The Impact of Voluntary Front-of-Pack Nutrition-Label Introduction on Purchase Behavior

Three Studies Analyzing Supermarket Scanner Data

Dissertation

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This work is dedicated to my parents.

Thank you for your unconditional love and your never ending support.

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1 General Introduction

"Labels can help some people sometimes in some cases".

(Rotfeld 2009, p. 375)

1.1 Relevance

As stated by the World Health Organization, health problems caused by unhealthy food intake are increasing (WHO 2012). Reduction of nutrition-related health problems is a major challenge of the 21st century, because millions of adults die each year as a result of being overweight or obese (Ng et al. 2014). Additionally, the incidents of diabetes, cancer, and cardiovascular diseases accountable to excessive consumption of unhealthy nutrition are steadily rising. Against this background, nutrition labeling is regarded as one potential instrument to induce the necessary dietary change and influence consumption behavior. Grunert and Wills (2007, p. 385) define nutrition labeling as "an attempt to provide consumers, at the point of purchase, with information about nutrition content of individual food products, in order to enable consumers to choose nutritionally appropriate food."

A large amount of research has analyzed different types and formats of nutrition labeling in respect to perception, understanding, and use (Campos et al. 2011; Cowburn and Stockley 2005; Drichoutis et al. 2006; Friedman 1972; Glanz and Mullis 1988; Glanz et al. 1992; Grunert and Wills 2007; Hersey et al. 2013; Mayer et al. 1989; Kiesel et al. 2011; Mhurchu and Gorton 2007; Moorman 1996; Seymour et al. 2004; van Kleef and Dagevos 2015; vant Riet 2012).

Research with self-reported study designs indicate that consumers have a positive attitude towards nutrition information on food packages and appear able to choose healthier options using any labeling scheme (Storcksdieck and Wills 2012). However, results based on self-reports can be biased by social desirability (Glanz et al. 1992), because respondents know that healthy purchase behavior is respected in society. Post-hoc rationalization is also stated as a source for bias of self-reports of nutrition label use and healthier purchase behavior (Malam et al. 2009). According to this so-called recall bias, respondents make decisions in a habitual way, where a post-hoc rationalization of label use does not necessarily have to match the real reasons for their decision. Furthermore, Radimer and Harvey (1998) and Rayner et al. (2001) have found that respondents reported label use and healthier consumption while their observed behavior did not confirm this. Therefore, consumers' self-reports of label use are not considered a reliable measure for the effectiveness of nutrition labeling in product choices (van Herpen et al. 2012). A general confirmation that nutrition labeling induces healthier purchase behavior in real-life settings is still missing. Research with real purchase data from supermarkets reveal mixed results regarding the effectiveness of nutrition labels in promoting healthier purchase behavior (see previous research section).

Therefore, many authors still call for more research with real purchase data that analyzes the impact of nutrition labels (Andrews et al. 2014; Hersey et al. 2013; Lachat and Tseng 2013; vant Riet 2012). In addition to the above mentioned drawbacks of self-reported study designs, a review by TinTin et al. (2007) constitutes that real purchase data should be regarded as superior for the examination of food purchase patterns.

The contribution of our three studies is to fill this research gap by analyzing the impact of nutrition label introduction with real purchase behavior. Our results will extend knowledge in this field in several ways. First, previous research analyzing the impact of nutrition labeling with real purchase data has utilized aggregated data. In our first study, we use a disaggregated approach to account for observed and unobserved heterogeneity of consumers. We compare these results to an aggregated counterpart.

Second, in most previous studies sales or market share was analyzed as dependent variable. We use the amount of sugar and fat purchased in the food products as dependent variable in our second study. Novel to nutrition label research is that we also examine the outcome for the retailer due to the voluntary introduction of nutrition labeling. So far, only experimental research has analyzed retailers benefits of voluntary nutrition labeling in terms of attitudes and behavioral intentions of respondents. Attitudes alone are often poor predictors of marketplace behavior (Ajzen 2001; Vermeir and Verbeke 2006) and, hence, research with observed behavior is deemed necessary to gain further insights into retailer benefits from voluntary nutrition labeling (Newman et al. 2014).

The voluntary nutrition label introduction under investigation provides the opportunity to analyze how the non-governmental induced labeling scheme may be attributed to marketing efforts rather than promoting healthier purchase behavior. Therefore, we analyze the dual role of voluntary nutrition labels in promoting healthier purchase behavior in our third study. While previous research has emphasized on a general effect of nutrition labeling towards healthier purchase behavior, we investigate more nuanced effects of voluntary nutrition disclosure.

1.2 Previous Research

In this section, we summarize the results of previous research analyzing the influence of nutrition labeling on consumer behavior through real purchase data from supermarkets. Our selection criterion were peer-reviewed published studies until 2013 which analyze the influence of nutrition disclosure at supermarkets using purchase data. We exclude results from away-from-home eating places due to different choice situations by consumers (for reviews to this topic, see Harnack and French 2008; Seymour et al. 2004; Swartz et al. 2011).

To obtain a comprehensive overview about nutrition labeling, we review several formats of nutrition disclosure available at the point-of-purchase. The formats are in-store-posters, shelf-labeling, back-of-pack (B-O-P), and front-of-pack (F-O-P) labels. We exclude research examining take-away booklets as the only format of nutrition disclosure (see, for example, Soriano and Dozier 1978). This is due to the fact that the process of collecting nutrition information by take-away booklets is different from the other mentioned formats. Consumers are actively involved in gaining access to nutrition information from booklets, while the other formats reveal the nutrition information unasked at the point-of-purchase.

This ensures comparability of the findings discussed in this section with the front-of-pack labeling implementation in our studies. In Tables 1 and 2, we summarize the relevant information from the previous studies plus our three studies.

We first describe the content of the last column to support the classification of the other columns. It summarizes the outcome of the studies according to five criteria. If there is no significant effect of the label implementation on the dependent variable, the results are classified as "Null result." When only a certain number of categories in the analysis show healthier purchase behavior the term "(X) out of (Y) categories" is used. If all analyzed categories show the same direction regarding healthiness this is indicated with "healthier purchases" or "unhealthier purchases." "Mixed results" indicate that the label introduction leads to healthier purchase behavior in some categories, and unhealthier purchase behavior in other categories.

Our first finding from Tables 1 and 2 is that 18 out of the 21 previous studies were conducted in the USA (Country). We summarize the number of different stores available in the datasets of the studies (# of stores), number of different food categories (# of categories) and the total number of different items in parentheses below (# of items). Six studies reveal an unambiguous significant effect of nutrition labeling, where five of these studies only utilize one category for analysis. This fact impairs the generalizability of these results. Therefore, we analyze different food categories across our studies to ensure a certain degree of generalizability.

The time-span of the studies (Time-span) ranges from 2 weeks to 9 years. Studies with short periods used for analysis do not allow to factor in seasonal characteristics or long-term response, therefore the time-span of our studies is chosen accordingly (at least 2 years). Furthermore, we classify the studies in Tables 1 and 2 into two different designs (Study design). Experimental designs are those where a set of treatment stores with nutrition labeling are compared to a set of control stores without this labeling. The Intervention designs examine introductions of nutrition labels by comparing purchase behavior before and after label implementation. The type of study design is related to the publication year of the study. The first studies, mostly experimental designs, have been the decision support for the real label implementations analyzed in follow-up studies since the 1990s. However, there appears no relationship between the study design and the outcome. The different label formats in our summary are in-store-posters, shelf-labeling, B-O-P and F-O-P labels, or any kind of combination of these different approaches (Label format). We observe the historical development of nutrition label formats in this column. Early realizations are in-store-posters in combination with take-away booklets which changed to B-O-P and, thereafter, F-O-P labels in subsequent years. We do not observe a relationship between the label formats and the outcome. According to Hersey et al. (2013), the two general types of label information in the previous studies are nutrient-specific labels and summary systems (Information). Nutrient-specific labels disclose a few key nutrition values, while summary systems provide an evaluation of the food products subject to certain health guidelines or claims, such as 'low fat.' In most previous studies, unit-sales or share of unit-sales of food products is assumed to be influenced by the label introduction (Effect on).

In summary, the results from the previous studies do not reveal a clear picture of the effectiveness of nutrition labeling on consumers' purchase patterns. The ability of nutrition labels to promote healthier purchase behavior, in general, is not supported. No specific label format or information type outperforms any other constellation when examined in a real-life setting, while other research has revealed that consumers prefer the easily accessible front-of-pack summary systems with low processing costs (Hersey et al. 2013; van Kleef and Dagevos 2015). Due to the ambiguous results of label research with real purchase data, authors demand more studies in this field (Andrews et al. 2014; Hersey et al. 2013; Lachat and Tseng 2013; vant Riet 2012). With our three studies, we aim to fill this important research gap and to contribute to the field of nutrition labeling through the application of real purchase data from a food retailer.

In the last three rows of Table 2, we summarize our three studies. Study 1 is the first study where disaggregated data is utilized to analyze response to nutrition labeling. We compare these results to an aggregated model with the same data and reveal that the different specifications yield in different results. Our results provide useful insights for consumer characteristics which may influence the effectiveness of nutrition label introduction to promote healthier purchase behavior.

In Study 2, we use the sugar and fat amount of food products as the dependent variable instead of sales or market share. Furthermore, this is the first study where the outcome of nutrition labeling for retailers is analyzed in a real-life setting. Combining consumer response with retailer's outcome sheds light into both sides which are affected by the introduction of nutrition labels.

In Study 3, we analyze the interaction between two types of nutrition information. A summary system, which was present before the nutrition label introduction, may lead to more nuanced effects of consumer response after the label introduction. Furthermore, we investigate how a specific component on the nutrition label chosen by the retailer can have an effect on consumer response. In our third study, we will give insights about the dual role of nutrition labels, which provides an explanation for mixed results.

Author	Country	# of stores	# of categories (# of items)	Time-span	Study Design	Label format	Information	Effect on	Results
Jeffery et al. (1982)	USA	8	6 categories (25 items)	10 month	Experimental	Shelf-label, In-store-poster, Booklet	Summary system	Share of Sales	Null result
Muller (1984)	Canada	2	5 categories (17 items)	2 weeks	Experimental	In-store-poster	Nutrient-specific	Sales	3 out of 5 categories
Levy et al. (1985)	USA	20	23 categories (1600 items)	2 years	Experimental	Shelf-label, Booklet	Summary system	Share of Sales	8 out of 16 labeled categories
Ernst et al. (1986)	USA	20	17 categories (246 items)	48 weeks	Experimental	Shelf-label, Booklet	Nutrient-specific	Sales	Null result
Russo et al. (1986) Experiment 1	USA	14	6 categories (498 items)	33 weeks	Experimental	In-store-poster, Booklet	Summary system	Food energy amount	Null result
Russo et al. (1986) Experiment 2	USA	2	1 category (82 items)	30 weeks	Experimental	In-store-poster, Booklet	Nutrient-specific	Sugar density	Healthier purchases
Achabal et al. (1987)	USA	372	2 categories (6 items)	12 weeks	Experimental	In-store-poster	Nutrient-specific	Sales	Null result
Patterson et al. (1992)	USA	40	8 categories	3 years	Experimental	Shelf-label	Summary system	Ounces, Share of Sales	Mixed results
Rodgers et al. (1994)	USA	40	8 categories	3 years	Experimental	Shelf label	Summary system	Sales	Mixed results
Schucker et al. (1992)	USA	20	49 categories (1200 items)	2 years	Experimental	Shelf-label, Booklet	Summary system	Sales	Mixed results
Mathios (1996)	USA	20	1 category (73 items)	8 month	Intervention	B-O-P label	Nutrient-specific	Unit-Sales, Share of Sales	Healthier purchases
Teisl and Levy (1997)	USA	25	6 categories (356 items)	4 years	Experimental	Shelf-label, In-store-poster, Booklet	Summary system	Share of Sales	Mixed results
Mathios (2000)	USA	20	1 category (86 items)	28 month	Intervention	B-O-P label	Nutrient-specific	Share of Sales	Healthier purchases

Table 1: Summary of previous research I

Author	Country	# of stores	# of categories (# of items)	Time-span	Study Design	Label format	Information	Effect on	Results
Mojduszka et al. (2001)	USA	64	1 category (200 items)	6 years	Intervention	B-O-P label	Nutrient-specific	Share of Sales	Null result
Teisl et al. (2001)	USA	25	6 categories (356 items)	4 years	Experimental	Shelf-label, In-Store-Poster, Booklet	Summary system	Share of Sales	Mixed results
Balasubramanian and Cole (2002)	USA	several stores	8 categories	9 years	Intervention	F-O-P label	Summary system	Share of Sales	Mixed results
Sacks et al. (2009)	UK	1000x	2 categories (18 items)	8 weeks	Intervention	F-O-P label	Nutrient-specific	Sales	Null result
Sutherland et al. (2010)	USA	168	3 health categories	3 years	Intervention	Shelf-label	Summary system	Share of Sales	Healthier purchases
Berning et al. (2011)	USA	10	1 category (274 items)	10 weeks	Experimental	Shelf-label	Summary system	Ounces, Sales	Unhealthier purchases
Sacks et al. (2011)	Australia	online	5 categories (53 items)	10 weeks	Experimental	F-O-P label	Nutrient-specific	Sales	Null result
Kiesel and Villas-Boas (2013)	USA	32	1 category (274 items)	14 weeks	Experimental	Shelf-label	Summary system	Sales	Unhealthier purchases
Study 1	UK	>2000	2 categories (3075 items)	2 years	Intervention	F-O-P label	Nutrient-specific	Sales / Choice	Healthier purchases in aggregated model / Mixed results in disaggregated model
Study 2	UK	2360	3 categories (568 items)	4 years	Intervention	F-O-P label	Nutrient-specific	Sugar and fat amount, Outcome for retailer	1 out of 3 categories, No benefit for Retailer
Study 3	UK	>1500	1 category (25 items)	2 years	Intervention	F-O-P label	Summary system and Nutrient-specific	Sales	Mixed results

Table 2: Summary of previous research II

1.3 Abstracts

Study 1

Front of pack (FOP) nutrition labeling has received extensive political attention within the last years. The European Commission proposed making FOP nutrition labeling mandatory in order to guide consumers toward making healthier food choices. Most studies looking at the influence of nutrition labeling focus on consumer attention to labels, and very few concentrate on the effects on actual purchase behavior. In this study, we present results from an analysis of scanner data provided by a large UK retailer. We focus on two food categories using store-brand products which are labeled with a front of pack monochrome guideline daily amount (GDA) label. The analyzes are based on economic methods at both an aggregated and disaggregated level to enable us to identify as many influencing factors on food choice as possible. We utilize the SSAg/1 health score for our food categories as a dependent variable for both models in order to obtain an objective measure of healthiness.

Our results suggest that GDA label introduction leads to healthier purchase behavior in the aggregated model, but not in the disaggregated model. Price and habitual purchase behavior generally have a larger impact on purchase behavior and product choice than the GDA label introduction.

Study 2

Nutrition labeling is considered a helpful tool to promote healthier food consumption. While governmental stakeholders repeatedly ask for improvement of mandatory labeling of food products, retailers have discovered voluntary front-of-pack labeling as a marketing strategy. Previous research has analyzed how consumers react and how retailers benefit from implementing such labeling schemes. While experimental research reveals healthier purchase behavior and improvement in attitudes towards retailers, research with real purchase data is still short of evidence about the effectiveness of front-of-pack nutrition labels or the impact on retailers' benefits. This study analyzes the impact of front-of-pack nutrition labeling on consumers' food energy purchase behavior and revenue-concerned metrics of retailers. Results suggest that the front-of-pack nutrition label leads to slightly healthier purchase behavior by the customers, but does not increase store loyalty intentions. If healthier purchase behavior is observed, it is accompanied with reduced volume and, therefore, less revenue. This shows that potential health benefits for customers can come at a cost for retailers.

Study 3

Consumers' attention to nutrition content in their food choice decision is steadily increasing. Food marketing has adapted this change in behavior by emphasizing nutritional advantages of particular food products. Hence, nutrition claims (e.g. 'low fat') and nutrition labels are popular means by marketers. Nutrition information should guide consumers to choose healthier food products, but the use of claims and labels can create health halos by increasing perceived healthiness when its not justified. This study uses supermarket scanner data to analyze the dual role of nutrition labels in fighting health halos.
On the one hand, results suggest that nutrition labels can correct for misleading nutrition claims. On the other hand, nutrition labels that report too small serving sizes as basis for recommended daily amount unjustifiably increase perceived healthiness, which leads to an increase in sales volume in our study. These results provide important implications for food marketers and public policy.

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2 Are Consumers Influenced in their Food Choice by Monochrome Guideline Daily Amount Nutrition Labels?

(with Yasemin Boztuğ, Hans J. Juhl and Morten B. Jensen)

This paper (Study 1) is based on:

EU Project FLABEL Deliverable (2012, Workpackage 6): How GDA-nutrition labels on food products affect product choice. *(Contract No: 211905)*

A previous version of this paper (Study 1) is published as:

Boztuğ, Juhl, Elshiewy, and Jensen (2012): Are Consumers influenced in their Food Choice by Health Labels? *Proceedings of the 41th EMAC Conference, Lisbon, Portugal.*

This version is currently under 3rd round review in *Food Policy.*

2.1 Study 1: Introduction

Lifestyle-related illnesses such as cardiovascular diseases can be attributed to poor diet and a lack of physical activity (Grunert et al. 2010; James et al. 2004; Schor et al. 2010; Verbeke 2008; WHO 2012). In many European countries, these adverse health behaviors lead to large costs for both the individual and for society. Nutrition labeling has been cited as a way of providing information to consumers that supports health-conscious food choices (Commission of the European Communities 2008). It is assumed that consumers are likely to use the nutritional information provided and change their behavior resulting in the purchase of healthier products (Grunert and Wills 2007; Russo et al. 1986)

In 1990, the US Food and Drug Administration Authority regulated that all pre-packed food products in the US should display nutritional information in the form of a NLEA label, which is typically cited on the back of the package (Nutrition Labeling and Education Act 1990). Nutrition labeling has also recently become mandatory within the European Union as a result of the 'Provision of Food Information to Consumers' legislation (EU No 1169/2011). This legislation requires pre-packaged foods to display energy value and amounts of fat, saturated fat, carbohydrates, protein, sugar, and salt in the same field of vision, most typically on the back of the package.

While comprehensive back-of-pack (BOP) nutrition information is already present on a wide range of foods across Europe (Storcksdieck et al. 2010), the average consumer has neither the time nor the inclination to analyze this level of information at the point of purchase (Drichoutis et al. 2006). In order to make it easier for the consumer to distinguish between healthy and less healthy products government bodies and the food industry have developed a variety of front-of-pack (FOP) nutritional labeling schemes.

One of the most prevalent FOP labeling schemes communicates the percentage of the Guideline Daily Amount (GDA) for energy, fat, saturated fat, sugar, and salt that a portion of food contains. The GDA is the labeling scheme that has typically been favored by the industry. Guideline Daily Amounts were derived from the COMA report (Wiseman 1992) on daily reference values and are promoted by the industry organization FoodDrinkEurope. Another prevalent system which was developed by the UK Food Standards Agency (2007) overlays interpretative color and text onto the nutritional values for fat, saturated fat, sugar, and salt. This scheme indicates the levels of those nutrients in 100 grams of the food as high (red), medium (amber), or low (green). A number of major retailers within the UK and across Europe have adopted the use of this type of traffic light FOP labeling (Grunert and Wills 2007). In a number of European countries, other retailers have taken a different route and adopted a more directive and aggregated system as FOP labeling approach. The Swedish keyhole (Larsson et al. 1999) and the smart choices logo (Lupton et al. 2010) are examples where a simple visual symbol or 'health logo' indicates a food item is healthier than others within the same food category without the need for the consumer to process any nutritional information (Hodgkins et al. 2012). A more detailed discussion of the various types of FOP nutrition labeling is given by Hersey et al. (2013) and van Kleef and Dagevos (2015).

The recent EU regulation (EU No 1169/2011) does not legislate mandatory front-of-pack nutrition labeling, but it does allow for the energy value to be repeated in the principal field of vision either alone or in conjunction with per-portion values for fat, saturated fat, sugar, and salt. Additional forms of expression and presentation of FOP labels, such as Guideline Daily Amounts (GDA), traffic lights or health logos, are currently being reviewed by the Commission.

Grunert and Wills (2007) present a review of European research on consumer response to nutrition information on food labels. The response variables include perception, liking, understanding and use of nutrition labels. Research with real purchase data from away-from-home eating places reveal mixed results regarding the effectiveness of nutrition labels in promoting healthier purchase behavior (for reviews, see Harnack and French 2008; Swartz et al. 2011). The same holds for research investigating the impact of nutrition labels at supermarkets (see e.g., Hersey et al. 2013; vant Riet 2012). Studies analyzing the influence of FOP labeling on consumer behavior using real purchase data are rare, so that many authors call for more research in this area (Andrews et al. 2014; Feunekes et al. 2008; Hersey et al. 2013; Lachat and Tseng 2013; vant Riet 2012). The few studies which use real purchase data do not show a generalizable impact of FOP labeling on consumer behavior at supermarkets. Balasubramanian and Cole (2002) found mixed results regarding healthier purchase behavior for eight different food categories. Similarly, Sacks et al. (2009) and Sacks et al. (2011) could not show an impact on the healthiness of foods purchased following the introduction of a traffic light FOP label.

The objective of our study is to gain further insights into consumers' response to the introduction of FOP nutrition labeling. Our study adds to existing literature in two ways. First, we analyze real purchase data as recommended by recent research. We have access to a large data set from a UK retailer including information about store brands sales, product characteristics, and consumer characteristics for one year before and after label introduction of a monochrome GDA labeling scheme (as shown in Figure 1). We study the potential effect of the GDA label introduction on market share and choice in selected food categories.

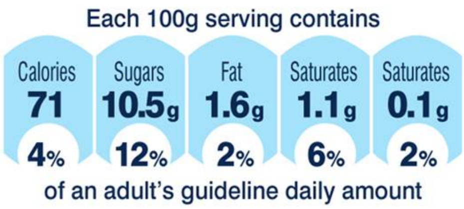

Figure 1: Example of a monochrome GDA label.

Second, we study the effects of the monochrome GDA label introduction not only on an aggregate level, as in all previous studies analyzing nutrition label effectiveness with purchase data, but also on an individual basis. We have information about two different food categories (yogurt and ready meals). To our knowledge, this is the first study analyzing FOP label effects at different data aggregation levels, comparing the outcome of both approaches. This is also the first study to investigate the effectiveness of the monochrome GDA label. We control for price, trends and seasonality at the aggregated market share level, but we also study the effects of the GDA labeling at the disaggregated level. This is accomplished by estimating the effects of the labeling format based on a discrete choice model with price, promotional activity, and consumer characteristics.

2.2 Study 1: Dataset

The data utilized for analysis is provided by a major retailer located in the United Kingdom. Three different datasets are available. The first dataset contains purchase transactions of loyalty card members purchasing the retailer's store brands. The time span of purchase transactions is from May 2005 until April 2007. The food categories yogurt and ready meals are available for analysis. Within each food category, we group the products based on an objective measure of healthiness, as will be explained later.

The dataset contains 75 different yogurt products accounting for nearly 20 million purchase transactions for the yogurt category as well as over 3,000 different ready meals products accounting for 30 million transactions. Furthermore, the transaction dataset provides information about the consumer ID, the date of purchase, the product ID, quantity, unit price in pennies and whether the product was purchased on discount. The second dataset provides information about the product IDs, with product size in grams, and different nutrition values per 100 grams. For each product ID, we calculate a health index using the SSAg/1 measure (Rayner et al. 2004) as described in Table 3. The SSAg/1 measure enables the calculation of an overall objective health score for a given product. In addition, the SSAg/1 measure focuses on unhealthy components of the food which are typically included in the monochrome GDA label (calories, fat, saturated fat, sugar, salt). Healthier food products have lower values of the SSAg/1 score.

SSAg/1
Scoring bands per 100 gram (g) as follows:
<u>Energy value</u>: 0-895kJ = 0; 895-1790kJ = 1; 1790-2685kJ = 2; etc.
<u>Saturated fat value</u>: 0-2.6g = 0; 2.6-5.2g = 1; 5.2-7.8g = 2; etc.
<u>Sugar value</u>: 0-6.3g = 0; 6.3-12.6g = 1; 12.6-18.9g = 2; etc.
<u>Sodium value</u>: 0-0.235g = 0; 0.235-0.470g = 1; 0.470-0.705g = 2; etc.
SSAg/1 value = Energy value + Saturated fat value + Sugar value + Sodium value

Table 3: Calculation of the SSAg/1 health score

In the yogurt category, we obtain health scores from 0 up to 3, while in the ready meals category, we end up with values in the range between 0 and 4 and a final group of products with health scores above 4 (5+).

The third dataset includes consumer-specific information stated at the time of the application for the loyalty card program such as gender. The share of female loyalty card holders purchasing during the time span of the study is 75% in the yogurt category and 73% in the ready meals category.

Combining product and consumer information with the transaction dataset generates the final dataset for the analysis. The GDA label introduction date is May 2006. Therefore, we use a dummy variable with "0" for the transactions before May 2006, and "1" for the periods May 2006 and later.

For our aggregated model, we calculate for each food category (yogurt and ready meals) and each health level (yogurt with $i = 0$ to 3 and ready meals with $i = 0$ to 5+) sales in kg ($sales_{it}$) and the mean price per kg ($price_{it}$) per week (t).

For the disaggregated model, we randomly select 400 consumers (n) with at least 20 purchase transactions for each product category to reduce computational costs for parameter estimation. Every purchase decision is taken as a choice among the different health levels. The mean price per kg ($price_{it}$) and the share of transactions on discount ($discount_{it}$) is calculated per week and per health level. For the repeated choices, a loyalty measure ($loyalty_{nit}$) for each individual, health level and week is calculated as introduced by Guadagni and Little (1983). We choose the value for α as 0.75 to weigh the last purchase with 75% and the smoothed average of the purchases before the last purchase with 25% (for a more detailed explanation, see Guadagni and Little 1983). The two variables included in the analysis which do not vary over alternatives are the gender dummy set as "1" for the female applicants ($gender_n$) and the label dummy set as "1" for the choice situations starting from May 2006 flagging the presence of the GDA label ($label_t$).

Tables 4 and 5 show summary statistics for sales in kg, price, and the share of transactions on discounts for the yogurt and ready meals data. The mean value (Mean) and the standard deviation (SD) is shown for each food category and health level, also supplemented with the overall mean and SD. Note that food products with higher health levels are classified as less healthy. Thus, the healthiest products in each food category have health levels of 0. The unhealthiest products in the yogurt category have the health level of 3. All products in the ready meals category with a health level of 5 and above are summarized into the least healthy level of 5+. In summary, the total sales in kg in the yogurt category exceed the sales in the ready meals category. The mean price per kg and the share of transactions on discount is higher for the ready meals category within each health level and across all health levels. A noteworthy observation is that the mean price per kg increases with increasing health level in the ready meals category. This implies that less healthy ready meals are, on average, more expensive than healthier ready meals. This fact confirms the need for price to be taken into account as an explanatory variable for the upcoming models.

	yogurt				
Health level	0	1	2	3	overall
$sales_{it}$					
Mean	9,554,786	26,002,991	25,245,382	4,363,407	16,291,642
SD	1,154,519	2,820,388	3,472,141	497,403	9,803,675
$price_{it}$					
Mean	124.6	119.5	117.7	141.2	125.8
SD	3.2	14.1	8.6	41.5	24.2
$discount_{it}$					
Mean	0	0.04	0.06	0	0.03

Table 4: Summary statistics for yogurt

	ready meals						
Health level	0	1	2	3	4	5+	overall
$sales_{it}$							
Mean	46,510	50,903	33,512	11,088	7,724	5,022	25,793
SD	6,947	5,164	9,607	5,627	2,276	1,301	19,582
$price_{it}$							
Mean	407.9	422.7	488.1	656.4	576.0	737.1	548.0
SD	22.6	17.6	23.3	51.4	49.9	51.8	126.8
$discount_{it}$							
Mean	0.27	0.22	0.19	0.17	0.15	0.24	0.21

Table 5: Summary statistics for ready meals

2.3 Study 1: Methodology

In previous research, different model types have been applied in order to estimate the effect of nutrition label introduction. The estimates were typically based on aggregated data. For example, Balasubramanian and Cole (2002) model market share as a function of market share in the previous period and did not include other explanatory variables apart from a label dummy indicating when the label was introduced. In Mathios (1996), a regression model is estimated with the number of units sold for a given product as the dependent variable. The model has labeling information, average consumer characteristics on store level and average price in the product category as explanatory variables. Mathios (1998, 2000) and Mojduszka et al. (2001) models were combinations of conditional logit models and sales models, but the dependent variable was the relative market share per week for a given product. Sacks et al. (2009) also conducted an aggregate sales analysis using a linear mixed model. Further studies were carried out as experiments with a comparison of treatment and control stores regarding the outcome of healthiness. For example, Berning et al. (2011) and Kiesel and Villas-Boas (2013) compared the influence of nutrition labeling on sales of unhealthy food products in treatment stores with nutrition labels to sales in control stores without nutrition labels using a difference-in-difference model.

We use two modeling approaches for our analysis. We start with an aggregated market share analysis based on a market share attraction model (MSA). Extending the time-series approach of Balasubramanian and Cole (2002), we include marketing-mix variables such as price, and we also adjust for effects across the different levels of healthiness. Furthermore, we estimate the label effect with a difference-in-difference approach taken from interrupted time series designs (see e.g. Morgan and Winship 2007; Capacci and Mazzocchi 2011). The outcome (market share attraction) in the aggregated model, which is influenced by the GDA label introduction, has a continuous level of measurement. The difference-in-difference approach, therefore, estimates the causal effect of the label introduction on market share attraction of each health category.

In a second step, we estimate a disaggregated choice model. Analyzing choices on a disaggregated level gives the opportunity to account for heterogeneous consumers and to gain insights into the underlying individual choice process. For this approach, we estimate a multinomial logit model (MNL) with the label introduction as well as price, promotional activity and consumer characteristics as explanatory variables for each individual. The outcome of this model is a discrete choice indicator for each alternative. The choice probability for the alternatives is derived by the difference of the explanatory variables so that external effects are captured by influencing all characteristics. This approach analyzes the influence on the purchase sequences of the consumers while the label effect remains comparable to the aggregated market share model. In the following section, we will explain both procedures in more detail.

Aggregated Market Share Model

The market share attraction model (MSA) was introduced by Nakanishi and Cooper (1974). A market share for a given brand or health level (in our case a group of yogurt or ready meals with the same level of healthiness) is defined as the share of attraction that this health level has in a market consisting of health levels. The attraction related to products at a given health level is assumed to be a function of a number of explanatory variables (e.g. price or product attributes). In particular, we assume that attraction also depends on the presence or absence of the GDA label.

We model the market share of health level i based on sales in kg compared to the healthiest level 0 as a function of price and presence/absence of the GDA label. In the appendix, we show how the parameters obtained from the estimation can be interpreted. We also discuss the expected signs of these differences.

To account for the causal effect of the GDA label introduction on the outcome with a continuous level of measurement, we apply a difference-in-difference estimation from interrupted time-series designs (Morgan and Winship 2007, p. 244). We estimate one market share attraction model for the periods before the label introduction (pre-model) and a second model for the periods after label introduction (post-model). We predict the time periods after the label introduction with the parameter estimates from the pre-model ($\tilde{Y}_0$) and the post-model ($\tilde{Y}_1$). As described by Capacci and Mazzocchi (2011), the treatment effect (GDA label introduction) is calculated as $E(\tilde{Y}_1) - E(\tilde{Y}_0)$. In our case, a positive (negative) treatment effect means that the attraction of health level i compared to health level 0 increases (decreases) after the GDA label introduction. We expect that the attraction of food products with higher health levels decreases compared to the healthiest level after GDA label introduction.

This approach takes into account a number of possible effects on the attraction of products belonging to a given health level. First, we model time-independent effects by the intercepts. Second, we also capture time-varying effects influencing all health levels, such as seasonality, by studying the fraction between market shares of different health levels. Third, we capture autocorrelation using lagged dependent variables. One possible explanation for significant autocorrelation is the existence of a persistence effect of consumption and, therefore, correction for such an effect is also included in our approach.

Disaggregated Choice Model

The multinomial logit model (MNL) was introduced by McFadden (1974). The model estimates the choice probability of a decision maker to choose an alternative out of a given choice set. The choice probability is modeled as a function of different types of explanatory variables. They are classified according to their variation across alternatives, decision makers, and/or time. In our case, the decision makers are the different consumers who choose a specific health level among the set of health levels from the healthiest to the unhealthiest alternative according to the SSAg/1 health score.

The explanatory variables *price* and *discount* vary across alternatives (health levels) and time. The *loyalty* measure varies across health levels and across consumers as well. The influence of these variables on choice probability is denoted by one parameter in the model for each explanatory variable, which captures the general linear effect of changes in the explanatory variables on the choice probability for each alternative (health level). To account for unobserved heterogeneity, these parameters are estimated as random coefficients via a mixing distribution leading to the random coefficient logit model (RCL). This approach leads to additional parameter estimates of the standard deviation for each parameter (*sd.price*, *sd.discount*, *sd.loyalty*). As explained by Train and Revelt (2000), the standard deviation can be interpreted as the variation in consumers' response to the marketing-mix variables (*price* and *discount*) and the variation of the influence of the past purchases (*loyalty*). In addition to the consideration of unobserved heterogeneity among consumers, the RCL overcomes other limitations of the MNL. First, the restriction of the independence-of-irrelevant-alternatives assumption does not hold anymore. This assumption denotes that the ratio of the probability of choosing one alternative to another is independent from other alternatives and their attributes. This can be unrealistic for the case where pairs of alternatives are perceived as more similar than other pairs of alternatives. Using the RCL allows a more realistic approach for our health levels, where consumers can perceive neighboring health levels as more similar than more distant health levels. The RCL relaxes this assumption by allowing for dependencies between the ratio of two alternatives and other alternatives (for further explanations, the reader is referred to Luce 2005). Second, the MNL cannot cover unobserved factors such as repeated observations which tend to be correlated over time. Both limitations can be fixed using a RCL model. A more elaborate description of the model is given in the Appendix.

The explanatory variables *gender* and *label* do not vary across alternatives, but across consumers and/or time. The number of parameters to be estimated for *gender* and *label* is equal to the number of alternatives minus one, because a baseline alternative (health level) whose parameter is normalized to zero must be chosen. For each of the other alternatives the explanatory variable enters as dummy variable. This approach is necessary in order to create differences over alternatives. The other parameter estimates can be interpreted as effects compared to this baseline alternative (see for example, Train 2009, p. 21). For our model, we have chosen the healthiest alternative (health level = 0) as the baseline alternative to simplify the interpretation of the effects of the less healthy levels.

This also enables the comparison of the results from the RCL model to the results from the MSA model because changes in health level attraction in the MSA model are also compared to the baseline category health level 0. Similar to the MSA model, we expect that the choice probability for food products with higher health levels decreases compared to the healthiest level after GDA label introduction. Furthermore, we include an interaction term for *gender* and *label* to model the effect on the choice probability for a female loyalty card holder facing the GDA label. Female consumers have higher health concerns than male consumers, and are therefore more likely to use nutrition labels (Drichoutis et al. 2006). We expect the effect for female customers to be stronger compared to male customers regarding healthier choice behavior.

2.4 Study 1: Results

Aggregated Market Share Model

We present the results for the MSA model in Tables 6 and 7. The dependent variable can be interpreted as the attraction of health level i compared to the healthiest level 0. The columns in the tables are classified according to the health level i (1-3 in the yogurt category and 1-5+ in the ready meals category). For each explanatory variable, we present the parameter estimates for the pre- and post-model in Tables 6 and 7.

We expect positive signs for $log(price_0)$ because the attraction of health level i should increase compared to the baseline alternative health level 0 if the price of the healthiest alternative increases. We expect negative signs for the parameter estimates of $log(price_i)$. If price increases, the attraction of health level i decreases compared to the baseline alternative. Our expectations regarding the price coefficients are met entirely in the ready meals category (see Table 7). All signs for $log(price_0)$ are positive and significant at the 1%-level. This significance level is met for the negative parameter estimates for $log(price_i)$ as well. We do not observe these results in the yogurt category. Some parameter estimates meet our expectations as well as showing significance levels below 10%. This can

Health Level	1	2	3
$E(\tilde{Y}_1) - E(\tilde{Y}_0)$	**0.01**	**-0.07*****	**-0.02***
μ_{i0} PRE	-1.873	8.171	-4.461**
μ_{i0} POST	7.502***	13.571***	5.684*
$log(price_0)$ PRE	0.177	-0.083	0.692*
$log(price_0)$ POST	-1.298***	-2.298***	-1.007*
$log(price_1)$ PRE	0.169*		
$log(price_1)$ POST	-0.121		
$log(price_2)$ PRE		-1.477	
$log(price_2)$ POST		-0.342***	
$log(price_3)$ PRE			0.076
$log(price_3)$ POST			-0.142***
$log(ms_{it-1})$ PRE	0.387**	1.197***	0.460***
$log(ms_{it-1})$ POST	0.745***	0.656***	0.661***
$log(ms_{0t-1})$ PRE	-0.814***	-0.737***	-0.635***
$log(ms_{0t-1})$ POST	-0.551***	-0.392***	-0.480***
$Adj.R^2$ PRE	0.82	0.94	0.33
$Adj.R^2$ POST	0.21	0.69	0.20

Table 6: Results of the MSA model for yogurt
*Significant at the 0.1 level, **Significant at the 0.05 level, ***Significant at the 0.01 level

be explained by less price conscious purchase behavior in the yogurt category. Nevertheless, with our parameter estimates for price level, we control for the influence of price while assessing the impact of the GDA label introduction. We also present the parameter estimates for the lagged dependent variables of the market shares of health level i ($log(ms_{it-1})$) and 0 ($log(ms_{0t-1})$) in Tables 6 and 7. We observe for both food categories a generalizable relationship between the lagged dependent variables and the dependent variables. The parameter estimates for $log(ms_{it-1})$ are all positive and significant at the 1%-level. High market shares in the previous period increases the attraction of health level i compared to health level 0 in the current period. This can be interpreted as a persistence of health level attraction, respectively consumption over time. The parameter estimates for $log(ms_{0t-1})$ are all negative and significant at the 1%-level. High attraction of health level 0 in the previous periods decreases attraction of health level i compared to health level 0 in the current period.

Health Level	1	2	3	4	5+
$E(\tilde{Y_1}) - E(\tilde{Y_0})$	**0.01**	**0.01**	**0.09*****	**-0.03*****	**-0.07*****
μ_{i0} PRE	1.528	1.014	7.124***	-4.292**	2.113
μ_{i0} POST	-3.953	8.264**	-15.795***	-14.408**	-17.430***
$log(price_0)$ PRE	2.610***	2.186***	2.116***	1.854***	1.524***
$log(price_0)$ POST	2.294***	2.170***	6.245***	3.674***	4.224***
$log(price_1)$ PRE	-2.810***				
$log(price_1)$ POST	-1.661***				
$log(price_2)$ PRE		-2.340***			
$log(price_2)$ POST		-3.531***			
$log(price_3)$ PRE			-3.238***		
$log(price_3)$ POST			-3.383***		
$log(price_4)$ PRE				-1.327***	
$log(price_4)$ POST				-1.454***	
$log(price_5)$ PRE					-1.857***
$log(price_5)$ POST					-1.394***
$log(ms_{it-1})$ PRE	0.365***	0.211**	0.234***	0.297***	0.467***
$log(ms_{it-1})$ POST	0.459***	0.227**	0.381***	0.378***	0.468***
$log(ms_{0t-1})$ PRE	-0.227***	-0.258**	-0.202	-0.561***	-0.323*
$log(ms_{0t-1})$ POST	-0.653***	-0.456***	0.283*	-0.672***	-0.409***
$Adj.R^2$ PRE	0.81	0.87	0.94	0.80	0.86
$Adj.R^2$ POST	0.66	0.88	0.89	0.74	0.60

Table 7: Results of the MSA model for ready meals
*Significant at the 0.1 level, **Significant at the 0.05 level, ***Significant at the 0.01 level

With the coefficients for price and the lagged dependent variables, we control for these influences on health level attraction while analyzing the impact of the GDA label introduction. The estimates for $E(\tilde{Y_1}) - E(\tilde{Y_0})$ in Tables 6 and 7 allow us to assess the impact of the GDA label introduction on the attraction of health level i compared to health level 0. For both food categories, we observe for the unhealthiest health levels (2 and 3 in the yogurt category and 4 and 5+ in the ready meals category) that their attraction compared to health level 0 decreases after the GDA label introduction. This can be interpreted as a health effect of nutrition labeling, where consumers reduce their intake of unhealthy nutrients by the offering of nutrition information (Teisl et al. 2001). It is important to emphasize that this effect is small compared to the influence of price and the lagged dependent variables.

In Tables 6 and 7, we also present the adjusted R^2, which measures the proportion of explained variance by the explanatory variables. In the yogurt category, we observe high as well as moderate values while all adjusted R^2 in the ready meals category are regarded as high.

Disaggregated Choice Model

We present the results from the estimation of the discrete choice model for the yogurt as well as for the ready meals category in Tables 8 and 9. For both categories, we have chosen the healthiest level (health level = 0) as the baseline alternative to be able to compare the results to the MSA model. Some parameters are estimated across all health levels (*price*, *discount* and *loyalty*), while the other parameters are estimated health level specific, as we expect that their values are influenced by the healthiness of a product (intercept, *label*, *gender*, and the interaction effect of *label* · *gender*). The health level specific effects are relative to the baseline alternative (health level = 0). Table 8 shows the results for the yogurt data, and in Table 9 we present the results for the ready meals data.

Health Level	All	1	2	3
Intercept		0.23*	0.33***	-0.16
label		**0.54******	**0.10**	**0.32**
gender		0.22	0.08	-0.24
label · *gender*		**-0.45****	**0.04**	**-0.19**
price	-0.47**			
sd.price	3.60***			
discount	0.15			
sd.discount	7.66***			
loyalty	3.25***			
sd.loyalty	0.51***			

Table 8: Results of the discrete choice model for yogurt
*Significant at the 0.1 level, **Significant at the 0.05 level, ***Significant at the 0.01 level

The marketing-mix variables *price* and *discount* reveal significant parameter estimates with the expected signs for both category estimations. For *price*, we expected a negative sign, and for *discount*, we expected a positive sign. This means that increasing price leads to lower choice probability and increasing share of transactions on discount increases choice probability across all health levels. For yogurt choices, the parameter for the share of transactions on discount is not significant, but the standard deviation of the random coefficients is. This can be explained by heterogeneous response to discounts among consumers in terms of increase or decrease of choice probability. The parameters for loyalty are positive and significant in both models. The choice probability for a certain health level increases if consumers have chosen this health level in previous choice situations. This means that consumers show strong persistence in choice behavior over time. The standard deviation for the loyalty measure is also significant revealing a heterogeneous response according to past purchases of individual consumers.

Health	All	1	2	3	4	5+
Intercept		0.53***	0.34***	-1.05***	-1.08***	-1.61***
label		**-0.19****	**-0.11**	**-0.31***	**-0.09**	**0.22**
gender		-0.20	-0.42***	-0.01	-0.03	-0.44**
label · gender		**0.02**	**0.14**	**0.11**	**-0.30**	**0.13**
price	-1.85***					
sd.price	12.23***					
discount	0.52***					
sd.discount	0.62***					
loyalty	0.58***					
sd.loyalty	0.93***					

Table 9: Results of the discrete choice model for ready meals
*Significant at the 0.1 level, **Significant at the 0.05 level, ***Significant at the 0.01 level

There are no generalizable results for less healthy levels to be chosen less likely compared to the healthiest levels after the label introduction. In the yogurt category, only the effect of *label* for health level 1 compared to health level 0 is significant. The sign is positive so that the choice probability for the unhealthier yogurt with health level 1 increases compared to the healthiest yogurt with health level 0 after GDA label introduction. In the ready meals category, the parameter for the label introduction is negative and significant for health level 1 compared to level 0, and for health level 3 compared to level 0. The choice probability for these unhealthier food products decreases after GDA label introduction. There are no significant effects for the other health levels, so that a generalization of healthier purchase behavior cannot be confirmed for both food categories after GDA label introduction.

It follows from the non-significant parameters for gender that female loyalty card applicants do not choose healthier food products in the yogurt category. In the ready meals category, the parameters for health level 2 compared to level 0, and for level 5+ compared to level 0, are significant with a negative sign. Female loyalty card applicants are less likely to choose ready meals with these health levels compared to the healthiest food products. Generally, healthier purchase behavior in both categories is not observed for female loyalty card applicants. The parameter for the interaction between label and gender measures the effect of female loyalty card applicants facing the GDA label. Only the parameter for health level 1 compared to health level 0 in the yogurt category is significant and negative. Female loyalty card applicants are less likely to choose the slightly unhealthier yogurt from health level 1 than the yogurt from health level 0 after the label introduction. In the ready meals category, all parameters for the interaction between label introduction and gender are not significant. We do not observe a generalizable effect of the label introduction on the purchase behavior of female customers.

The McFadden-R^2 for the discrete choice model for yogurt is 0.435, which can be interpreted as high, while the McFadden-R^2 of the discrete choice model for ready meals only reaches a moderate level of 0.115.

In both food categories, we do not observe healthier purchase behavior in terms of choice probability after the GDA label introduction. The effect is also absent when female customers are considered separately. Both categories reveal that price has a large influence on choice probability. Loyalty shows a very large influence on choice probability which means that consumers show high persistence in their choice behavior.

2.5 Study 1: Discussion

In our paper, we investigate the effect of introducing a GDA label in two product categories. We use two modeling approaches, one on an aggregated level and another one on a disaggregated level. To our knowledge, this is the first study analyzing and comparing nutrition label effects at different data aggregation levels. We control for price, trends, and seasonality in the aggregated model, and for price, promotional activity, consumers characteristics, and unobserved heterogeneity in the disaggregated model.

In the aggregated model, we observe that the attraction of the unhealthiest food products compared to the healthiest food products slightly decreases after GDA label introduction in both food categories in terms of market share. This suggests that the GDA label introduction led to healthier purchase behavior. In the disaggregated choice model, however, this relationship is blurred. Although we observe a decrease in choice probability of some unhealthy alternatives compared to the healthiest option, no generalizable pattern emerges. This means that some unhealthy alternatives (including the unhealthiest options) were as likely to be chosen after the GDA label introduction. Moreover, we find partially significant effects for gender, label and their interaction. As before, these results also cannot be generalized in terms of healthier purchase behavior.

One reason for the more nuanced results in the disaggregated model is that this approach accounts for observed and unobserved heterogeneity of the customers. Some of the parameter estimates for gender are significant. Furthermore, the random coefficients, which account for unobserved heterogeneity, are highly significant. These influences are not captured in the aggregated model and, thus, can account for the different outcomes. Furthermore, the disaggregated model accounts for differences between the explanatory variables. Price for all health levels influences the choice probability, while in the aggregated model only two price covariates are possible for each equation to avoid problems with multicollinearity. Even though both modeling approaches have a similar interpretation of the parameter estimates for the GDA label introduction, they have different maximization strategies for their obtainment. Another reason for the difference between the results of the models is that our disaggregated model accounts for loyalty to a much greater extent than the aggregated market share model. The lagged dependent variables show tendencies towards persistence in consumer behavior with significant parameter estimates and higher magnitudes than the GDA label effect. The loyalty variable in the discrete choice model captures this effect on an individual level with further incorporation of unobserved heterogeneity in the random coefficients. Product loyalty may actually lead consumers to avoid package search and therefore not pay attention to the new GDA label (Jacoby et al. 1977). This strong effect in the discrete choice model can probably mask minor effects of healthier purchase behavior in terms of choice probability.

One additional finding from our study is that price in both models (and promotional activity in the discrete choice model) has a large impact on purchase and choice behavior. These findings are in line with many previous research studies, which reveal that marketing-mix variables have a larger influence on food choice than health concerns (Levy et al. 1985; Ma et al. 2013; Mojduszka et al. 2001). Our findings furthermore support Chandon and Wansink (2012) who state that price has a high influence on consumers' energy intake while the effectiveness of nutrition labels is overestimated.

The internal validity of our analysis is considered to be high, as we rely on established methods analyzing market share and choice data. We control for dynamics in the aggregated model and also rely on a counterfactual approach to assess the impact of the GDA label introduction on health level attraction. In the disaggregated model, we control for observed and unobserved heterogeneity as well as dynamics.

We have some limitations in our data set. We were only able to access purchase data on store brands although these account for more than 50% of the purchases in the categories. In the estimation of our aggregated market share model, we explicitly model the effect of price at different health levels. However, price from national brands are not taken into account, as we do not have access to this information. Non-price related marketing decisions such as allocation of shelf space, may of course also influence the market share or choice probability of an alternative. This information is also not included in our data. Nevertheless, our models include more explanatory variables compared to similar previous studies. The results from our analyzes support the current discussion about the usefulness of nutrition labeling. We have not found a systematic shift toward purchases of healthier food due to the introduction of GDA labels. We observe a slight decrease in attraction for the unhealthier food products compared to the healthiest category. Based on our results, we agree that GDA labels are not sufficient to substantially change consumer behavior towards healthier alternatives. Following studies could concentrate on analyzing the influence of other FOP label types on healthier purchase behavior in real-life settings. That being said, there is still the possibility that GDA labels can affect first-time choices. While most consumers appear to make habitual purchases, consumers who buy yogurt or ready meals for the first time could be guided by nutrition labels. This possibility deserves attention in future studies.

2.6 Study 1: Appendix

The Market Share Attraction Model (MSA)

The market share attraction (MSA) model describes the market share of a health level via the relative attractiveness of that health level in relation to a baseline health level on the market.

We let A_{it} denote the sales in kg of health level i at time t. The associated market share ms_{it} is defined by

$$ms_{it} = \frac{A_{it}}{\sum_i A_{it}} \qquad with\ i = 0, ...I\ and\ t = 1, ...T \tag{1}$$

In order to estimate the model we can log-linearize it using health level 0 as the base health level

$$log\left(\frac{ms_{it}}{ms_{0t}}\right) = \mu_{i0} + \beta_{1i0} log(price_0) + \beta_{2i0} log(price_i) + \\ \beta_{3i0} log(ms_{0t-1}) + \beta_{4i0} log(ms_{it-1}) + \varepsilon_{it} \tag{2}$$

For each health level i, we estimate one equation. The system of $(I - 1)$ equations can be estimated by a Seemingly Unrelated Regression (SUR; Zellner 1962). This procedure allows estimating several regression equations where the error terms ε_{it} are assumed to be correlated across the equations. Capturing the correlation between residuals of the different equations enables us to control for common unobserved factors influencing the dependent variables.

An increase in $log\left(\frac{ms_{it}}{ms_{0t}}\right)$ is interpreted as an increase in attraction of health level i compared to health level 0. Therefore, we expect that the sign for β_{1i0} is positive, because the attraction of health level i increases with increasing price of health level 0. The sign for β_{2i0} is expected to be negative because if price of the health level i increases this should lead to a decrease in attraction compared to health level 0. The signs for β_{3i0} and β_{4i0} depend on the type of dynamics inherent in the consumer behavior and product category. For example, if β_{4i0} is positive, consumers show a persistence in their purchase behavior across time periods.

The Random Coefficient Multinomial Logit Model (RCL)

The probability P_{ni} of consumer n to choose alternative i among the M alternatives with index j has the following form (McFadden 1974):

$$P_{ni} = \frac{\exp(\beta \cdot x_i)}{\sum\limits_{j=1}^{M} \exp(\beta \cdot x_i)} \tag{3}$$

β includes the parameters for the effect of the explanatory variables x_i from alternative i. To simplify our model presentation, we subsume all variables in one explanatory variable. Later on we will present explicitly the equation with all explanatory variables. In the RCL model, the choice probability P_{ni} for consumer n to choose alternative i can be expressed as (Train 2009, p. 135):

$$P_{ni} = \int\limits_{-\infty}^{\infty} \left(\frac{\exp(\beta \cdot x_i)}{\sum_{j=1}^{M} \exp(\beta \cdot x_i)} \right) f\left(\beta\right) d\beta \tag{4}$$

P_{ni} becomes the weighted average of the standard MNL equation at different values of β, with the weights given by the mixing distribution $f\left(\beta\right)$. The β coefficients can be estimated with a Simulated-Maximum-Likelihood procedure (Train 2009, p. 144).

To take the repeated choices by the consumers into consideration, the Panel-Data-Technique (Revelt and Train 1998) should be applied. In this case the likelihood for a consumer is the product of the likelihood for the consumer's T choice situations.

This leads to the following expression for choice probability P_{ni}:

$$P_{ni} = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \left(\frac{\exp(\beta \cdot x_i)}{\sum_{j=1}^{M} \exp(\beta \cdot x_i)} \right) f(\beta)\, d\beta \tag{5}$$

Our discrete choice model with r as the baseline alternative from the M alternatives has the following specification:

$$\begin{aligned} \beta \cdot x_i = & \sum_{j=1;j\neq r}^{M} \beta_j + \beta_1 price_{it} + \beta_2 discount_{it} + \beta_3 loyalty_{it} + \\ & \sum_{j=1;j\neq r}^{M} \beta_{gender,j} gender_i + \sum_{j=1;j\neq r}^{M} \beta_{label,j} label_t + \sum_{j=1;j\neq r}^{M} \beta_{label\cdot gender,j} label_t \cdot gender_i \end{aligned} \tag{6}$$

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3 Consumers' Response and Retailers' Benefits due to Voluntary Front-of-Pack Nutrition Labeling on Store Brands

(with Yasemin Boztuğ)

This paper (Study 2) is based on:

Elshiewy (2013). The Impact of Nutrition Labeling on Consumers Energy Intake and Retailers Revenues - A Study with Supermarket Scanner Data. *Presentation at EMAC 26th Doctoral Colloquium, Istanbul, Turkey.*

A previous version of this paper (Study 2) is published as:

Elshiewy and Boztuğ (2013). The Impact of Nutrition Labeling on the Purchased Amount of Sugar in Sweet Food Products. *Proceedings of the 42th EMAC Conference, Istanbul, Turkey.*

This version is currently invited for 2nd round review in *Journal of Retailing.*

3.1 Study 2: Introduction

Health problems caused by unhealthy food intake are increasing (WHO 2012). Reduction of nutrition-related health problems is a major challenge of the 21st century because millions of adults die each year as a result of being overweight or obese (Ng et al. 2014). Against this background, nutrition labeling is regarded as a potential instrument to induce necessary dietary changes and to influence consumption behavior (WHO 2012). Back-of-pack nutrition information is already mandatory for prepackaged food in many developed countries (Kasapila and Shaarani 2014). Governments aim to induce a health effect, meaning that consumers reduce their intake of unhealthy nutrients by the offering of health-related information (Teisl et al. 2001). This would lead to less nutrition-related health problems and therefore less health costs. In addition, both food manufacturers and retailers have voluntarily implemented front-of-pack nutrition labeling as part of their marketing strategy (van Kleef and Dagevos 2015). From a shopper marketing perspective, this aims to influence the customer along and beyond the act of purchasing (Newman et al. 2014; Shankar et al. 2011). Retailers try to create value for customers and to obtain their store loyalty by voluntary nutrition labeling. The latter outcome has not yet been explored scientifically in a real-life setting, so that the decision to implement voluntary nutrition labeling may have been based on an erroneous assumption.

Nutrition labeling is defined as "an attempt to provide consumers, at the point of purchase, with information about nutrition content of individual food products, in order to enable consumers to choose nutritionally appropriate food" (Grunert and Wills 2007, p. 385). A large amount of research has analyzed front-of-pack nutrition labeling and how consumers respond to different labeling schemes (for recent reviews, see Hersey et al. 2013; van Kleef and Dagevos 2015; vant Riet 2012). Consumers have a positive attitude towards nutrition information on food packages and appear able and willing to choose healthier options using any labeling scheme (Storcksdieck and Wills 2012). The provision of nutrition information increases consumers' awareness of health benefits achieved by consumption of specific foods (Newman et al. 2014). Research using real purchase data is still short of evidence about the success of nutrition labels to promote healthier purchase behavior. Hence, many authors call for more research about consumers' response to nutrition labeling with real purchase data, in particular for research analyzing the influence of front-of-pack labels (e.g., Andrews et al. 2014; Hersey et al. 2013; Lachat and Tseng 2013).

Despite the fact that research is still short of evidence about the effectiveness of front-of-pack nutrition labels in real-life settings (or perhaps for this reason), numerous retailers have voluntarily introduced such labeling schemes (van Kleef and Dagevos 2015). Theoretical frameworks deriving the benefits of voluntary nutrition labeling for retailers have been established. For example, according to signaling theory, if the nutritional composition of a food product is considered with product quality only firms with lower quality would refuse to voluntarily reveal their product characteristics (Mojduszka and Caswell 2000). This enables retailers to increase perceived product quality by voluntary front-of-pack nutrition labeling. Attribution theory provides another explanation how voluntary nutrition labeling affects consumer's perceptions. The label introduction may be attributed to the retailer's concern for the customers and result in improved attitudes towards the retailer and increased patronage intentions (Newman et al. 2014). Studies have shown that customer goodwill (Russo et al. 1986) and store image (Achabal et al. 1987) increase due to labeling. While the current state of research claims that retailers benefit from voluntary nutrition labeling through improved attitudes, no research has investigated whether retailers benefit with improved revenue-concerned metrics. Attitudes alone are often poor predictors of marketplace behavior (Ajzen 2001; Vermeir and Verbeke 2006) and, hence, research with observed behavior is deemed necessary to gain further insights into retailer benefits from voluntary nutrition labeling (Newman et al. 2014).

Our study aims to fill this research gap by comparing revenues before and after nutrition labeling and by measuring changes in the number of loyalty card applications. To our knowledge, no previous study has examined how voluntary nutrition labeling affects retailers' benefits analyzing real purchase data. We therefore contribute to the growing literature on how retailers benefit from voluntary nutrition labeling. Moreover, our results will guide retailers in their decision to implement front-of-pack labeling as part of their marketing strategy.

We make a further contribution by providing insights for the impact of voluntary front-of-pack nutrition labeling on consumers' real purchase behavior. We compare the amount of sugar and fat purchased in food products before and after nutrition labeling. These measures are more likely to determine healthier purchase behavior than changes in sales or market share as examined in previous research from this area. Our results will support policy makers and retailers when considering the front-of-pack labeling scheme from our study and shed light on its effectiveness in promoting healthier purchase behavior.

The supermarket purchase data for our study is provided by a major retailer located in the UK. The retailer voluntarily introduced a front-of-pack Guideline Daily Amount (GDA) nutrition facts label on all of its own store brands in 2007 (see Figure 2, left panel). It displays the amount of calories (in kcal) as well as sugar, fat, saturated fat, and salt (in grams) per serving. These are supplemented with the percentage of recommended daily amount of the displayed nutrition values consumed per serving. This percentage is calculated for an adult requiring 2,000 calories per day. Prior to the introduction of the GDA label on the front of the food package, a mandatory back-of-pack Nutrition Information (NI) panel existed and remains available (see Figure 2, right panel). The NI panel displays the food energy content in kJ and kcal, along with the same nutrition values as the GDA label, as well as others such as protein or fiber. These values are presented in grams per 100 grams and are not supplemented with a percentage of recommended daily amount.

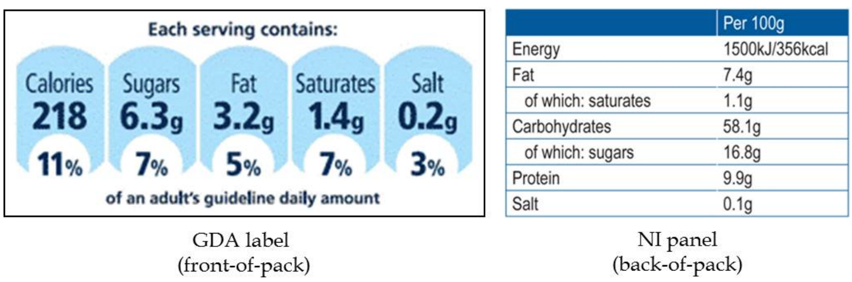

Figure 2: GDA label (left) / NI panel (right)

The dataset contains purchase transactions two years before and after the label introduction for three food categories: biscuits, breakfast cereals, and soft drinks. To analyze the label effect, we apply a seemingly unrelated regression model that accounts for trends and seasonality as well as explanatory variables to capture time-dependence and marketing-mix effects.

The remainder of the paper starts with a discussion of existing literature on consumers' response and retailers' benefits due to voluntary front-of-pack nutrition labeling. We introduce the dataset provided for the study and describe the data processing steps. We explain our model specification and estimation procedure. Afterwards, we describe our results followed by a summary and discussion of these results in the conclusion. Finally, we conclude with implications for retailers as well as opportunities for future research.

3.2 Study 2: Conceptual Background

Consumer Response to Nutrition Labeling

As stated by previous research, consumers are more concerned with avoiding unhealthy nutrition content such as sugar and fat rather than ingesting healthy nutrients such as vitamins or fiber (Balasubramanian and Cole 2002; Heimbach 1981). In a study by Prior et al. (2011), 84% of the respondents from the UK knew that they should be eating the smallest amount of foods high in sugar or fat. Nutrition labels disclose nutrition content and aim to increase consumers' attention towards it (Russo et al. 1986). With the GDA label, the disclosed nutrition values are limited to unhealthy nutrition content. Posting the label on the front of the package draws consumers' attention more effectively. Compared to the NI panel, consumers have to evaluate less information which is easier accessible and more relevant due to the solely disclosure of unhealthy nutrients.

The GDA label also increases nutrition knowledge compared to the NI panel by disclosing the percentage of recommended daily amount of nutrition content consumed per serving. From the perspective of reference point theory, such information is regarded essential because numerical nutrition content will only be meaningfully interpreted with comparison to other information (van Herpen et al. 2014; Visschers and Siegrist 2009; Viswanathan

1994). As nutrition labels can transform food products concerning their nutritional properties from credence-goods to search-goods (Caswell and Mojduszka 1996), disclosing the recommended daily amount of unhealthy nutrition content becomes part of the food choice decision. In this context, three types of costs are mentioned by Russo et al. (1986) when choosing food products based on nutrition information:

(i) Collection cost is the time and effort required to collect the nutritional information, (ii) computation costs to evaluate the collected information and (iii) comprehension costs depending on consumers nutrition knowledge. Type (i) and (ii) are reduced by the front-of-pack GDA label compared to the back-of-pack NI panel. Collection costs decrease because customers face the nutrition information on the front of the food package making it conceivably unnecessary to even pick up the item under consideration. The smaller number of relevant unhealthy nutrition values presented in a user-friendly label format with larger font furthermore reduces collection costs. Computation costs to evaluate the nutritional quality is reduced by disclosing the percentage of recommended daily amount so that customer can get rid of doing the math by them self. Comprehension costs are not necessarily decreased because the label does not explicitly communicate that the disclosed nutrition values are unhealthy, neither that the total daily amount should be 100%. The GDA label can conceivably induce a demand for learning if consumers lack the knowledge to process the disclosed information.

In summary, the GDA label has potential in reducing search and processing costs, which simplifies the decision process for consumers when choosing among prepackaged foods with the goal to avoid unhealthy nutrition content (Kiesel et al. 2011). Reducing the intake of unhealthy nutrients by the offering of health-related information is called the health effect (Teisl et al. 2001). A potential threat to the health effect is that consumers consider changes in behavior as costs. Unhealthy food attributes such as sugar and fat are associated with taste and pleasure by consumers (Belei et al. 2012; Raghunathan et al. 2006). If this applies, the intake of unhealthy nutrients will not necessarily decrease after the GDA label introduction. Research has shown that consumers prefer taste over nutrition content when making their food choice decision (Chandon and Wansink 2012;

Grunert et al. 2010; Mojduszka et al. 2001). According to Dhar and Simonson (1999), switching from tasty and unhealthy food to less tasty but healthy food results in a loss in taste and a gain in health. The authors furthermore contend that switching to healthier food with losses in taste seems less attractive because losses weigh more than gains. As a consequence, consumers' trade-off considerations between taste and health can lead to different results than the health effect would suggest.

From this background, the GDA label will only induce healthier purchase behavior for a subset of customers. As described by Burton and Kees (2012), the subset of consumers affected by nutrition labeling must have specific characteristics. First, consumers must recognize the label. Then they must be motivated and able to process the information and also able to use this information for a change in behavior. The disclosed information must increase nutrition knowledge, induce a desire for dietary change and turn any trade-off considerations in favor of health. Consumers who fulfill these characteristics will reduce their purchase volume of unhealthy nutrients after the GDA label introduction.

Retailer Benefits of Voluntary Nutrition Labeling

Attitudes towards retailers as well as perceptions and behaviorial intentions of customers may be influenced by voluntary nutrition labeling. For example, Russo et al. (1986) found an increase in customer goodwill towards the retailer as a result of nutrition labeling and Achabal et al. (1987) revealed an improvement in store image. Voluntary nutrition labeling is part of retailers' corporate social responsibility (CSR) strategy. Attribution theory suggests that consumers' positive experience with front-of-pack nutrition labeling will be attributed to the retailer. Consumers' perception of a retailer that is concerned about its customers well-being can lead to more positive attitudes and increase patronage intentions (Newman et al. 2014). Positive CSR beliefs by customers are associated with greater purchase likelihood and long-term loyalty, especially when the CSR strategy is integrated into the firm's core business (Du et al. 2007). We assume that this holds for food retailers implementing voluntary nutrition labeling on their own store brands.

According to Grossman's (1981) signaling theory, the voluntary introduction of nutrition labels can increase the perceived product quality. If the nutritional composition of a food product is considered with product quality only firms with lower quality would refuse to voluntarily reveal their nutrition values (Mojduszka and Caswell 2000). This leads to the possibility for retailers to enhance the perceived product quality, especially with voluntary front-of-pack labeling implemented for the own store brands which are compared to national brands in the same store. Higher perceived quality for store brands increases their share of sales (Sethuraman and Gielens 2014; Steenkamp and Geyskens 2014) and increases store loyalty intentions (Sirohi et al. 1998).

In summary, retailers aim to benefit by voluntary nutrition labeling on their store brands. Purchase volume and share of sales of store brands can increase if the perceived product quality of customers increases. Improvement of customers attitudes towards the retailer should result in increased store loyalty.

3.3 Study 2: Purchase Data

The purchase data is provided by a major retailer located in the UK. It contains purchase transactions of the retailer's store brands from 2,360 different supermarket branches during a time-span of four years (2005-2008). The share of store brands available in the retailer's supermarkets exceeds 50% and generates almost the same proportion of total sales. The retailer's product variety covers low-priced products (34% of its store brand volume), standard quality products (61%) and high quality products (5%). The purchase transactions are scanner data from the loyalty card members from the food categories biscuits, breakfast cereals and soft drinks. We assume that purchase behavior for sweet and rather unhealthy food products has a greater likelihood to be affected by the disclosure of unhealthy nutrition values.

Each purchase transaction provides the shopping date as week number, the Unique Product Code (UPC) of the purchased product, the quantity purchased, the unit price, and a 0/1-dummy if the product was purchased with discount. We link each UPC in the purchase transactions with the product size (in grams) and nutrition content of the specific product. The information for each UPC is also provided by the retailer. This offers the possibility to calculate the purchased total volume in grams as well as the total amount of sugar and fat (in grams) purchased in the food products for each purchase transaction. Changes in the nutritional composition of the food products are not present in the time-span of our study. We multiply unit price with the purchased quantity to obtain the retailer's revenues.

Each food category has different numbers of UPC: biscuits with 278, breakfast cereals with 55, and soft drinks with 198 alternatives. This enables the customers to choose among a broad range of products with respect to the level of nutrition values. Figure 3 shows the distribution of the sugar and fat values per 100 grams for the three food categories. The plots demonstrate the variety of different nutrition amounts per 100 grams between and within the food categories.

We have two additional variables on a weekly basis for our analysis. For each week, we have information about the number of loyalty card members who produced the total amount of purchase transactions in the three food categories. We also have the total number of applications for the retailer's loyalty card per week. We aggregate the variables for the analysis into four-week periods. This produces 13 periods per year and 52 periods in total. We add the last four-week period in 2004 as initial period which results into $T = 53$ time periods. This aggregation helps to capture the seasonal characteristics of our variables in combination with a sufficient number of periods for parameter estimation. For each food category and period, we determine the total volume in grams and the sum of sugar and fat in grams purchased in the food products (*tvolume*, *tsugar*, *tfat*) as well as the total revenues (*trevenue*). We summarize the number of loyalty card members who produce the purchase transactions into the total number of customers per food category and period (*tcustomer*). The variables for volume, sugar and fat assess consumers' purchase behavior in terms of healthiness. Revenues evaluate the outcome for the retailer by possible changes in expenditure by the customers. The total of the dependent variables can be influenced by either changes in the number of customers or

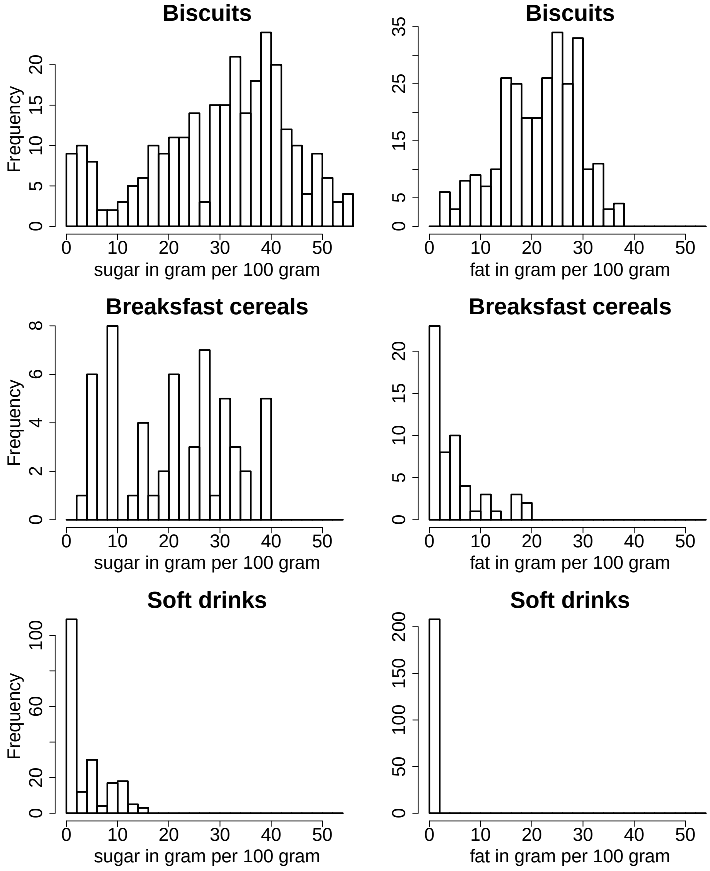

Figure 3: Histogram: Sugar and fat content

by changes in the behavior of customers. Therefore, we use the number of customers (*tcustomer*) purchasing in the food categories to distinguish between these two effects on *tvolume*, *tsugar*, *tfat* and *trevenue*. We divide the total amounts of volume, sugar, fat and revenue by *tcustomer*. This results into additional dependent variables: the mean volume (*cvolume*), the mean sum of sugar and fat (*csugar*, *cfat*) and the mean revenues (*crevenue*) per customer. With our dependent variables, we are able to cover different response patterns of the customers who induce the health effect as a result of the nutrition disclosure. If the customers start choosing healthier alternatives from the same food category, we expect the amount of sugar and fat to decrease, while the purchased volume remains unchanged. If sugar, fat and volume decreases, customers induce their reduction of unhealthy nutrients by reducing their purchased volume or even by quitting to purchase products from the unhealthy food category. The effect on the retailer's revenues will depend on the revealed response behavior of the customers.

For each time period, we also calculate the total number of loyalty card applications (*card*). This information is used as a proxy for customers store loyalty intentions which ideally leads to additional future revenues for the retailer. Customers with the intention to continue shopping and to increase purchases would benefit financially from the retailer's loyalty card program. As found by Meyer-Waarden (2007), customers who participate in loyalty programs have longer lifetimes and increased expenditure.

The explanatory variables in each food category and period are the mean price per kg in pennies (*price*) and the share of transactions with discount (*promo*). Previous studies emphasize the importance of considering marketing-mix variables due to their great influence on food choice (Levy et al. 1985; Ma et al. 2013; Mojduszka et al. 2001). We also calculate general price and promotion levels without food category separation for the model with *card* as dependent variable. We provide plots of our variables over time in Figures 4 and 5. We standardize our variables to zero mean and unity variance to compare the course for the same variables from the different food categories in one plot. Figures 4 and 5 reveal trends and seasonal patterns which will be considered in our modeling approach.

The introduction date of the GDA label is stated as "end of 2006." Hence, we assume that the label effect occurs in the years 2007 and 2008. We operationalize this by a 0/1 dummy variable with "0" in 2005 and 2006, and "1" for the periods in 2007 and 2008 (*label*).

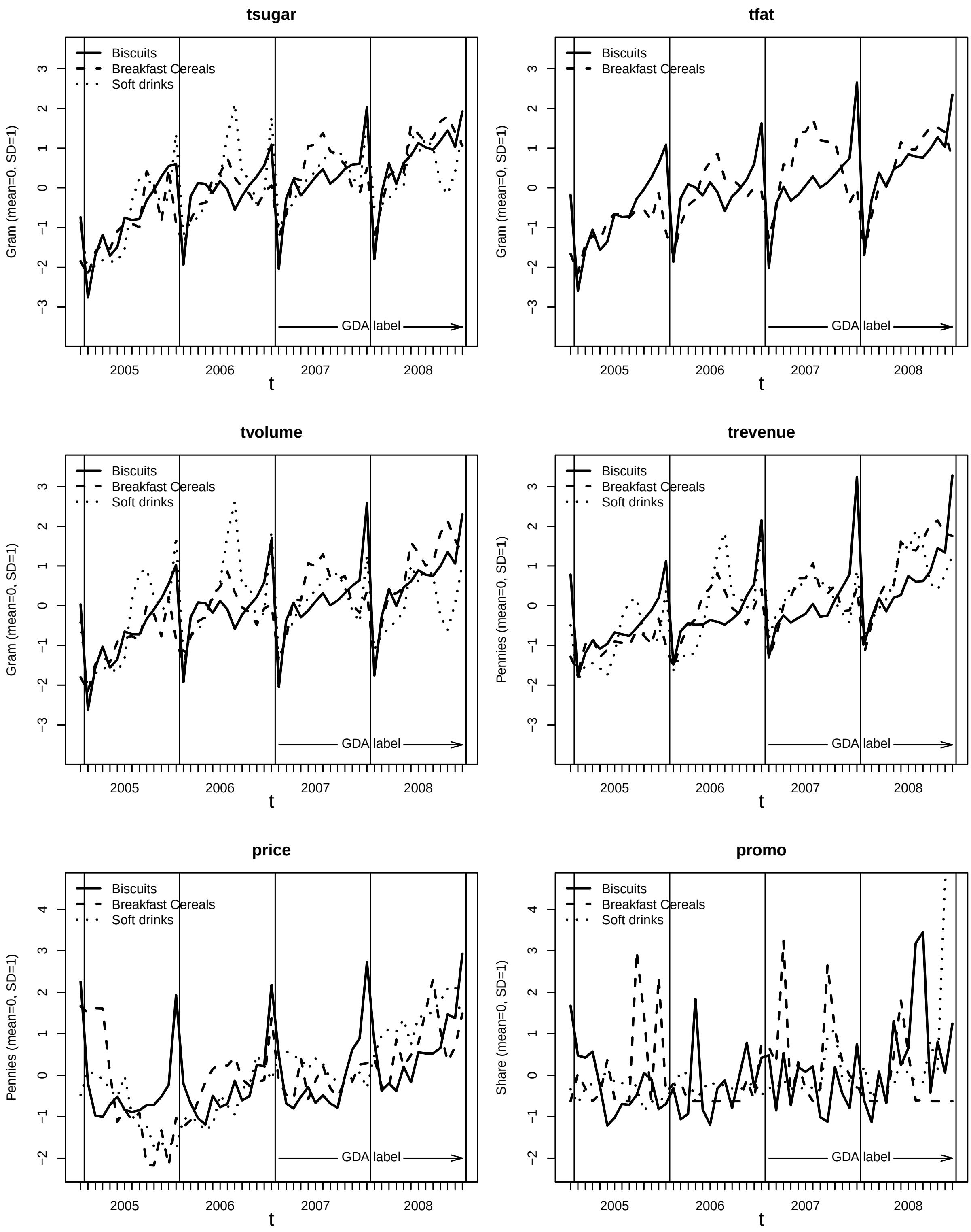

Figure 4: Line plots: *tsugar*, *tfat*, *tvolume*, *trevenue*, *price*, *promo*

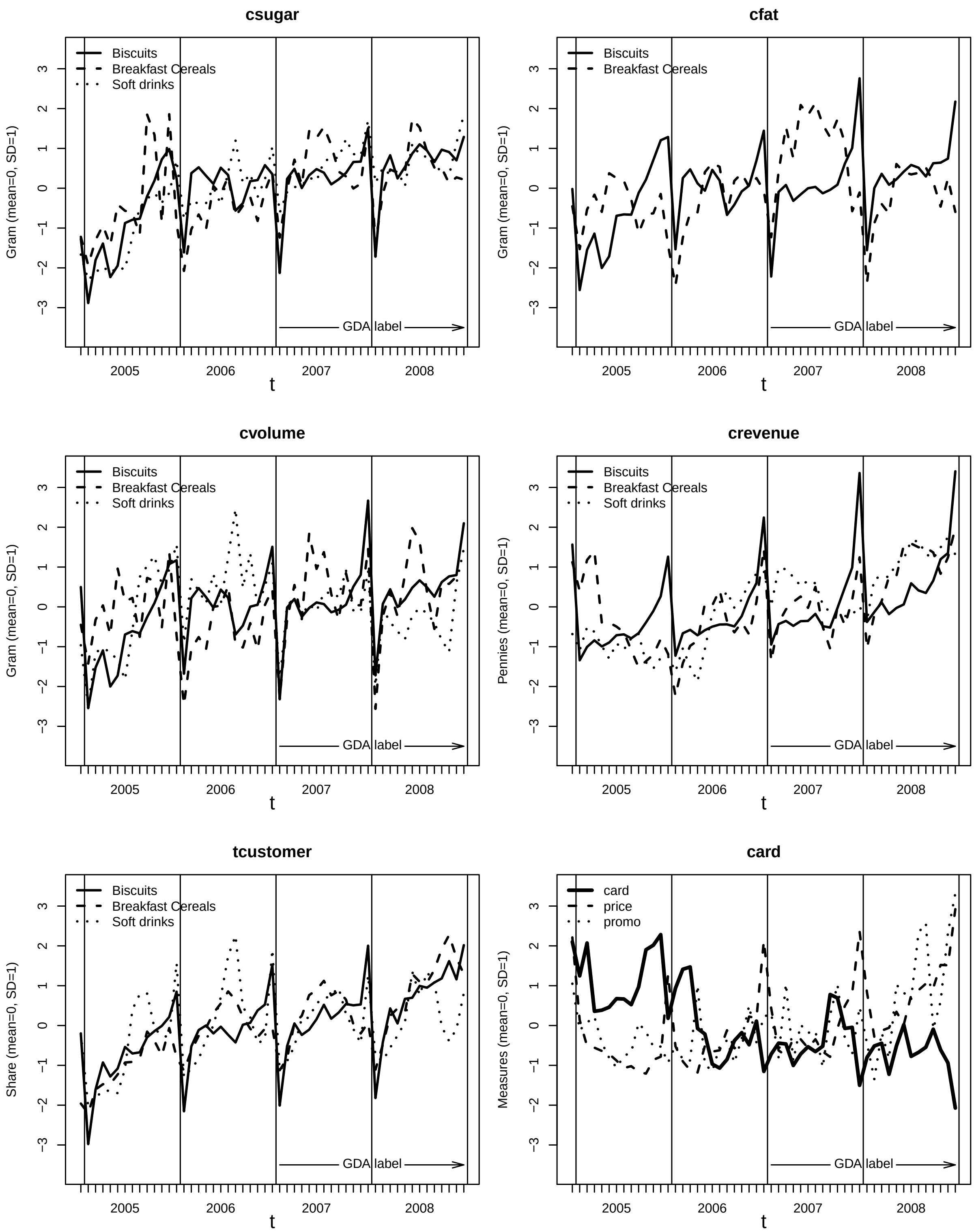

Figure 5: Line plots: *csugar*, *cfat*, *cvolume*, *crevenue*, *tcustomer*, *card*

3.4 Study 2: Modeling Approach

Model Specification

For each dependent variable, we build a model to examine the effect of the label introduction. We analyze each dependent variable for each food category (except for *card*) to account for category heterogeneity. We control for the marketing-mix effects of *price* and *promo*. We include dynamic components by a lagged dependent variable ($Y_{i(t-1)}$) because of the time-series dimension of our data. The effect of *label* on the dependent variable Y is of interest to examine the effect of the GDA label. The model for food category i at time t with error ε has the form:

$$\begin{aligned} Y_{it} = \beta_{i0} + \beta_{i1} label_t + \beta_{i2} price_{it} + \beta_{i3} promo_{it} + \\ \beta_{i4} Y_{i(t-1)} + \varepsilon_{it} \end{aligned} \tag{7}$$

We do not include instrumental variables (IV) in our model specification as the marketing-mix variables *price* and *promo* capture general levels of price and promotional activity for each food category on a time-series dimension. In such cases, the need for IV methods becomes less strong (Rossi 2014). Without IV, we account for the structural quantity of general marketing-mix activity across all of the retailer supermarkets and avoid biased parameter estimates by weak or invalid instruments.

We estimate our models as a system of equations with the three food categories and their specific set of dependent and explanatory variables. We apply the seemingly unrelated regression model (SUR; Zellner 1962) for the M equations to capture common unobserved factors that influence the dependent variables. For $M = 1$, the SUR model becomes a univariate regression model. Our SUR model for each dependent variable and the system of $M = 3$ equations (one for each food category i) over the time-span T with X as explanatory variables has the form:

$$
\begin{aligned}
& Y_i = X_i\beta_i + \varepsilon_i, \\
& (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t})' \sim N(0, \Sigma), \quad \text{with} \quad t = 1, ..., T
\end{aligned}
\tag{8}
$$

For ease of presentation we combine the $M = 3$ equations into one equation:

$$
\begin{aligned}
& Y = X\beta + \varepsilon \qquad \varepsilon \sim N(0, \Sigma \otimes I_T) \\
& \text{with} \\
& Y = (Y_1, Y_2, Y_3), \quad X = \begin{bmatrix} X_1 & 0 & 0 \\ 0 & X_2 & 0 \\ 0 & 0 & X_3 \end{bmatrix}, \\
& \beta = (\beta_1, \beta_2, \beta_3), \quad \varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3)
\end{aligned}
\tag{9}
$$

Differencing

It is necessary to ensure that the expected value and variance of Y_{it} are independent over time. This enables to control for trends and seasonality in Y_{it} when assessing the impact of the label introduction. It also provides an unbiased β-effect for the lagged dependent variable $Y_{i(t-1)}$. We eliminate trends and seasonality in Y_{it} by differencing the original values. We omit the index i for the different food categories to simplify the presentation of the equations. To eliminate a trend, we difference Y_t at lag 1, which leads to the detrended variable $\Delta_1 Y_{t'}$.

$$
\begin{aligned}
& \Delta_1 Y_{t'} = Y_t - Y_{t-1} \\
& \text{with} \quad t = 1, ..., T \quad \text{and} \quad t' = 1, ..., (T-1)
\end{aligned}
\tag{10}
$$

To account for seasonality, we difference $\Delta_1 Y_{t'}$ at lag 13 which corresponds to the length of the seasonal cycle with 13 periods per year:

$$\begin{aligned} &\Delta_{13}\Delta_1 Y_{t*} = \Delta_1 Y_{t'} - \Delta_1 Y_{t'-13} \\ &\text{with} \quad t* = 1, .., (T-1) - 13 \end{aligned} \tag{11}$$

We apply hypothesis testing to verify that $\Delta_{13}\Delta_1 Y_{t*}$ does not have a trend (KPSS-test by Kwiatkowski et al. 1992) or a seasonal pattern (CH-test by Canova and Hansen 1995). We difference the explanatory variables in the same way as their corresponding dependent variable.

Parameter Estimation

We estimate the parameters for the SUR model of the detrended variables $\Delta_{13}\Delta_1 Y$ and $\Delta_{13}\Delta_1 X$ with a Bayesian MCMC approach. This helps to overcome asymptotic properties of classical SUR estimates due to our reduced number of data points after differencing ($T^* = (T-1) - 13$). The first step is to specify conjugate prior distributions for the parameters β and Σ from equation (9). We apply the normal prior for $\beta \sim N(\bar{\beta}, A^{-1})$ and the Inverted Wishart prior for $\Sigma \sim IW(v_0, V_0)$. The posterior distribution for the parameters of the SUR model are simulated by Gibbs sampling as described by Rossi et al. (2005, p. 65). Given Σ, equation (9) is transformed into a system with uncorrelated errors by the root of the cross-equation covariance matrix $\Sigma = U'U$. Due to $(U^{-1})'\Sigma U^{-1} = I$, multiplying both sides of equation (9) with $(U^{-1})' \otimes I$ leads to the transformed system with uncorrelated errors which holds:

$$\tilde{Y} = \tilde{X}\beta + \tilde{\varepsilon} \tag{12}$$

with

$$\tilde{Y} = (U^{-1})' \otimes I_{T^*})\Delta_{13}\Delta_1 Y$$

$$\tilde{X} = (U^{-1})' \otimes I_{T^*})\Delta_{13}\Delta_1 X,$$

$$var(\tilde{\varepsilon}) = E[(U^{-1})' \otimes I_{T^*})\varepsilon\varepsilon'(U^{-1})' \otimes I_{T^*})]$$

The posterior distribution of β given Σ becomes:

$$\beta|\Sigma, Y, X \sim N\left(\tilde{\beta}, (\tilde{X}'\tilde{X} + A)^{-1}\right) \tag{13}$$
$$\text{with} \quad \tilde{\beta} = (\tilde{X}'\tilde{X} + A)^{-1}(\tilde{X}'\tilde{Y} + A\bar{\beta})$$

The posterior distribution of Σ given β becomes:

$$\Sigma|\beta, Y, X \sim IW\left(M + T^*, S + M + T^*\right) \tag{14}$$
$$\text{with} \quad S = E'E, \quad E = (\varepsilon_1, \varepsilon_2, \varepsilon_3)$$

After specifying the prior values for $\bar{\beta}$ and A, we start the Gibbs sampler with (β_1, Σ_1) and draw $\beta_2|\Sigma_1$ from equation (13) and $\Sigma_2|\beta_2$ from equation (14). We use OLS residuals from the untransformed equation (9) to obtain Σ_1. The sampling procedure is repeated D times to obtain D values for the posterior distribution of β and Σ. We compute the mean of the posterior distribution ($E(\beta)$) as the β-effects in equation (7). Our measure of significance for the β-effects is the share of β-draws with the opposite algebraic sign as the mean of the posterior distribution (posterior probability $P(\beta \gtrless 0)$, see Fong et al. 2012; Rossi et al. 1996).

Model Diagnostics

To evaluate the model fit and check for model assumptions we calculate different diagnostic measures. The coefficient of determination (R^2) gives the proportion of variance of the dependent variable explained by the explanatory variables. Furthermore, we calculate the Variance Influence Factor (VIF) to check for multicollinearity, the p-value of the studentized Breusch-Pagan test by Koenker (1981) (sBP) to test for homoscedasticity and the Breusch-Godfrey (Breusch 1978) test ($BG_{AR(3)}$) to ensure the absence of serial autocorrelation of order up to three. We obtain the fitted values and residuals by predicting Y with $E(\beta)$.

3.5 Study 2: Results

Differencing

We detrend all dependent variables at lag 1 to eliminate the linear trends exposed in Figures 4 and 5. The null hypothesis of the KPSS-test ("no trend") is not rejected for all dependent variables after differencing at lag 1. We perform seasonal differencing at lag 13 for all dependent variables, except *card*, to account for the seasonal patterns visible in Figures 4 and 5. The null hypothesis of the CH-test ("no seasonal pattern") is not rejected after differencing at lag 13. The dependent variable *card* passes the CH-test without seasonal differencing. The differencing procedure leads to a reduced number of data points for each model ($(53-1)-13=39$ and $53-1=52$ for the model with *card*). We difference the explanatory variables in the same way as their corresponding dependent variable. This allows us to interpret the parameter estimates for *price*, *promo* and $Y_{i(t-1)}$ as slope coefficients and the parameter estimate for *label* as level change in the dependent variable due to the GDA label introduction. After differencing, we standardize all variables to zero mean and unity variance to enable the comparison of the magnitude of the parameter estimates. Both differencing and standardization eliminates the effect of the intercept β_{i0}.

Parameter Estimation

For the Bayesian parameter estimation, we choose different priors for $\bar{\beta}$ and A to ensure independence from this specification for the posterior distribution. For $\bar{\beta}$, we specify the diffuse prior with all values equal 0 as well as OLS estimates and the values of 1 and -1 in line with our expected outcome (e.g. -1 for *price* according to the "law of demand"). For the precision matrix A, we also vary the priors from 0.001 to 1 to control for flat and peaked prior distributions. All specifications yield in very similar results. We present the parameter estimates from the diffuse prior specification of $\bar{\beta} = 0$ and the precision matrix A as $0.01I$. We use $D = 10,000$ draws to simulate the posterior distribution and calculate $E(\beta)$ with the 9,000 draws after the burn-in period of 1,000 draws. All MCMC chains meet convergence within the burn-in period of 1,000 draws. Summarizing the posterior distribution with the high number of 9,000 remaining draws ensures accuracy of $P(\beta \gtrless 0)$.

Purchase Data

We present $E(\beta)$ and $P(\beta \gtrless 0)$ for the purchase data models in Tables 10 to 14 (see Appendix). We highlight $E(\beta)$ in bold if $P(\beta \gtrless 0) \leq .10$. This threshold supports a significant effect of the explanatory variable. We consider an effect as a tendency to influence the dependent variable if $P(\beta \gtrless 0) < .20$ and present these parameter estimates underlined. In Tables 10 to 14, we also present the model diagnostics. The values for max(VIF) for all explanatory variables from each equation do not show any multicollinearity. We do not reject the null hypothesis of homoscedasticity (sBP) for any of the equations due to high p-values. We also do not reject the null of the Breusch-Godfrey-test $BG_{AR(3)}$ ("no serial autocorrelation up to order three") for any of the 26 equations, except for one (Table 13, breakfast cereals, *crevenue*). There are two equations where we remove remaining autocorrelation by an additional lagged dependent variable (see Tables 11 and 12, breakfast cereals, *cfat* and *crevenue*). This attempt does not support the null hypothesis of $BG_{AR(3)}$ for the equation in the breakfast cereals category with *crevenue* as dependent variable.

We do not draw implications from this equation because the parameter estimates can be biased by serial autocorrelation. We do not observe endogeneity bias for our equations in terms of correlation between explanatory variables and residuals ($Cov(\varepsilon_{it}, X_{it}) = 0$). Almost all $E(\beta)$ for the lagged dependent variables have a negative sign and most estimates show significant effects at the level $P(\beta \gtrless 0) \leq .10$. We do not describe these estimates in detail because they are rather directed towards capturing time-dependency than for interpretation purposes.

In Tables 10 and 11, we present $E(\beta)$ for the food energy amounts in total and the mean amount per customer. For the amount of sugar the marketing-mix variables *price* and *promo* reveal a large impact on total and per customer purchase behavior in our models. $E(\beta)$ for *price* has a negative sign and $E(\beta)$ for *promo* has a positive sign. We conclude that the volume of sugar in total and per customer increases with lower price levels and with increased promotional activity. None of the estimates for *label* are significant at the level $P(\beta \gtrless 0) \leq .10$. In the soft drinks category, we observe for the total amount of sugar (*tsugar*) and per customer (*csugar*) a tendency for decreased sugar volume after the GDA label introduction. The explanatory variables do not show a generalizable impact on the amount of fat in total (*tfat*) and per customer (*cfat*). We observe an impact of *price* on the mean amount of fat per customer in the biscuits category, and otherwise does *promo* affect fat volume significantly in both food categories. Models for the soft drinks category with fat volume as dependent variable are not useful because these products do not contain any mentionable amounts of fat (see Figure 3). The GDA label introduction significantly increases the mean amount of fat per customer in the breakfast cereals category.

In Table 12, we present $E(\beta)$ for the volume in grams in total (*tvolume*) and per customer (*cvolume*). $E(\beta)$ for *price* (*promo*) is negative (positive) for all models, which is according to the "law of demand." These estimates are significant at the level $P(\beta \gtrless 0) \leq .10$ for almost all models, thereby controlling for the marketing-mix effects when interpreting the influence of the GDA label introduction. All $E(\beta)$ for *label* are negative, but none is significant. Only the models in the soft drinks category and the total volume (*tvolume*) in the breakfast cereals category show tendencies of reduced volume after the GDA label introduction.

In Table 13, we present the results for revenues in total (*trevenue*) and per customer (*crevenue*). For the marketing-mix variables *price* and *promo*, we observe the expected outcome which are significant at the level $P(\beta \gtrless 0) \leq .10$ for all models except *price* in the soft drinks category with total revenues ($P(\beta \gtrless 0) = .49$) and *promo* in the biscuits category with revenues per customer ($P(\beta \gtrless 0) = .14$). Increasing price and promotional activity increases revenues for the retailer in our models. The effect of *label* is negative for all models. Both models in the soft drinks category have significant effects for *label*. We observe that revenues in total and per customer decrease after the GDA label introduction. The models with revenues per customer in the biscuits category and with total revenue in the breakfast cereals category show tendencies towards decreased revenues after GDA label introduction.

We present the results for the total number of customers (*tcustomer*) in Table 14. In our models, the number of customers purchasing in the food categories is highly influenced by promotional activity due to the positive and significant estimates for *promo*. The effect of *price* is only significant in the soft drinks category and shows a tendency to influence the number of customers in the breakfast cereals category. The estimates for *label* are negative in all three food category. $E(\beta)$ for the effect of *label* is significant in the breakfast cereals category at the level $P(\beta \gtrless 0) \leq .10$ and shows tendencies for the other two food categories. In our models, the number of customers who purchase the food products appears to decrease after the GDA label introduction.

We present $E(\beta)$ for the model with the number of loyalty card applications (*card*) as dependent variable in Table 14. We recognize that the number of loyalty card applications is significantly increased when the general price level is low due to the negative sign of $E(\beta)$ and $P(\beta \gtrless 0) \leq .10$. We do not observe that the GDA label introduction does affect the number of loyalty card applications.

Annual Report Data

The purchase data contains only information about the store brands from the three food categories. From this background, we also extract the revenues from the retailer's financial statements of 2005 to 2008. This enables the comparison to the overall performance of the retailer to any changes in store brand purchases. The fiscal year of the retailer is shifted by less than 10 weeks from the year ascribed in the purchase data. We consider the overlap between the annual time periods as sufficient for our comparison. Figure 6 shows the total revenues from the annual report for the fiscal years 2005 to 2008. To ensure anonymity of the retailer, we standardize the total revenues. The overall price measure for the model with *card* as dependent variable is hereby summarized for the four periods to control for a general price level.

We estimate a model with total revenues from the annual report as dependent variable and the two explanatory variables *label* and *price* aggregated to the four time periods (see Figure 6). After differencing at lag 1, we obtain the parameter estimates with $D = 1,000$. We use 100 draws as burn-in period and calculate $E(\beta)$ and $P(\beta \gtrless 0)$ with the 900 remaining draws. The results for $E(\beta)$ ($P(\beta \gtrless 0)$) are .122 (.42) for *label* and .766 (.15) for *price*. We do not observe a significant effect of the GDA label introduction on the overall performance. The general price level only reveals a tendency that increased price level leads to increased total revenues. This outcome is helpful to relate the results from the purchase data. Changes in the store brand purchases in our data are not connected to changes in the overall performance of the retailer.

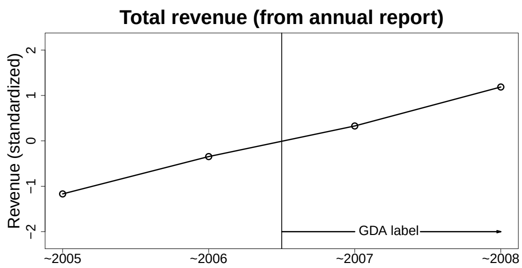

Figure 6: Line plot: Total revenue from annual report

3.6 Study 2: Conclusions

Summary and Discussion

Our study reveals minor effects towards healthier purchase behavior after GDA label introduction. This finding is in line with our expectation that the front-of-pack nutrition labeling will only induce healthier purchase behavior for a subset of customers. We do not observe any benefits for the retailer in terms of revenues or an increase in store loyalty intention after GDA label introduction. This outcome contradicts our expectations of retailer benefits due to voluntary front-of-pack nutrition labeling.

In our study, the amount of sugar in total and per customer tends to decrease after the GDA label introduction only in the soft drinks category. We observe a tendency that less customers purchase soft drinks and that the remaining customers furthermore tend to purchase a reduced volume from this food category. A possible explanation for this slight health effect is that the nutrition content in the soft drinks category is evaluated with less processing costs because it only contains sugar as unhealthy nutrient while biscuits and breakfast cereals also contain fat. Ma et al. (2013) report that sugar reduction can be obtained when low-sugar alternatives are available for consumers with a desire of dietary change. We do not observe that customers maintain their purchase volume and switch to soft drinks with lower sugar content, even though this food category provides a high number of such alternatives in our dataset. The slight reduction in sugar and volume comes at the expense of the retailer. Our models reveal that revenues in total and per customer decrease significantly after the GDA label introduction in the soft drinks category. If we relate this finding to the rather unaffected overall performance of the retailer, the GDA label introduction did more harm than good for the retailer in this food category. Only cross-category effects, like an increase in healthier food categories after the GDA label introduction, can possibly compensate the loss in the soft drinks category. Due to data limitations we can not control for these effects.

We find that the amount of fat per customer increases significantly in the breakfast cereals category after the GDA label introduction. On the other hand, we observe that the number of customers purchasing breakfast cereals declines after GDA label introduction and that the total volume tends to decrease. This leads us to the conclusion that less customers purchase breakfast cereals and that the remaining customers reveal unhealthier purchase behavior after GDA label introduction. Due to the fact that the mean volume per customer does not increase in our models, we conclude that the remaining customers choose breakfast cereals with higher fat content after the GDA label introduction. An increase in unhealthy nutrition content can be attributed to customers who make trade-off consideration when faced with the GDA label. For example, customers can seek to maximize taste, as discussed in our conceptual background, or increase the ratio of nutrients-for-money rather than to choose healthier options (Briers and Laporte 2013).

Another explanation for increased nutrition purchases can be a positive disconfirmation of consumers' expectations. Findings from Burton et al. (2009) suggest that consumers' response to nutrition information is driven by the relationship between expected and actual nutrition levels rather than by the information itself. Confronted with the percentage of GDA by the new labeling format, consumers' expectation regarding the recommended daily amount can be confirmed or disconfirmed. Positive disconfirmation can lead to healthier perception of food products and increase energy intake. If this applies, the results in the breakfast cereals category would be attributed to a positive disconfirmation of consumers' expectations regarding the amount of fat in breakfast cereals. However, this is in contrast to our observation that the number of customers purchasing breakfast cereals decreases after GDA label introduction. We can only assume a gap between the expectations of different customers regarding the fat amount in breakfast cereals. For the retailer, the tendency of decreased total volume after GDA label introduction leads to a tendency of loss in total revenue in our study.

In the biscuits category, we do not observe any significant changes in purchase behavior after the GDA label introduction. We observe the minor health effects in the rather utilitarian food categories breakfast cereals and soft drinks. If we assume that consumers perceive food products from the biscuits category as hedonic food items, the absence of a health effect in this food category can be explained by customers justification process of hedonic goods (Okada 2005). Another reason for a missing health effect in the biscuits category can be that consumers' expectations regarding the healthiness in this food category were confirmed by the GDA label. A confirmation of expected and actual nutrition information will not induce a change in consumer behavior (Burton et al. 2009).

Previous research suggests a positive impact of voluntary nutrition labeling on store loyalty or patronage intentions (Du et al. 2007; Newman et al. 2014; Sirohi et al. 1998). Our model with number of loyalty card applications as dependent variable does not exhibit any changes after the GDA label introduction. Customers with the intention to continue shopping and to increase purchases would benefit from the retailer's loyalty card.

In summary, we observe minor healthier purchase behavior but no additional benefits for the retailer due to voluntary front-of-pack nutrition labeling. When we observe healthier purchase behavior after the GDA label introduction, it appears to be caused by reduced volume and therefore less revenue. We consider the subset of customers who seem ready to bear the costs of the health effect to be small in our study. Our results support Chandon and Wansink (2012), who state that price is among the strongest marketing strategies influencing energy intake, while the effectiveness of nutrition information is overestimated. Our study suggests that health benefits for customers can come at a cost for retailers without that customers compensate these losses by increased store loyalty. In addition, we observe that a decrease in price level increases the story loyalty intention of the customers.

Implications for Retailers

While in theory, retailers benefit from voluntary nutrition labeling, our study did not reveal this for revenues or the number of loyalty card applications. This can be explained by the well known attitude-behavior gap (Ajzen 2001). Positive attitudes towards nutrition labeling, which will be attributed to the retailer, may suggest a specific behavior when considered in isolation. This does not have to apply in a real-life purchase decision, where consumers tend to incorporate more complex motivations (Vermeir and Verbeke 2006). We do not observe a decrease in total revenues from the annual report data after the GDA label introduction. This means that losses which we observe for the sweet food products seem to be compensated in other food categories. If retailers consider to implement nutrition labels, cross-category compensation by customers, who decide to reduce their intake of unhealthy nutrients, must be taken into account. This helps to prevent that potential losses in unhealthy food categories affect the overall performance. Those who choose not to provide voluntary nutrition labeling should keep in mind that the prevalence of front-of-pack nutrition labeling systems is increasing. While, from our results, retailers do not enhance benefits from the label introduction, consumers could regard voluntary front-of-pack nutrition labeling as a hygiene factor for store and product choice. It follows that voluntary nutrition labeling can become a need for retailers to maintain customer relationships rather than a marketing strategy to improve overall performance.

Implications for Future Research

We recommend additional research to investigate the impact of voluntary nutrition labeling on the outcome of retailers and food manufacturers. Future research should test different labeling schemes, ideally with quasi-experimental field studies as already claimed by Newman et al. (2014). Of utmost interest, would be to investigate if consumers already regard voluntary front-of-pack nutrition labeling as a hygiene factor in the choice of their food retailer. We furthermore recommend to incorporate a broader range of categories regarding healthiness to investigate possible cross-category effects induced by shifts in purchase behavior. Individual household panel data with complete food retailing information would support capturing these effects. Future research must gain insights how both sides can benefit from healthier purchase behavior induced by better informed customers.

Study 2: Appendix

	Biscuits		Breakfast cereals		Soft drinks	
	tsugar	*csugar*	*tsugar*	*csugar*	*tsugar*	*csugar*
label	-.020	.045	-.094	.112	-.<u>151</u>	-.<u>108</u>
	(.45)	(.39)	(.28)	(.22)	(.14)	(.19)
price	-.079	**-.325**	**-.215**	**-.189**	**-.405**	**-.568**
	(.32)	(.04)	(.09)	(.10)	(.00)	(.00)
promo	**.360**	**.214**	**.355**	**.369**	**.272**	**.336**
	(.01)	(.09)	(.01)	(.00)	(.02)	(.00)
Y_{t-1}	**-.324**	**-.225**	**-.219**	**-.382**	**-.334**	**-.296**
	(.02)	(.09)	(.07)	(.00)	(.01)	(.01)
R^2	.279	.226	.310	.424	.455	.620
max(VIF)	1.1	1.2	1.4	1.4	1.0	1.0
sBP	.215	.395	.119	.343	.976	.770
$BG_{AR(3)}$	.629	.573	.843	.921	.596	.161

Table 10: Parameter estimates and diagnostics for *tsugar* and *csugar*
($E(\beta)$ with $P(\beta \gtrless 0)$ in parenthesis below;
$E(\beta)$ in **bold** if $P(\beta \gtrless 0) \leq .10$ and <u>underlined</u> if <.20)

	Biscuits		Breakfast cereals	
	tfat	*cfat*	*tfat*	*cfat*
label	-.021	.029	-.023	**.253**
	(.45)	(.43)	(.45)	(.07)
price	-.117	**-.472**	.006	.<u>228</u>
	(.23)	(.01)	(.48)	(.12)
promo	**.258**	.122	**.315**	**.261**
	(.05)	(.21)	(.03)	(.08)
Y_{t-1}	**-.280**	-.069	-.<u>191</u>	**-.506**
	(.04)	(.35)	(.15)	(.00)
Y_{t-3}				**.426**
				(.02)
R^2	.180	.238	.151	.319
max(VIF)	1.1	1.1	1.4	1.6
sBP	.431	.724	.615	.926
$BG_{AR(3)}$	.642	.561	.444	.189

Table 11: Parameter estimates and diagnostics for *tfat* and *cfat*
($E(\beta)$ with $P(\beta \gtrless 0)$ in parenthesis below;
$E(\beta)$ in **bold** if $P(\beta \gtrless 0) \leq .10$ and <u>underlined</u> if <.20)

	Biscuits		Breakfast cereals		Soft drinks	
	tvolume	*cvolume*	*tvolume*	*cvolume*	*tvolume*	*cvolume*
label	-.069	-.032	-.167	-.010	-.154	-.138
	(.34)	(.42)	(.16)	(.47)	(.14)	(.17)
price	-.071	**-.440**	**-.222**	**-.326**	**-.313**	**-.355**
	(.34)	(.01)	(.09)	(.03)	(.01)	(.01)
promo	**.329**	.157	**.330**	**.330**	**.256**	**.395**
	(.02)	(.17)	(.03)	(.01)	(.03)	(.00)
Y_{t-1}	**-.237**	-.092	-.158	**-.453**	**-.372**	**-.292**
	(.06)	(.30)	(.15)	(.00)	(.01)	(.02)
Y_{t-4}				**-.192**		
				(.07)		
R^2	.189	.240	.264	.542	.388	.408
max(VIF)	1.1	1.2	1.4	1.5	1.0	1.0
sBP	.401	.956	.520	.379	.912	.489
$BG_{AR(3)}$	.859	.839	.782	.442	.825	.590

Table 12: Parameter estimates and diagnostics for *tvolume* and *cvolume* ($E(\beta)$ with $P(\beta \gtrless 0)$ in parenthesis below; $E(\beta)$ in **bold** if $P(\beta \gtrless 0) \leq .10$ and underlined if $<.20$)

	Biscuits		Breakfast cereals		Soft drinks	
	trevenue	*crevenue*	*trevenue*	*crevenue*	*trevenue*	*crevenue*
label	-.126	-.156	-.187	-.025	**-.278**	**-.180**
	(.22)	(.17)	(.14)	(.43)	(.05)	(.10)
price	**.266**	**.385**	**.213**	**.806**	.004	**.532**
	(.05)	(.01)	(.10)	(.00)	(.49)	(.00)
promo	**.288**	.148	**.318**	**.228**	**.261**	**.233**
	(.02)	(.14)	(.02)	(.03)	(.04)	(.06)
Y_{t-1}	**-.302**	-.142	-.089	-.094	**-.255**	.122
	(.02)	(.16)	(.28)	(.21)	(.06)	(.21)
R^2	.270	.202	.199	.619	.261	.412
max(VIF)	1.1	1.1	1.4	1.4	1.1	1.1
sBP	.889	.465	.581	.143	.592	.437
$BG_{AR(3)}$	.223	.257	.862	.004	.769	.949

Table 13: Parameter estimates and diagnostics for *trevenue* and *crevenue* ($E(\beta)$ with $P(\beta \gtrless 0)$ in parenthesis below; $E(\beta)$ in **bold** if $P(\beta \gtrless 0) \leq .10$ and underlined if $<.20$)

tcustomer				
	Biscuits	Breakfast Cereals	Soft drinks	*card*
label	-.158	**-.233**	-.164	-.135
	(.16)	(.09)	(.14)	(.22)
price	.120	-.182	**-.249**	**-.721**
	(.22)	(.15)	(.03)	(.10)
promo	**.513**	**.363**	**.217**	.015
	(.00)	(.02)	(.05)	(.40)
Y_{t-1}	-.114	.018	**-.354**	-.046
	(.23)	(.46)	(.01)	(.42)
R^2	.347	.221	.317	.436
max(VIF)	1.2	1.4	1.0	1.2
sBP	.391	.823	.807	.373
$BG_{AR(3)}$	.607	.972	.628	1.000

Table 14: Parameter estimates and diagnostics for *tcustomer* and *card* ($E(\beta)$ with $P(\beta \gtrless 0)$ in parenthesis below; $E(\beta)$ in **bold** if $P(\beta \gtrless 0) \leq .10$ and underlined if $< .20$)

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4 How Nutrition Labels Alter Health Halos: Misleading Nutrition Claims and Health Framing

(with Steffen Jahn and Yasemin Boztuğ)

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4.1 Study 3: Introduction

The relevance to account for nutrition and health aspects in food marketing has reached an all-time high. From this background, food manufacturers and retailers increasingly aim to address this issue with a variety of means (Chandon and Wansink 2012; Mohr et al. 2012). For example, package-based claims and labels have become popular strategies to influence consumer's perceptions of the healthiness of food products (Chandon 2013). In particular, marketers make use of nutrition claims (e.g., 'low fat') and voluntary nutrition labels, posted on the front of the package, to emphasize the nutritional advantage of their food products (Newman et al. 2014).

Decades of marketing and nutrition research was devoted to analyze how consumers process, perceive and respond to nutrition claims and labels on food products (for reviews, see Chandon and Wansink 2012; Chandon 2013; Hersey et al. 2013). One finding is that nutrition claims increase the perceived healthiness of food products (Andrews et al. 1998; Belei et al. 2012; Geyskens et al. 2007; Wansink and Chandon 2006). Studies using real purchase data from supermarkets show that nutrition claims (especially 'low fat' claims) have a positive impact on sales (Levy et al. 1985; Schucker et al. 1992; Teisl et al. 2001; Balasubramanian and Cole 2002). The downside of these findings is that misleading nutrition claims can be responsible for overconsumption and, hence, obesity (Belei et al. 2012; Wansink and Chandon 2006). The so-called health-halo effect is mentioned to be responsible for this outcome. For nutrition claims, such as 'low fat', consumers may tend to overgeneralize the information from the claim and rate the product as being healthy on other nutrients not mentioned in the claim (Andrews et al. 1998; Roe et al. 1999). The perceived healthiness will be biased if the food product has, for example, a 'low fat' claim but is high in sugar content. This means that consumers will overestimate the healthiness of the food product and underestimate the food energy content which in the end will result in overeating (Chandon and Wansink 2007).

Biased perceptions by misleading nutrition claims are assumed to be corrected by more comprehensive nutrition information (Chandon 2013). Previous research has found that consumers change their product attitude and behavior when claim-induced healthiness perceptions are disconfirmed by comprehensive nutrition disclosure (Ford et al. 1996; Garretson and Burton 2000; Keller et al. 1997; Kozup et al. 2003). The change in nutrition attitude results in a decrease in purchase intention of these food products as well as a decrease in trust (Garretson and Burton 2000) and credibility towards the food manufacturer (Keller et al. 1997; Kozup et al. 2003). It is questionable, however, if these outcomes also occur in real-life settings as respondents in experimental settings may be prone to less truncation to appear diligent and well-informed (Roe et al. 1999). Changes in perceived healthiness and purchase intention, which will be attributed to a nutrition claim disconfirmation, may suggest a specific behavior when considered in isolation. This does not have to apply in a real-life purchase decision, where consumers tend to incorporate more complex motivations (Vermeir and Verbeke 2006).

Among the studies using supermarket purchase data, the effectiveness of comprehensive nutrition disclosure in promoting healthier purchase behavior is mixed (for reviews, see Hersey et al. 2013; Moorman 1996; Russo et al. 1986). Nevertheless, the prevalence of voluntary front-of-pack nutrition labels on food products is steadily rising (Newman et al. 2014). Only a subset of consumers which are characterized by specific information processing behavior, motivations and knowledge are assumed to respond to nutrition labels (Burton and Kees 2012; Chandon 2013). Therefore, authors call for research to investigate more nuanced effects of nutrition disclosure, like the ability of nutrition labels to correct for misleading nutrition claims in real-life settings (Andrews et al. 2014).

Moreover, nutrition labels could additionally exert adverse effects. Most nutrition labels present the nutrition values as a percentage of the recommended daily amount per serving. A lower 'per serving basis' results in lower nutrition values in total and percentage. Consumers tend to evaluate the healthiness of food products by the values on the label and neglect the 'per serving basis' which leads to the health-framing effect (Mohr et al. 2012). As with the misleading nutrition claims, consumers will repeatedly overestimate the healthiness of the food product and underestimate the food energy content. Consumers do not tend to consume the 'per serving basis' (Ueland et al. 2009) but rather consume a single entity (Geier et al. 2006) or are influenced by the package size (Chandon 2013). Hence, health framing becomes another mean for marketers to increase the perceived healthiness of food products, leading to a health-halo effect which results in overeating and potential obesity (Chandon and Wansink 2012).

Using supermarket purchase data, this study seeks to explore the relationship between nutrition labels and health halos. We contend that front-of-pack nutrition labels can fight health halos, but only for a subset of food products. Instead of a general effect on healthful consumption, we argue that nutrition labels can evoke aversion behaviors toward food products that try to mislead consumers and, hence, strategically try to exploit health halos. That is, nutrition label introduction should lead to decreased consumption of food that claims to be, for example, 'low fat' but is high in sugar. While in this case a nutrition label could prevent a health halo, it may promote health halos by allowing marketers to manipulate the 'per serving basis' for the percentage of recommended daily amount (Mohr et al. 2012). We study the dual role of nutrition labels in altering health halos. We use supermarket scanner data covering two years and a large number of purchase transactions. We estimate a fixed-effects panel model to test our hypotheses, while controlling for different explanatory variables and unobserved heterogeneity.

With the present research, we contribute to the food marketing literature in several ways. First, we contend that nutrition labels do not affect food purchase behavior in general, but have more nuanced effects. In contrast to the assumption that nutrition labels generally decrease calorie intake or improve consumption of healthful food (or fail to achieve these goals), we only expect effects for products that claimed to be healthful but turned out to be rich in other unhealthy nutrients. This means that we suggest an "aversion effect" rather than a general "calorie intake reduction effect." Second, we show the differential effect of nutrition label introduction on food sales. While the aversion effect is one outcome that diminishes the consequences of health halos, serving size-related health framing is seen as a strategy to increase consumption of less healthful food products. Third, this study contributes to the growing number of studies using actual purchase data to investigate the real-world consequences of food marketing related to health aspects.

4.2 Study 3: Conceptual Background

Consumers that pursue the healthiness goal tend to choose products carrying a nutrition claim such as 'low fat' (Belei et al. 2012; Wansink and Chandon 2006). One reason is that these consumers could read a claim saying 'low fat' and infer that it is also low in overall calories (and, hence, more healthy). This has become known as the health-halo effect, a phenomenon that occurs when consumers infer the overall healthiness from one single attribute (Chandon and Wansink 2007). If additional information on a nutrition label supports such claims, it can even be expected that people will increasingly consume this product (Wansink and Chandon 2006). Sometimes, however, nutrition labels reveal that consumer inferences regarding the healthiness of the product are incorrect. In this case, consumers correct their expectations after exposure to objective nutrition information (Burton et al. 2014). However, an interesting case remains where discrepancies between expected and actual nutrition content is not based on poor nutrition knowledge but strategic deception by food marketers.

Consider the case of yogurt. By nature, yogurt contains fat and people are aware of it, making fat a relevant attribute for yogurt choice. Food manufacturer, then, have the opportunity to reduce the amount of fat and to communicate the respective information (e.g., 'low fat') on the food packaging. In order to keep the yogurt's tastiness, the same food manufacturer could increase the amount of sugar and other carbohydrates to compensate for the fat reduction (Brennan and Tudorica 2008). Food manufacturers often substitute one unhealthful nutrient for another; hoping consumers would not notice (Peretti 2012). The outcome is, that consumers may think they would eat a healthy yogurt (which is low in fat) without paying attention to the (potentially) excessive amount of sugar. The health-halo effect suggests that this systematic bias in calorie estimation can induce justification processes that lead to increased consumption of the respective yogurt (Chandon and Wansink 2007; Wansink and Chandon 2006).

We contend that, when detecting a mismatch between nutrition claim and content of other unhealthy nutrients, consumers would be dissatisfied as their expectations are negatively disconfirmed (Oliver 2010). The nutritional properties of the food product do not support the healthiness goal which is intended with the purchase. When food manufacturers replace a salient unhealthful product attribute (e.g., fat content for yogurt) with another unhealthful yet less salient attribute (e.g., sugar content) such practice is comparable to covert marketing. Covert marketing is a "paid form of communication in which the commercial source is concealed and the marketing message is passed off as news [...] in an effort to minimize audience skepticism toward the message" (Ashley and Leonard 2009, p. 213). Research has shown that consumers that become aware of covert marketing by a brand they use have lower intentions to repurchase this brand (Ashley and Leonard 2009). In a similar manner, consumers who become aware of marketer deception through misleading nutrition claims may reduce their purchases of the respective food product (aversion effect). Notably, without nutrition labels it is difficult to detect such deception. Front-of-pack nutrition information, in contrast, allows simple assessment of such misleading practices (Chandon 2013). In this case, the health halo may disappear after nutrition label introduction.

The aversion effect does not only entail decreasing purchase of the "misleading products," but also stable purchase of those products that contain many calories without claiming to be low in calories. For example, Greek yogurt is known to be rich in fat. According to our theorizing, after introduction of a nutrition label consumers are expected to continue buying it as it was never claimed to be healthful. Accordingly, there is no need to punish sugar-rich or calorie-rich products per se. Rather, only sales of 'low fat' products that contain high amounts of sugar are expected to decrease after label introduction. This leads to our first hypothesis:

H1: The introduction of a front-of-pack nutrition label reduces sales of products with 'low fat' claims that contain high amounts of sugar.

A second deception strategy marketers could use to make their products appear healthier (or less unhealthy) regards the serving size information. If a product contains high amounts of fat and/or sugar, the calories per 100g will be high. However, if the food manufacturer decides to define 50g as a "typical serving size," this health framing artificially reduces the reported amount of calories per serving (Mohr et al. 2012). Yet, the actual serving size is often one unit of the product (Geier et al. 2006) or determined by package size (Scott et al. 2008). Hence, the biased calorie report can lead consumers to overeating. Although consumers have the opportunity to detect this strategy when carefully reading the nutrition label, intense information processing is required.

Unlike the mentioned aversion effect that may result from nutrition label introduction, the health framing effect can lead to two different results. First, presentation of a small 'per serving basis' reduces the values of recommended daily amount on the nutrition label. As a result, consumers may have biased (lower) calorie estimates which can lead them to consume more units. In a series of experiments Mohr et al. (2012) manipulated the 'per serving basis' and showed effects on anticipated guilt of consumption, purchase intentions, and choice behavior. Against this background, it is even possible that purchase intentions and choice behaviors correspond to the degree of health framing, increasing sales of products that use a small 'per serving basis.' A possible second result is that consumers could notice the biased 'per serving basis' (since it is indicated on the label), infer strategic reporting and, in a similar way as before, become averse to purchase the food product. Of the two possible outcomes, results from existing research seems to favor the first (Mohr et al. 2012), leading to increased purchase of the respective product. One reason is that the second outcome requires consumers to make a series of combined inferences and projections regarding their future behavior (e.g., estimating their actual serving size), which is less likely. This leads to our second hypothesis:

H2: The introduction of a front-of-pack nutrition label increases sales of products according to their degree of health framing.

In summary, we argue that the introduction of nutrition labels can alter health halos in two ways. First, health halos should diminish for products that strategically try to mislead consumers by reducing the amount of one unhealthy nutrient while, at the same time, increasing the amount of another (less salient) unhealthy nutrient. Second, health halos should flourish for products that strategically use too small ‘per serving basis’ on nutrition labels. We test this framework using supermarket scanner data spanning two years.

4.3 Study 3: Data

Two datasets are utilized for our analysis, which have been provided by an European supermarket chain.

The first dataset contains purchase transactions from the yogurt category of the retailer’s own store brands. These purchase transactions were collected for two years as checkout scanner data from 1,552 different supermarkets of the chain across the UK. The time span of two years covers one year before and one year after label introduction. The purchase transactions contain information of 25 different yogurt items which are identified by their unique product code (UPC). In addition to the UPC, each purchase transaction provides information on the shopping date, the purchased quantity (in units) and the actual unit price (in pennies) paid at the checkout.

The second dataset contains product information for the UPC. Each UPC is described by its unit size (in g) and if the product’s legal name refers to a ‘low fat’ nutrition claim. The nutrition information which is disclosed to customers by the nutrition label is also provided. The implemented label is the front-of-pack Guideline Daily Amount (GDA) nutrition facts label. It displays the amount of calories (in kcal) as well as sugar, fat, saturated fat and salt (in g) per serving together with the percentage of recommended daily amount per serving. This percentage is calculated for an adult consuming 2,000 calories per day (see Figure 7). To calculate our variables for the upcoming analysis the product

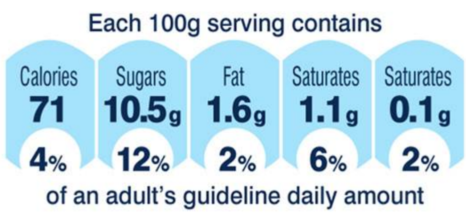

Figure 7: GDA label

information for each UPC from the second dataset is merged to the corresponding UPC in the dataset with the purchase transactions. For each purchase transaction, we convert the unit size from g to kg and calculate the total sales (in kg) by multiplying the sold quantity (in units) with the unit size. Moreover, we divide the unit price by unit size (in kg) to obtain a standardized price per kg for each purchase transaction.

We aggregate the two variables from the purchase transactions on a weekly basis. This type of aggregation helps capturing the best possible seasonal characteristics of the measures in combination with a sufficient number of periods for parameter estimation ($t = 1, .., 104$). For each UPC and each week, we calculate the sum of total sales in kg of all corresponding transactions ($saleskg$). This measure will serve as our dependent variable measuring the sales volume for each UPC on a weekly basis during the time span of the study.

The price per kg is aggregated by the mean value for each UPC and week ($price$). This variable serves as a control in the analysis. Label introduction is operationalized as a 0/1 dummy, with "0" for the weeks before, and "1" for the weeks after the label introduction ($label$). This variable flags the absence and presence of the GDA nutrition label.

Next, we derive the measures that remain constant during the two-year time span. The first variable indicates whether the yogurt contains a 'low fat' nutrition claim in the product legal name visible on the front of the package ($lowfat$). Including the claim in the legal name of the product is the common way the retailer uses nutrition claims. We use a 0/1 dummy which classifies the yogurt as "1" if the product name contains a 'low fat' nutrition claim, else "0." Furthermore, we calculate a variable that reveals if a product's sugar content should be classified as high ($sugarhigh$). We used the respective threshold of 10g of sugar per 100g. Figure 8 shows a scatterplot with each yogurt regarding their nutrition content (left panel).

Less than 25 different yogurt products are visible in the plots because some UPC are superimposed upon each other. On the left panel, the vertical axis shows the amount of fat in g per 100g and the horizontal axis shows the amount of sugar in g per 100g. These values are objective measures of the healthiness of the yogurt products. The products are furthermore marked in accordance to their status of 'low fat' nutrition claim in the product name (see legend in Figure 8, left panel). The hatched area marks the area where the products are classified as high in sugar content as well as low in fat content. The threshold of 3g fat per 100g as low is classified by the UK Food Standards Agency (2007) and allows the use of a 'low fat' nutrition claim. We observe that 18 from the 25 yogurts have a 'low fat' claim. From these 18 'low fat' yogurts, 10 are high in sugar. Only one yogurt is high in sugar and does not have a 'low fat' claim. As previously mentioned, the

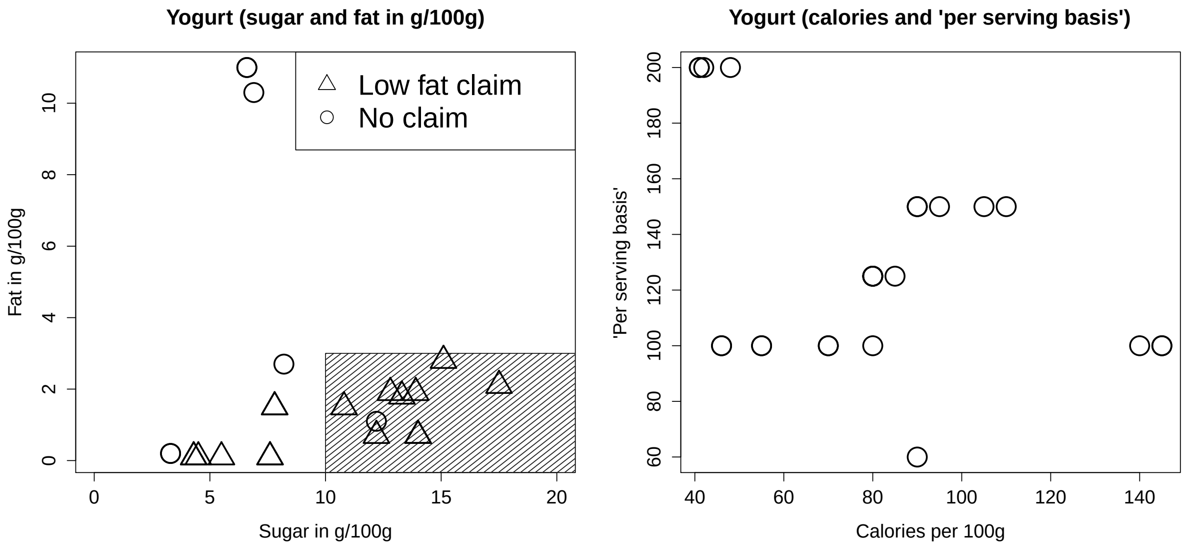

Figure 8: Scatter plots: Sugar and fat in g per 100g (left panel) and Calories per 100g and 'per serving basis' for yogurt (right panel)

GDA label displays the percentage of recommended daily amount based on the serving size. Due to the voluntary introduction of the GDA label, the retailer has no requirements regarding the 'per serving basis.' A lower 'per serving basis' leads to lower nutrition values in total and percentage on the label, which leads to a healthier perception (Mohr et al. 2012). Therefore, we treat the 'per serving basis' for each UPC as a measure of health framing by the retailer. The 'per serving basis' in the data set varies from 60g to 200g in the yogurt category (see Figure 8, right panel). This leads to the interpretation of smaller 'per serving basis' as higher levels of health framing. Accordingly, we multiply each serving size with -1 and add the maximum value of 200, resulting in a measure where higher values suggest higher degrees of health framing ($healthframing$). In Figure 8 (right panel), we present a scatterplot for the yogurt products according to their 'per serving basis' and the objective measure of healthiness as calories per 100g.

4.4 Study 3: Modeling

In our model, we assume that the latter explained variables affect sales volume. Therefore, $saleskg_{it}$ is our dependent variable for UPC i at week t. Our model contains three different types of explanatory variables. The variables with index it differ across UPC and week (e.g. $price_{it}$). The explanatory variables with index i differ across UPC but are time-invariant (e.g. $lowfat_i$) and the index t is for variables which differ across weeks but are invariant across the UPC (e.g. $label_t$). δ, γ and β are the effects of the corresponding explanatory variables on $saleskg_{it}$. Our model also holds an intercept α and the error term ε_{it} for UPC i and week t. The following equation represents the structure of our model:

$$\begin{aligned} saleskg_{it} = \alpha &+ \delta_1 label_t + \gamma_1 lowfat_i + \gamma_2 sugarhigh_i + \gamma_3 healthframing_i + \gamma_4 kcal_i + \\ &\beta_1 (label \cdot lowfat)_{it} + \beta_2 (label \cdot sugarhigh)_{it} + \\ &\beta_3 (label \cdot lowfat \cdot sugarhigh)_{it} + \beta_4 (label \cdot healthframing)_{it} + \\ &\beta_5 (label \cdot kcal)_{it} + \beta_6 price_{it} + \beta_7 saleskg_{i(t-1)} + \varepsilon_{it} \end{aligned} \tag{15}$$

Based on the longitudinal structure of our data, we estimate fixed-effects models to account for unobserved heterogeneity across individual units (UPC) and time periods (week). The main procedure of the fixed-effects model is to introduce dummy variables for each UPC and week to allow for effects of omitted variables, which avoids endogeneity bias in the parameter estimates (Rossi 2014). This model is called the two-way fixed-effects model (hereafter: 2W-FE). The 2W-FE model does not require the dummy variables for the individual and time effects to enter the set of explanatory variables (Hsiao 2003). With Y as the dependent variable and X as explanatory variables the data is transformed in the following manner:

$$\tilde{Y}_{it} = Y_{it} - \bar{Y}_{i\cdot} - \bar{Y}_{\cdot t} + \bar{\bar{Y}} \tag{16}$$

$$\tilde{X}_{it} = X_{it} - \bar{X}_{i\cdot} - \bar{X}_{\cdot t} + \bar{\bar{X}} \tag{17}$$

$\bar{Y}_{i\cdot}$ and $\bar{X}_{i\cdot}$ are the means for UPC i. $\bar{Y}_{\cdot t}$ and $\bar{X}_{\cdot t}$ are the means for week t. $\bar{\bar{Y}}$ and $\bar{\bar{X}}$ are the overall means. The 2W-FE model is a least square regression of $\tilde{Y}_{it}$ on $\tilde{X}_{it}$ (Baltagi 2008). The 2W-FE model "sweeps out" the intercept, the variables with no variation within each UPC and the variables with no variation within each week. Hereby, the parameter estimates for these explanatory variables are missing but their influence captured with the data transformation. From this, the parameter estimates (β) for the variables with index it are given by:

$$\tilde{\beta} = \left(\tilde{X}'\tilde{X}\right)^{-1} \tilde{X}\tilde{Y} \tag{18}$$

The fixed effects for UPC i (μ_i) and week t (θ_t) are obtain by:

$$\mu_i = \left(\bar{Y}_{i\cdot} - \bar{\bar{Y}}\right) - \tilde{\beta}(\bar{X}_{i\cdot} - \bar{\bar{X}}) \tag{19}$$

$$\theta_t = \left(\bar{Y}_{\cdot t} - \bar{\bar{Y}}\right) - \tilde{\beta}(\bar{X}_{\cdot t} - \bar{\bar{X}}) \tag{20}$$

From this, our equation of the 2W-FE model holds:

$$\begin{aligned} saleskg_{it} = {} & \tilde{\beta}_1(label \cdot lowfat)_{it} + \\ & \tilde{\beta}_2(label \cdot sugarhigh)_{it} + \\ & \tilde{\beta}_3(label \cdot lowfat \cdot sugarhigh)_{it} + \\ & \tilde{\beta}_4(label \cdot healthframing)_{it} + \\ & \tilde{\beta}_5(label \cdot kcal)_{it} + \\ & \tilde{\beta}_6 price_{it} + \tilde{\beta}_7 saleskg_{i(t-1)} + \mu_i + \theta_t + \tilde{\varepsilon}_{it} \end{aligned} \tag{21}$$

We estimate two models to test our hypotheses. Our first model (Model 1) includes only yogurt with 'low fat' nutrition claims ($lowfat = 1$, $N = 18$). This enables to assess the effect of the misleading nutrition claim in comparison to products without misleading nutrition claim. Therefore, we can exclude the explanatory variables $(label \cdot lowfat)_{it}$ and $(label \cdot lowfat \cdot sugarhigh)_{it}$ from equation (21). In this model, we test Hypothesis 1 with $\tilde{\beta}_2$. We test our second hypothesis with $\tilde{\beta}_4$. In our second model (Model 2), we use all yogurt products ($N = 25$) and exclude $(label \cdot sugarhigh)_{it}$ as explanatory variable to avoid multicollinearity with $(label \cdot lowfat \cdot sugarhigh)_{it}$, because these variables only differ for one yogurt (high in sugar without nutrition claim). In Model 2, we test our first hypothesis with $\tilde{\beta}_3$ and the second, repeatedly, with $\tilde{\beta}_4$.

We use a lagged dependent variable in our equations to account for time-dependence in our models ($saleskg_{i(t-1)}$). For fixed-effects models, this leads to correlation between the lagged dependent variable and the error term ($\tilde{\varepsilon}_{it}$) by construction. The resulting bias in parameter estimates is not negligible for panel data with few numbers of time periods but will diminish when T gets large (Baltagi 2008; Hsiao 2003). Nickell (1981) provides an approximate formula for the bias in $\tilde{\beta}_7$ in a fixed-effects model. With $|\tilde{\beta}_7| < 1$ in dynamic panel models and $T = 104$ in our data, this bias can not exceed $|.02|$. We can include $saleskg_{i(t-1)}$ for first time period because we have $saleskg$ for the week before $t = 1$. We want to emphasize that our number of periods ($T = 104$) is more than sufficient to account for this bias. Instrumental variable approaches which can be applied to account for such deviations can yield in larger bias if instruments are weak or invalid (Rossi 2014) especially when the number of individual units is small (Nelson and Startz 1990).

In dynamic panel models, the standard error of the parameter estimates can be biased by heteroskedasticity and serial autocorrelation (Stock and Watson 2008) while the parameter estimates will be consistent. In case of biased standard errors the significance of our parameter estimates will be incorrect and result in wrong hypothesis testing. We therefore apply a so-called sandwich estimator to obtain a heteroskedasticity-and-autocorrelation-consistent (HAC) covariance matrix of our parameter estimates. Arellano (1987) suggests a variance estimation that clusters the individual units in a fixed-effects model and computes the standard errors from a HAC covariance matrix. We follow Stock and Watson (2008) who recommend this type of procedure for general serial correlation.

4.5 Study 3: Results

We present our results in Figure 9 and Table 15. In Figure 9, we plot the fixed effects for each UPC i (μ_i) as density function (left panel) and week t (θ_t) as a line plot over the time-span of the study (right panel). The fixed-effects plot for both models are similar, with neglectable differences for μ_i, therefore, we only show the fixed effects for the model with all yogurt products ($N = 25$).

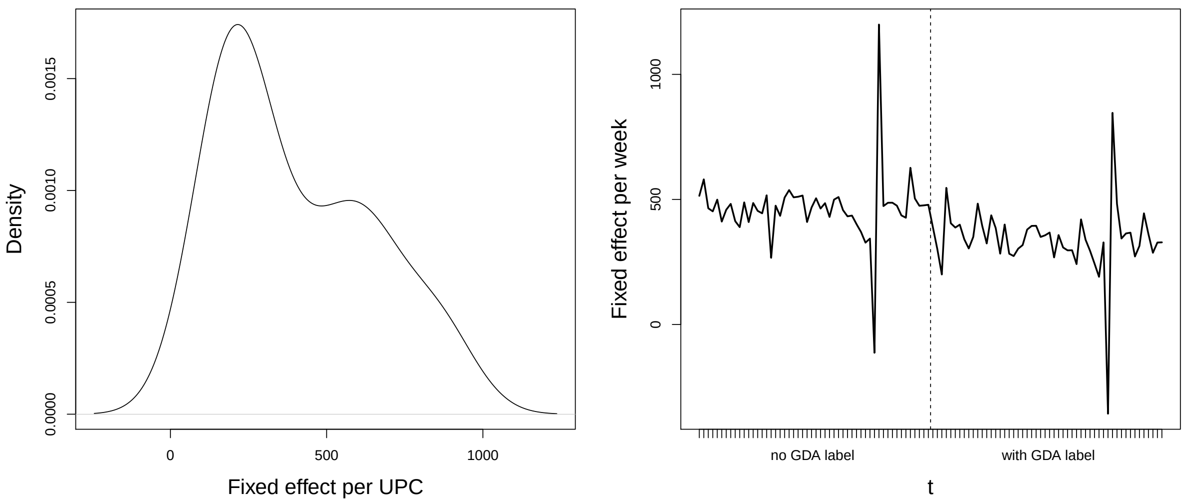

Figure 9: Plots of fixed effects for UPC (left panel) and week (right panel)

The fixed effects for the weeks capture common seasonal effects and trends. Especially the two Christmas periods with fewer purchase opportunities and the following period with increased demand for restocking are clearly visible. A slight downward trend is also apparent. These time-effects are captured in the fixed effects, so that the parameter estimates for hypothesis testing are unbiased regarding seasonality and trends. The fixed effects for the UPC show time-invariant heterogeneity between the yogurt products.

In Table 15, the parameter estimates are presented in bold with the robust t-values in parenthesis below. We use the HAC covariance matrix to calculate the standard errors which yield into the robust t-values. We want to emphasize that our number of periods

($T = 104$) is sufficient to account for the bias of lagged dependent variables in fixed-effects models. Our parameter estimate for the lagged dependent variable ($\tilde{\beta}_7$) is .79 in both models. With $T = 104$, this produces a bias in these estimates by -.018. The effect on the standard errors, other parameter estimates and their standard errors does not exceed this deviation for our magnitudes of $\tilde{\beta}_7$ (Kiviet 1995). Therefore, we neglect this deviation on the second decimal for our hypothesis testing. This avoids potential larger biases for alternative methods which aim to correct for this deviation but were mainly established for panels with large numbers of units and small numbers of time periods. The inclusion

Yogurt	Model 1 ($N = 18$)	Model 2 ($N = 25$)
$label \cdot lowfat$ ($\tilde{\beta}_1$)		**87.85***
		(2.41)
$label \cdot sugarhigh$ ($\tilde{\beta}_2$)	**-143.37*****	
	(-4.26)	
$label \cdot lowfat \cdot sugarhigh$ ($\tilde{\beta}_3$)		**-66.17****
		(-2.76)
$label \cdot healthframing$ ($\tilde{\beta}_4$)	**.66**$^+$	**.61**$^+$
	(1.71)	(1.77)
$label \cdot kcal$ ($\tilde{\beta}_5$)	**2.63*****	**.63***
	(3.24)	(2.00)
$price$ ($\tilde{\beta}_6$)	**-.83****	**-.68****
	(-2.62)	(-2.63)
$sales_{(t-1)}$ ($\tilde{\beta}_7$)	**.79*****	**.79*****
	(27.96)	(34.22)
$Adj.R^2$	.670	.651

Table 15: Parameter estimates and model fit for yogurt.
β in **bold** with robust t-value in parenthesis below
Robust p-values: <0.001=*** / <0.01=** / <0.05=* / <.10=$^+$

of the lagged dependent variable ($saleskg_{t-1}$) furthermore accounts for time-dependence. We also estimate our models without the lagged dependent variable. We do not obtain different results with respect to signs or significance of the parameter estimates. Changes in the magnitude of the parameter estimates from the models when including the lagged dependent variable are connected with biases arising because the time-dependence of the yogurt demand is omitted. From this, as well as substantially larger Adjusted R^2, we conclude that the dynamic models show substantially higher model fit and therefore should not be neglected for testing our hypothesis.

The parameter estimates of *price* are negative and significant in both models. This relationship is according to the "law of demand," thus, we control for this effect. The effect of the lagged dependent variable $saleskg_{t-1}$ is positive and significant in both models and captures the influence of demand in the previous period for the current period.

We test our first hypothesis with the parameter estimate $\tilde{\beta}_2$ in the model with only 'low fat' yogurts (Model 1). In this model, all yogurts with high sugar ($sugarhigh = 1$) have a 'low fat' nutrition claim, therefore $label \cdot sugarhigh$ captures the effect of the nutrition label introduction on sales of yogurt with low fat claims that contain high amounts of sugar. The parameter estimate is negative and significant ($\tilde{\beta}_2 = -143.37$, p-value=<.001). This confirms our first hypothesis in Model 1. The purchase volume for yogurt products with 'low fat' claims that contain high amounts of sugar decreases after nutrition label introduction. In Model 1, we test our second hypothesis with the parameter estimate of $healthframing$. The effect is positive and significant ($\tilde{\beta}_4 = 0.66$, p-value=<.10). This confirms our second hypothesis in Model 1. We observe that health framing with the 'per serving basis' on the nutrition label increases sales for 'low fat' yogurt.

In Model 2, we test our hypotheses using all yogurt products ($N = 25$). For Hypothesis 1, we use $\tilde{\beta}_3$, which captures the effect on sales volume of all 'low fat' yogurt with high sugar content after the label introduction. The parameter estimate is negative and significant ($\tilde{\beta}_3 = -66.17$, p-value=<.01). The effect of $healthframing$ is positive and significant ($\tilde{\beta}_4 = 0.61$, p-value=<.10) in Model 2. Therefore, we can repeatedly confirm both hypotheses in Model 2.

4.6 Study 3: Conclusions

In summary, our results show that nutrition labels can correct for misleading nutrition claims. The sales in kg decreased significantly for yogurt with 'low fat' claims but high sugar content after nutrition label introduction.

Our results contribute to the growing literature in food marketing by revealing that consumers show aversion towards food products that use misleading claims. As assumed by Chandon (2013), nutrition labels appear able to correct for health halos induced by misleading 'low fat' nutrition claims. While our results can certify an impact on sales by an uncovered scam further impact on attitudes towards the food manufacturer (Kozup et al. 2003) may lead to even more adverse consequences in a real-life setting. With increasing prevalence of nutrition labels on food products, marketers should stop using misleading nutrition claims to avoid potential losses. Federal agencies should regard nutrition labels as a mean to protect consumers from overeating induced by misleading claims. We expect the aversion effect to be higher, the easier consumers can uncover the scam (see e.g. Ford et al. 1996). This makes front-of-pack labeling schemes like the Traffic-Light-System appear more attractive compared to numerical nutrition labels like the Guideline-Daily-Amount label. In the case of the Traffic-Light-System, high nutrition content would be accentuated with a red colored background, so that consumers would just have to search for colors instead of processing numbers.

While our results show that nutrition labels are effective in the case of misleading claims, we observe that serving size manipulation can lead to increased sales, thus consumption. The higher the degree of health framing, which is chosen by the retailer, the higher the increase in sales after nutrition labeling. With our results, we support the findings of Mohr et al. (2012) and, furthermore, reveal that the magnitude of health framing is relevant. The effect in the yogurt category can be explained by the utilitarian nature of this food category, where consumers seek healthier options.

From our results, marketers appear able to increase sales by health framing. Although this strategy may currently appear attractive, consumers could possibly uncover this manipulation tactic and respond according to the aversion effect. Implications for public policy are that binding rules for the recommended 'per serving basis' for nutrition values can prevent overeating induced by health framing. This should result in standardization for this basis on nutrition labels to increase comparability of food products healthiness.

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5 General Conclusions

Our major findings from the three studies contribute to the literature of nutrition labeling in several ways.

We found that price has a large impact on sales, product choice and energy intake, while the effectiveness of nutrition labels is overestimated. With this result, we support the findings of a review by Chandon and Wansink (2012). Providing financial incentives for healthy purchase behavior or penalizing unhealthy purchases can therefore be considered helpful to promote healthier purchase behavior (Yang et al. 2012). Recent findings by Waterlander et al. (2013) have found that financial incentives in combination with nutrition information support healthier purchase behavior. Even though our results can support the findings that the purchased amount of nutrition content is influenced by price, research by Talukdar and Lindsey (2013) has found that these demand-response patterns are not necessarily symmetric for healthy and unhealthy food products. The authors found that for healthy food, demand sensitivity is greater for a price increase than for a price decrease. For unhealthy food, the opposite is revealed. Therefore, price should not be considered as a panacea for promoting healthier purchase behavior.

Nutrition labels do not appear effective for a substantial change of consumer behavior. A number of reasons have been identified in our three studies. As assumed by Jacoby et al. (1977), loyalty towards food products will lead to truncation of product package processing and, therefore, people might not recognize the label. Moreover, loyal customers may not be ready to bear the costs of changes in consumer behavior. In our disaggregated models in Study 1, we have identified very strong effects of loyalty on choice behavior, so that the nutrition label introduction was not effective.

Our results from Study 2 and 3 suggest that lower processing costs for the evaluation of the food products healthiness can lead to healthier purchase behavior. For example, in Study 2 we found a slight decrease in sugar volume for products where consumers only had to evaluate sugar content on the nutrition label. This finding is comparable to the results found by Russo et al. (1986). Only nutrition disclosure of sugar content in a simple per spoon unit led to healthier purchases in their experiments. In Study 3, we have also found that sugar content on the nutrition label with an easily recognizable great difference to other nutrients (low in fat but high in sugar) led to healthier purchase behavior. From this, we contend that lower processing costs can have a positive influence on the effectiveness of nutrition labels.

Furthermore, the results from Study 3 suggest that the response is highly influenced by the difference between expected and actual nutrition content. This finding is supported by the results in Study 2, where utilitarian food products, which are known to be unhealthy and consumed for indulgence (Belei et al. 2012) showed no tendencies towards healthier purchases after label introduction. These assumptions have repeatedly been stated by authors (Burton et al. 2009, 2014) and are confirmed by our results.

One major finding from Study 3 is that a voluntary nutrition label, which is mainly introduced as a marketing strategy, can easily be used as a tool to manipulate perceived healthiness. From this background, we emphasize the importance of public policy to increase efforts towards higher regulation standards for voluntary nutrition labels. Especially, future research must differ between nutrition labels as public policy instrument or as part of food marketing. The objectives and, accordingly, the design of the labels differ substantially between the two entities responsible for the introduction.

For those with an interest in promoting healthier purchase behavior, we recommend to emphasize their efforts toward increasing consumers' motivation to purchase healthier food products. Nutrition labels can play a supporting role by providing knowledge. The fact that consumers prefer taste over health should especially be considered. Vyth et al. (2010) recommend higher attention towards such "hedonistic aspects" to stimulate consumers to chose nutritionally favorable food products.

As stated by Lachat and Tseng (2013, p. 382) there is still "an urgent need to conduct real-life intervention studies with nutrition labels that measure the effect on hard outcomes." From our results, we furthermore recommend that these real-life intervention studies must account for heterogeneous response of consumers to nutrition labeling. Future research with experimental field studies will be able to manipulate more of the possible interventions which are assumed to promote healthier purchase behavior. In particular, the role of nutrition labeling in increasing knowledge should remain the focus of future research. The nutrition labels should be considered as a supporting tool for other interventions (i.e. price, product assortment) which have the potential to increase consumers' motivation to purchase healthier food products. Non-Use Benefits of nutrition label use (Caswell and Padberg 1992; Padberg 1977), which occurs if food manufacturer compete in these product attributes to serve consumers' demand for nutritionally optimized products has not been proved to support healthier product development and consumption so far (Moorman et al. 2012).

"You can give me the information but you can't make me stop eating the six cream cakes, can you? I have to make that decision for myself."
(Member of a group discussion from Barker et al. 2012)

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