Simon Gächter. 2000. Fairness and retaliation: The economics of reciprocity. *The Journal of Economic Perspectives*, pages 159–181.

Donelson R Forsyth, Linda E Zyzniewski, and Cheryl A Giammanco. 2002. Responsibility diffusion in cooperative collectives. *Personality and Social Psychology Bulletin*, 28(1):54–65.

Stephen Freeman, Marcus R Walker, Richard Borden, and Bibb Latane. 1975. Diffusion of responsibility and restaurant tipping: Cheaper by the bunch. *Personality and Social Psychology Bulletin*, 1(4):584–587.

Gertrud M Fremling and Richard A Posner. 1999. Market signaling of personal characteristics. *University of Chicago Law School, John M. Olin Law & Economics Working Paper,* 87.

Edward L Glaeser, Bruce I Sacerdote, and Jose A Scheinkman. 2003. The social multiplier. *Journal of the European Economic Association,* 1(2-3):345–353.

Vladas Griskevicius, Joshua M Tybur, and Bram Van den Bergh. 2010. Going green to be seen: status, reputation, and conspicuous conservation. *Journal of Personality and Social Psychology*, 98(3):392.

Benedetto Gui and Robert Sugden. 2005. *Economics and Social Interaction: accounting for inter-personal relations.* Cambridge University Press.

Young Jee Han, Joseph C Nunes, and Xavier Drèze. 2010. Signaling status with luxury goods: The role of brand prominence. *Journal of Marketing*, 74(4).

James J Heckman. 1979. Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153–161.

Haiyan Hu and Cynthia R Jasper. 2006. Social cues in the store environment and their impact on store image. *International Journal of Retail and Distribution Management,* 34(1):25–48.

Sheena S Iyengar and Mark R Lepper. 2000. When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, 79(6):995.

Olof Johansson-Stenman and Peter Martinsson. 2006. Honestly, why are you driving a bmw? *Journal of Economic Behavior & Organization,* 60(2):129–146.

Daniel Kahneman, Edward Diener, and Norbert Schwarz. 1999. *Well-being: Foundations of hedonic psychology*. Russell Sage Foundation.

Bruce D Keillor, R Stephen Parker, and Charles E Pettijohn. 2000. Relationship-oriented characteristics and individual salesperson performance. *Journal of Business & Industrial Marketing*, 15(1):7–22.

Dana N Lascu. 1991. Consumer guilt: examining the potential of a new marketing construct. *Advances in Consumer Research*, 18(1):290–295.

Donald R Lichtenstein, Nancy M Ridgway, and Richard G Netemeyer. 1993. Price perceptions and consumer shopping behavior: a field study. *Journal of Marketing research*, 234–245.

Lawrence S Lockshin and W Timothy Rhodus. 1993. The effect of price and oak flavor on perceived wine quality. *International Journal of Wine Marketing,* 5(2/3):13–25.

Xueming Luo. 2005. How does shopping with others influence impulsive purchasing? *Journal of Consumer Psychology,* 15(4):288–294.

William Michael Lynn. 2006. Tipping in restaurants and around the globe: An interdisciplinary review. *Working Paper.*

Matthew Rabin. 1993. Incorporating fairness into game theory and economics. *The American Economic Review,* 1281–1302.

Edna I Rawlings. 1970. Reactive guilt and anticipatory guilt in altruistic behavior. *Altruism and Helping Behavior*, 163–177.

Mari Rege. 2008. Why do people care about social status*? Journal of Economic Behavior & Organization*, 66(2):233–242.

Simone Renner, Jörg Lindenmeier, Dieter K Tscheulin, and Florian Drevs. 2013. Guilt appeals and prosocial behavior: an experimental analysis of the effects of anticipatory versus reactive guilt appeals on the effectiveness of blood donor appeals. *Journal of Nonprofit & Public Sector Marketing,* 25(3):237–255.

Marsha L Richins. 1994. Special possessions and the expression of material values. *Journal of Consumer Research*, 522–533.

Derek D Rucker and Adam D Galinsky. 2009. Conspicuous consumption versus utilitarian ideals: How different levels of power shape consumer behavior. *Journal of Experimental Social Psychology*, 45(3):549–555.

Barry Schwartz. 2004. *The paradox of choice: Why more is less.* Ecco New York.

Robert Sugden. 1984. Reciprocity: the supply of public goods through voluntary contributions. *The Economic Journal*, 772–787.

Tom Truyts. 2010. Social status in economic theory. *Journal of Economic Surveys*, 24(1): 137–169.

U.S. Department of Commerce. 2015. Quarterly retail e-commerce sales, 2nd quarter 2015. *U.S. Census Bureau News,* 2015. URL http://www.census.gov/retail.

Thorstein Veblen. 1899. *The Theory of the Leisure Class*, chapter *Conspicuous Consumption*, pages 64–70. NY: Macmillan.

Willem Verbeke, Bart Dietz, and Ernst Verwaal. 2011. Drivers of sales performance: a contemporary meta-analysis. have salespeople become knowledge brokers? *Journal of the Academy of Marketing Science*, 39(3):407–428.

Jeffrey M Wooldridge. 2010. *Econometric analysis of cross section and panel data.* MIT press.