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Effect of environmental food labeling on customers food purchase

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Abstract

The scientific community agrees that emission levels from food production and consumption have to decrease in order for the world to reach climate targets. Environmental food labeling is becoming a policy tool to motivate consumers in their behavior of food purchase and consumption. This study examined sales data over 42 days from a major student cafeteria at the University of Oslo before and after the introduction of a traffic-light labeling system. In addition, the traffic-light labeling system's effect on food purchase was compared to two other labeling systems, green-only and red-only labeling systems. The traffic-light labeling marked all dishes as red (highest environmental impact), yellow (medium environmental impact) or green (lowest environmental impact). The red-only labeling system denoted only the highest environmental impact dish with red. In the green-only label system only the dish with the lowest environmental impact was labeled green. We analyzed two food products, meat and vegetarian dishes, investigating the percentage change in sales for the entire 42 days treatment period and for the 20 first and 22 last days separately. Independent t-test and ordinary least squares (OLS) method were used for analyzing the effectiveness of the food labeling systems. For the first 20 days of the experiment, traffic-light labeling led to a significant reduction in sales share of meat dishes (highest environmental impact dishes). Both statistical tests supported these results. Furthermore, the OLS method found a significant effect on sales share of meat dishes under traffic-light labeling for the whole 42 days treatment period. Traffic-light, red-only and green-only labeling did not have a significant effect on sales share of the vegetarian dishes (lowest environmental impact dishes). Looking at the results, one may claim that costumers need to compare the environmental information of one product to other products in order for an eco-label to influence purchase behavior. At the current level of evidence, eco-labels cannot be recommended as a single strategy for changing consumer behavior. Since the present study showed a small, but a significant, reduction of one labeling system on the purchase of meat dishes, further research on the influence of eco-labels are needed before these labeling formats can be recommended as a public environmental intervention.

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Table of contents

1. Introduction

Over the last decades, the public has increasingly recognized the importance of environmental issues. The scientific community and the United Nations Intergovernmental Panel on Climate Change (IPCC) acknowledge that global warming is “extremely likely” (>95% chance) to be primarily caused by human activities (IPCC, 2013). Greenhouse gas (GHG) emission from human activities is the most significant driver of observed climate change since the mid-20th century (IPCC, 2014). The primary GHG caused by human activity are carbon dioxide (CO_2) and methane (CH_4). IPCC states that temperature rises of 4 degrees Celsius or more will lead to serious and irreversible effects for the wellbeing of our planet (IPCC, 2014). In order to combat climate change and its damaging impacts, cuts in global emissions are urgently required.

As a consequence of climate change consumers have become more aware that changes in their personal lives are needed to reduce global GHG emission levels. Research carried out by Pew Research Center found that 67 percent of the global public agrees that people will have to make major changes in their lives in order to decrease the effects of climate change (Pew Research Center, 2015). As a consequence of this development, a rising number of people are increasing their pro-environmental behavior. Hence, changing individuals’ lifestyle towards a more environmentally friendly behavior has become an ongoing and important challenge for policy makers. The need for policies that foster environmental conscious consumption has been recognized as a priority at European and international levels (World Business Council for Sustainable Development, 2008).

Food and beverage consumption and production is responsible for one third of European households’ total environmental impact and is one of the most important sectors from an environmental perspective (European Environmental Agency, 2015; Tukker, et al., 2006). GHG emissions vary markedly across production of different food products (Vermeulen, Campell & Ingram, 2012). A growing body of research suggests that in order to reduce GHG emission levels, one must not only address how food products are produced and distributed, but also consider what kind of food people consume. In particular, a number of studies have found the reduction in meat and dairy food production to be the most efficient contributor (Audsley et al., 2010; Garnett, 2010; Goodland, 1997; Goodland & Anhang, 2009; Stehfest, Bouwman, Vuuren, Elzen, Eickhout, & Kabat, 2009). Individual and societal behavioral changes are therefore essential to moderate the food sector's contribution to climate change. According to the head of IPCC, Rajendra Pachauri, reduced consumption of meat and dairy products is the most efficient way to tackle climate change (Pachauri, 2008). Consequently, one effective way to reduce global GHG levels is by altering diets (Deckers, 2010a; Deckers, 2010b; Freibauer, et al., 2011; Krystallis, Grunert, Barcellos, Perrea & Verbeke, 2012; Gerber et al., 2013). A study that analyzed the GHG impact of diets found that an average vegetarian diet produces 33 percent less GHG emission relative to a meat-eater diet (Scarborough, et al., 2014).

Changing dietary patterns may however be difficult because eating preferences seem deeply embedded in cultural, social and economic factors (Cinciripini, 1984; FAO, 2010). Thus, changing diets may best be achieved by implementing intervention programs at the first line of food choice, such as in supermarkets and cafeterias. The leading public intervention strategies to shift people's diets have been information and education campaigns and campaigns promoting vegetarianism, but these have had limited success (FAO, 2010; Ranganathan et al., 2016). Another public effort is to increase the use of environmental labels (eco-labels). At the turn of the millennium some European countries implemented environmental information labeling for foods sold in supermarkets (Spaargaren, Koppen, Janssen, Hendriksen & Kolfschoten, 2013). The reasoning behind introducing eco-labels is that costumers unknowingly perform actions that increase or decrease their environmental impact (Gatersleben, Steg, & Vlek, 2002). Eco-labels thus can enable consumers to make more informed purchasing decisions (Levy, Riss, Sonnenberg, Barraclough, & Thorndike, 2012; Johnston, Fanzo, & Cogill, 2014)

Compared to other sectors, global recognition of the livestock sector's significant contribution to climate change is considerably low (Bailey, Froggatt, & Wellesley, 2014). A report by the Norwegian National Institute for Consumer Research investigated Norwegian customers' attitude towards reducing the consumption of beef. The results indicated that Norwegian consumers have little knowledge about livestock's production environmental consequences (Bellika, 2013). In addition, only 11 percent of the subjects believed a reduction in livestock consumption to be an effective way to reduce global GHG levels (Bellika, 2013). Increasing public awareness and understanding of the livestock sector's contribution to climate change is a precondition for voluntary consumer action to reduce emissions from meat and dairy products. Consumers with a higher level of awareness are more likely to reduce their meat consumption for climate objectives (The Climate Group, 2006). Closing the awareness gap is therefore likely to be an important precondition for behavioral change (Bailey et al., 2014). Eco-labeling can consequently contribute to raise the awareness about livestock's impact on climate change and potentially reduce GHG emissions from food consumption.

However, increasing public awareness alone is not sufficient to encourage reduction in consumption of livestock products (Jeffery, Pirie, Rosenthal, Gerber, & Murray, 1982). The ability of eco-labels to significantly reduce consumption of food with high GHG emission ultimately depends on the consumers' response to labeling. Previous studies suggest that even when consumers report motivation for sustainable behavior, it does not necessarily translate into more sustainable food choices (Barcellos, Krystallis, Saab, Kügler, & Grunert, 2011; Bray, Johns, & Kilburn, 2011; Boer, Boersema, & Aiking, 2009; Chatzidakis, Hibbert, & Smith, 2007; Krystallis et al., 2009). This gap between consumers' environmental motivation and their actual behavior can be explained by a lack of accessible and relevant environmental information (Corral-Verdugo, 1997; Hainmueller & Hiscox, 2012). As existing eco-labels have only been moderately successful in shifting consumers to more sustainable diets, it is necessary to develop better labeling strategies that influence and engage costumers more actively than existing eco-labels. Based on theoretical and empirical insights we conducted a field experiment to test how traffic-light labels, green labels and red labels impacted food purchase patterns in a cafeteria. To identify the target group's perception of the applied eco-labels, a customer survey was handed out to cafeteria customers.

The remains of this paper are structured as follows. Section two gives a brief description of different food products' and diets' subsequent impact on the environment. The following section three provides an overview of underlying theoretical and empirical literature of importance for the current study. Insights from behavioral economics on eco-labeling influenced the choice of the study's design. The hypotheses are explained in the last part of section three. The methodological approach for the field experiment and customer survey is outlined in section four. Section five gives a description of the data sources and how the data were analyzed. The results of the field experiment and the customer survey are shown in section six. Section seven provides a broader discussion of the study results. Section eight includes strengths and limitations of the present research and section nine gives suggestions for future research. Finally, section ten highlights the concluding remarks.

2. Environmental impact of different food products and diets

A number of methods exist in order to evaluate the environmental impact of food product and dietary choices. For instance, one could consider food consumption's impact on climate change, land degradation, water depletion, biodiversity, and air pollution (FAO, 2006). For the sake of simplicity, this study only looked at food products' impact on climate change by solely referring to the products' associated GHG emission. GHG emission levels are measured in carbon dioxide equivalent (CO_2-eq).

> CO_2 equivalent emissions is the amount of CO_2 emission that would cause the same time-integrated radioactive forcing, over a given time horizon, as an emitted amount of a long-lived GHG or a mixture of GHGs. The equivalent CO_2 emission is obtained by multiplying the emission of a GHG by its global warming potential for the given time horizon (IPCC, 2007, p. 36).

A recent study by World Resources Institute (WRI), a US-based think tank, together with the French agricultural research institutions CIRAD and INRA, created data for comparing the CO_2-eq level of different food products per unit of protein (Ranganathan et al., 2016). The data presented by WRI were based on global means of current agricultural production, masking variations among locations, production systems and farming management practice. The difference in emissions associated with meat and vegetable products is the largest and most noticeable (Carlsson-Kanyama, 1998a). The emission gap is mainly caused by ineffective use of cereal crops for animal feed instead of using it for direct human consumption. In addition, ruminants' digestive system alone contributes with 2.5 percent to total global GHG emissions (Costales, Gerber, & Steinfeld, 2006). On a commodity basis beef, lamb and goat are by far the most emission-intensive livestock products. The estimates show that beef emits about 20 times more than plant-based foods such as beans, chickpeas and lentils, measured by CO_2-eq per ton protein consumed (Ranganathan et al., 2016). Poultry and pork both emit three times more than plant-based products, measured by CO_2-eq per ton protein consumed. Farmed fish, including all aquatic animal products, have a lower CO_2-eq score than pork, chicken and dairy products but higher emission levels than most plant-based products (Ranganathan et al., 2016; Winther, Hognes & Ellingsen, 2009)

Even though plant-based food products on average have a much lower CO_2-eq per gram of protein, results from a Swedish study by Dutilh and Kramer (2000) showed large variations in emissions within the plant product category. In many countries heated greenhouses are used for improving the quality and yield of plant-based foods. The use of greenhouses in production increases the overall energy requirements for production of vegetables. In addition, importing products from other regions can further raise the energy requirement by a factor of 10, depending on the means of transportation. Airplanes use the largest fraction of energy, while rail transport and ship transport have the smallest energy requirement. In addition, preservation techniques such as heat treatment, freezing, and drying add additional energy consumption in the production process (Dutilh & Kramer, 2000).

The large variation in the CO_2-eq levels of food products has also direct implications for different diets' environmental impact. A study conducted by the British Sustainable Development Commission (2009) and another study by Green et al. (2015) concluded that a global shift towards a more plant-based diet is necessary in order to overcome the worst climate change scenario. Going vegan is considered one of the most efficient ways to fight global warming since it reduces emissions from the livestock sector extensively (Sustainable Development Commission, 2009; Green, et al., 2015). However, a complete vegan diet may be unrealistic due to the current global dietary pattern, even if it meets the nutritional recommendations, (American Dietetic Association, 2009).

According to Green et al. (2015) a shift in consumption of animal products from those associated with higher to lower emissions, and reduction of other non-animal food products with high emission levels such as pasta, pizza and savory snacks, may alone lead to a 40 percent reduction in emissions from diets (Green, et al., 2015). WRI modeled how a reduction of animal protein in diets influenced the environmental impact of an average American diet (Ranganathan et al., 2016). The researchers found that a reduction in animal protein by one half, which cut people's meat/dairy/fish/egg consumption in half, reduced GHG emission per person by nearly 50 percent. Such a change reduced GHG emissions almost as much as replacing the average meat based diet with a vegetarian diet (Ranganathan et al., 2016). The environmental benefits of changes in diets can therefore also be achieved with relatively small changes in current diets (Tilman & Clark, 2014).

3. Theoretical framework and hypotheses

3.1. Environmental food labels' influence on purchase behavior

Eco-labels exist in various formats and some give more detailed information than others. The two most common types of indicators of environmental quality are 1) labels showing detailed information about environmental performance and 2) simple icons or graphics that indicate that a product complies with a specific set of criteria. Most nutrition label formats belong to the first type and provide consumers with detailed information about a food product's calories, serving size, values of several macronutrients (such as fat, carbohydrates and protein), vitamins, and minerals (Miller & Cassady, 2015). An example of a label belonging to the second category is traffic-light labeling. This type of label gives information regarding the level (i.e. high, medium or low) on products' environmental performance by using color-coding red (high), yellow (medium) and green (low).

How environmental attributes are communicated to customers seems to matter. Manrai et al. (1997) demonstrated that customers prefer more detailed or specific information to support green claims (Manrai, Manrai, Lascu, & Ryans, 1997). However, Jacoby et al. (1974) showed that even though consumers' satisfaction increases when they have more information, their ability to make a decision decreases (Jacoby, Speller, & Berning, 1974). The assumption that more information is not always better is the basis for the concept of information overload (Iyengar & Lepper, 2000). Information-processing theories suggest that there is a limit to how much information a consumer should get. This means that when customers are given too much information about products, they cannot process it in the time available (Iyengar & Lepper, 2000; Mitchell, Walsh, & Yamin, 2005). Understanding detailed labeling information requires high levels of literacy and numeracy (Rothman, et al., 2006). Since food products are fast moving goods, meaning that customers spend little time deciding what products to purchase, customers seem to prefer simpler information to more detailed information (BIO Intelligence Service, 2012;

Upham & Bleda, 2011; Wansink, Sonka, & Hasler, 2004). In Great Britain a detailed environmental label, reflecting the grams of CO_2 emissions from a product, was introduced to the marked in 2006 (Carbon Trust, 2016). Two studies found that customers did not understand if, for instance, a product with an emission level of 100 g $C0_2$ was a signal for a green product or not (Beattie, & Sale, 2010; Kortelainen, Raychaudhuri, & Roussillon, 2015). A study by BIO Intelligence Service examined customers' preference of various labels with and the results showed that customers needed a labeling system that lets them compare an item to other products in the same category in order to better understand the nature of a label (BIO Intelligence Service, 2012). Hence, if consumers have problems understanding detailed labels they do not obtain the knowledge required to make informed food selections, and their purchase will not be affected by the labeling (Spronk, Kullen, Burdon & O'Connor, 2014).

A simpler labeling scheme, as the traffic-light labeling, has shown to be more efficient than detailed labels to increase pro-environmental purchase. One can assume that consumers have knowledge about the traffic context, meaning that the color red signals unfavorable outcome, while the color green signals a favorable behavior (Bargh, 1992). This makes traffic-light labels easy to understand by consumers. Traffic-light labels also give a basis for comparison and may make it easier for consumers to identify the most and the least environmental friendly product. A study conducted by Borgmeier and Westenhöfer (2009) confirmed that such schemes empower consumers to correctly identity the healthiest food product (Borgmeier & Westenhoefer, 2009). Several studies on promoting healthy food consumption show that increasing consumers' nutrition knowledge through traffic-light labeling reduces their intake of unhealthy food products (Madhvapaty & DasGupta, 2015; Thorndike, Sonnenberg, Riis, Barraclough, & Levy, 2012; Variyam, Blaylock & Smallwood, 1995). There is however an underrepresentation of research on traffic-light labeling for promoting of pro-environmental behavior. In a field experiment Vanclay et al., (2011) studied the effect of environmental traffic-light labeling in an Australian grocery store. They found that the labeling had a small positive impact on sales of low CO_2 intensive products and a negative impact on sales of the high CO_2 intensive products. Their results may capture a real market behavior, but the duration of the study was too limited to draw decisive conclusions (Vanclay et al., 2011).

Even though traffic-light labeling has many advantages, the system may not always lead to the maximum benefits of a labeling system (e.g. get people to switch from red-labeled to green-labeled items). Marketing literature supports that introducing a scale may lead to the food decision being affected by the compromise effect (Carroll & Vallen, 2014). First demonstrated by Simonson (1989), the compromise effect arises when the popularity of an item increases as a result of it becoming the intermediate and compromise option in the choice set (Simonson, 1989; Simonson & Tversky, 1992). A food alternative will therefore tend to gain market share when it becomes the middle option in the choice set. Consider that A is the extreme option, with the lowest GHG level (green-labeled), while B is the intermediate (yellow-labeled), and C the other extreme option with the highest GHG level (red-labeled). If the compromise effect is present, the choice share of B will increase when C is present compared to a situation with only two options (A and B). The compromise effect has been demonstrated in studies for promoting healthy food consumption. A study by Sharpe et al. (2008) showed that the compromise effect changes consumers' choice of soft drink size. By adding a larger and a smaller drink size option to the choice, the middle size became more likely to be purchased (Sharpe, Staelin, & Huber, 2008). Another study conducted by Carroll and Vallen (2014) also demonstrated a significant difference in food choice of the target item based on whether it was the intermediate option of choice or not. They found that when customers were introduced to focus on calorie content of a product they avoided the largest and smallest caloric items and chose the items in between (Carroll & Vallen, 2014). The mentioned studies showed that food labels' information is not assessed isolated, and that the compromise effect has the potential to impact food choices. Related to the context of eco-labeling, introducing a traffic-light system may therefore lead to an increase in sales of the yellow-labeled options. If customers initially were planning to buy the red-labeled item, a traffic-light labeling system could lead to a positive environmental shift in sales. However, according to the compromise effect, a traffic-light labeling system may not facilitate an increase in green-labeled products.

A lab study by Temple et al. (2011) found that the use of another simple labeling system may be more suitable than traffic-light labeling (Temple et al., 2011). Results showed that the use of a green labeling system to denote the healthiest food and a red labeling system to denote unhealthy food options reduced purchase of red labeled food and increased the purchase of green labeled food (Temple et al., 2011). Another study found that the use of green labeling and red labeling were efficient to assist a shift towards healthier diets in a cafeteria setting (Thorndike et al., 2012). Being exposed to labeling extremes, red or green, may according to Temple et al. (2011) and Thordike et al. (2012) be more efficient to influence costumers' choice. Only labeling the red and green products may more directly help customers to identify which products to avoid and which products to purchase. The use of only green and red labeling tests the idea that customers may respond differently to different framed labels. The understanding of the framing effect can be applied to create more efficient labeling strategies.

3.2. Message framing's influence on purchase behavior

The previous section has pointed out that the degree to which environmental attributes are communicated determines how the information will affect purchase of eco-friendly products. Varied labeling approaches have been discussed. To sum up, existing studies have not given conclusive results as to how effective traffic-light labeling is to increase sales of environmental friendly products. Moreover, the effectiveness of traffic-light labels may be challenged by the compromise effect. Other labeling designs should therefore also be considered as labels that highlight the key information. Literature on information processing clearly indicates that the way information of environmental attributes is framed greatly influences consumers' decision. In the following section the effect of message framing will be reviewed with the help of Kahneman & Tversky's prospect theory. Then empirical research on the effect of positive and negative message framing related to pro-environmental behavior will be provided.

3.2.1. Positive and negative message framing

Kahneman and Tversky´s (1981) prospect theory is a commonly used behavior model to predict consumer behavior. An outcome of a decision can either be framed in terms of perceived positive outcome or perceived negative outcome from some particular neutral reference outcome, which is assigned a value of zero (Tversky & Kahneman, 1981). This relationship is presented in the proposed value-function. The theory suggests that decision-makers evaluate an outcome depending on gains and losses rather than considering the final value of a choice. How a factually equivalent message is framed may therefore determine the individual's attention, interpretation and behavior (Meyers-Levy & Maheswaran, 2004; Maheswaran & Meyers-Levy, 1990).

Individual evaluation of an outcome is reference dependent; what the individual planned to do before being exposed to a framed message, determines how she/he will react when exposed to a framed message (Jones & Richardson, 2007). The positioning of the reference point is therefore important because it affects whether the consumer evaluates an outcome as a gain or a loss (Jones & Richardson, 2007).

Although the subjective value of an outcome will be different among individuals, the theory proposes that people in general will respond to loss more extreme than to an equivalent gain. The fact that people are more sensitive to losses than gains is also referred to as loss aversion. This is because the value-function is steeper in the negative than the positive domain. For example, the displeasure of losing 100 $ is higher than the pleasure by winning 100 $. We can apply Kahneman and Tversky's logic to food labeling strategies. Let us assume we have three products that can be ranked according to their environmental impact: red-labeled (highest environmental impact), yellow-labeled (medium environmental impact) and green-labeled (lowest environmental impact) product. Labeling only the red product (red-only labeling system) will in this case represent a negative message frame, whereas labeling only the green product (green-only labeling system) will represent a positive message frame. We also assume that people have an individual reference point on an "environmental impact scale" that may vary depending on how concerned individuals are about environmental issues (Bamberg, 2003). Introducing a color labeling system will increase people's awareness of the environmental impact and whether their choice of food is above or below their reference point.

When individuals choose a product with lower environmental impact than their reference point, the choice will be viewed as a gain. On the other hand, choosing a product with a higher environmental impact than their reference point will be viewed as a loss. Consequently, if people are loss averse and have a reference point in the middle (neutral environmental impact) the red-only label system will have larger effect than a green-only label system.

However, it should be noted that the labeling system in itself could serve as a reference point. It may be that observing a green (or red) label can be interpreted as what other people do and therefore what is expected of the individual in a particular situation. In that case a green-only labeling system will actually have a larger effect than a red-only labeling system. This is because choosing other products than the red product in the red-only system will be viewed as a gain, whereas choosing other products in the green-only system will be viewed as a loss. Hence, whether the negative or positive message frame is most effective depends on whether people are loss averse or not and whether people's reference point is fixed or influenced on the labeling system.

3.2.2. Research on message framing

Application of prospect theory and the framing effects in the context of promoting green consumption is scarce. Existing research has come up with mixed results on if positive or negative message framing is more persuasive. A study conducted by White, MacDonnell and Dahl (2011) found that negative framing was more efficient than positive framing in order to influence customers' recycling intention. However, participants' degree of environmental concern seemed to have a moderating effect on the effectiveness of the framed messages (Bamberg, 2003). Individuals with high environmental concern were more influenced by the negative framed message than the positive framed message. Customers with low environmental concern did not respond differently when exposed to a negative or a positive framed message (White, MacDonnell & Dahl, 2011). A study by Maheswaran and Meyers-Levy also found that a negative framed message is more persuasive when consumers care about the particular issue (Maheswaran & Meyers-Levy, 1990). A different study by Changa, Zhangb and Xie (2015) found that a positive message increased purchase intention of environmental friendly products more than a negative message. However, the effect on message framing was lower for customers with low environmental concern (Changa, Zhangb, & Xie, 2015). To conclude, the mentioned studies illustrated that the effectiveness of different messages for pro-environmental behavior depends on the individuals' environmental concern.

Since the issue of food's environmental performance can be considered an unfamiliar issue to most consumers, they are likely to have difficulty projecting the consequences of purchasing the product due to lack of experience, which adds uncertainty to the decision process (Broemer, 2004). According to Broemer, message framing should be positive for unfamiliar products because it gives consumers knowledge about the benefits of using the product and makes the decision process easier (Broemer, 2004). Obermillera (1995) however, found that negative framed messages were more effective for promoting problems that consumers found unimportant or were unaware of. In addition, the study found that a positive framed message was more efficient when consumers had awareness and concern about a particular issue (Obermillera, 1995).

To sum up, existing research does not give a clear indication whether a positive or a negative labeling system is more effective for promoting environmentally friendly behavior. The context of the situation may impact how efficient positive and negative message frames are. Prospect theory provides a predictive of costumer behavior, but does not evaluate these context features on how efficient message frames are. For promotion of pro-environmental behavior the existing research shows that especially customers' concern and their awareness about the environmental problem, will impact how efficient the labeling systems are. Therefore research on message framing needs to consider the particular context to better understand how framing influences individuals' choices.

3.3. Hypotheses

Based on the theories and research mentioned in the previous sections, four hypotheses were formulated. This study aimed to gain insight into the likely effectiveness of different eco-labeling systems as a possible mean to shift purchase behavior to more environmentally friendly food products. In this study we presumed that people in general consider eco-friendly food as a positive product attribute.

Literature on information processing indicates that exposing consumers to neutral environmental information through traffic-light labeling will trigger a transition to the purchase of environmental friendly products. According to Borgmeier and Westenhoefer (2009), traffic-light labeling has been identified as a labeling system that empowers customers to identify the best and worst products in a category (Borgmeier & Westenhoefer, 2009). In addition, traffic-light labeling has shown to efficiently reduce the share of unhealthy food items and increase the share of healthy items purchased (Signal, Lanumata, Robinson, Tavila, Wilton, & Mhurchu, 2008; Kelly, et al., 2009; Thorndike et al., 2012). By labeling food with traffic-light according to the products environmental performance, consumers get informed about the actual environmental impact of their choices.

If the labeling is efficient, the purchase of the products with the highest environmental impact within its product category (i.e. red products) will be reduced. Furthermore, labeling can contribute to increase purchase of products with low environmental impact within its product category (i.e. green products). The first hypothesis of this study aimed to investigate whether traffic-light labeling was suitable to promote environmental friendly food choices in a cafeteria setting.

H1a: A traffic-light labeling system will lead to a higher purchase frequency of green food products compared to no labeling.

H1b: A traffic-light labeling system will lead to a lower purchase frequency of red food products compared to no labeling.

The literature on information processing may however be oversimplified and may ignore other important influences on customers' behavior (Blake, 1999). Marketing literature supports that the introduction of a traffic-light labeling system may lead to the food decision being affected by the compromise effect (Simonson, 1989). The compromise effect indicates that if a costumer initially planned to buy the red product, introducing a traffic-light label system will make him or her consider other alternatives. Traffic-light labeling may increase both the share of yellow-labeled products (a shift from red to yellow) and the share of green-labeled products (a shift from red to green). Since the labeling system intends to get people to choose less red products, both shifts represent positive environmental shifts. However, it is important to note that a traffic-light system may not necessarily maximize sales of green-labeled products. Therefore, other labeling systems, which more directly target an increase of green products, should be considered.

Turning to the prospect theory, the theory states that individuals' choice can be influenced not only by the content of the communicated information, but also by how the information is framed. Food labels can frame the information in terms of emphasizing the positive or negative effect of an outcome. In this paper the negative frame is defined as a labeling system that only labels the red products by highlighting negative product information (i.e. red-only labeling). A positive frame is a labeling system that only labels the green products with positive product information (i.e. green-only labeling). If one believes that the effect of positive or negative message framing to a larger degree than neutral information will change purchase behavior, green-only and red-only labeling systems will be more efficient than traffic-light labeling. Thus we predicted that:

H2: Green-only and red-only labeling systems will increase the purchase frequency of green dishes more than the traffic-light labeling system

First, with reference to the prospect theory, we assume that individuals tend to respond to loss more extremely than to an equivalent gain. Second, we assume that the eco-labeling system by itself affects individuals' reference point. In the green-only labeling system, the green product will serve as a reference point for customers. If customers choose a non-green product within the green-only labeling system, this will be perceived as a loss in eco-friendliness. Within the red-only labeling system the red product will serve as a reference point. Thus, choosing other products than the red product will be perceived as a gain in eco-friendliness. Since the prospect theory states that customers are loss averse, they will consequently react stronger to the green-only labeling system than the red-only labeling system. Based on stated assumptions and mentioned research, the next hypothesis is as follows:

H3: Green-only labeling will lead to higher purchase frequency of green food products than red-only labeling

4. Methods

In this section the methodological approach of the present research is explained. The study used a real life cafeteria setting and investigated the impact of introducing eco-food labeling systems on food product sales. The first part of this section describes the field experiment's research setting, the participants, the design of the cafeteria intervention and how data were collected. In addition to the field experiment, cafeteria customers were asked to answer a survey related to the cafeteria intervention. The survey contributed to better understand the effectiveness of the eco-labeling systems in this particular experiment setting. Customers were asked about their understanding and notion of the labels, their personal involvement and their awareness about the particular environmental issue addressed by the labels. The costumer survey was not considered to be a separate study but serves as a contribution to the discussion of the study findings. The last part of this section therefore describes the survey's design and how survey data were collected.

4.1. Field experiment

4.1.1. Research setting

The next largest cafeteria at the University of Oslo was chosen as the location for the study. According to the cafeteria operator, the number of daily customers on a regular day was 773. The student cafeteria was located at the Faculty of Social Sciences and is one out of 18 on-campus cafeterias. The cafeteria operator runs all the student cafeterias in Oslo. The cafeteria served three different warm dishes every day; one meat, one fish and one vegetarian dish. The study took place over a 5-month period from October 2015 to February 2016. The different labeling systems were, however, not introduced before November 2nd. Hence, the month of October 2015 served as an unaltered control period and November 2015 to February 2016 as the treatment period.

Only warm dishes sold in the cafeteria were part of the labeling intervention. The prices for the warm dishes were the same during the entire study period, and the customers could choose between a normal and a big sized warm dish portion. The price for a normal portion was 55 Norwegian Crowns (NOK) and 77 NOK for a big portion. The price did not depend on the kind of dish. Besides offering warm dishes the cafeteria sold wraps, sandwiches, snacks, hot and cold beverages and had a salad bar.

The dishes served each day varied. For instance, some days the vegetarian based dish was a vegetarian curry with rice and salad, and another day sweet potatoes with bread and salad were served. This variation in meals may have influenced consumers' purchase because some dishes were considered more popular than others. Each day was divided into three time periods: from 11:00 a.m. to 01:00 p.m., from 01:00 p.m. to 03:00 p.m. and from 03:00 p.m. to 06:00 p.m. The different labeling-systems randomly rotated between the different time periods as shown in Appendix 1. An even distribution amongst the three labeling designs was ensured. By rotating the labeling systems depending on time period and day, the experiment enabled randomization.

Since we in this study compared the effect of the different labeling systems to each other, we needed to make sure that the impact of "popular dishes" was not mistaken for the effect of the labeling intervention. Arranging that the three different labeling system was at place every day, reduced the likelihood that the effect of the labeling interventions was mistaken for the impact of "popular dishes", when we compared the labeling treatments effect to each other.

4.1.2. Participants

The cafeteria was frequented by Bachelor students, Master students and PhD students as well as employees and visitors associated to the Faculty of Social Sciences. The students, who constitute the majority of the customers, may have attended different study programs and may have been at different stages in their studies. Considering that most of the customers in the cafeteria were likely to be connected to the University of Oslo, one could expect most of them to have a higher level of education than the general population. Since environmental labels are not common for food products in Norway, it was assumed that participants did not have any prior experience with eco-labeling of food products.

4.1.3. Assignment of environmental impact labels

The cafeteria served nearly 100 different dishes during the 42 days of the cafeteria intervention, and calculating each dish' exact $C0_2$-eq level per protein would be complicated and very time consuming. In order to rank and categorize the dishes according to their environmental performance some simplification had to be made. The dishes were therefore labeled according to their associated food category's average $C0_2$-eq level during the lifecycle of the product. These assessments were based on a report by Ranganathan et al. (2016), which gave clear indications that meat based dishes in general have a higher environmental impact compared to fish and vegetarian based dishes. For estimations on the fish dishes' environmental impact we based the calculations on a report by Tukker et al. (2006). In addition, Will Nicholson, founder of a company who has created a software to calculate the environmental impact of different food types, was consulted in order to check the categorization. Based on these simplifications, all meat dishes were assigned a "High CO_2" label. Fish dishes were marked with a "Medium CO_2" label. Vegetarian dishes usually have the lowest environmental impact and were assigned a "Low CO_2" label. The designs of these three different labeling systems are shown in Table 1. The labels referred to CO_2 and not CO_2-eq, since simpler units are easier understood by customers than technical descriptions for customers (BIO Intelligence Service, 2012).

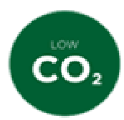
4.1.4. Cafeteria intervention

Control sales data were collected for 17 days prior to the introduction of the labeling systems in the cafeteria. We used a pre-intervention control period and no parallel control period so that the measured purchase behavior during the control period was completely unaffected by the labeling intervention. In other words this study design guaranteed that there were no carryover effects between the control period and the treatment period. A disadvantage of a pre-intervention control period is that one does not have control over other elements that are also changing at the same time as the intervention is implemented. The next section provides a description of the cafeteria intervention by giving a detailed description of the labeling systems' design and the poster's design.

4.1.4.1. Labeling systems design

The labeling strategy targeted the three warm dishes served in the cafeteria every day. The treatments consisted of three different labeling systems: traffic-light labeling, only-green labeling and only-red labeling. As discussed previously in this paper, the designs of the labels were based on prior research and theory on message framing. As shown in Table 1, the traffic-light labeling system labeled all three warm dishes. The lowest, medium and highest environmental impact dish were respectively labeled with a green "Low CO_2", a yellow "Medium CO_2" and a red "High CO_2" sign. The only-green labeling format exclusively marked the dish with the lowest environmental impact with the “Low CO_2” label. In contrast, the only-red labeling system exclusively marked the highest environmental impact dish with a “High CO_2” label. The labels used a simple color-coded scheme in combination with words inside the labels to visualize the environmental impact of the dish. A combination of visual and verbal cues in this way has been found to improve the efficacy eco-labels (Tang, Fryxell, & Chow, 2004). In this study the labels were placed on the menu board next to the dish description where consumers ordered their food. Menu labeling made sure that consumers were exposed to the active labeling formats during the time of decision making. Photos illustrating the placement of the labels on the menu board are provided in Appendix 2.

Table 1 - The three different labeling systems used in the experiment

Traffic-light labeling system	Only-green labeling system	Only-red labeling system
		

4.1.4.2. Poster design

During the eco-labeling intervention, posters were placed in the cafeteria, explaining the newly introduced labeling system and the climate impact of some vegetable, some meat and some fish products. By providing customers with relevant information, they were enabled to make more environmentally friendly food choices in the cafeteria. Based on Golan et al.’s (2000) recommendations, information on the posters was held clear, concise and informative to avoid the possibility of information overload (Golan, Kuchler, Mirchell, Greene, & Jessup, 2000). According to Weiss & Tschirhart (1994), the posters should correspond with prior knowledge of the target audience (Weiss & Tschirhart, 1994). We expected customers to have knowledge about carbon dioxide impact on climate change. However, we did not assume consumers as much knowledge about the environmental consequences of livestock production. The posters therefore did not explain carbon dioxide, but focused on meat products’ environmental impact. This was illustrated by comparing meat, fish and vegetarian dishes’ CO_2 emission level. As suggested by

Cote et al. (2005) one should include a specific action to a pro-environmental advertisement to encourage the wanted behavior (Coulter, Moore, & Cotte, 2005). In order to encourage the purchase of vegetarian dishes the sentences "Go for green, and brake for red!" and "Choosing to eat more fish, grains and vegetable rather than meat will help contribute to a better environment" were added to the posters. The design of the posters is shown in Appendix 3, and both an English and a Norwegian version was used.

The posters were present and had the same design during the entire treatment period. The posters were placed both at the entrance of the cafeteria and on a shelf next to the warm dishes. Besides, table cards with the same design as the posters were placed on the tables in the cafeteria. Customers were therefore exposed to the same poster throughout the time they spent in the cafeteria. The placement of the posters is shown in Appendix 2.

4.1.5. Data collection

Data collection for the field experiment was done by using cash register data to track all purchases of warm dishes made in the cafeteria during the control period and under the treatment period. Prior to collecting any data, the cafeteria's cash registers were programmed to capture the information needed to identity the warm meat, fish and vegetarian dishes. The cafeteria staff was informed about the purpose of the experiment and they were asked to not influence the customers' dish choice. The data registered the time of the sale and the type of the purchased dish. The data did not distinguish between portion sizes. Throughout the study, sales of warm dishes were registered daily for the 53 days.

4.2. Customer survey

4.2.1. Survey design

The first page of the survey had a short description of the topic of the research without revealing the actual purpose of the study. Participants were also given an explanation on how to complete the questionnaire. A picture of the poster used in the experiment and a photo of the menu-board were also included. On the next pages a set of questions followed. Customers were asked to fill out their age, gender and choice of dish. This was done to evaluate if the survey sample was roughly representative for the sample group in the field experiment. The next question asked participants whether they had noticed the labeling system. This question could be answered by "yes and "no". According to Weiss and Tschihart (1994) the eco-labels need to be understood by the target audience for them to have the wanted effect (Weiss & Tschirhart, 1994). The survey therefore included a question mapping to which degree the consumers found the labeling system to be easy/hard to understand. For the following questions a 7-point Likert Scale was used. The survey questions are shown in Appendix 4.

Previous research points to the fact that environmental information is more likely to be efficient if customers are highly concerned about environmental issues (Bamberg, 2003; Changa, Zhangb, & Xie, 2015; Ishaswini, & Datta, 2011; Obermillera, 1995) and are highly involved in environmental behavior (Maheswaran & Meyers-Levy, 1990; White, MacDonnell & Dahl, 2011). Since environmental concern is better measured indirectly by asking customers about which pro-environmental activities they perform (Bamberg, 2003; Celsi & Olson, 1988), we chose to include questions regarding environmental activities and not environmental concern. Five questions related to customers' environmental activates were included in the survey. The 7-point Likert scale was coded 1 for environmental activities (e.g. recycling, reduce aboard trips, buy eco-labeled products) that customers performed to a "very high extend" and 7 for activities that they performed to a "very low extent".

Customers' awareness and understanding of the livestock sector's contribution to climate change is likely to impact how efficient the eco-labels convince individuals to reduce their meat consumption (Bailey et al., 2014). To reveal respondents' problem awareness about livestock production impact on climate change, they were asked to rate the following statements: (1) I have knowledge about livestock's high environmental impact; (2) I believe the environmental consequences associated with the meat industry are important and that I should pay attention to them; (3) I am aware that meat dishes have higher carbon emission level than vegetable dishes; (4) I believe that carbon dioxide emission in the production process of food products to be important information when I choose a warm dish. These questions were answered on a 7-point scale, where 1 indicated that they "strongly agreed" and 7 that they "strongly disagreed". Generally speaking, customers are likely to prioritize factors with direct personal consequences as taste, price, and health when deciding which dish to purchase (Bailey, Fruggatt, & Wellesley, 2014). More indirect societal consequences such as animal welfare or climate impact are often evaluated as more secondary considerations (Bailey, Fruggatt, & Wellesley, 2014). To evaluate if this also was the case for this particular customer group, participants were asked to rank how important they believed the following food attributes to be; environmental friendliness, nutrition value, locally produced, taste, organic and ensure animal welfare. On the 7-point Likert scale 1 indicated "very important" and 7 stood for "absolutely unimportant".

4.2.2. Data collection

To collect data for the costumer survey, we approached costumers who had purchased a warm dish in the cafeteria. They were told that the labeling system was part of the cafeteria operator's sustainability strategy and asked to fill out some questions regarding the labels. The questionnaire was distributed as randomly as possible. The distribution was not totally randomized since it was dependent on customers' immediate accessibility to the researcher. Therefore the sample may not be validly representative for the cafeteria customers, but should give an indication of the general consensus amongst average customers. The collection of the surveys took place during the last week of the experiment to ensure that the customers' response to the cafeteria intervention was not too much influenced by the costumer survey. In order to increase the response rate, participants were given a free coffee for participating in the survey. In total 49 replies were used in the analysis.

5. Data analysis

5.1. Field experiment

The cafeteria intervention was carried out over a period of 42 days following a 17 days control period. The cafeteria was open 5 days a week and served warm dishes from 11:00 a.m. to 6:00 p.m. Fridays were not included in the sample due to short opening hours (until 3:00 p.m.). Moreover, the days the cafeteria sold out warm dishes before closing hour and/or only offered two dishes were also excluded. Furthermore, the days from December 14th to December 17th 2015 were taken out of the sample because the cafeteria replaced the warm dishes with traditional Norwegian Christmas meals. The number of observations during the control period was 51 (3 per day x 17 days) and 42 for each labeling treatment, giving a total of 126 for the treatment period (3 per day x 42 days). The total number of observations for the whole experiment period was 177. Since the research aimed to identify the labeling treatments' effect on relative changes in dish purchases, the sales data were converted from absolute numbers into share of total sales each day. If no sales took place, zero was added to the data set. The treatment period (42 days) was divided into fall 2015 (first 20 days) and winter 2016 (remaining 22 days).

Excel tools were used creating descriptive statistics as shown under results. SPSS (a software package for statistical analysis; version 22.0, IBM, Armonk; NY, USA) was used for statistical analysis of hypothesis testing. For statistical control two main statistical analysis techniques were applied: the independent-samples t-test (or independent t-test for short) and the estimation technique Ordinary Least Squares (OLS). We chose independent t-test because it easily compares the mean of two unrelated treatment groups, in this context meaning no labeling versus traffic-light labeling, traffic-light labeling versus green-only labeling, traffic-light labeling versus red-only labeling and green-only labeling versus red-only labeling. The OLS controlled for other variables not captured by the labeling systems in order to best isolate the true relationship between the sales share of meat and vegetarian dishes and the three labeling systems. Independent variables were categorical and were converted to binary dummy variables before serving as inputs for the estimated regression model using OLS. The results from the statistical tests were considered significant for $\alpha = 0.1$.

5.1.1. Assumptions for statistical tests

5.1.1.1. Assumptions for the independent t-test

For the independent t-test to provide valid results, the data sample has to pass some fundamental assumptions. The first assumption is that of independence of observations, which means that there should be no relationship between the observations in each group or between the groups (Field, 2009). In order to examine if this assumption held, we divided the treatment period into two periods (fall 2015 and winter 2016) with a Christmas break of 21 days in between. Around 700 customers visited the cafeteria every day, and the labeling-system treatment rotated during the day and from day to day. With this study design we hoped to avoid that the same costumer's response to the same labeling treatment was captured in the data several times. Therefore, we believed that after having been exposed to a labeling system costumers' purchase pattern captured the effect of the present labeling systems that day, and was not influenced by the labeling system they had been exposed to the day(s) before. This assumption should at least be true in the short run as it is less likely to observe the same customer several times within a short time period than over a long period of time. The effect of the different labeling systems on purchase was thus assumed to be independent from each other. We therefore believe the assumption of independence between the labeling groups to hold, at least in the short-term (fall 2015).

Another important assumption is that of homogeneity of variance, meaning that the different groups have similar or equal variance (Field, 2009). This assumption was tested by using the Levene's test of Equality of Variances. The results of the Levene's test are shown in the first column under Independent Sample Test in Appendix 6.1-6.4. If the p-value of the test is greater than 0.05, the groups have equal variance. For the groups tested the p-values were greater than 0.05. Thereby the assumption of homogeneity of variance was met.

Another essential requirement is that the dependent variable for each category of the independent variable is approximately normally distributed (Field, 2009). Normal distribution of the data was tested with the Shapiro-Wilk test of normality. If the p-value of the test is greater than 0.05, the variable's distribution is close to normal distribution. Shapiro-Wilk test statistic was higher than

0.05 for all tested variables, confirming that we had approximately normal distribution. In order to verify the results of the Shapiro-Wilk test, we performed a graphical interpretation of the dependent variables histograms. Full output of the Test of Normality and the histograms are presented in Appendix 5.1.-5.2.The histograms showed approximately bell shaped curves. However, none of the histograms had clear symmetrical distribution. Since we were working with real sales data, and since the independent t-test is relatively robust to violations of normal distribution, we did not consider this to be a further problem.

5.1.1.2. Assumptions for OLS regression

There are several critical assumptions relating to the classical linear regression model that are important to evaluate to be sure OLS estimation technique was applicable for our data (Hayashi, 2000). The first assumption for regression models requires that the average value of the constant term is zero ($E(\varepsilon_i) = 0$). This assumption is only violated if the regression does not have a constant term. As shown in the table "Coefficients" for each regression in Appendix 7, all the regressions have constant terms. This assumption was therefore considered to be met.

A second assumption is that the error terms have constant variance, meaning that the variance of the error terms are constant and finite over all values of x_i ($Var(\varepsilon_i) = \sigma^2$) (Hayashi, 2000). The assumption is also referred to as the assumption of homoscedasticity. The assumption was tested with the help of scatter plots as shown in Appendix 7 under "Assumptions test: Scatterplot". We plotted the standardized residuals (ZRSID) versus the standardized predicted values (ZPDEC). All the scatter plots showed residuals that were approximately randomly and evenly spread throughout the scatter plot. This pattern indicated that the assumption of homoscedasticity was met.

A third assumption, the non-autocorrelated assumption, requires that the error terms are uncorrelated and statistically independent of each other ($Cov(\varepsilon_i, \varepsilon_j) = 0$) (Hayashi, 2000). Since our data were collected for the same variables over time, we suspected autocorrelation between the error terms. This assumption was tested with the help of Durbin-Watson statistic. The corresponding Durbin-Watson statistic for each regression is shown in Table 2 to Table 5 in section 6.1.2. under "Hypotheses testing". A Durbin-Watson value far below or above 2 is a sign of autocorrelations between the error terms. The regressions showed Durbin-Watson statistic around 1.7 and around 2.7. The Durbin-Watson statistics are given under “Assumptions test: Model Summary” for each regression in Appendix 7. According to Field (2009), Durbin-Watson statistics below 1 and higher than 3, are of serious concern (Field, 2009). The values for some of the regressions were close to 3, indicating possible positive autocorrelation between the error terms (Williams, 2015). If the assumption of non-autocorrelation is violated, it may lead to bias estimators from the OLS regressions. Especially if we have positive autocorrelation (Durbin-Watson statistic > 2), one runs the risk of estimated parameters appear more precise than they really are (Williams, 2015). One might therefore wrongly confirm a relationship between the dependent and independent variable. To correct for autocorrelation between the error terms, one can cluster the standard errors for daily sales. Since SPSS does not provide a simple command for clustering standard errors, we were not able to perform clustering.

A fourth assumption is the assumption of normality ($\varepsilon_{i,} \sim N(0,\sigma^2)$), meaning that the error terms are normally distributed (Hayashi, 2000). To detect non-normal errors we performed a graphical interpretation normal probability plot of residuals. The normal probability plots are shown for each regression in Appendix 7 under “Assumptions test: P-P plot”. For all regressions the plot of residuals was approximately linear, which supported the condition that the error terms were normally distributed. We also tested for outliers, which is an observation that appears to deviate from the observations of the sample. To test for outliers we looked at the Cock’s distance given in the “Assumptions test: Residual statistics”, Appendix 7. For cases where the value was smaller than 1, outliers did not have an individual influence on the regression’s ability to predict outcomes (Myers, 2000). None of the regressions showed values larger than 1. Outliers therefore did not seem to be a problem in the regressions.

A fifth assumption is that there should be no relationship between the error and the corresponding x values ($Cov(\varepsilon_{i,} x_{i,}) = 0$) (Hayashi, 2000). If this assumption is broken most of the variation in the dependent variable can be attributed to the error term and not to the variation in the chosen independent variables. Adjusted R square shows the explanatory power of the regression models and was therefore used to evaluate this assumption. As shown in Table 2, 3 and 4 and Appendix 7 under “Assumptions test: Model Summary”, adjusted R square was relatively low for all regressions, indicating that little of the variation in the sales share could be explained by the independent variables. Since this might indicate that there is a relationship between the error terms and the independent variables the estimated coefficients for the regression models could be biased (Hayashi, 2000).

A last assumption is that none of the regressions should have perfect multicollinearity, implicating that the independent variables should not be too highly correlated (Hayashi, 2000). This assumption was tested by using one of the "Assumptions test: Collinearity diagnostics" shown separately for each regression in Appendix 7. According to Myers (2000) the variance inflation factor (VIF) should be lower than 10 and tolerance should be higher than 0.1 (Myers, 2000). The VIF values were below 10 and tolerance statistics were above 0.1 for all regressions. We therefore concluded that there was no collinearity within our data.

5.2. Costumer survey

The main aim of analyzing customers' answers in the questionnaire was to make interference about the population's major objectives and characteristics. To make sense of the respondents' answers, the frequency data on gender, age, dish purchase, and if customers had understood and seen the labeling systems, were accompanied by percentages. For the questions regarding costumers' environmental involvement, problem awareness and ranking of the different food attributes importance, means and standard deviation was computed. Table 4 shows a simple summary of the participants' characteristics. Cronback's alpha was calculated and provided to measure the internal consistency of the questions. A Cronback alpha above 0.7 is deemed valid (Saunders, Thornhill, & Lewis, 2009).

Based roughly on Zaichkowsky's (1985) classification we batched the participant as a group into one of three different involvement classifications (Zaichkowsky, 1985). According to how the participants answered the questions related to environmental involvement and problem awareness, the participant group was categorized as a group with low, medium or high involvement or problem awareness. The cataloging was as following: If the sample group average scored between 1 and ≤ 2 on the Likert scale, the sample group was categorized as highly involved/high problem awareness. For scores > 2 and ≤ 5 respondents were classified as medium involved/medium problem awareness. If they scored > 5 the participants were classified as low involved/low problem awareness.

6. Results

This section is divided into three parts. First, the descriptive results from the field experiment are presented. This part presents the data and summarizes the sales data for the different labeling systems and the different time periods. The next part describes the conclusions about the hypotheses. Finally, the survey results are demonstrated.

6.1. Field experiment results

6.1.1. Descriptive results

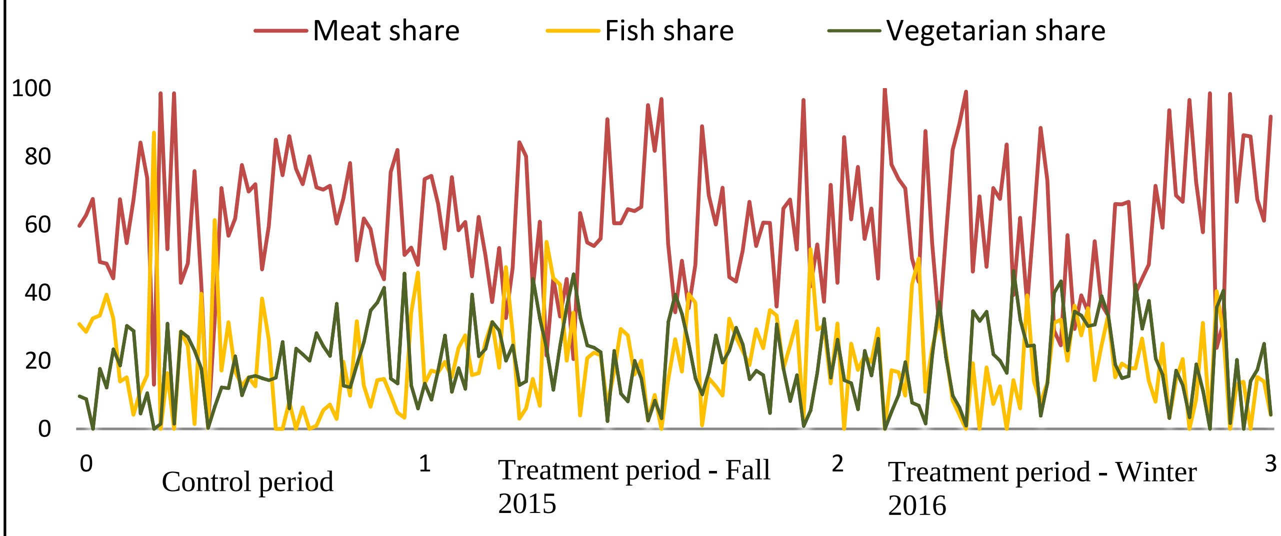
Total sales of warm dishes per day were the same during the control period and treatment period. Average sales of warm dishes were 183 per day throughout the control period and 184 per day for the treatment period. One might suspect that other food products served in the cafeteria, such as salads, wraps, and sandwiches to some extent could be seen as substitutes for the warm dishes. Since total sales did not change, consumers did most likely not replace warm dishes with cold food products as a consequence of the labeling intervention.

Table 2 presents average sales share of vegetarian and meat dishes in the cafeteria before and after the introduction of the labeling systems. As shown in Table 2 and Figure 1, average sales of meat dishes were higher than vegetarian dishes throughout the whole experiment period. This indicated that meat dishes on average were more popular than vegetarian dishes. The standard deviations in Table 2 show a relatively large spread in the sales data, indicating that the sales of each dish highly fluctuated. The same tendency is also illustrated in Figure 1. The figure shows how sales of meat, fish and vegetarian dishes varied over time from the control period to the treatment period. When comparing the sales shares with the overview of what kind of dishes that were served each day, one can see that some dishes were much more popular than others. For instance, the meat dish "stuffed pork roasted with apples, potatoes, gratin, and vegetables" made up a proportion of 100 percent of purchase on February 18th between 11:00 a.m. and 1:00 p.m. In contrast, none of the meat dish called "croque-monsieur" was sold on November 10th between 03:00 p.m. and 06:00 p.m. The variation in sales was also large for vegetarian dishes. For example, the dish "hummus served with champignons, grilled tomato, and bread" accounted for 87 percent of sales on November 10th between 03:00 p.m. and 06:00 p.m. On the other hand, sales data revealed that no sales were made of the dish called "falafel served with couscous, salad, and bread" on February 16th between 03:00 p.m. and 06:00 p.m.

Table 2 – Percent of total meat and vegetarian dishes sales (mean ± standard deviation)

	Control	Treatment groups		
	No labeling	Green-only labeling	Red-only labeling	Traffic-light labeling
Whole period				
Meat share	62.83±16.59	62.22±20.69	61.42±18.82	57.14±18.82
Vegetarian share	18.47±10.73	19.66±12.53	19.36±10.91	21.25±11.81
Fall 2015				
Meat share	62.83±16.59	59.20±20.24	60.04±19.02	54.03±12.64
Vegetarian share	18.47±10.73	19.96±11.10	18.68±10.73	21.96±10.45
Winter 2016				
Meat share	62.83±16.59	64.97±21.89	62.69±19.00	59.96±23.00
Vegetarian share	18.47±10.73	19.40±13.97	19.98±11.28	20.60±13.13

Figure 1 - Percentage of total sales: 0-1 control period, 1-3 whole treamtent period



6.1.2. Hypotheses testing

6.1.2.1. Hypothesis 1 – Traffic-light labeling versus no labeling

H1a: A traffic-light labeling system will lead to a higher purchase frequency of green products compared to no labeling.

H1b: A traffic-light labeling system will lead to a lower purchase frequency of red dishes compared to no labeling.

H1a states that traffic-light labeling versus no labeling increases sales shares of green-labeled vegetarian dishes. H1b states that traffic-light labeling versus no labeling reduces sales shares of red-labeled meat dishes. For the hypothesis testing we assumed that the difference in sales between the control and treatment period was explained by the introduction of the traffic-light labeling system itself and not by the month of the year or other events. In the statistical tests we had two dependent variables; sales share of vegetarian dishes and sales share of meat dishes.

Figure 2 shows the average sales of vegetarian and meat dishes for the control period (no labeling) and the traffic-light treatment (traffic-light labeling) for the whole treatment period. Figure 3 and 4 show the mean sales of dishes sold under the control period and for the traffic-light labeling treatment, for fall 2015 and winter 2016 respectively. As shown in all three figures, the sales share of vegetarian dishes was 18 percent and the sales share of meat dishes was 63 percent during the control period.

As illustrated in the figures, sales of vegetarian dishes increased for all treatment periods under traffic-light labeling. At the same time, average sales of meat dishes were reduced for all treatment periods under traffic-light labeling. However, when analyzing the average sales share with the help of the independent t-test, it was discovered that the difference in average sales was only significant for meat dishes during the experiment period of fall 2015 ($p = 0.04$). The full independent t-tests are provided in Appendix 6.1-6.2.

Figure 2 - Traffic-light versus no labeling, whole treatment period

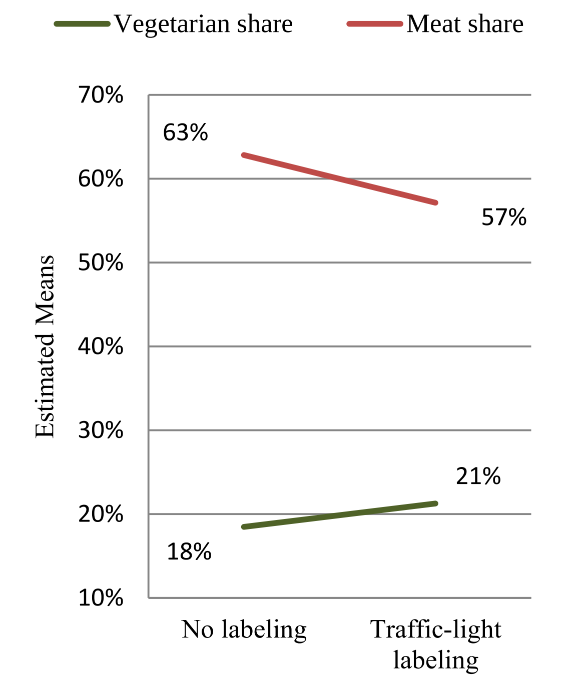


Figure 3 - Traffic-light versus no labeling, fall 2015

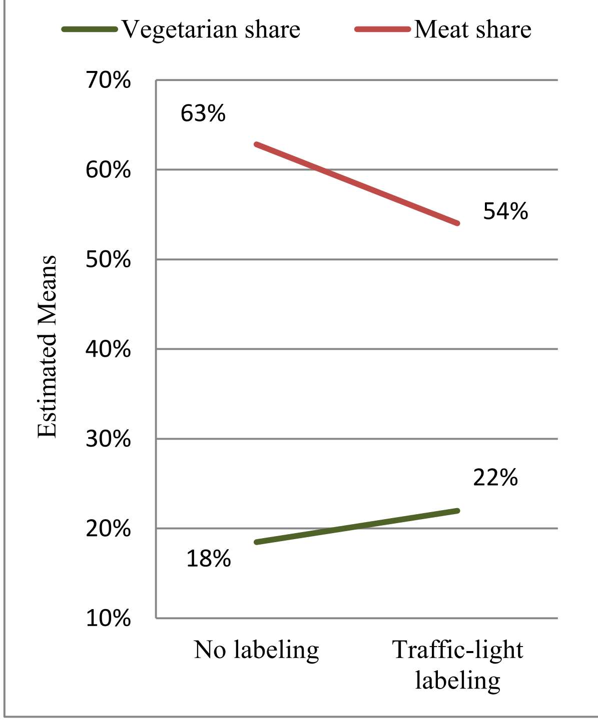
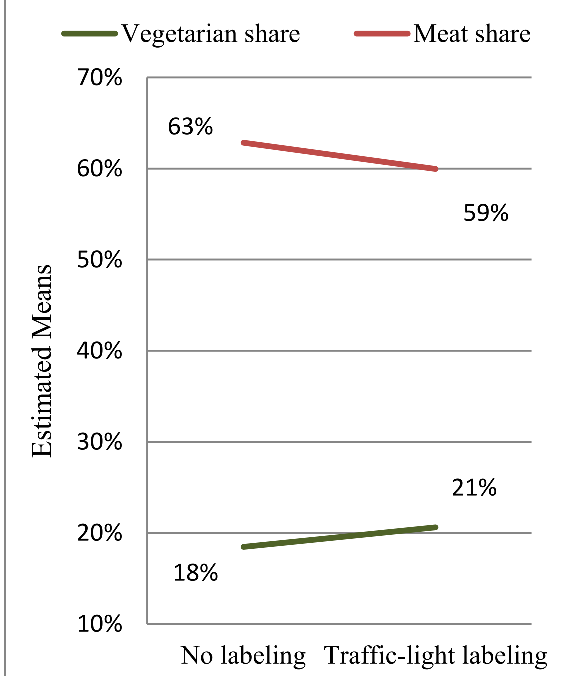


Figure 4 - Effect of traffic-light versus no labeling, winter 2016



For testing the hypotheses H1a and H1b we also used ordinary least squares (OLS). The dependent variable in the regressions related to H1a was vegetarian sales share, and the dependent variable for the regressions related to H1b was meat sales share. These regressions were applied in order to test if the difference in sales share could be explained by the traffic-light labeling when controlling for the effect of weekday and time of the day. The categorical variables included in this analysis were therefore Traffic-light labeling (0 = no labeling, 1 = traffic-light labeling), Monday (0 = not Monday, 1= Monday), Tuesday (0 = not Tuesday, 1 = Tuesday), Wednesday (0 = not Wednesday, 1 = Wednesday), Thursday (0 = not Thursday, 1 = Thursday), 11:00-1:00 (0 = not 11:00-1:00, 1 = 11:00-1:00), 1:00-3:00 (0 = not 1:00-3:00, 1 = 1:00-3:00) and 3:00-6:00 (0 = not 3:00-6:00, 1 = 3:00-6:00). For each category one variable was excluded from the regression to avoid perfect multicollinearity in the regression model. The coefficient for the independent variable traffic-light labeling was interpreted as the estimated difference in sales share between no labeling (0) and traffic-light labeling (1).

Table 3 summarizes the regression results for testing hypothesis H1a. For the regression on the whole treatment period the traffic-light labeling had no significant effect on vegetarian dishes' sales share ($p = 0.19$). Moreover, for the treatment periods fall 2015 and winter 2016 traffic-light labeling was not a significantly predictor of sales of vegetarian dishes either ($p = 0.28$ and $p = 0.53$ respectively). The output of the regressions can be seen in Appendix 7.1-7.2.

Table 3 - Regression results for vegetarian dishes sales share

	Whole treatment period	Fall 2015 treatment period	Winter 2016 treatment period
Constant	0.195(0.021)***	0.18(0.025)***	0.189(0.026)***
Traffic-light labeling	0.025(0.019)	0.029(0.026)	0.017(0.027)
Weekday dummies	YES	YES	YES
Time of the day dummies	YES	YES	YES
Durbin-Watson statistics	1.365	1.457	1.401
Adjusted R-square	0.045	-0.005	0.083
No of observations	177	111	117

Standard errors are reported in parentheses
*, **, *** indicate significance at the 90%, 95% and 99 % level respectively

The results of the regressions related to testing hypothesis H1b are shown in Table 4. The regression results show that traffic-light labeling had a significant influence on the sales share of meat dishes for the whole treatment period ($p = 0.06$). All else equal, the coefficient of traffic-light labeling estimated that sales share of meat dishes were 5.9 percent lower under traffic-light labeling than under no labeling. In the regression analysis for fall 2015 the coefficient for traffic-light labeling was as well significant ($p = 0.10$). Other things being equal, traffic-light labeling reduced sales share of meat dishes by 6.9 percent compared to no labeling. Traffic-light labeling did not have a significant effect on sales of meat dishes during the treatment period winter 2016 ($p = 0.38$).

Table 4 - Regression results for meat dishes sales share			
	Whole treatment period	Fall 2015 treatment period	Winter 2016 treatment period
Constant	0.654(0.034)***	0.647(0.033)***	0.658(0.042)***
Traffic-light	-0.059(0.031)*	-0.069(0.042)*	-0.038(0.044)
Weekday dummies	YES	YES	YES
Time of the day dummies	YES	YES	YES
Durbin-Watson statistics	1.717	1.764	1.856
Adjusted R-square	0.061	0.015	0.066
No of observations	177	111	117

Standard errors are reported in parentheses
*, **, *** indicate significance at the 90%, 95%and 99 % level respectively

Summarizing the results of independent t-test and OLS for testing hypothesis H1a, we can conclude that traffic-light labeling compared to no labeling had no effect on sales share of vegetarian dishes. We therefore reject H1a. Concerning hypothesis H1b, we came to the conclusion that traffic-light labeling compared to no labeling seemed to have a significant effect on sales share of meat dishes for the whole treatment period based on OLS ($p = 0.04$), whereas a significant effect was demonstrated for the treatment period fall 2015 in both independent t-test and OLS ($p < 0.1$). Since OLS controls for other factors than the traffic-light labeling that may cause variability in the dependent variable, we consided the results from OLS to be more precise than the results achieved by the independent t-test. The different outcome of these two statistical tests calls for caution in generalizing these results.

6.1.2.2. Hypothesis 2 – Green-only and red-only labeling versus traffic-light labeling

H2: Green-only and red-only labeling systems will increase the purchase frequency of green dishes more than the traffic-light labeling system

The second hypothesis states that the green-only and red-only labeling systems increase sales share of vegetarian dishes more than traffic-light labeling. Figure 5, 6 and 7 show the average sales share of vegetarian dishes for the whole experiment period, fall 2015 and winter 2016 respectively. For all experiment periods, sales share of vegetarian dishes were largest under traffic-light labeling compared to green-only and red-only labeling. The figures indicate that the results of the experiment were opposite of what was predicted by hypothesis H2. Test results from the independent t-test showed that none of the sales share of vegetarian dishes were significantly different under traffic-light, green-only and red-only labeling system ($p > 0.1$ for all tests). All independent t-tests related to testing hypothesis H2 can be found in Appendix 6.3.

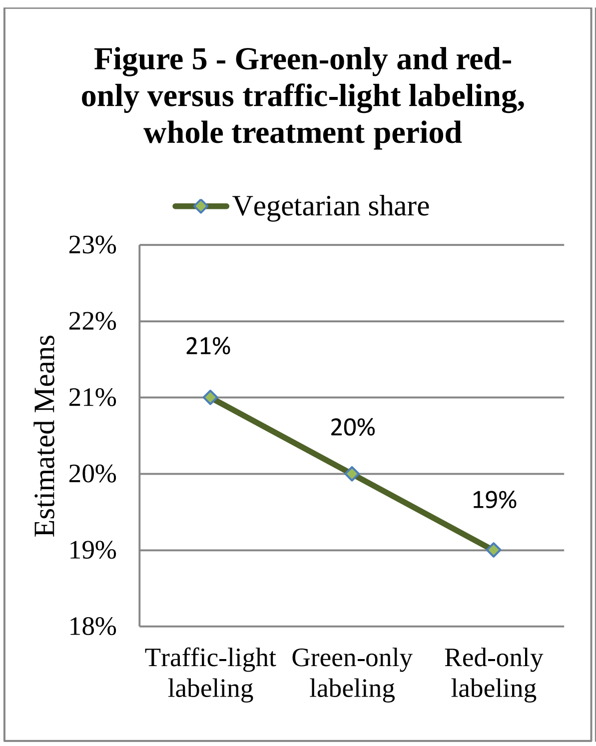


Figure 5 - Green-only and red-only versus traffic-light labeling, whole treatment period

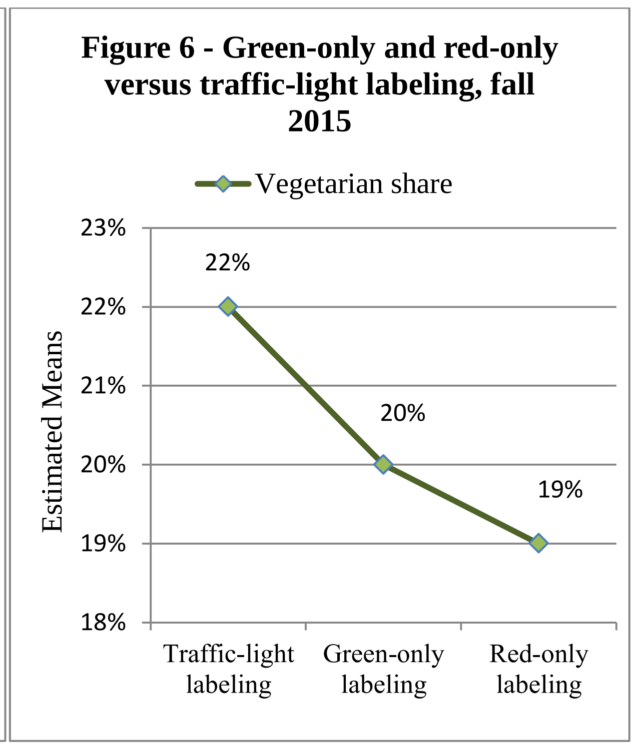
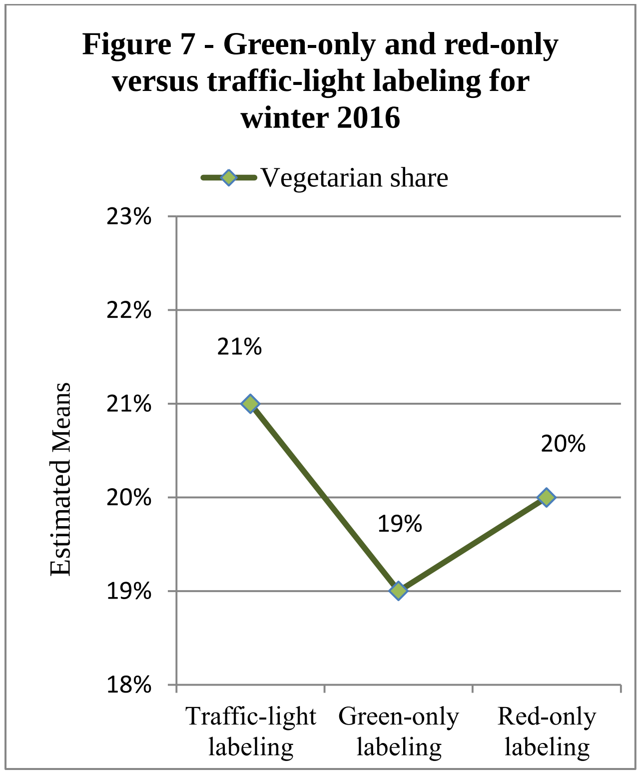


Figure 6 - Green-only and red-only versus traffic-light labeling, fall 2015



OLS was also used to test hypothesis H2. The dependent variable related to this analysis was sales share of vegetarian dishes. The regression used the independent variables, green-only labeling (1 = green-only, 0 = not green-only), red-only labeling (1 = red-only, 0 = not-red-only), and one dummy variable for each day. Traffic-light labeling served as the reference group. The day dummies controlled for the effect of "popular dishes" in order to ensure that the effect of "popular dishes" was not mixed together with the effect of the different labeling systems. We did not control for the effect of weekday since it correlated with the effect of the specific day. Including both day dummies and weekday dummies could distort the estimates of the coefficients and thereby the statistical power of the regression.

The regression outputs related to hypothesis H2 are displayed in Table 5. As one can see none of the labeling systems' coefficients were significant for any of the treatment periods. Appendix 7.3 presents the regression output. The regressions did not show any effect on sales share of vegetarian dishes under green-only and red-only labeling compared to traffic-light labeling ($p > 0.1$). To sum up, both the independent t-test and OLS did not find any support for H2. As a result, we rejected H2.

Table 5 - Regression results for vegetarian dishes sales share			
	Whole treatment period	Fall 2015 treatment period	Winter 2016 treatment period
Constant	0.152(0.053)**	0.198(0.054)***	0.146(0.057)**
Green-only labeling	-0.012(0.020)	-0.015(0.028)	-0.10 (0.028)
Red-only labeling	-0.019(0.020)	-0.034(0.028)	-0.004(0.028)
Specific day dummies	YES	YES	YES
Durbin-Watson statistics	2.768	2.710	2.776
Adjusted R-square	0.385	0.313	0.372
No of observations	177	111	117

Standard errors are reported in parentheses
*, **, *** indicate significance at the 90%, 95%and 99 % level respectively

6.1.2.3. Hypothesis 3 – Green-only versus red-only labeling

H3: Green-only labeling will lead to higher purchase frequency of green food products than red-only labeling

This hypothesis states that green-only labeling can lead to higher sales share of vegetarian dishes than the red-only labeling. As shown in Figure 5, 6 and 7 the average difference in sales share under green-only labeling was 1 percent higher than for red-only labeling for the whole treatment period and for the fall 2015 treatment period, while it was 1 percent lower for the treatment period winter 2016. Results from the independent t-test illustrate that sales share of vegetarian dishes did not show a statistically different between green-only and red-only labeling for any of the treatment periods ($p > 0.1$). The independent t-test results are put on view in Appendix 6.4.

The OLS for testing hypothesis H3 used vegetarian sales share as the dependent variable. The independent variables were green-only labeling and the specific day dummies. Hence, red-only labeling served as the reference group. The regression results are described in Table 6. The results of the OLS analysis confirmed that green-only labeling did not have any predictive power for sales share of vegetarian dishes. The green-only labeling coefficient was not significant for the whole treatment period ($p = 0.862$). Additionally, there was no significant effect found for green-only labeling during the treatment period fall 2015 (p = 0.917) and winter 2016 (p= 0.745). Based on the results from the independent t-test and OLS, we did not find any support for hypothesis H3, and consequently the hypothesis was rejected. The regressions output is presented in Appendix 7.4.

Table 6 - Regression results for vegetarian dishes sales share

	Whole treatment period	Fall 2015 treatment period	Winter 2016 treatment period
Constant	0.142(0.052)**	0.181(0.052)***	0.144(0.055)**
Green-only labeling	-0.003(0.017)	0.003(0.024)	-0.008(0.024)
Specific day dummies	YES	YES	YES
Durbin-Watson statistics	2.758	2.672	2.777
Adjusted R-square	0.386	0.309	0.380
No of observations	177	111	117

Standard errors are reported in parentheses
*, **, *** indicate significance at the 90%, 95%and 99 % level respectively

6.2. Customer survey descriptive results

6.2.1. Respondents' profile

In total 49 responses were collected and used in the subsequent analysis. This was above the minimum requirement for sample size (Cohen, 1992). Table 7 gives an overview of the sample statistics from the costumer survey. According to the survey 59 percent of the participants were male. The majority (81 percent) of the participants were between the age of 18 and 30. Looking at what dish the participants had purchased we noticed that 60, 11 and 30 percent of the participants had bought the meat, fish and vegetarian dish respectively. The composition of dishes was thus different compared to average sales during the field experiment period. The answers from the survey may therefore not have been completely representative for the customers of the cafeteria in general, but gave nevertheless useful insights into what might have shaped consumers' food choices.

6.2.2. Response to eco-labels, personal involvement and problem awareness

With respect to the participants' self-reported awareness of the labels and posters, results shown in Table 7 demonstrate that 90 percent of the consumers had noticed the food labeling system and the posters placed in the cafeteria. Moreover, the data revealed that as many as 80 percent reported that the labels and posters were easy to understand. The results gave evidence that the labeling system and cafeteria intervention had attracted the attention of the customers.

Concerning the questions regarding consumer involvement in environmental activities, one found that most participants performed at least one or more of the described pro-environmental activities. The results indicated that recycling was the most common activity (Mean = 2.41). Based on the survey, the least common environmental activity was reducing trips abroad (Mean = 4.39). The Cronbach´s alpha was 0.75, which was considered satisfactory. According to Zaichkowsky's categorization the sample group was categorized as medium involved in environmental issues since the mean ranked between 2.41 and 4.39.

For the questions regarding the participants' knowledge about livestock's environmental impact, participants mostly agreed with the statement that livestock has a high environmental impact (Mean = 2.71), and that meat dishes have a higher environmental impact than vegetarian dishes (Mean = 2.71). Fewer respondents believed that environmental impact information on dishes was important information (Mean = 3.40). The four questions showed a mean rank between 2.71 and 3.20, and according to Zaichkowsky's categorization, respondents were evaluated as having medium problem awareness (Cronach's alpha = 0.67).

Results shown in Table 7 indicate that the most important factors influencing respondents' choice of dish in the cafeteria was taste (Mean = 1.69). As many as 96 percent of respondents answered that taste was extremely (= 1) or very important (= 2) for the purchase of products in the cafeteria. Taste was followed by nutrition value and price (both Mean = 2.10). The participants considered environmental friendliness as the least important food attribute (Mean = 5.18). Only 20 percent believed the environmental friendliness of food to be extremely (= 1) or very important (= 2).

Table 7 - Sample statistics on participant characteristics

	Percent (Frequency)
Gender (male)	59 (29)
Age	
18-20	4 (2)
21-25	57(28)
26-30	20(10)
30+	18(9)
Dish purchased	
Meat dish	59(27)
Fish dish	11(5)
Vegetarian dish	30(14)
Had seen the labels and posters	90(44)
Had understood the labels and posters	90(44)
	Mean (SD)
Consumers' involvement in environmental issues [1]	
(1) Recycle	2,41 (1,67)
(2) Buy second hand/used products	4,20 (1,90)
(3) Buy eco-labeled products	3,73 (1,64)
(4) Reduce trips abroad	4,39 (1,95)
(5) Reduce car use	2,92 (1,89)
Awareness about meat products' environmental impact [1]	
(1) Knowledge about livestock's high environmental impact	2,71(1,65)
(2) Knowledge about livestock's high environmental impact and paid attention to it when choosing a dish	3,20 (1,56)
(3) Knowledge about meat dishes' higher environmental impact compared to vegetarian dishes	2,71(1,65)
(4) Regard environnemental information as important information about the dish	3,20(1,67)
Food attributes that are important to consumers [1]	
(1) Environmental friendliness	5,18(1,58)
(2) Nutrition value	2,10(1,07)
(3) Locally produced	3,73(1,54)
(4) Taste	1,41(0,57)
(5) Price	2,10(1,08)
(6) Organic	3,78(1,77)
(7) Animal welfare	2,90(1,98)

n = 49

[1] Based on 7-point Likert scale

Calculations done in Microsoft Excel 2010

7. Discussion

Overall, we expected the labels to effectively increase purchase of vegetarian dishes and reduce purchase of meat dishes. By labeling the dishes according to their environmental impact and hang up posters promoting more environmentally friendly food consumption, we believed that the consumers' awareness about the issue would increase and that this again would lead to more environmentally friendly food purchase. We hypothesized that a green-only labeling system would be the most efficient one to increase sales of vegetarian dishes, followed by red-only and traffic-light labeling.

However, as previously described, the study results did not confirm all the hypotheses. Our findings allow us to discuss several important issues. First of all, traffic-light labeling in the student cafeteria statistically significantly reduced sales of red-labeled meat dishes during the first 20 days of the labeling intervention. This effect was both confirmed in the independent t-test as well as by the OLS regression. Furthermore the OLS found a significant effect of traffic-light labeling versus no labeling for the whole treatment period. When looking at the results as a whole, one may suspect that the overall reduction was due to the decline during the first 20 days of the labeling intervention. None of the other labeling systems had a statistically significant effect on sales. These findings support the concept that providing customers with objective information on a scale leads to more eco-friendly food consumption. It may look like that costumers need a basis for comparison for the labeling system to change purchase behavior. These conclusions are also consistent with research on health labeling that found traffic-light labeling to reduce purchase of unhealthy food (Madhvapaty & DasGupta, 2015; Thorndike, Sonnenberg, Riis, Barraclough, & Levy, 2012; Variyam, Blaylock & Smallwood, 1995).

Under traffic-light labeling, sales of meat dishes decreased by 9 percent for the first 20 days of the experiment and by 5 percent when looking at the whole experiment period. At the same time sales of vegetarian dishes increased by 4 percent for the first 20 days of the traffic-light labeling intervention and by 3 percent during the whole experiment period. Since the reduction in meat sales was larger than the increase in vegetarian dishes, the traffic-light labeling also led to an increase in sales of the yellow-labeled fish dishes. This could support the presence of the compromise effect, meaning that the traffic-light labeling led to an increase of the middle option.

The effect of the compromise effect may however have been limited. Since customers probably considered meat, fish and vegetarian dishes as very different types of dishes, the costumers' choice of a fish dish under traffic-light labeling did not necessarily represent a compromise, but could have rather been influenced by other factors such as taste and nutritional value. The costumer survey used in this study also confirmed that nutritional value and taste were important influencers of food choice.

When evaluating the results from the traffic-light labeling system in more detail, one noticed that the effect of traffic-light labeling was strongest during the first 20 days of the treatment period. A cafeteria setting can be considered as relatively low involvement choice setting where customers do not actively process available information about the food alternatives. Conversely, the unexpected display of eco-labels on the menu board may have led to more effortful attention of customers. Customers seamed to react favorable to the labeling when first introduced, but their eco-friendly behavior declined over time and almost returned to control period behavior after some weeks. These results could be interpreted as an evidence for customers developing "fatigue" for the labels over time, and that the eco-labels' effect is only relatively short lived. These findings may reflect real costumer behavior. In order to draw more decisive conclusions, further studies on traffic-light labeling need to be done.

Based on the prospect theory we predicted that framing the environmental labels in terms of emphasizing the positive (green-only) or negative (red-only) outcomes would be more efficient than objective traffic-light labels to change costumers' behavior. However, results from the analysis did not find that framing effect had a statistically significant influence on behavioral response compared to traffic-light labeling. The prospect theory suggests that people want to avoid loss. Green-only labeling implicates that the choice of other products than the green-labeled ones are considered an environmental loss. On the other hand red-only labeling indicates that other products than the red-labeled ones are environmental gains. Since costumers are considered to be loss averse, the green-only labeling system should have the strongest effect on individuals' pro-environmental behavior. When analyzing the effect of green-only versus red-only labeling we found that green-only increased sales of vegetarian dishes more than red-only labeling, but this difference was not statistically significant. This means that the study results showed little support for predictions derived from prospect theory.

There may have been many different reasons for why green-only and red-only labeling systems did not facilitate a larger change in consumers' purchase behavior and why the effect of the traffic-light labeling only was significant in the short-term. The fact that the experiment was performed in a cafeteria setting may have influenced the results. Having cafeteria lunch is regarded as a highly routinized practice where customers eat lunch at a fixed and limited time slot. Trying to change customers' choice in such a setting may therefore be difficult. The effect of the labeling systems may therefore be weaker in a cafeteria setting than in restaurants or grocery stores, where customers in general spend more time. Therefore, the outcome of this study may be representative for a cafeteria setting and not for other arenas for food shopping.

Our findings may also be dependent on the characteristics of the participant group and research context. The customer survey showed that customers had noticed and understood the labeling systems. This indicated that the formatting of the labeling was not a problem. The customer survey showed that as many as 51 percent strongly/very/moderately agreed that they should take the environmental impact of different food products into account when choosing a dish. In addition, 50 percent of the sample group strongly/very/moderately agreed that the environmental impact of the meat industry is an environmental problem. The warm dish customers in general seemed to be moderately involved in environmental activities and had moderate awareness about livestock's impact on climate change. The self-reported environmental consciousness was, however, not reflected to the same extent in the sales pattern. The majority of participants were students, who were likely to have a lower consume than the general public concerning material items and travelling. They may therefore have believed that their living situation as students compensated for the climate impact of their food consumption. The price for all dishes was the same even though meat dishes are more costly in production. Thus, one can assume that the customers felt that they had made a better deal when purchasing a meat dish rather than a vegetarian dish. Another possible explanation for the low influence of the interventions, except for traffic-light labeling, was that the majority of customers may have had an even lower motivation to eat environmental friendly under the control period than presumed. Behavior theories argue that customers who are already motivated to change their behavior may react stronger to an intervention (The Climate Group, 2006). Therefore the labeling systems may only have changed behavior of people who prior to the cafeteria intervention were environmentally motivated, reflected by a relatively small change in overall sales in this study.

Several researchers have claimed that food labeling as a public policy still should be considered effective, even when they lead to small changes in food consumption. Estimates by Ranganathan, et al. (2016), show that a reduction in animal protein of one half cuts an individual's dietary GHG emission level almost as much as if the same individual had chosen a vegetarian diet (Ranganathan et al., 2016). This manifests that even small changes in dietary patterns can have large long-term effect on reducing the environmental impact of food consumption. Finally, considering the relative contribution of eco-food labeling to climate change policies, we think it is important not only to assess its effects in terms of direct behavioral changes, but also take the indirect effects of increased dialogue and knowledge into account. If labels contribute to discussions about livestock's and diets' environmental impact, it might have positive long-term effects on diets choice.

8. Strengths and limitation

A notable strength of the present study is that we used a real life setting of food consumption rather than relying on self-reported purchase behavior. Previous studies suggest that people in general exaggerate their sustainable behavior when asked in questionnaires (Bray, Johns, & Kilburn, 2011; Boer, Boersema, & Aiking, 2009; Chatzidakis, Hibbert, & Smith, 2007). By using the cafeteria operator’s overall design for the labels and posters (colors, typography and logos) one camouflaged the experiment. Making customers believe that the labels’ and posters’ originated from the cafeteria’s operator may have increased the labels and posters credibility (Weiss & Tschirhart, 1994). Since customers were not aware that they were part of an experiment, they were less liable to modify their behavior (Benz, 2008; Monahan & Fisher, 2010). The cafeteria employees collected sales data electronically through the cash register. Furthermore, the participants were not aware that their food purchase was being analyzed. Therefore, there was a low possibility for researcher or participant bias. Neither the researcher, nor the participants were able to manipulate the collected data. This supports that the observed effect was strongly related to the introduction of the labeling systems as opposed to a confounding bias. Conversely, using real sales data in a normal cafeteria setting may have limited our ability to control for external factors or events that might have occurred during the cafeteria intervention compared to a laboratory experiment.

The study design can be considered both a strength and weakness of the study. By dividing the treatment period into two periods (fall 2015 and winter 2016) with a Christmas break in between it was more likely that the observations were independent. This can be considered at a strength of the study. One could recognize that the Christmas break reset the costumers’ purchase behavior to almost pre-intervention level. Thereby the spillover effect of the labeling system seemed to be low, meaning that the label had to be in place in order to have an effect on customers’ purchase. Additionally, a low spillover effect means that being exposed to for instance a green-only label one day should not influence costumers’ reaction to the traffic-light label at a different time. On the other hand, the fact that data were collected over time in this study opened for the possibility that the observations were generated from the same subjects several times. The risk of including the same individuals several times increased with the length of the study. The majority of the cafeteria visitors were students, likely to frequent the cafeteria several times during the study.

The two last mentioned facts may lead to a partly dependence of observations, being a weakness of the study design.

An important limitation of this study is the relatively low number of observations (n = 177). Due to large day-to-day variations in sales shares, it was difficult to detect a trend caused by the labeling systems. If we had had more observations it would have been more likely to find statistically significant results, and to reduce the margin of error (Cohen, 1992). Large data sets may be necessary to spot the small effects of the labeling systems on eco-friendly food purchase.

The participants in the experiment were mainly students from the Faculty of Social Sciences at the University of Oslo. Since this target group had similar characteristics, the population could be considered internally relatively homogenous. This represents a strength, because a relatively homogenous group eliminates some of the variance that might be caused by between-subject variation. However, this group may not be considered representative for the general public. The cafeteria customers are higher educated and younger compared to the general public and may have more environmental knowledge than is typical (TNS Gallup, 2016). Another study analyzing customers' understanding of nutrition labels, did however not find education level to affect how well participants understood the food labels (Borgmeier, 2009). Even though education level may not impact how customers use and understand eco-labels, it is still possible that the effects found in this study are only representative for this particular group. This may therefore be considered a limitation of the study.

Given the quest for internal validity, we designed a fictional labeling system for this study. Using a fictional label instead of a well-known eco-label reduces the risk of consumers having prior knowledge, connection to or association to the label. However, using fictional labels may also have limitations. A fictional label may have lower credibility compared to a well-known eco-label. Since the study was primarily concerned with customers' response to labeling, controlling for the effect of consumer information was considered most important, and the reliability of labeling was a secondary concern. Another limitation of the labeling systems was that we only evaluated simple labeling systems. Using other methods, which use numerical codes instead of categorical symbols, may have been more effective. Along with this, the labels referred to CO_2

emissions and no other greenhouse gas emissions or other sustainability criteria. Well-informed consumers may therefore believe that the labeling systems were too simple. This may have caused some loss in credibility, limiting the effect of the labeling systems.

An additional limitation is that the labeling system only included warm dishes. One may argue that the labeling system would have had a greater and more detectable effect on sales if all food products in the cafeteria had been labeled. This would have allowed customers to more directly compare the environmental information provided by the labels across products.

It is also important to note that the study's hypotheses were based on findings from studies conducted in other countries than Norway. It may be that this Norwegian sub-population differs substantially from the characteristics of the population examined in other international studies. Taking into account that other European countries may have higher public awareness about food's environmental impact and may already have introduced eco-food labeling, the studies from these countries may not necessarily be transferable to a Norwegian setting.

9. Future Research

Few studies have been done upon testing the use of environmental labels to promote more environmental friendly food consumption in a real life setting. Our results point to the need for further examination of the impact of eco-labels on food purchase.

New studies are needed to draw more decisive conclusions to whether traffic-light, green or red eco-labels are efficient strategies. First of all, this study was based on data collected over 42 days (177 observations), which is a relatively short time frame. Further research is necessary to address the long-term effects of the eco-labels. Furthermore, new studies could investigate the effectiveness of eco-labels on other food products than warm dishes, or in a setting where all products are part of a labeling system.

New research could also focus on a wider and more representative sample group. How university students react to eco-labels may not be representative for other populations, especially in terms of income and education. The survey showed that customers ranked environmentally friendliness as the least important product attribute. Taste and nutritional value remained more salient factors in the purchasing decision than did the potentially environmentally adverse effect of consuming a particular dish. Understanding the extent to which selected subgroups of consumers are willing to trade off taste and nutritional value for improved environmental friendly food consumption could also be an area for future research.

Another issue to address in this context could be on how different individuals react towards the eco-labels. A study by Grunert, Hieke and Wills (2014) investigated the relationship between costumers' use of food eco-labels and demographic characteristics. They found a significantly stronger effect on self-reported use of eco-labels for women, younger people and people with a higher level of education (Grunerta, Hieke, & Wills, 2014). In the present study we only had knowledge about some general characteristics of the costumers as a group. A field study where sales data are linked to demographic identifiers of costumers could explain possible individual differences on the effect of the labeling systems.

A study by Thorndike et al. (2012) found that traffic-light labeling was efficient in combination with choice architecture intervention to promote healthier food choices in a cafeteria. As part of choice architecture the healthiest food items were made easier available and more visible (Thorndike et al., 2012). Dayan and Bar-Hillel (2011) found that items on top and bottom on a menu board to be more popular than the middle options (Dayan & Bar-Hillel, 2011). In our research setting the menu placement was the same every day and placed the meat dish on top, the fish dish in the middle and the vegetarian dish at the bottom on the menu board. Studies done within choice architecture concerning the visibility of a product could inspire further research on positioning of eco-labeled food.

Emphasizing the link between environmental and health benefits of shifting diets towards more plant-based alternatives, is something that could be of interest for a study. The customer survey in this study indicated that nutritional value was one of the most salient factors in the purchase decision, ranked much higher than environmental impact of food products. Presumed that eco-labeling should be implemented as a public strategy to improve sustainability of food consumption it could be interesting to conduct studies in which health and environmental labeling are combined in one single label.

10. Conclusion

The current study aimed to test if eco-labels on food products could increase the purchase of environmental friendly products. Previous research has found mixed results concerning the effect of the kind of labeling formats and the impact of eco-labeling on purchase behavior. This study provided evidence that the introduction of traffic-light labeling significantly reduced the purchase of meat dishes (least environmental friendly alternative), with the exception of the last 22 days of the treatment period. None of the three labeling systems investigated had any significant effect on sales of vegetarian dishes (most environmental friendly alternative). Furthermore, the present research showed that green-only and red-only labeling had a lower impact than traffic-light labeling on food purchase. However, this difference was not statistically significant.

Looking at the results as a whole, one may claim that costumers need to compare the environmental information of one product to other products in order for an eco-label to influence purchase behavior. Including a middle option as done in the traffic-light labeling system may seem to be a good option to facilitate environmental friendly food purchase.

The findings in this study may therefore be of interest to consumer researchers, policy makers and companies to understand how eco-labels can be used to reduce the environmental impact of food consumption. One can claim that food labeling as a public policy still should be considered effective, even when it just leads to small changes in food consumption. Smaller changes in dietary patterns can probably have large long-term effects on reducing the environmental impact of food consumption. At the current level of evidence eco-labels cannot be recommended as a single strategy for changing consumer behavior. Although the interventions used in this study turned out to only moderately be effective, the fundamental problem of overconsumption of meat in many parts of the world is still present. Policy makers should aim to address the issue. Since “harder” policies, such as tax breaks or bans, have been difficult to implement, the answer may still be labeling- in one way or another.

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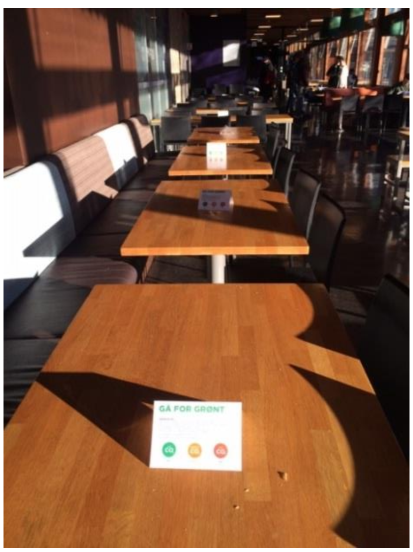
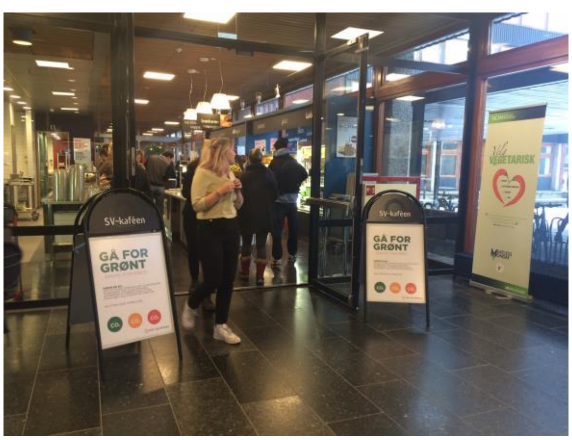
Appendix

Appendix 1 - Research setting

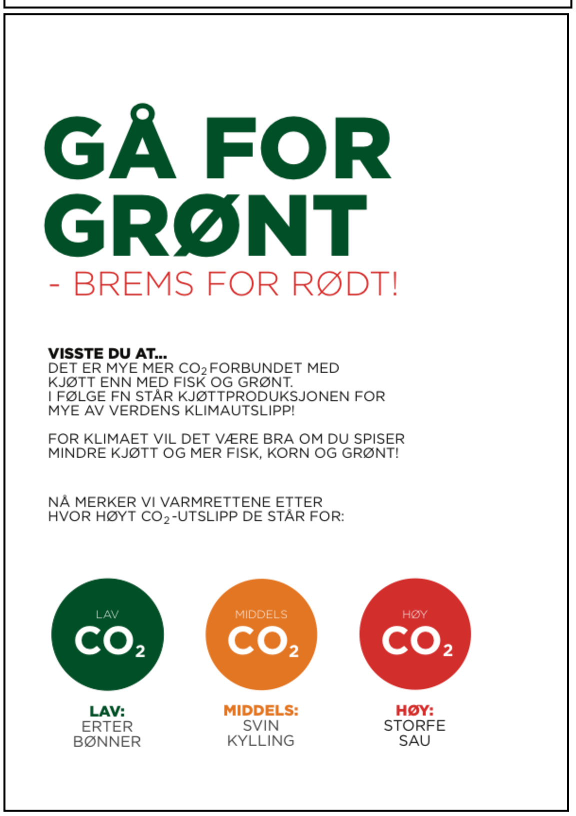
Design experiment period					
Date	*2015-11-02*	*2015-11-03*	*2015-11-04*	*2015-11-10*	*2015-11-11*
Time: 11:00-1:00	Green-only	Traffic-light	Red-only	Green-only	Traffic-light
Time: 1:00-3:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Time: 3:00-6:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Date	*2015-11-12*	*2015-11-16*	*2015-11-17*	*2015-11-18*	*2015-11-19*
Time: 11:00-1:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Time: 1:00-3:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Time: 3:00-6:00	Green-only	Traffic-light	Red	Green-only	Traffic-light
Date	*2015-11-23*	*2015-11-24*	*2015-11-26*	*2015-11-30*	*2015-12-01*
Time: 11:00-1:00	Traffic-light	Red-only	Traffic-light	Red-only	Green-only
Time: 1:00-3:00	Green-only	Traffic-light	Green-only	Traffic-light	Red-only
Time: 3:00-6:00	Red-only	Green-only	Red-only	Green-only	Traffic-light
Date	*2015-12-02*	*2015-12-03*	*2015-12-07*	*2015-12-08*	*2015-12-10*
Time: 11:00-1:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Time: 1:00-3:00	Green-only	Traffic-light	Red-only	Green-only	Traffic-light
Time: 3:00-6:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Date	*2016-01-18*	*2016-01-19*	*2016-01-20*	*2016-01-21*	*2016-01-25*
Time: 11:00-1:00	Green-only	Traffic-light	Red-only	Green-only	Traffic-light
Time: 1:00-3:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Time: 3:00-6:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Date	*2016-01-26*	*2016-01-27*	*2016-01-28*	*2016-02-01*	*2016-02-02*
Time: 11:00-1:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Time: 1:00-3:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Time: 3:00-6:00	Green-only	Traffic-light	Red-only	Green-only	Traffic-light
Date	*2016-02-03*	*2016-02-04*	*2016-02-08*	*2016-02-09*	*2016-02-10*
Time: 11:00-1:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Time: 1:00-3:00	Green-only	Traffic-light	Red-only	Green-only	Traffic-light
Time: 3:00-6:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Date	*2016-02-11*	*2016-02-15*	*2016-02-16*	*2016-02-17*	*2016-02-18*
Time: 11:00-1:00	Green-only	Traffic-light	Red-only	Green-only	Traffic-light
Time: 1:00-3:00	Red-only	Green-only	Traffic-light	Red-only	Green-only
Time: 3:00-6:00	Traffic-light	Red-only	Green-only	Traffic-light	Red-only
Date	*2016-02-23*	*2016-02-24*			
Time: 11:00-1:00	Red-only	Green-only			
Time: 1:00-3:00	Traffic-light	Red-only			
Time: 3:00-6:00	Green-only	Traffic-light			

Appendix 2 - Labeling system design





Appendix 3 - Poster design



Appendix 4 - Costumers survey

Alder
18-20
21-25
26-39+

Kjønn
Kvinne¨
Man

1. Hvilken rett har du spist i kantinen i dag (kjøttretten/fiskeretten/vegetarretten)?

Kjøtt
Fisk
Vegetar

2. Har du lagt merke til plakaten og den nye $C0_2$-merkingen av maten i SV-kantinen?

Ja Nei

3. Har du forstått den nye $C0_2$-merkingen av maten i SV-kantinen?

Ja Nei

4. I hvor stor grad gjør du en eller flere av følgende aktiviteter?

I veldig stor grad (= 1) Hverken i stor eller liten grad (= 4) I veldig liten grad (= 7)	1	2	3	4	5	6	7
Kildesorterer							
Kjøper brukt (Fretex, Finn.no osv.)							
Kjøper miljømerkede produkter (Svanemerket osv.)							
Begrenser utenlandsreiser							
Begrenser bilbruken av miljøhensyn							

5. I hvor stor grad er du enig med følgende utsagn:

Veldig enig (= 1) Hverken enig eller uenig (= 4) Veldig uenig (= 7)	1	2	3	4	5	6	7
(1)Jeg har kjennskap til kjøttproduksjons store miljøpåvirkning							
(2)Jeg mener at klimautfordringene forbundet med kjøttindustrien ikke er viktige nok til at jeg skal ta							
hensyn til det når jeg velger hva jeg skal spise (3) Jeg er bevist at kjøtt retter har høyere $C0_2$ utslipp en vegetar rettene							
(4) Jeg mener at $C0_2$ nivået til en rett er viktig informasjon når jeg skal velge varmrett i kantinen							

6. I hvor stor grad vil de følgende faktorene påvirke hva du velger å spise i SV-kantinen?

Veldig viktig (= 1) Hverken viktig eller uviktig (= 4) Ikke viktig i det hele tatt (= 7)	1	2	3	4	5	6	7
At maten er sunn							
At maten er kortreist							
At maten smaker godt							
At maten er økologisk							
At maten sikrer dyrevelferd							
At maten er billig							
At maten er miljøvennlig							

Appendix 5 - Assumptions of Independent t-test

5.1. Assumption independent t-test for vegetarian share

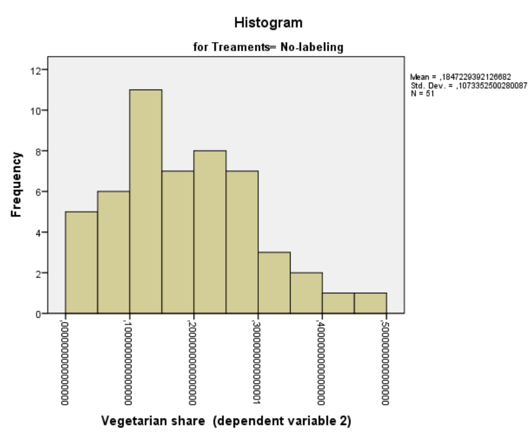
5.1.1. Whole treatment period – vegetarian share

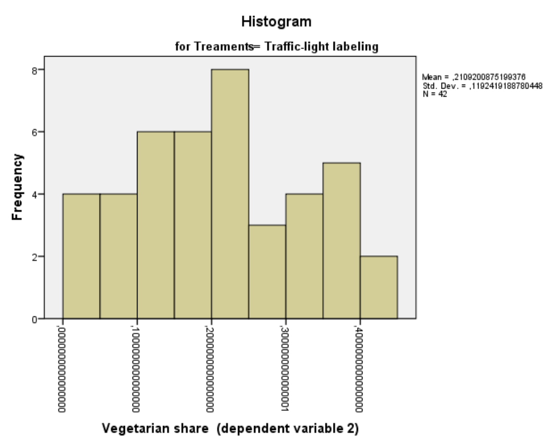
Tests of Normality

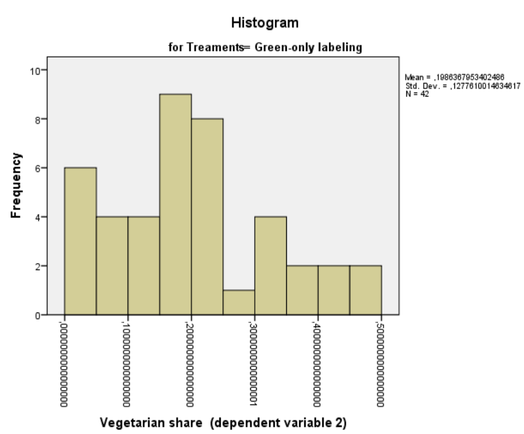
		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Treaments	Statistic	df	Sig.	Statistic	df	Sig.
Vegetarian share (dependent variable 2)	No-labeling	,095	51	,200*	,979	51	,486
	Traffic-light labeling	,063	42	,200*	,975	42	,477
	Green-only labeling	,101	42	,200*	,950	42	,064
	Red-only labeling	,074	42	,200*	,964	42	,205

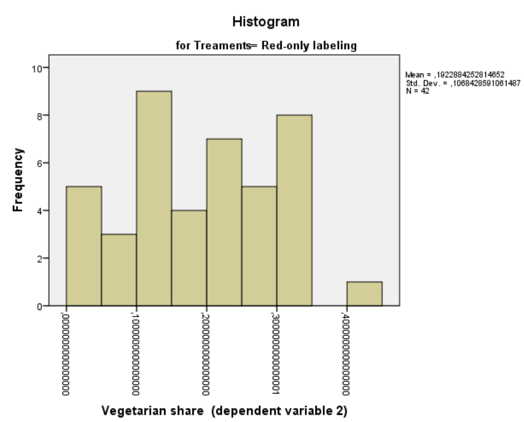
*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction









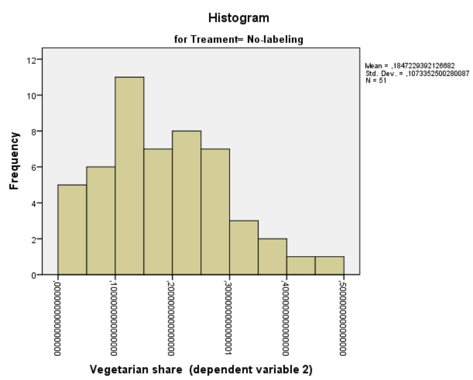
5.1.2. Fall 2015 treatment period – vegetarian share

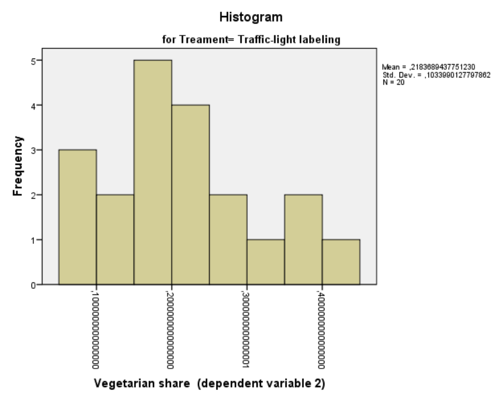
Tests of Normality

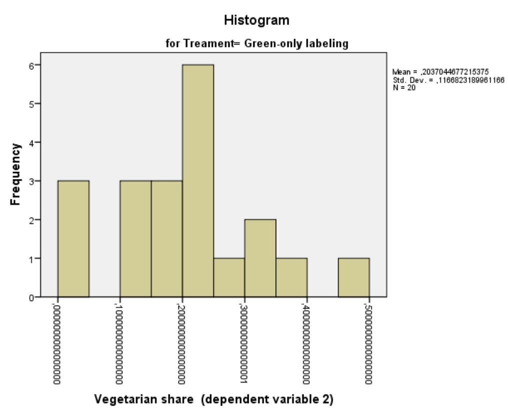
	Treament	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Vegetarian share (dependent variable 2)	No-labeling	,095	51	,200*	,979	51	,486
	Traffic-light labeling	,121	20	,200*	,948	20	,338
	Green-only labeling	,111	20	,200*	,972	20	,805
	Red-only labeling	,138	20	,200*	,949	20	,353

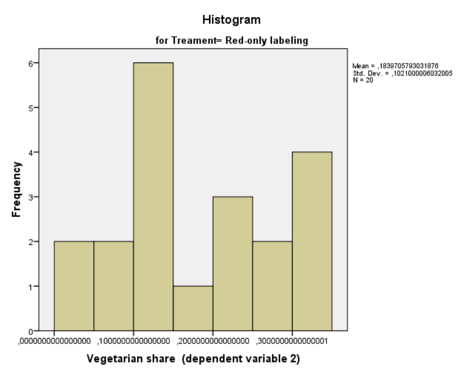
*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction









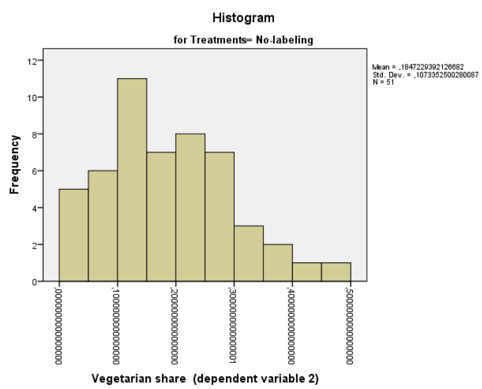
5.1.3. Winter 2016 treatment period – vegetarian share

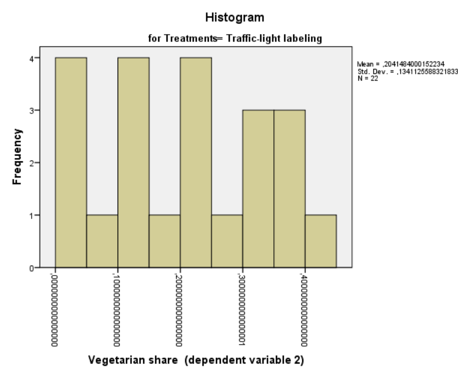
Tests of Normality

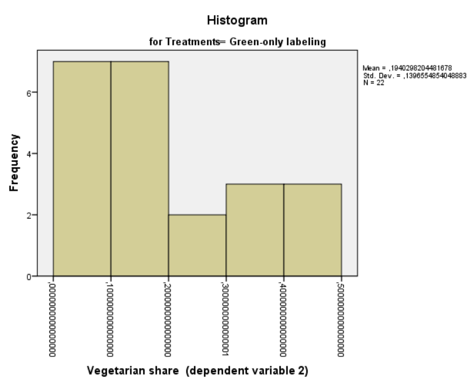
	Treatments	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Vegetarian share (dependent variable 2)	No-labeling	,095	51	,200*	,979	51	,486
	Traffic-light labeling	,108	22	,200*	,948	22	,283
	Green-only labeling	,149	22	,200*	,921	22	,078
	Red-only labeling	,084	22	,200*	,964	22	,584

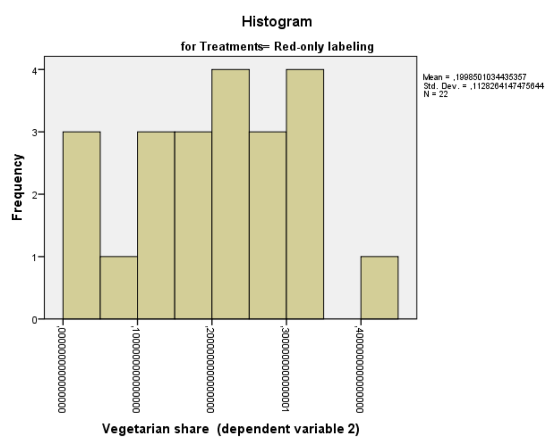
*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction







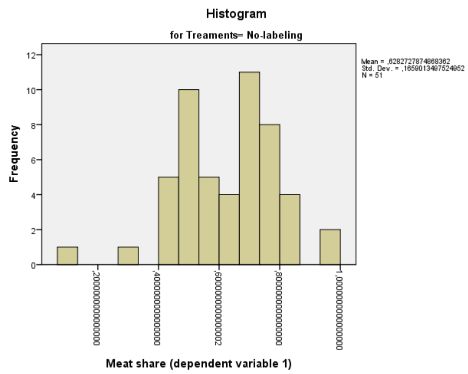


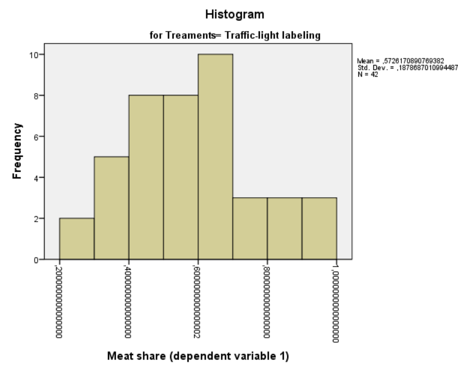
5.2. Assumptions independent t-test for meat share

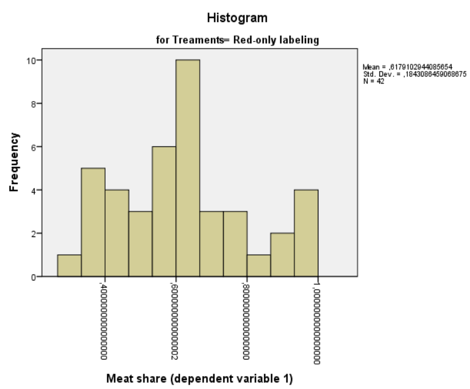
5.2.1. Whole treatment period – meat share

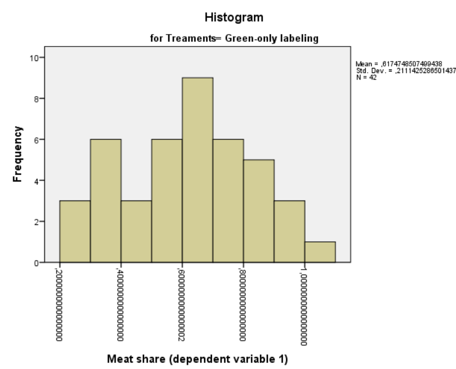
Tests of Normality

	Treaments	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Meat share (dependent variable 1)	No-labeling	,092	51	,200*	,978	51	,440
	Traffic-light labeling	,093	42	,200*	,971	42	,368
	Green-only labeling	,071	42	,200*	,978	42	,598
	Red-only labeling	,086	42	,200*	,968	42	,280









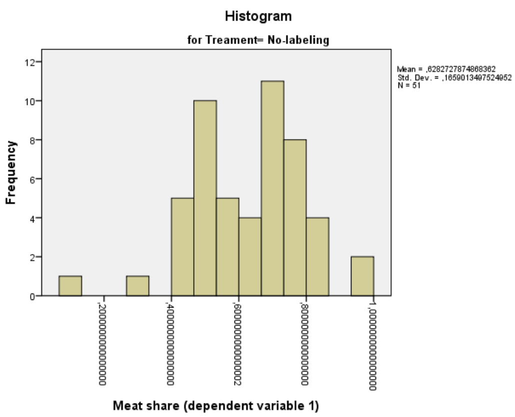
5.2.2. Fall 2015 treatment period – meat share

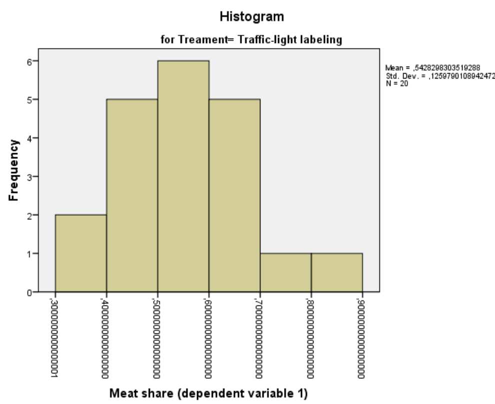
Tests of Normality

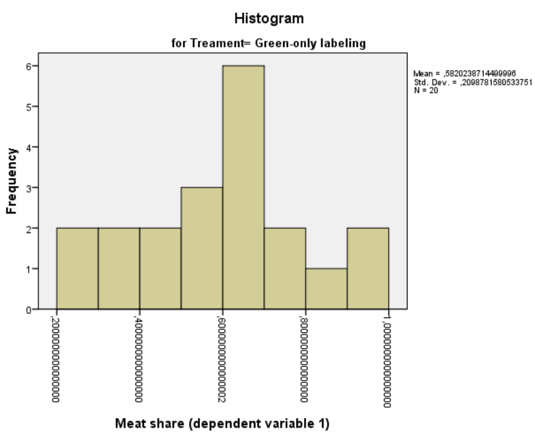
	Treament	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Meat share (dependent variable 1)	No-labeling	,092	51	,200*	,978	51	,440
	Traffic-light labeling	,150	20	,200*	,972	20	,806
	Green-only labeling	,093	20	,200*	,973	20	,814
	Red-only labeling	,124	20	,200*	,948	20	,338

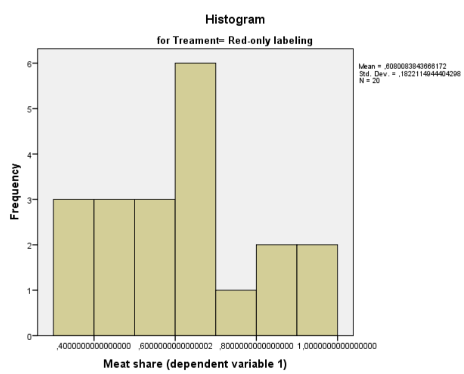
*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction









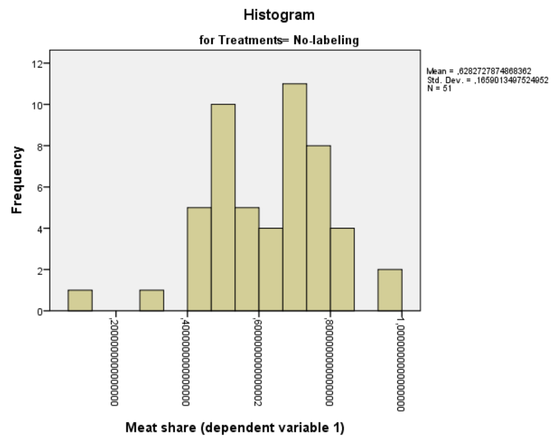
5.2.3. Winter 2016 treatment period – meat share

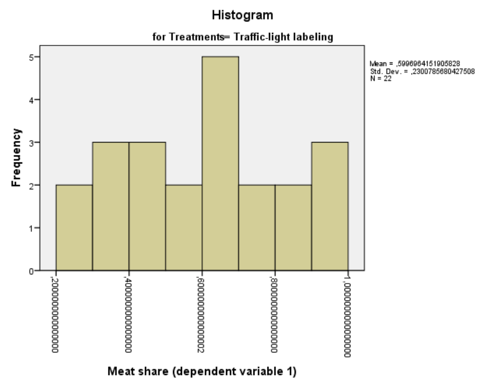
Tests of Normality

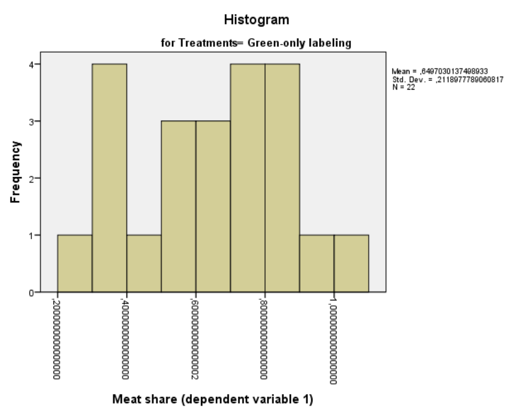
	Treatments	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Meat share (dependent variable 1)	No-labeling	,092	51	,200*	,978	51	,440
	Traffic-light labeling	,096	22	,200*	,959	22	,475
	Green-only labeling	,123	22	,200*	,954	22	,373
	Red-only labeling	,106	22	,200*	,974	22	,804

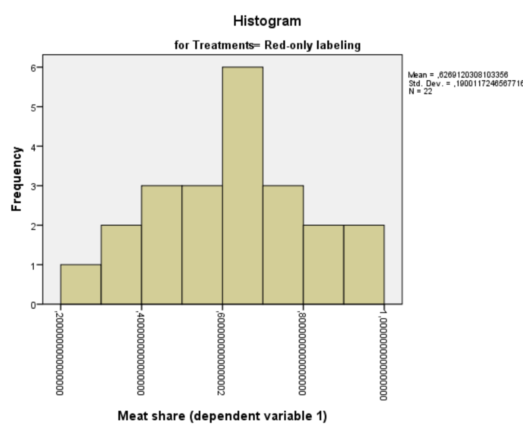
*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction









Appendix 6 – Test results Independent t-test

6.1. Hypothesis H1a independent-test results

6.1.1. H1a: Whole treatment period – vegetarian share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,515	,475	-1,114	91	,268	-,026197148307269	,023515490619618	-,072907781649014	,020513485034476
	Equal variances not assumed			-1,103	83,489	,273	-,026197148307269	,023757905400548	-,073446571062019	,021052274447481

6.1.2. H1a: Fall 2015 treatment period – vegetarian share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,081	,777	-1,200	69	,234	-,033646004562455	,028036451092190	-,089577194124687	,022285184999777
	Equal variances not assumed			-1,220	36,008	,230	-,033646004562455	,027576564823377	-,089573457610749	,022281448485840

6.1.3. H1a: Winter 2016 treatment period – vegetarian share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	1,892	,173	-,657	71	,513	-,019425460802555	,029563352483433	-,078373111418168	,039522189813058
	Equal variances not assumed			-,601	33,146	,552	-,019425460802555	,032302518486371	-,085134469159368	,046283547554258

6.2. Hypothesis H1b independent t-test results

6.2.1. H1b: Whole treatment period – meat share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Meat share (dependent variable 1)	Equal variances assumed	,534	,467	1,516	91	,133	,055655698409898	,036701618196807	-,017247557506418	,128558954326214
	Equal variances not assumed			1,498	82,627	,138	,055655698409898	,037148627225680	-,018236365889550	,129547762709346

6.2.2. H1b: Fall 2015 treatment period – meat share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Meat share (dependent variable 1)	Equal variances assumed	2,472	,120	2,077	69	,042	,085442957134907	,041139832996707	,003371235919866	,167514678349949
	Equal variances not assumed			2,340	45,614	,024	,085442957134907	,036513111095027	,011929092738148	,158956821531667

6.2.3. H1b: Winter 2016 treatment period – meat share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Meat share (dependent variable 1)	Equal variances assumed	4,003	,049	,598	71	,551	,028576372296253	,047746932800568	-,066628307696390	,123781052288897
	Equal variances not assumed			,527	30,825	,602	,028576372296253	,054275779534016	-,082145274593786	,139298019186293

6.3. Hypothesis H2 independent t-test results

6.3.1. H2: Whole treatment period – vegetarian share

6.3.1.1 Traffic-light versus Green-only labeling

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,201	,655	,754	82	,453	,018631662238472	,024704940589213	-,030514334528595	,067777659005540
	Equal variances not assumed			,754	81,031	,453	,018631662238472	,024704940589213	-,030523135379340	,067786459856284

6.3.1.2. Traffic-light versus Red-only labeling

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,169	,682	,456	82	,650	,012283292179689	,026966252592323	-,041361174518640	,065927758878018
	Equal variances not assumed			,456	81,613	,650	,012283292179689	,026966252592323	-,041364987268837	,065931571628214

6.3.2. H2: Fall 2015 treatment period – vegetarian share

6.3.2.1 Traffic-light versus Green-only labeling

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,184	,671	,421	38	,676	,014664476053585	,034861238797657	-,055908412315124	,085237364422295
	Equal variances not assumed			,421	37,458	,676	,014664476053585	,034861238797657	-,055941953754664	,085270905861835

6.3.2.2. Traffic-light versus Red-only labeling

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,097	,757	1,059	38	,296	,034398364471935	,032492896121312	-,031380064804638	,100176793748509
	Equal variances not assumed			1,059	37,994	,296	,034398364471935	,032492896121312	-,031380410040443	,100177138984314

6.3.3. H2: Winter 2016 treatment period – vegetarian share

6.3.3.1 Traffic-light versus Green-only labeling

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,012	,912	,245	42	,808	,010118579567056	,041280544085667	-,073188931134606	,093426090268717
	Equal variances not assumed			,245	41,931	,808	,010118579567056	,041280544085667	-,073192975020134	,093430134154246

6.3.3.2. Traffic-light versus Red-only labeling

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,781	,382	,115	42	,909	,004298296571688	,037365503233297	-,071108341820021	,079704934963396
	Equal variances not assumed			,115	40,805	,909	,004298296571688	,037365503233297	-,071173819745382	,079770412888758

6.4. Hypothesis H3 independent t-test results

6.4.1. H3: Whole treatment period – vegetarian share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,768	,384	,247	82	,806	,006348370058784	,025698929955917	-,044774988201064	,057471728318631
	Equal variances not assumed			,247	79,511	,806	,006348370058784	,025698929955917	-,044798957192067	,057495697309634

6.4.2. H3: Fall 2015 treatment period – vegetarian share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,033	,857	,569	38	,573	,019733888418350	,034669275799680	-,050450391177566	,089918168014266
	Equal variances not assumed			,569	37,342	,573	,019733888418350	,034669275799680	-,050491009110758	,089958785947458

6.4.3. H3: Winter 2016 treatment period – vegetarian share

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Vegetarian share (dependent variable 2)	Equal variances assumed	,924	,342	-,152	42	,880	-,005820282995368	,038277369571247	-,083067142159110	,071426576168374
	Equal variances not assumed			-,152	40,224	,880	-,005820282995368	,038277369571247	-,083168338355157	,071527772364422

Appendix 7 – Test results OLS regression

7.1. Hypothesis H1a OLS results

7.1.1. H1a: Whole treatment period – vegetarian share

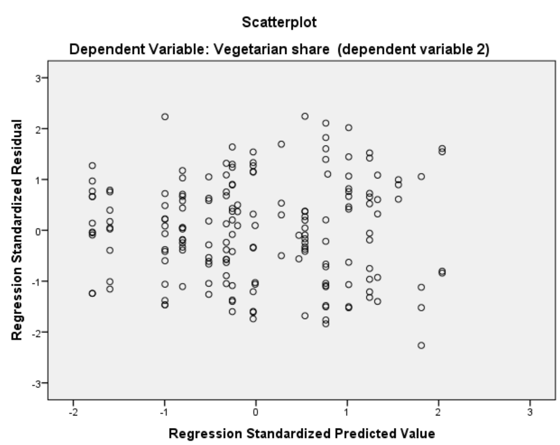
7.1.1.1. Coefficients table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,195	,021		9,347	,000		
	Traffic-light	,025	,019	,098	1,324	,187	,995	1,005
	Monday	-,050	,024	-,186	-2,075	,040	,676	1,478
	Tuesday	-,007	,023	-,028	-,313	,755	,664	1,506
	Wednesday	-,056	,024	-,209	-2,332	,021	,678	1,475
	11:00-13:00	,025	,021	,104	1,226	,222	,748	1,336
	13.00-15:00	,041	,021	,167	1,967	,051	,750	1,334

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.1.2. Assumption test: Scatterplot



7.1.1.3. Assumptions test: Model Summary

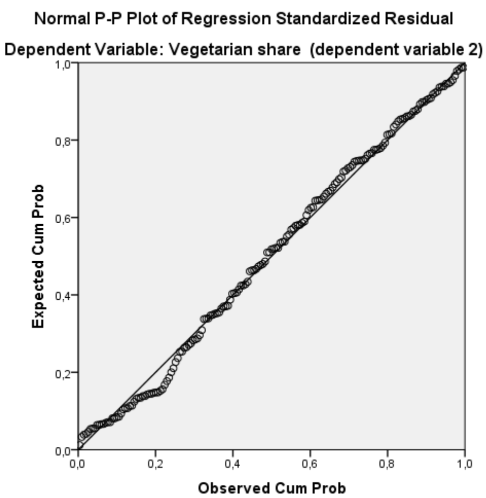
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,278[a]	,077	,045	,112052667160862	,077	2,369	6	170	,032	1,365

a. Predictors: (Constant), 13.00-15:00, Wednesday, Traffic-light (treatment 3), Monday, 11:00-13:00, Tuesday

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.1.4. Assumptions test: Normal P-P Plot



7.1.1.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,138985544443131	,260930508375168	,196036004755906	,031846185325516	177
Std. Predicted Value	-1,791	2,038	,000	1,000	177
Standard Error of Predicted Value	,020	,038	,022	,002	177
Adjusted Predicted Value	,133590802550316	,266918778419495	,195994117429706	,032101127122024	177
Residual	-,253659367561340	,251184940338135	,000000000000000	,110126116675710	177
Std. Residual	-2,264	2,242	,000	,983	177
Stud. Residual	-2,322	2,281	,000	1,003	177
Deleted Residual	-,266918778419495	,260042160749435	,000041887326200	,114666898787574	177
Stud. Deleted Residual	-2,353	2,310	,000	1,007	177
Mahal. Distance	4,880	19,742	5,966	1,548	177
Cook's Distance	,000	,040	,006	,007	177
Centered Leverage Value	,028	,112	,034	,009	177

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.2. H1a: Fall 2015 treatment period – vegetarian share

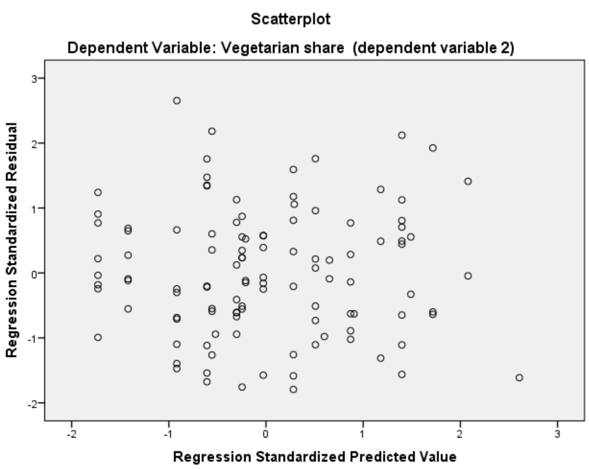
7.1.2.1. Coefficients table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,180	,025		7,302	,000		
	Traffic-light (treatment 3)	,029	,026	,104	1,088	,279	,998	1,002
	Monday	-,019	,028	-,078	-,680	,498	,695	1,438
	Tuesday	,021	,028	,089	,766	,445	,684	1,461
	Wednesday	,009	,029	,033	,294	,769	,709	1,411
	11:00-13:00	-,007	,025	-,033	-,297	,767	,749	1,334
	13.00-15:00	,027	,025	,118	1,068	,288	,749	1,334

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.2.2. Assumption test: Scatterplot



7.1.2.3. Assumptions test: Model Summary

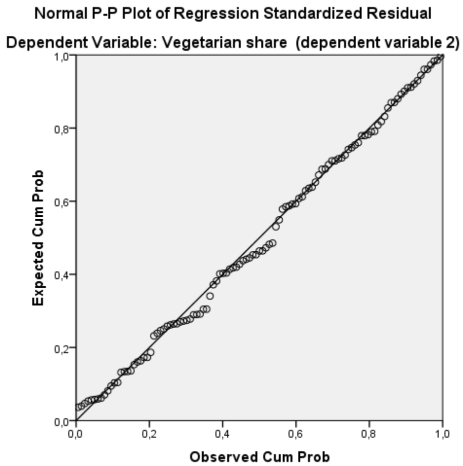
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,223[a]	,050	-,005	,107129568295256	,050	,908	6	104	,492	1,457

a. Predictors: (Constant), 13.00-15:00, Wednesday, Traffic-light (treatment 3), Monday, 11:00-13:00, Tuesday

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.2.4. Assumptions test: Normal P-P Plot



7.1.2.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,152853503823280	,256207764148712	,194069817259847	,023837018889988	111
Std. Predicted Value	-1,729	2,607	,000	1,000	111
Standard Error of Predicted Value	,025	,034	,027	,003	111
Adjusted Predicted Value	,144768774509430	,273222655057907	,194063177352115	,024830110847155	111
Residual	-,192239597439766	,284332513809204	,000000000000000	,104166886115297	111
Std. Residual	-1,794	2,654	,000	,972	111
Stud. Residual	-1,844	2,728	,000	1,004	111
Deleted Residual	-,203079178929329	,300321072340012	,000006639907732	,111009811112442	111
Stud. Deleted Residual	-1,866	2,817	,001	1,012	111
Mahal. Distance	4,806	10,144	5,946	1,688	111
Cook's Distance	,000	,060	,009	,012	111
Centered Leverage Value	,044	,092	,054	,015	111

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.3. H1a: Winter 2016 treatment period – vegetarian share

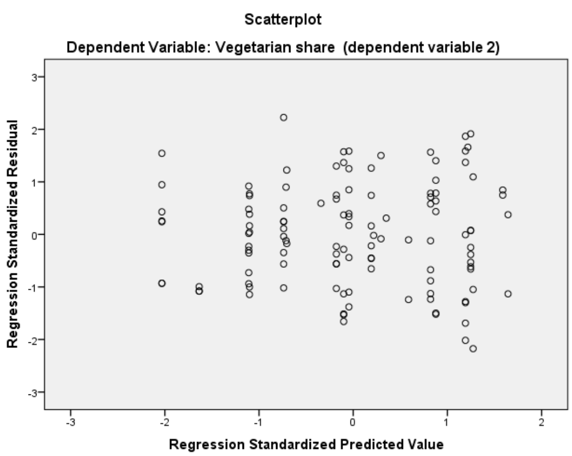
7.1.3.1. Coefficients table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,189	,026		7,245	,000		
	Traffic-light (treatment 3)	,017	,027	,056	,629	,530	,998	1,002
	Monday	-,043	,030	-,153	-1,419	,159	,684	1,462
	Tuesday	,002	,029	,009	,082	,935	,672	1,489
	Wednesday	-,083	,029	-,305	-2,813	,006	,672	1,489
	11:00-13:00	,055	,026	,221	2,149	,034	,749	1,334
	13.00-15:00	,040	,026	,157	1,533	,128	,749	1,334

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.3.2. Assumption test: Scatterplot



7.1.3.3. Assumptions test: Model Summary

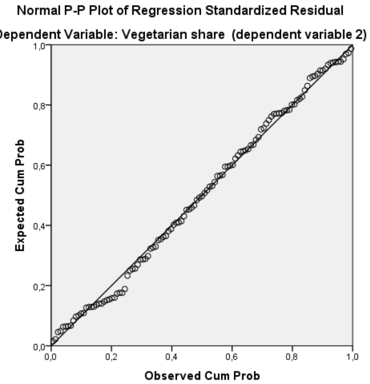
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,361[a]	,130	,083	,113818490627923	1,401

a. Predictors: (Constant), 13.00-15:00, Wednesday, Traffic-light (treatment 3), Monday, 11:00-13:00, Tuesday

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.1.3.4. Assumptions test: Histogram



7.1.3.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,105920933187008	,263388901948929	,192970025861525	,042843699119211	117
Std. Predicted Value	-2,032	1,644	,000	1,000	117
Standard Error of Predicted Value	,026	,035	,028	,003	117
Adjusted Predicted Value	,096077427268028	,275676131248474	,192949270182399	,043315773154786	117
Residual	-,247508436441422	,253312855958939	,000000000000000	,110835827993403	117
Std. Residual	-2,175	2,226	,000	,974	117
Stud. Residual	-2,276	2,286	,000	1,004	117
Deleted Residual	-,271125078201294	,267344117164612	,000020755679127	,117947780687600	117
Stud. Deleted Residual	-2,321	2,332	,000	1,010	117
Mahal. Distance	5,021	9,700	5,949	1,599	117
Cook's Distance	,000	,071	,009	,011	117
Centered Leverage Value	,043	,084	,051	,014	117

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.2. Hypothesis H1b OLS results

7.2.1. H1b: Whole treatment period – meat share

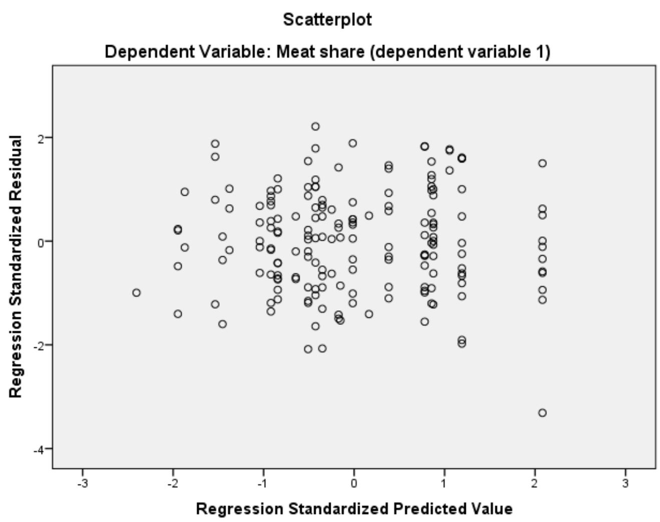
7.2.1.1. Coefficients table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,654	,034		19,444	,000		
	Traffic-light (treatment 3)	-,059	,031	-,139	-1,898	,059	,995	1,005
	Monday	,004	,039	,010	,111	,912	,676	1,478
	Tuesday	,023	,038	,056	,625	,533	,664	1,506
	Wednesday	,074	,039	,170	1,912	,057	,678	1,475
	11:00-13:00	-,069	,033	-,174	-2,063	,041	,748	1,336
	13.00-15:00	-,097	,033	-,245	-2,909	,004	,750	1,334

a. Dependent Variable: Meat share (dependent variable 1)

7.2.1.2. Assumption test: Scatterplot



7.2.1.3. Assumptions test: Model Summary

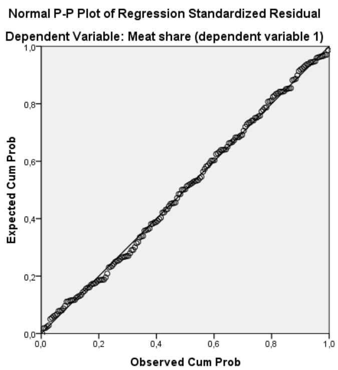
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,305[a]	,093	,061	,180740149954686	,093	2,914	6	170	,010	1,717

a. Predictors: (Constant), 13.00-15:00, Wednesday, Traffic-light (treatment 3), Monday, 11:00-13:00, Tuesday

b. Dependent Variable: Meat share (dependent variable 1)

7.2.1.4. Assumptions test: Histogram



7.2.1.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,473014950752258	,728635013103485	,610045231636822	,056965652611250	177
Std. Predicted Value	-2,405	2,082	,000	1,000	177
Standard Error of Predicted Value	,033	,062	,036	,003	177
Adjusted Predicted Value	,494373023509979	,751292169094086	,610104385434061	,057134749418584	177
Residual	-,598764836788178	,399763822555542	,000000000000000	,177632637814152	177
Std. Residual	-3,313	2,212	,000	,983	177
Stud. Residual	-3,375	2,252	,000	1,003	177
Deleted Residual	-,621421992778778	,414412051439285	-,000059153797239	,184948089297264	177
Stud. Deleted Residual	-3,484	2,280	,000	1,008	177
Mahal. Distance	4,880	19,742	5,966	1,548	177
Cook's Distance	,000	,062	,006	,008	177
Centered Leverage Value	,028	,112	,034	,009	177

a. Dependent Variable: Meat share (dependent variable 1)

7.2.2. H1b: Fall 2015 treatment period – meat share

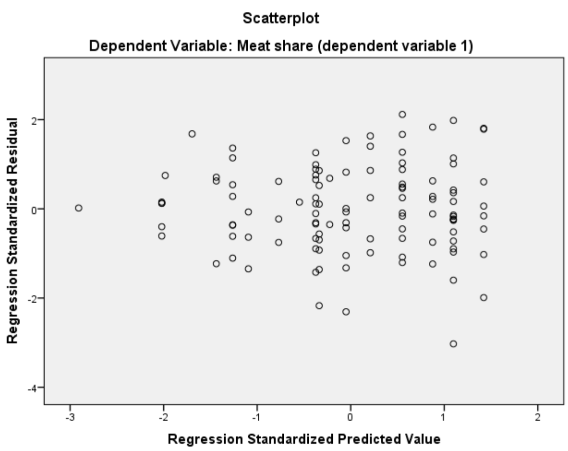
7.2.2.1. Coefficients table

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,647	,033		19,460	,000		
	Traffic-light (treatment 3)	-,069	,042	-,155	-1,640	,104	,998	1,002
	Monday	-,037	,040	-,094	-,929	,355	,881	1,136
	Tuesday	,014	,039	,035	,350	,727	,880	1,137
	11:00-13:00	-,023	,040	-,063	-,578	,564	,749	1,334
	13.00-15:00	-,062	,040	-,170	-1,559	,122	,749	1,334

a. Dependent Variable: Meat share (dependent variable 1)

7.2.2.2. Assumption test: Scatterplot



7.2.2.3. Assumptions test: Model Summary

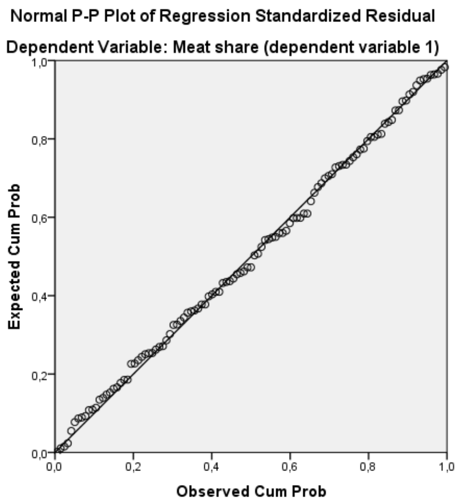
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change	Durbin-Watson
1	,244[a]	,060	,015	,170836092170495	,060	1,335	5	105	,255	1,764

a. Predictors: (Constant), 13.00-15:00, Tuesday , Traffic-light (treatment 3), Monday, 11:00-13:00

b. Dependent Variable: Meat share (dependent variable 1)

7.2.2.4. Assumptions test: Normal P-P Plot



7.2.2.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,478478640317917	,660726070404053	,600893278245041	,042084808470645	111
Std. Predicted Value	-2,909	1,422	,000	1,000	111
Standard Error of Predicted Value	,033	,053	,039	,006	111
Adjusted Predicted Value	,478164315223694	,679895639419556	,600900218509256	,043240283672467	111
Residual	-,517221271991730	,361393421888351	,000000000000000	,166908300647365	111
Std. Residual	-3,028	2,115	,000	,977	111
Stud. Residual	-3,087	2,157	,000	1,003	111
Deleted Residual	-,537589192390442	,375834256410599	-,000006940264215	,176010323634142	111
Stud. Deleted Residual	-3,222	2,196	-,001	1,014	111
Mahal. Distance	3,177	9,730	4,955	1,928	111
Cook's Distance	,000	,063	,009	,013	111
Centered Leverage Value	,029	,088	,045	,018	111

a. Dependent Variable: Meat share (dependent variable 1)

7.2.3. H1b: Winter 2016 treatment period – meat share

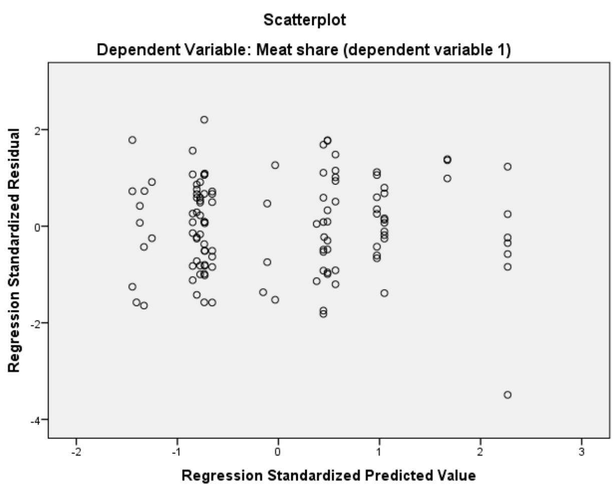
7.2.3.1. Coefficients table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,658	,042		15,615	,000		
	Traffic-light (treatment 3)	-,038	,044	-,079	-,882	,380	,998	1,002
	Monday	,005	,049	,011	,104	,918	,684	1,462
	Tuesday	-,003	,048	-,006	-,055	,956	,672	1,489
	Wednesday	,115	,048	,265	2,418	,017	,672	1,489
	11:00-13:00	-,079	,042	-,196	-1,887	,062	,749	1,334
	13.00-15:00	-,084	,042	-,207	-2,001	,048	,749	1,334

a. Dependent Variable: Meat share (dependent variable 1)

7.2.3.2. Assumption test: Scatterplot



7.2.3.3. Assumptions test: Model Summary

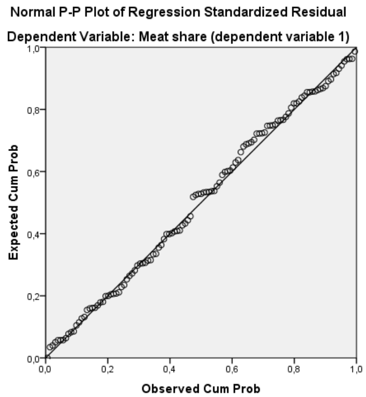
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,339[a]	,115	,066	,184224055664703	1,856

a. Predictors: (Constant), 13.00-15:00, Wednesday, Traffic-light (treatment 3), Monday, 11:00-13:00, Tuesday

b. Dependent Variable: Meat share (dependent variable 1)

7.2.3.4. Assumptions test: Normal P-P Plot



7.2.3.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,533366739749908	,773047685623169	,626673198943132	,064561162748370	117
Std. Predicted Value	-1,445	2,267	,000	1,000	117
Standard Error of Predicted Value	,042	,056	,045	,005	117
Adjusted Predicted Value	,502002775669098	,809095203876495	,626706702020107	,065264261566080	117
Residual	-,643177509307861	,406241029500961	,000000000000000	,179396384833896	117
Std. Residual	-3,491	2,205	,000	,974	117
Stud. Residual	-3,588	2,265	,000	1,005	117
Deleted Residual	-,679225087165833	,428447514772415	-,000033503076974	,191146112547059	117
Stud. Deleted Residual	-3,801	2,309	-,002	1,016	117
Mahal. Distance	5,021	9,700	5,949	1,599	117
Cook's Distance	,000	,103	,009	,014	117
Centered Leverage Value	,043	,084	,051	,014	117

a. Dependent Variable: Meat share (dependent variable 1)

7.3. Hypothesis H2 independent t-test results

7.3.1. H2: Whole treatment period – vegetarian share

7.3.1.1. Coefficients table

Coefficients[a]

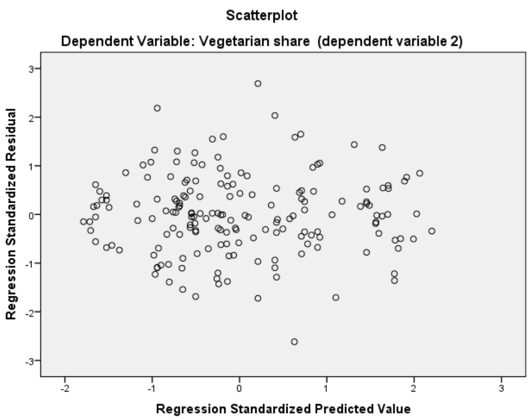
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,152	,053		2,854	,005		
	Green-only (treatment 1)	-,012	,020	-,046	-,626	,532	,656	1,525
	Red-only (treatment 2)	-,019	,020	-,069	-,950	,344	,656	1,525
	1	-,090	,074	-,102	-1,216	,226	,497	2,013
	2	,026	,074	,029	,344	,732	,497	2,013
	3	,107	,074	,121	1,445	,151	,497	2,013
	4	-,101	,074	-,114	-1,365	,175	,497	2,013
	5	-,039	,074	-,044	-,524	,601	,497	2,013
	6	,110	,074	,125	1,485	,140	,497	2,013
	7	,023	,074	,025	,304	,762	,497	2,013
	8	3,118E-6	,074	,000	,000	1,000	,497	2,013
	9	-,016	,074	-,018	-,218	,828	,497	2,013
	10	-,004	,074	-,005	-,056	,955	,497	2,013
	11	,032	,074	,036	,433	,666	,497	2,013
	12	,082	,074	,092	1,102	,273	,497	2,013
	13	,123	,074	,139	1,662	,099	,497	2,013
	14	-,006	,074	-,006	-,075	,941	,497	2,013
	15	,173	,074	,195	2,329	,022	,497	2,013
	16	,080	,074	,091	1,080	,282	,497	2,013
	17	,063	,074	,071	,849	,398	,497	2,013
	18	-,011	,073	-,012	-,144	,886	,509	1,966
	19	,046	,073	,052	,626	,532	,509	1,966
	20	,101	,073	,114	1,370	,173	,509	1,966
	21	,138	,073	,156	1,881	,062	,509	1,966
	22	,050	,073	,056	,682	,497	,509	1,966

23	,161	,073	,181	2,187	,031	,509	1,966
24	,057	,073	,065	,779	,438	,509	1,966
25	,239	,073	,270	3,258	,001	,509	1,966
26	,095	,073	,107	1,296	,197	,509	1,966
27	-,023	,073	-,026	-,311	,756	,509	1,966
28	,002	,073	,002	,021	,984	,509	1,966
29	-,095	,073	-,107	-1,294	,198	,509	1,966
30	,207	,073	,234	2,827	,006	,509	1,966
31	,025	,073	,028	,342	,733	,509	1,966
32	,071	,073	,080	,964	,337	,509	1,966
33	,117	,073	,132	1,598	,113	,509	1,966
34	,017	,073	,019	,230	,819	,509	1,966
35	,036	,073	,040	,485	,629	,509	1,966
36	-,059	,073	-,066	-,799	,426	,509	1,966
37	,040	,073	,045	,547	,585	,509	1,966
38	,044	,073	,049	,594	,553	,509	1,966
39	-,001	,073	-,001	-,010	,992	,509	1,966
40	-,001	,073	-,001	-,011	,992	,509	1,966
41	-,025	,073	-,029	-,346	,730	,509	1,966
42	-,088	,073	-,099	-1,195	,234	,509	1,966
43	,126	,073	,142	1,712	,090	,509	1,966
44	-,085	,073	-,096	-1,156	,250	,509	1,966
45	,195	,073	,220	2,650	,009	,509	1,966
46	,053	,073	,060	,727	,469	,509	1,966
47	,201	,073	,227	2,741	,007	,509	1,966
48	-,002	,073	-,002	-,021	,983	,509	1,966
49	,214	,073	,241	2,910	,004	,509	1,966
50	,185	,073	,209	2,527	,013	,509	1,966
51	,202	,073	,228	2,751	,007	,509	1,966
52	,023	,073	,026	,311	,756	,509	1,966
53	,224	,073	,253	3,049	,003	,509	1,966
54	-,009	,073	-,010	-,121	,904	,509	1,966
55	-,030	,073	-,034	-,410	,683	,509	1,966
56	-,041	,073	-,046	-,559	,577	,509	1,966
57	,119	,073	,134	1,616	,109	,509	1,966

58	-,027	,073	-,030	-,364	,716	,509	1,966

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.3.1.2. Assumption test: Scatterplot

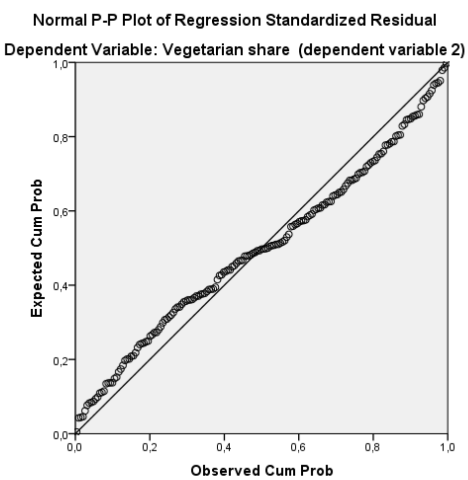


7.3.1.3. Assumptions test: Model Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,771[a]	,595	,385	,089891118842551	2,768

7.3.1.4. Assumptions test: Normal P-P Plot



7.3.1.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,038017470389605	,390731036663055	,196036004755906	,088409355733532	177
Std. Predicted Value	-1,787	2,202	,000	1,000	177
Standard Error of Predicted Value	,052	,053	,053	,001	177
Adjusted Predicted Value	,014492753893137	,418483048677444	,196036004755906	,096351029918872	177
Residual	-,235208645462990	,241851612925529	,000000000000000	,072977578150012	177
Std. Residual	-2,617	2,690	,000	,812	177
Stud. Residual	-3,244	3,295	,000	1,002	177
Deleted Residual	-,361418157815933	,362777411937714	,000000000000000	,111269580497508	177
Stud. Deleted Residual	-3,387	3,446	,001	1,014	177
Mahal. Distance	57,672	60,466	59,661	1,269	177
Cook's Distance	,000	,093	,009	,014	177
Centered Leverage Value	,328	,344	,339	,007	177

7.3.2. H2: Fall 2015 treatment period – vegetarian share

7.3.2.1. Coefficients table

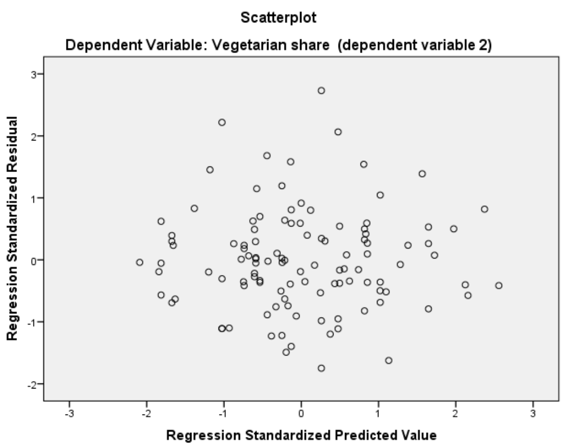
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,198	,054		3,690	,000		
	Green-only (treatment 1)	-,015	,028	-,053	-,524	,602	,610	1,640
	Red-only (treatment 2)	-,034	,028	-,124	-1,228	,223	,610	1,640
	1	-,137	,074	-,208	-1,843	,069	,489	2,043
	2	-,021	,074	-,032	-,279	,781	,489	2,043
	3	,061	,074	,093	,824	,412	,489	2,043
	4	-,148	,074	-,225	-1,992	,050	,489	2,043
	5	-,085	,074	-,130	-1,149	,254	,489	2,043
	6	,064	,074	,098	,865	,390	,489	2,043
	7	-,024	,074	-,036	-,319	,750	,489	2,043
	8	-,046	,074	-,070	-,624	,535	,489	2,043
	9	-,062	,074	-,095	-,842	,403	,489	2,043
	10	-,050	,074	-,077	-,680	,499	,489	2,043
	11	-,014	,074	-,021	-,190	,850	,489	2,043
	12	,036	,074	,054	,480	,632	,489	2,043
	13	,077	,074	,118	1,042	,301	,489	2,043
	14	-,052	,074	-,079	-,699	,487	,489	2,043
	15	,127	,074	,193	1,711	,091	,489	2,043
	16	,034	,074	,052	,459	,648	,489	2,043
	17	,017	,074	,026	,227	,821	,489	2,043
	18	-,051	,072	-,077	-,702	,485	,514	1,946
	19	,006	,072	,009	,080	,937	,514	1,946
	20	,060	,072	,092	,835	,407	,514	1,946
	21	,098	,072	,149	1,354	,180	,514	1,946
	22	,010	,072	,015	,136	,892	,514	1,946
	23	,120	,072	,183	1,665	,100	,514	1,946
	24	,017	,072	,026	,235	,815	,514	1,946
	25	,199	,072	,303	2,752	,007	,514	1,946
	26	,055	,072	,084	,760	,450	,514	1,946

27	-,063	,072	-,096	-,872	,386	,514	1,946
28	-,039	,072	-,059	-,535	,595	,514	1,946
29	-,135	,072	-,206	-1,869	,066	,514	1,946
30	,167	,072	,255	2,314	,024	,514	1,946
31	-,015	,072	-,023	-,209	,835	,514	1,946
32	,031	,072	,047	,423	,674	,514	1,946
33	,077	,072	,118	1,066	,290	,514	1,946
34	-,023	,072	-,036	-,323	,748	,514	1,946
35	-,005	,072	-,007	-,063	,950	,514	1,946
36	-,099	,072	-,151	-1,366	,176	,514	1,946

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.3.2.2. Assumption test: Scatterplot



7.3.2.3. Assumptions test: Model Summary

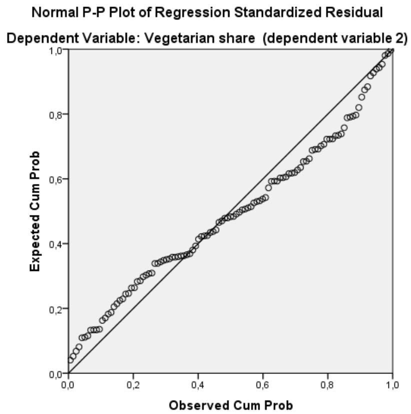
Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,742[a]	,551	,313	,08855189473 1992	,551	2,321	38	72	,001	2,710

a. Predictors: (Constant), 36, 35, 1, 34, 33, 32, 31, 30, 29, 28, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 23, 22, 21, 20, 19, 16, 15, 14, 13, 18, 17, 26, Red-only (treatment 2), 25, 24, Green-only (treatment 1) , 27

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.3.2.4. Assumptions test: Histogram



7.3.2.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,028300063684583	,396780312061310	,194069817259847	,079286606642211	111
Std. Predicted Value	-2,091	2,557	,000	1,000	111
Standard Error of Predicted Value	,051	,054	,052	,001	111
Adjusted Predicted Value	,014492753893137	,418074190616608	,194069817259847	,088142888285487	111
Residual	-,154841065406799	,241851612925529	,000000000000000	,071642010299002	111
Std. Residual	-1,749	2,731	,000	,809	111
Stud. Residual	-2,142	3,345	,000	1,003	111
Deleted Residual	-,232261598110199	,362777411937714	,000000000000000	,110082044182700	111
Stud. Deleted Residual	-2,198	3,614	,004	1,024	111
Mahal. Distance	35,676	39,342	37,658	1,836	111
Cook's Distance	,000	,143	,014	,022	111
Centered Leverage Value	,324	,358	,342	,017	111

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.3.3. H2: Winter 2016 treatment period – vegetarian share

7.3.3.1. Coefficients table

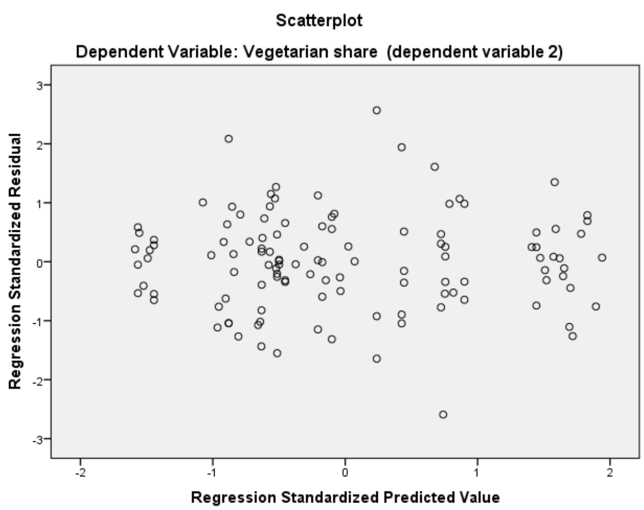
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,146	,057		2,573	,012		
	Green-only (treatment 1)	-,010	,028	-,033	-,356	,723	,616	1,624
	Red-only (treatment 2)	-,004	,028	-,014	-,151	,880	,616	1,624
	38	-,085	,079	-,113	-1,079	,284	,491	2,037
	39	,031	,079	,041	,395	,694	,491	2,037
	40	,113	,079	,151	1,435	,155	,491	2,037
	41	-,096	,079	-,128	-1,219	,226	,491	2,037
	42	-,033	,079	-,045	-,425	,672	,491	2,037
	43	,116	,079	,155	1,473	,145	,491	2,037
	44	,028	,079	,037	,357	,722	,491	2,037
	45	,006	,079	,007	,070	,944	,491	2,037
	46	-,011	,079	-,014	-,136	,893	,491	2,037
	47	,001	,079	,002	,017	,987	,491	2,037
	48	,038	,079	,050	,479	,633	,491	2,037
	49	,087	,079	,117	1,111	,270	,491	2,037
	50	,129	,079	,172	1,640	,105	,491	2,037
	51	-4,815E-5	,079	,000	-,001	1,000	,491	2,037
	52	,178	,079	,238	2,270	,026	,491	2,037
	53	,086	,079	,115	1,090	,279	,491	2,037
	54	,069	,079	,092	,872	,386	,491	2,037
	75	,044	,077	,058	,567	,572	,513	1,949
	76	-,001	,077	-,001	-,009	,993	,513	1,949
	77	-,001	,077	-,001	-,010	,992	,513	1,949
	78	-,025	,077	-,034	-,330	,742	,513	1,949
	79	-,088	,077	-,117	-1,141	,257	,513	1,949
	80	,126	,077	,168	1,634	,106	,513	1,949
	81	-,085	,077	-,113	-1,103	,273	,513	1,949
	82	,195	,077	,260	2,530	,013	,513	1,949
	83	,053	,077	,071	,694	,490	,513	1,949

84	,201	,077	,269	2,617	,011	,513	1,949
85	-,002	,077	-,002	-,020	,984	,513	1,949
86	,214	,077	,285	2,778	,007	,513	1,949
87	,185	,077	,248	2,412	,018	,513	1,949
88	,202	,077	,270	2,626	,010	,513	1,949
89	,023	,077	,030	,297	,767	,513	1,949
90	,224	,077	,299	2,910	,005	,513	1,949
91	-,009	,077	-,012	-,115	,909	,513	1,949
92	-,030	,077	-,040	-,391	,697	,513	1,949
93	-,041	,077	-,055	-,534	,595	,513	1,949
94	,119	,077	,158	1,543	,127	,513	1,949
95	-,027	,077	-,036	-,348	,729	,513	1,949

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.3.3.2. Assumption test: Scatterplot



7.3.3.3. Assumptions test: Model Summary

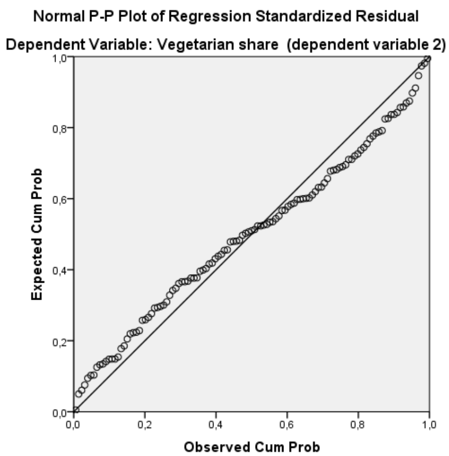
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,767[a]	,589	,372	,094170639926746	2,776

a. Predictors: (Constant), 95, 94, 93, 92, 91, 90, 89, 88, 87, 86, 85, 84, 83, 82, 81, 80, 79, 78, 77, 76, 75, 54, 53, 52, 51, 50, 49, 48, 47, 46, 45, 44, 43, 42, Red-only (treatment 2), 41, 40, 39, Green-only (treatment 1) , 38

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.3.3.4. Assumptions test: Normal P-P Plot



7.3.3.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,048263676464558	,369887560606003	,192970025861525	,091159325710306	117
Std. Predicted Value	-1,587	1,941	,000	1,000	117
Standard Error of Predicted Value	,054	,057	,056	,001	117
Adjusted Predicted Value	,014492753893137	,417499423027039	,192970025861525	,100024173450941	117
Residual	-,244042649865150	,241851612925529	,000000000000000	,076224278660037	117
Std. Residual	-2,591	2,568	,000	,809	117
Stud. Residual	-3,249	3,145	,000	1,004	117
Deleted Residual	-,383495599031448	,362777411937714	,000000000000000	,117334330688507	117
Stud. Deleted Residual	-3,478	3,350	,001	1,025	117
Mahal. Distance	37,675	41,190	39,658	1,751	117
Cook's Distance	,000	,147	,013	,022	117
Centered Leverage Value	,325	,355	,342	,015	117

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.4. Hypothesis H3 independent t-test results

7.4.1. H3: Whole treatment period – vegetarian share

7.4.1.1. Coefficients table

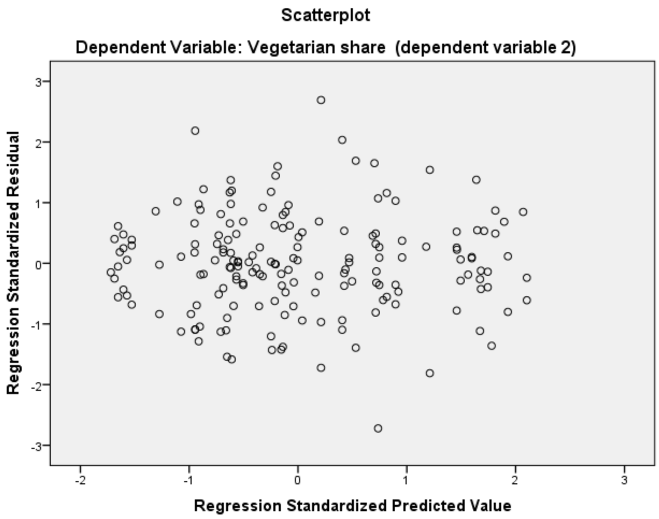
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,142	,052		2,727	,007		
	Green-only (treatment 1)	-,003	,017	-,011	-,175	,862	,874	1,144
	1	-,081	,074	-,091	-1,101	,273	,506	1,978
	2	,035	,074	,039	,474	,637	,506	1,978
	3	,117	,074	,132	1,585	,116	,506	1,978
	4	-,092	,074	-,104	-1,251	,213	,506	1,978
	5	-,030	,074	-,033	-,402	,688	,506	1,978
	6	,120	,074	,135	1,626	,107	,506	1,978
	7	,032	,074	,036	,433	,666	,506	1,978
	8	,009	,074	,011	,127	,899	,506	1,978
	9	-,007	,074	-,008	-,093	,926	,506	1,978
	10	,005	,074	,006	,070	,944	,506	1,978
	11	,041	,074	,047	,564	,574	,506	1,978
	12	,091	,074	,103	1,239	,218	,506	1,978
	13	,133	,074	,150	1,804	,074	,506	1,978
	14	,004	,074	,004	,051	,959	,506	1,978
	15	,182	,074	,206	2,478	,015	,506	1,978
	16	,090	,074	,101	1,217	,226	,506	1,978
	17	,072	,074	,082	,984	,327	,506	1,978
	18	-,011	,073	-,012	-,144	,886	,509	1,966
	19	,046	,073	,052	,626	,532	,509	1,966
	20	,101	,073	,114	1,370	,173	,509	1,966
	21	,138	,073	,156	1,882	,062	,509	1,966
	22	,050	,073	,056	,682	,497	,509	1,966
	23	,161	,073	,181	2,188	,031	,509	1,966
	24	,057	,073	,065	,779	,438	,509	1,966
	25	,239	,073	,270	3,259	,001	,509	1,966
	26	,095	,073	,107	1,297	,197	,509	1,966

27	-,023	,073	-,026	-,312	,756	,509	1,966
28	,002	,073	,002	,021	,984	,509	1,966
29	-,095	,073	-,107	-1,294	,198	,509	1,966
30	,207	,073	,234	2,828	,006	,509	1,966
31	,025	,073	,028	,342	,733	,509	1,966
32	,071	,073	,080	,964	,337	,509	1,966
33	,117	,073	,132	1,598	,113	,509	1,966
34	,017	,073	,019	,230	,819	,509	1,966
35	,036	,073	,040	,485	,629	,509	1,966
36	-,059	,073	-,066	-,799	,426	,509	1,966
37	,040	,073	,045	,548	,585	,509	1,966
38	,044	,073	,049	,595	,553	,509	1,966
39	-,001	,073	-,001	-,010	,992	,509	1,966
40	-,001	,073	-,001	-,011	,992	,509	1,966
41	-,025	,073	-,029	-,346	,730	,509	1,966
42	-,088	,073	-,099	-1,196	,234	,509	1,966
43	,126	,073	,142	1,712	,089	,509	1,966
44	-,085	,073	-,096	-1,156	,250	,509	1,966
45	,195	,073	,220	2,651	,009	,509	1,966
46	,053	,073	,060	,727	,469	,509	1,966
47	,201	,073	,227	2,743	,007	,509	1,966
48	-,002	,073	-,002	-,021	,983	,509	1,966
49	,214	,073	,241	2,912	,004	,509	1,966
50	,185	,073	,209	2,528	,013	,509	1,966
51	,202	,073	,228	2,752	,007	,509	1,966
52	,023	,073	,026	,311	,756	,509	1,966
53	,224	,073	,253	3,050	,003	,509	1,966
54	-,009	,073	-,010	-,121	,904	,509	1,966
55	-,030	,073	-,034	-,410	,683	,509	1,966
56	-,041	,073	-,046	-,560	,577	,509	1,966
57	,119	,073	,134	1,617	,109	,509	1,966
58	-,027	,073	-,030	-,364	,716	,509	1,966

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.1.2. Assumption test: Scatterplot



7.4.1.3. Assumptions test: Model Summary

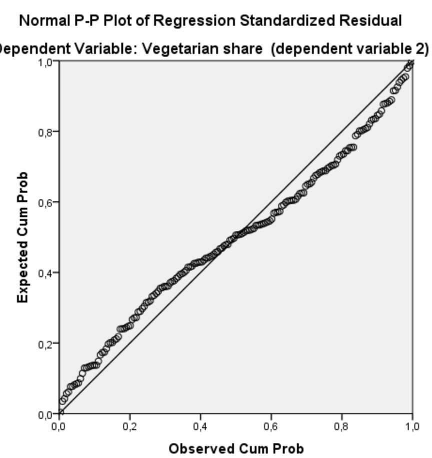
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,769[a]	,592	,386	,089853530017266	,592	2,873	59	117	,000	2,758

a. Predictors: (Constant), 58, 57, 56, 55, 54, 53, 52, 51, 50, 49, 48, 47, 46, 45, 44, 43, 42, 41, 40, 39, 38, 37, 36, 35, 34, 33, 32, 31, 30, 29, 28, 27, 26, 25, 24, 23, 22, 18, 17, 16, 12, 11, 10, 9, 8, 7, 6, 3, 5, 4, 2, Green-only (treatment 1) , 1, 21, 13, 20, 15, 19, 14

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.1.4. Assumptions test: Normal P-P Plot



7.4.1.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,044365841895342	,381415188312531	,196036004755906	,088174793485765	177
Std. Predicted Value	-1,720	2,102	,000	1,000	177
Standard Error of Predicted Value	,052	,053	,052	,000	177
Adjusted Predicted Value	,014492753893137	,418483048677444	,196036004755906	,095749359029671	177
Residual	-,244524478912354	,241851612925529	,000000000000000	,073260814134175	177
Std. Residual	-2,721	2,692	,000	,815	177
Stud. Residual	-3,343	3,297	,000	1,003	177
Deleted Residual	-,368983030319214	,362777411937714	,000000000000000	,110783818883093	177
Stud. Deleted Residual	-3,500	3,446	,000	1,015	177
Mahal. Distance	57,672	60,466	58,667	1,049	177
Cook's Distance	,000	,095	,009	,014	177
Centered Leverage Value	,328	,344	,333	,006	177

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.2. H3: Fall 2015 treatment period – vegetarian share

7.4.2.1. Coefficients table

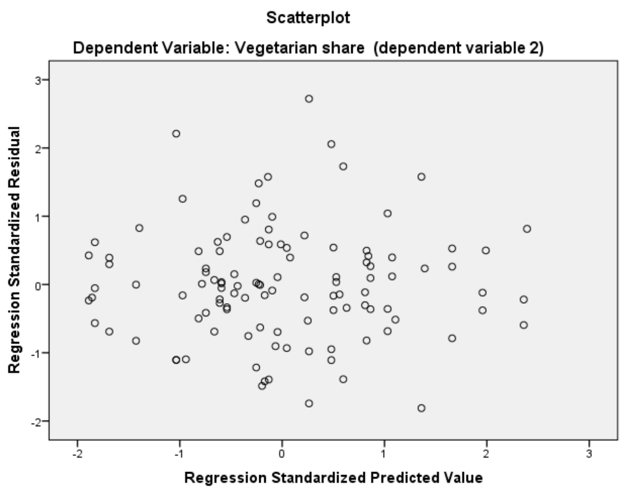
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,181	,052		3,478	,001		
	Green-only (treatment 1)	,003	,024	,009	,104	,917	,813	1,230
	1	-,119	,073	-,182	-1,635	,106	,508	1,970
	2	-,003	,073	-,005	-,048	,962	,508	1,970
	3	,078	,073	,119	1,072	,287	,508	1,970
	4	-,130	,073	-,199	-1,786	,078	,508	1,970
	5	-,068	,073	-,104	-,931	,355	,508	1,970
	6	,081	,073	,124	1,113	,269	,508	1,970
	7	-,006	,073	-,010	-,089	,930	,508	1,970
	8	-,029	,073	-,044	-,398	,692	,508	1,970
	9	-,045	,073	-,069	-,619	,538	,508	1,970
	10	-,033	,073	-,051	-,455	,651	,508	1,970
	11	,003	,073	,005	,043	,966	,508	1,970
	12	,053	,073	,080	,723	,472	,508	1,970
	13	,094	,073	,144	1,293	,200	,508	1,970
	14	-,035	,073	-,053	-,474	,637	,508	1,970
	15	,144	,073	,219	1,972	,052	,508	1,970
	16	,051	,073	,078	,701	,485	,508	1,970
	17	,034	,073	,052	,466	,642	,508	1,970
	18	-,051	,073	-,077	-,699	,487	,514	1,946
	19	,006	,073	,009	,080	,937	,514	1,946
	20	,060	,073	,092	,832	,408	,514	1,946
	21	,098	,073	,149	1,349	,181	,514	1,946
	22	,010	,073	,015	,136	,892	,514	1,946
	23	,120	,073	,183	1,659	,101	,514	1,946
	24	,017	,073	,026	,234	,816	,514	1,946
	25	,199	,073	,303	2,742	,008	,514	1,946
	26	,055	,073	,084	,757	,451	,514	1,946
	27	-,063	,073	-,096	-,869	,388	,514	1,946

28	-,039	,073	-,059	-,533	,596	,514	1,946
29	-,135	,073	-,206	-1,863	,067	,514	1,946
30	,167	,073	,255	2,306	,024	,514	1,946
31	-,015	,073	-,023	-,208	,836	,514	1,946
32	,031	,073	,047	,421	,675	,514	1,946
33	,077	,073	,118	1,062	,292	,514	1,946
34	-,023	,073	-,036	-,322	,749	,514	1,946
35	-,005	,073	-,007	-,063	,950	,514	1,946
36	-,099	,073	-,151	-1,362	,178	,514	1,946

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.2.2. Assumption test: Scatterplot



7.4.2.3. Assumptions test: Model Summary

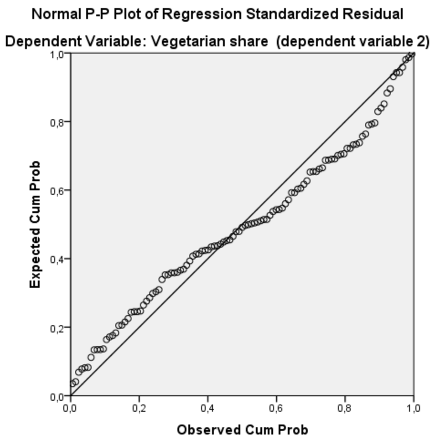
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,736[a]	,541	,309	,088860057374249	,541	2,326	37	73	,001	2,672

a. Predictors: (Constant), 36, 35, 1, 34, 33, 32, 31, 30, 29, 28, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 23, 22, 21, 20, 19, 16, 15, 14, 13, 18, 17, 26, Green-only (treatment 1) , 25, 24, 27

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.2.4. Assumptions test: Normal P-P Plot



7.4.2.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,045499246567488	,382115840911865	,194069817259847	,078605330864134	111
Std. Predicted Value	-1,890	2,392	,000	1,000	111
Standard Error of Predicted Value	,051	,054	,052	,001	111
Adjusted Predicted Value	,014492753893137	,407008826732636	,194069817259847	,086977607914530	111
Residual	-,160988703370094	,241851612925529	,000000000000000	,072388849916676	111
Std. Residual	-1,812	2,722	,000	,815	111
Stud. Residual	-2,233	3,333	,000	1,004	111
Deleted Residual	-,244539797306061	,362777411937714	,000000000000000	,109880772999115	111
Stud. Deleted Residual	-2,297	3,595	,004	1,025	111
Mahal. Distance	35,676	39,342	36,667	1,326	111
Cook's Distance	,000	,146	,014	,023	111
Centered Leverage Value	,324	,358	,333	,012	111

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.3. H3: Winter 2016 treatment period – vegetarian share

7.4.3.1. Coefficients table

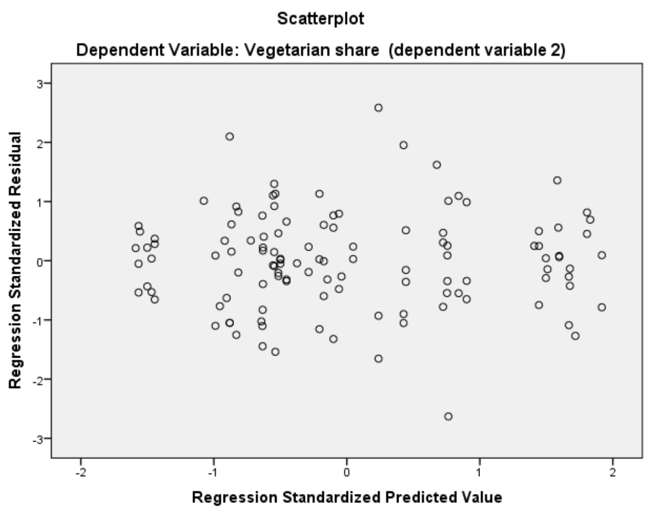
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,144	,055		2,635	,010		
	Green-only (treatment 1)	-,008	,024	-,026	-,326	,745	,821	1,218
	38	-,083	,077	-,110	-1,076	,285	,507	1,971
	39	,033	,077	,044	,432	,667	,507	1,971
	40	,115	,077	,154	1,496	,139	,507	1,971
	41	-,094	,077	-,125	-1,220	,226	,507	1,971
	42	-,031	,077	-,042	-,407	,685	,507	1,971
	43	,118	,077	,158	1,535	,129	,507	1,971
	44	,030	,077	,040	,393	,695	,507	1,971
	45	,008	,077	,010	,100	,921	,507	1,971
	46	-,009	,077	-,011	-,111	,912	,507	1,971
	47	,003	,077	,005	,045	,964	,507	1,971
	48	,040	,077	,053	,518	,606	,507	1,971
	49	,089	,077	,120	1,165	,248	,507	1,971
	50	,131	,077	,175	1,706	,092	,507	1,971
	51	,002	,077	,003	,027	,978	,507	1,971
	52	,181	,077	,241	2,351	,021	,507	1,971
	53	,088	,077	,117	1,144	,256	,507	1,971
	54	,071	,077	,094	,920	,360	,507	1,971
	75	,044	,076	,058	,571	,570	,513	1,949
	76	-,001	,076	-,001	-,009	,993	,513	1,949
	77	-,001	,076	-,001	-,010	,992	,513	1,949
	78	-,025	,076	-,034	-,332	,741	,513	1,949
	79	-,088	,076	-,117	-1,148	,254	,513	1,949
	80	,126	,076	,168	1,644	,104	,513	1,949
	81	-,085	,076	-,113	-1,110	,270	,513	1,949
	82	,195	,076	,260	2,546	,013	,513	1,949
	83	,053	,076	,071	,698	,487	,513	1,949
	84	,201	,076	,269	2,634	,010	,513	1,949

85	-,002	,076	-,002	-,021	,984	,513	1,949
86	,214	,076	,285	2,796	,007	,513	1,949
87	,185	,076	,248	2,427	,018	,513	1,949
88	,202	,076	,270	2,643	,010	,513	1,949
89	,023	,076	,030	,299	,766	,513	1,949
90	,224	,076	,299	2,929	,004	,513	1,949
91	-,009	,076	-,012	-,116	,908	,513	1,949
92	-,030	,076	-,040	-,393	,695	,513	1,949
93	-,041	,076	-,055	-,537	,593	,513	1,949
94	,119	,076	,158	1,553	,125	,513	1,949
95	-,027	,076	-,036	-,350	,727	,513	1,949

a. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.3.2. Assumption test: Scatterplot



7.4.3.3. Assumptions test: Model Summary

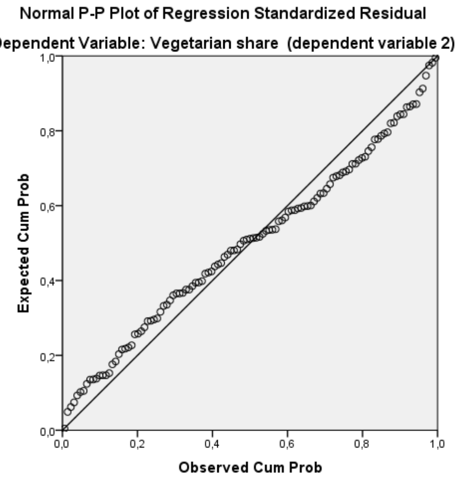
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,767[a]	,588	,380	,093571248298572	2,777

a. Predictors: (Constant), 95, 94, 93, 92, 91, 90, 89, 88, 87, 86, 85, 84, 83, 82, 81, 80, 79, 78, 77, 76, 75, 54, 53, 52, 51, 50, 49, 48, 47, 46, 45, 44, 43, 42, Green-only (treatment 1) , 41, 40, 39, 38

b. Dependent Variable: Vegetarian share (dependent variable 2)

7.4.3.4. Assumptions test: Normal P-P Plot



7.4.3.5. Assumptions test: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,048263676464558	,367738395929337	,192970025861525	,091149715802019	117
Std. Predicted Value	-1,588	1,917	,000	1,000	117
Standard Error of Predicted Value	,054	,056	,055	,001	117
Adjusted Predicted Value	,014492753893137	,417499423027039	,192970025861525	,099255664437877	117
Residual	-,246191799640656	,241851612925529	,000000000000000	,076235770019145	117
Std. Residual	-2,631	2,585	,000	,815	117
Stud. Residual	-3,241	3,166	,000	1,004	117
Deleted Residual	-,373532384634018	,362777411937714	,000000000000000	,115835143745306	117
Stud. Deleted Residual	-3,465	3,372	,001	1,025	117
Mahal. Distance	37,675	41,190	38,667	1,283	117
Cook's Distance	,000	,136	,013	,022	117
Centered Leverage Value	,325	,355	,333	,011	117

a. Dependent Variable: Vegetarian share (dependent variable 2)