Research Paper 32 | **2014**

CLEAN SUBSTITUTES AND THE EFFECTIVENESS OF CARBON FOOTPRINT LABELS VS. PIGOVIAN SUBSIDIES: EVIDENCE FROM A FIELD EXPERIMENT

B. LANZ, J.-D. WURLOD, L. PANZONE, AND T. SWANSON

Clean substitutes and the effectiveness of carbon footprint labels vs. Pigovian subsidies: Evidence from a field experiment*

Bruno Lanz[†] Jules-Daniel Wurlod[‡] Luca Panzone[§] Timothy Swanson[†]

September 2014

Abstract

We study how substitutability between clean and dirty alternatives affects the effectiveness of environmental regulation in a field experiment that controls for the choice set of respondents. We consider four product categories with clean and dirty alternatives: (i) cola products in plastic bottles vs. in aluminum cans; (ii) skimmed vs. whole milk; (iii) chicken meat vs. beef meat; and (iv) margarine vs. butter. We employ two neutrally framed treatments to quantify the willingness to substitute between clean and dirty alternatives in each product market, namely a change in relative prices and the removal of the dirty alternative, leaving respondents the option of buying one of the remaining clean alternatives or nothing. We then compare the impact of a carbon footprint label and a Pigovian subsidy to the clean alternatives. While both instruments increase the market share of the clean products, their impact is higher when clean and dirty alternatives are close substitutes. We also find evidence that motivation crowding is present and increases with substitutability. Our results highlight the importance of product markets in the design of consumer-orientated policies.

Keywords: Field experiments; Environmental policy; Market-based instruments; Information provision; Clean substitutes; Motivation crowding; Carbon footprint.
JEL Codes: C25; C91; D12; D64; L15; L50; Q58.

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*We benefited from comments and discussions with Emi Uchida, seminar participants at the 2014 BIOECON Conference and at the World Congress of Environmental and Resource Economists. We also thank Grischa Perino and Denise Leung for their involvement in the field work. Any remaining errors are ours.

[†]Department of Economics and Centre for International Environmental Studies, Graduate Institute of International and Development Studies, Switzerland.

[‡]Corresponding author. Centre for International Environmental Studies, Graduate Institute of International and Development Studies, Maison de la Paix, Chemin de Eugène Rigot 2, 1202 Geneva, Switzerland; Tel: +41 79 664 53 27; email: jules-daniel.wurlod@graduateinstitute.ch

[§]School of Agriculture, Food and Rural Development, Newcastle University, UK.

1 Introduction

Policy interventions to regulate the provision of public goods in general and environmental externalities in particular can take different forms: market-based instruments such as taxes and subsidies, direct regulation and standards, and information provision favoring voluntary contributions. While there are good theoretical arguments favoring market-based instruments for their efficiency property, recent empirical evidence suggests that labels can also have a significant impact on the behavior of consumers (e.g. Teisl et al., 2002). There exists, however, little evidence comparing the effectiveness of different policy instruments across different products, even though the availability of clean substitutes will be a key driver of the response to policy instruments.[1]

In this paper we employ a controlled field experiment on consumption choices across a range of products, offering the possibility to investigate how characteristics of products and policy instruments interact. While the importance of substitutability between clean and dirty alternatives is recognized in the literature (see Bjorner et al., 2004), substitution possibilities are difficult to empirically identify from market transactions as the full choice set of the consumer is typically unobserved. Existing studies have addressed this issue by using ad-hoc assumptions on the structure of demand, either considering only subgroups of products (as in Teisl et al., 2002; Vanclay et al., 2011; Michaud et al., 2013, for example), or making assumptions on the choice set available to consumers (Bjorner et al., 2004).

The field experiment we consider provides evidence about consumers' real purchasing decisions by manipulating information about the carbon footprint of four different products: cola-type sodas in aluminum cans and in plastic bottles, spreads (margarine and butter), milk, and meat (fresh chicken and beef). As described in detail below (see also Panzone et al., 2011 and Perino et al., 2014), each product category has an exhaustive set of options to consumers, with clean and dirty alternatives determined by their carbon footprint. The experiment then offers consumers the possibility to revise an initial consumption choice after being subject to one of

[1] Interestingly, consumers' willingness to substitute among goods is a key criterion to define product markets for the purpose of competition and market regulation policies. Thus far however environmental policies have not explicitly used that idea to design incentive mechanisms.

two randomly assigned treatments: (i) an information label showing the carbon footprints of products and (ii) the same information about the carbon footprint with, in addition, a Pigovian subsidy to the product with the low carbon footprint. Importantly, our experiment uses real consumption decisions and is incentive-compatible.

Information about the carbon footprint of products works through two channels. On the one hand, the information provided by the label makes consumers more aware of the environmental impacts associated with their choices, effectively turning a 'credence' good into a 'search' good (Cohen and Vandenbergh, 2012). On the other hand, its impact on consumer choices is driven by the existence of preferences for public vs. private goods attributes of each product, which has long been recognized in the literature (Harsanyi, 1955; Margolis, 1982; Nyborg, 2000).[2] The subsidy treatment will include a monetary incentive on top of the implicit information provision about the public good content of products (here the carbon footprint). According to standard economic theory, the subsidy should reinforce substitution away from dirty alternatives because it combines both monetary and information-based incentives. However, the literature on motivation crowding highlights that regulatory interventions adding a monetary reward when participation to public goods is voluntary can be counter-productive, as both stimuli can interact in non-trivial ways. Monetary instruments may thus affect intrinsic motivation positively (crowding-in), but, more often, negatively (crowding-out) (Frey and Jegen, 2001; Nyborg et al., 2006; Bowles, 2008). Our paper contributes to this literature by observing to what extent this mechanism is altered by the availability of close substitutes.

The effectiveness of the policy treatments hinges upon interactions between private and public good attributes. In the case we consider, carbon footprint is tied to product characteristics such as packaging, and the willingness to switch to clean alternatives will depend on whether the clean and dirty alternative are perceived to be close substitutes or not. In addition some product categories are expected to be more 'essential' in the consumption basket. Because the experimental setting allows us to control for the choice set available to consumers, we exploit

[2] Our paper also follows the extensive literature on altruism and private provision of public goods (Olson, 1965; Sen, 1977; Kotchen, 2005), which identifies different sources of gains from public good provision. First, agents derive utility from the (shared) private benefits from the public good. Second, benefits from public good participation can originate from pure altruism (see Becker, 1974; Cornes and Sandler, 1986; Kotchen, 2006). Third, consumers might also derive direct utility from their own contribution, through a *warm-glow of giving* (Andreoni, 1990).

further two "neutrally framed" treatments to quantify substitutability between clean and dirty alternatives. First, we use a neutral price change treatment, where the price of the clean alternative is reduced relative to the dirty product, in order to identify the demand price elasticity of the clean product. Second, we use a neutrally framed removal of the dirty alternative, giving participants the option to either chose one of the remaining clean alternatives or purchase nothing at all. This treatment allows us to identify the essentiality of product category by observing whether consumers prefer to buy nothing instead of the clean alternative.

In order to quantify how experimental treatments affected the market share of products, we model directly the substitution among clean and dirty options based on their underlying attributes and consumers' tastes for these in the random utility model (RUM) framework (Lancaster, 1966).[3] The RUM framework provides a rich basis to understand consumers' preferences for the characteristics of products, and how choices are affected by policy treatments controlling for preferences over attributes. We find that, on average, all our instruments increase the market share of the clean alternative. However, the significance of the impact (economic and statistical) is directly related to the substitutability between clean and dirty alternatives: as expected when the clean option is a good substitute for the dirty option, policy instruments perform better. In addition, we find that the magnitude of motivation crowding mechanisms identified in Perino et al. (2014) is affected by the availability of substitutes: if dirty alternatives in the choice set are not considered close substitutes (i.e. the cost of switching is high), the label and the subsidy treatments have a similar impact on the market share of the clean product. This suggests that when choices are mainly determined by preferences over private attributes the monetary incentive does not crowd out voluntary contributions (although it does not enhance it either).

Our study is related to the growing body of empirical evidence on the effectiveness of information labels on consumption behavior.[4] Several market-based studies have found a potential for eco-labels to affect market outcomes. Teisl et al. (2002) provide evidence about a positive

[3] Crucially this is possible because the experiment offered an exhaustive set of options to consumers.

[4] Panzone et al. (2011) and Perino et al. (2014) also analyze the data from this experiment but did not look specifically at differences across goods nor did they control for preferences over product characteristics. Thus the key contribution of the present paper is to employ a micro-consistent RUM framework that controls for initial preferences for clean and dirty alternatives and compare the impact of instruments on choice probabilities both within and across products in relation to substitution possibilities.

impact of eco-labels using data on the consumption of "Dolphin-friendly" canned tuna in the United States. Bjorner et al. (2004), using a large Danish consumer panel from 1997 to 2001, have identified a positive effect of the "Nordic Swan" label on consumers' marginal willingness to pay. Blamey and Bennett (2001) and Bennett et al. (2001) have also used a real market behavior setting to analyze demand for toilet paper products, and have observed that some labels have had an impact (recycled paper), while other do not (unbleached paper), suggesting that product characteristics matter in the effectiveness of labels. Finally the study by Vanclay et al. (2011) considers multiple products, but without explicitly modeling preferences for product attributes. Specifically they report that adding a green label on a set of 37 products increased the market shares of the clean products by 4 percent, and that this shift was greater for relatively cheap products. More interestingly, the authors have also observed a role of product attributes. When there was evidence about strong preferences for particular private attributes of the goods – in this case the packaging of milk products – then information-based instruments had no impact on market shares.

The remaining of this paper proceeds as follows. In Section 2, we describe the experimental setting, including the four different consumption goods we consider and the five policy treatments. In Section 3 and 4 we present our empirical specification and the results from our estimation. Section 5 concludes.

2 Experimental design

Data on consumer choices are collected in an experiment conducted in seven supermarkets in the greater London area in February and March 2010. Consumers entering the supermarket are offered to participate voluntarily in a "university-sponsored grocery shopping study". The experiment is described as neutrally as possible, "studying how people make REAL LIFE grocery shopping decisions". No other information on the purpose of the experiment is provided. In particular, environmental motivations are not mentioned at any point during the recruitment phase to avoid self-selection of environmentally friendly respondents. Respondents also have to complete the task independently, without the help of the experimenter.

Participants make initial purchasing decisions on a computer at the entrance of the supermarket.[5] Those who intend to buy products selected for the experiment, namely cola-type sodas, spreads (margarine and butter), milk, and meat (fresh chicken and beef), are then offered a £5 voucher to participate in the experiment, provided that they actually purchase the goods they chose in the experiment. The enforcement by making payment conditional on the actual purchase of goods selected is a key condition of the experiment: data collected represent revealed consumer preferences for food consumption, and indicate real market behavior. The compliance rate is 96 percent, and non-compliers are dropped from the sample.

Table 1 summarizes products and their public-good contents. In each of these categories, a range of options are offered to the consumers, each catering different private- and public-good components. The number of options is 12 for Cola products, 3 for milk, 10 for spreads and 7 for fresh meat products. The public good component here is the carbon footprint of the product over its life-cycle.[6] Each product category includes a number of clean and dirty options, and the differences in private attributes between the clean and the dirty option vary across product categories.

The categories of products presented to consumers allows us to observe substitutability between clean and dirty options. In particular, we expect that the substitutability between products will be higher in the case of cola products (cola in 2L PET bottle vs. cola in cans) and milk (decrease in fat content) than in the case of meat (chicken vs. beef) or spread (butter vs. margarine). Indeed in the case of cola products, only the packaging varies: the low-footprint product is cola in 2L PET bottle, whereas the high footprint is cola in aluminum cans. For milk, only the fat content changes the carbon footprint.[7] In the fresh meat category, the low-footprint product is chicken, whereas the high-footprint product is beef. The cost in terms of private preferences caused by the policy treatments will be higher for consumers if the type of meat matters. For the substitution between butter and margarine, which are not made of the same raw material – butter is made of milk, while spread is produced with vegetable oil – we expect substitution to be low. In addition, the importance of each product category in the consump-

[5] Screenshots of the tasks are provided in Appendix A.

[6] Note that the carbon footprint of the products does not affect consumer choice through private benefits since carbon emissions is a global public bad. Separating public and private attributes allows having a clearer picture of how private and public good characteristics each enter the consumers' choice process.

[7] A decrease for whole milk to skimmed milk decreases the carbon footprint in parallel.

Table 1: Products and options

Product category	Options dirty/clean	Carbon footprint (public good)	Taste/brand (private good)
Cola	Aluminum can PET bottle	1,020g 500g	Coca Cola, Pepsi Cola, Diet Coke, Diet Pepsi, Coke Zero, Pepsi Max
Milk	Whole Semi-skimmed Skimmed	1,800g 1,600g 1,400g	Sainsbury's own brand fresh milk
Spread	Butter Margarine	11,900g 675g	Lurpak, Anchor, Countrylife, Kerrygold, Sainsbury's own brand
Meat	Beef Chicken	16,000g/kg of beef 5,000g/kg of chicken	Minced meat, casserole steak, braising steak chicken breast, mini chicken fillet, drumsticks

Notes: Cola, milk and spreads products all have the same weight across versions.

tion basket also varies. For example, milk is expected to be more important in the consumption basket as compared to cola products.

In a second step, participants are randomly assigned to one of four treatments: an information label showing the carbon footprints of products, a Pigovian subsidy on the low-footprint product, a neutral price change of the same amount than the subsidy, and a removal of the high-footprints goods (for reasons unrelated to carbon footprints). Instruments are discussed more in details in the following sub-Sections. After being subject to the treatment, respondents are allowed to revise their initial choice. Finally, consumers are asked to purchase their final choice to get the £5 voucher. After the experiment, socio-demographic data on the respondents are collected.

A total of 993 shoppers completed the task (independently) and complied with all terms and conditions of the experiment, and are included in the sample, for a total of 1336 purchases of milk, 704 of butter, 506 of meat, and 556 of cola products. While our sample is not random, participants have diverse socio-economic background (see Appendix B). Age varied from 21-80 years of age (mean: 37), and a wide range of incomes, educational backgrounds, family status and political, ethnic and religious groups were included.

2.1 Carbon footprint labeling treatment

The labeling treatment consists in a carbon footprint label in the form of a stylized footprint and shows the amount of carbon dioxide equivalent GHG emissions (in grams) caused over the life-cycle of the product. As shown in Table 1, the difference in carbon footprints between clean and dirty alternatives varies across product categories. Simultaneously nutritional information is also provided to prevent respondents to easily guess the purpose of the experiment (see Appendix A, Figure A2).

2.2 Pigovian subsidy to the clean alternative

The Subsidy treatment decreases the price of the low-footprint good. For example, in the case of cola products, respondents are told that "There has been a price change. Products in plastic bottles have a 5p discount due to a GOVERNMENT SUBSIDY received on account of its low carbon footprint". Consumers would understand that the change in prices is caused by a government intervention. In addition, the same labels than in the labeling treatment are provided (see Appendix A, Figure A3).

The value of the subsidy is calibrated on the externality created by the consumption of the products. Starting from an estimate for the social cost of carbon of $£$70/tonne that is used in the UK (DEFRA, 2002; Pearce, 2003), we convert it into $£/kg$ of product using the following conversion equation:

$$70\frac{£}{tC} \times \frac{12}{44}\frac{tC}{tCO_2} \times 10^6\frac{gCO_2}{tCO_2} \times \Delta CF\frac{gCO_2}{kg} \tag{1}$$

were CF indicates the carbon footprint. In the case of milk and cola, the resulting value is below 0.5 pennies, therefore invisible to consumers. Consequently, the resulting value was multiplied by 10 in the case of cola products, while in the case of milk, instead of the difference in carbon footprint (200g CO_2) the value used is the full carbon footprint of whole milk (1800g CO_2).[8]

[8] This corresponds to the resulting value of the tax multiplied by 9.

The final values of the subsidies were: £ 0.05 for cola products in aluminum cans; £0.03 for semi-skimmed milk, or £0.06 for skimmed milk; £0.21 per kilo of chicken (absolute amount of discount depends on the weight of the chicken product chosen); and £0.43 for margarine.

2.3 Neutrally-framed price reduction of the clean alternative

The change in price in this treatment is identical to the subsidy, but the justification of the change in prices is framed in a neutral manner. For example the neutral price change for cola products is presented as follows: "There has been a price change. Products in plastic bottles have a 5p discount because of a change in the price of materials" (see Appendix A, Figure A4). The change in prices is thus caused by market conditions unrelated to environmental dimensions, making this treatment “environmentally neutral”. This treatment (which we label as “Dprice”) will allow us to identify how an exogenous price changes induces consumers to substitute towards the clean alternative without providing information about the environmental impact of each alternative.

2.4 Neutrally-framed removal of dirty alternatives

In this treatment all high-footprint alternatives are removed from the options available to the respondents, leaving consumers the choice between clean products in the choice set and alternatively not purchasing any of the remaining products. It is introduced with the following statement (in the case of Cola): "There has been a change in product availability. Products are not supplied in cans on account of the lack of availability of the necessary materials" (see Appendix A, Figure A5). This treatment will also allow us to identify the willingness of consumers to switch to the clean alternatives without information about the environmental impact of the products. In addition, it allows us to observe the “essentiality” of the product category by observing the share of customers opting out of the market.

3 Estimation strategy

For each category of product, there is a finite set of option from which the consumers can choose from, and each individual product is described by an exhaustive set of characteristics or

Table 2: Options, attributes and policy treatments

	Cola	Milk	Spread	Meat
Nr. of options	12	3	10	6
Product attributes				
Attribute 1	Can (=1)	Whole milk (=1)	Butter (=1)	Beef (=1)
Attribute 2	–	Semi-skim. milk (=1)	–	–
Attribute 3	Coca-Cola brand (=1)	–	Lurpak brand (=1)	Protein (in g)
Attribute 4	Light (=1)	–	Sainsbury brand (=1)	Salt (in g)
Attribute 5	Zero/Max (=1)	–	Anchor brand (=1)	Fat (in g)
Attribute 6	–	–	Kcal	–
Attribute 7	–	–	Proteins (in g)	–
Attribute 8	–	–	Carbohydrates (in g)	–
Attribute 9	–	–	Fat (in g)	–
Attribute 10	–	–	Salt (in g)	–
Policy treatments				
Info	Diff. in carbon footprint between clean and dirty alternative (in kg of CO_2)			
Subsidy	Subsidy to the price of the clean options (in GBP cents)			
Dprice	Decrease in price of clean options (in GBP cents)			
Removal	Removal of the dirty options (=1)			

Notes: Attribute 1 and 2 are directly related to the carbon footprint of the good (i.e. defines the 'dirty' product), except for milk in which the semi-skimmed alternative has a carbon footprint in between that of whole milk and skimmed milk alternatives.

attributes: price, brand and nutritional features. These are summarized in Table 2. For instance, in the case of cola products, characteristics are packaging (2L PET bottle or cans), brand (Coca-Cola or Pepsi), and "Light" or "Zero/Max" versions. For all product categories attribute 1 is a categorical variable equal to one if the product is one of the dirty option, i.e. the attribute that determines whether the item has a high carbon footprint. In the case of milk, because there are 3 different carbon footprints instead of 2, an additional attribute is used. Categorical variables are also used to measure brands, while nutritional values were coded as continuous variables, usually in grams.

An important feature of our experiment is that we observe 2 choices for each respondent. In the initial choice, the consumer reveals preferences for the attributes of each product by selecting his preferred alternative. In the second choice, product characteristics are manipulated by our treatments, altering the public good attributes (label and subsidy treatments) and relative prices (neutral price change). In the case of the removal treatments, consumers can choose to opt out of the market and we include an "outside option" as an additional alternative. This design allows us to estimate the impact of the treatments on choice probability separately from the inherent preferences for the goods on offer.

In this section we describe our basic approach to the analysis of observed choices, and how we identify substitutability of clean and dirty alternatives.

3.1 Multinomial choice model

Because the choice set for each product category includes a finite set of options we analyze choices in a standard multinomial logit (MNL) framework. Importantly, the behavioral foundation underpinning the MNL model is derived from Lancaster's RUM framework (Lancaster, 1966). In this setting, an individual n chooses an alternative i out of an exhaustive, finite set of mutually exclusive options if the utility of i is greater than any other alternatives in the choice set, with a probability given by:

$$Prob(U_{ni} > U_{nj}), \forall i \neq j \tag{2}$$

with $n = 1, \ldots, N$, $j = 1, \ldots, J$. Utility U_{nj} is decomposed into a deterministic part observed by the researcher, V_{nj}, and a random, unobserved part, ϵ_{nj}. Assuming that our utility function is linear in parameters, we obtain:

$$U_{ni} = V_{ni} + \epsilon_{ni} = \beta' X_{ni} + \epsilon_{ni} \tag{3}$$

where X_{ni} is a vector of alternative-specific covariates. In consequence, the probability that individual n chooses alternative i is:

$$P_{ni} = Prob(\epsilon_{ni} - \epsilon_{nj} < V_{ni} - V_{nj}), \forall i \neq j \tag{4}$$

i.e. if the unobserved part of utility overcompensates the difference in the observable utility. Assuming further that ϵ_{ni} is iid and follows a Gumbel distribution, we have the choice probabilities from the MNL specification:

$$P_{ni} = Prob(Y_n = i) = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \tag{5}$$

As well known, the ratio of choice probabilities depends only on attributes of alternatives i and j, giving rise to the so-called independence of irrelevant alternatives (IIA) property of the MNL model. As robustness check, we estimate a mixed logit model (MXL) that allows to relax the assumption of independence of irrelevant alternatives often biasing results in discrete choice estimations (McFadden and Train, 2000). For the mixed logit model, choice probabilities are:

$$P_{ni} = \int \frac{e^{x'_{ni}\beta}}{\sum_{j=1}^{J} e^{x'_{nj}\beta}} f(\beta|\theta) d\beta \tag{6}$$

As can be shown, the ratio of choice probabilities P_{ni}/P_{nj} in the case of MXL depends also on attributes of alternatives other than i or j, thereby avoiding the assumption of IIA.[9]

The estimation of the parameters is based on the following log-likelihood function:

$$logL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \log Prob(Y_n = j) \tag{7}$$

where d_{nj} is an indicator function equal to 1 if $Y_n = j$ and zero otherwise.

Our empirical specification allows us to identify choice patterns as triggered by our instruments free of other variations, as we control for preferences over product characteristics entering the choice set. However, because a change in the set of attributes will affect the choice probabilities of all options, the vector of estimated coefficients is not directly tied to the marginal effects. In addition, the estimated coefficients are not separately identified from the variance of the error term, so that they cannot be directly compared across models estimated for each product category. We thus consider two further measures derived from the estimation. First, we calculate elasticities of probability of choices w.r.t. a change in a given attribute from a given alternative i:

$$E_{iz_{ni}} = \frac{\partial P_{ni}}{\partial z_{ni}} \frac{z_{ni}}{P_{ni}} = \frac{\partial V_{ni}}{\partial z_{ni}} (1 - P_{ni}) \bar{z}_{ni} = \beta_z \bar{z}_{ni} (1 - P_{ni}) \tag{8}$$

[9] See Train (2009) for a detailed description of the MXL specification.

Second, we calculate the odds ratios, measuring the marginal impact of treatments on the ratio of the probabilities of choosing each option:

$$OR_{jk} = \frac{e^{\beta' x_{nj+1}} / \sum_j e^{\beta' x_{nj+1}}}{e^{\beta' x_{nj}} / \sum_j e^{\beta' x_{nj}}} \tag{9}$$

where we index utility by pre- and post- treatments (t and $t+1$). These two measures will allow us to compare estimation results both across instruments and across products.

3.2 Measuring substitutability between clean and dirty alternatives

Notionally, a key determinant of the effectiveness of policies is the availability of substitutes to the dirty alternative. In an MNL framework the neutrally framed treatments provide two natural measures of substitutability. First, we use the neutrally framed price change of the clean alternative to measure the price responsiveness of consumers. Because the availability of close substitutes is directly related to the demand price elasticity, we expect that if clean alternatives on offer for a given product category are considered as close substitute for the dirty alternative, the price elasticity of demand will be high. In other words, if clean and dirty alternatives are close substitutes the neutral price change will induces a large shift towards the clean product, translating into a large impact on choice probabilities.

The second measure of substitutability is afforded by the "exogenous removal" policy treatment. In this treatment, we observe how consumers behave when their (preferred) dirty version is removed from the choice set. We recover an estimate of the utility derived from the outside option associated with the choice of consumers not to purchase any product in the choice set. The rationale is that if utility of the clean (non-preferred) version i is too far from the preferred dirty version and does not reach minimal threshold, i.e. if they are not considered substitutes, the individual prefers not to purchase any of the clean alternatives. However, the estimate associated with the utility of the outside option also captures the importance or "essentiality" of the product category in the consumption basket. All else equal, consumers are more likely to opt out when their preferred version is removed from the choice set if the product category is non-essential, even if the remaining option is perceived to be relatively good substitute.[10]

4 Data and estimation results

4.1 Descriptive statistics of observed choices

Table 3 shows the number of 'clean' purchases across products and treatments before (t) and after the treatment ($t + 1$). In the case of the removal treatment, respondents could either purchase one of the clean versions of the product category or buy nothing (i.e. choose the outside good). The initial market shares of dirty alternatives are important – ranging from 49 percent for butter, to 62 percent for cola in cans, 80 percent for beef and 88 percent for whole and semi-skimmed milk. These figures show that dirty products account for a significant share of the market of each product categories, suggesting a role to play for policy intervention.

Descriptive statistics also suggest that instruments performed best for cola products. Note also that the case of milk is particular because the carbon footprint is not binary – high or low – but continuous. The impact of our treatment is twofold: respondents who initially purchased whole milk can purchase both semi-skimmed or skimmed options, and those who initially purchased semi-skimmed milk could purchase skimmed milk. Taken together, the overall impact on the semi-skimmed option may be ambiguous.

4.2 Econometric results

We now turn to the estimation of a discrete choice model specified in equations (2) to (9). Once estimated, this model allows us to: (i) quantify the impact of the policy treatments across products free of other variation; (ii) obtain a measure of substitutability directly estimated from the data; and (iii) evaluate how the impact of policy instruments varies with the substitutability between clean and dirty alternatives.

Estimation results from the MNL model are reported in Table 4. To make instruments comparable *across* product categories, we code them as continuous variables (see Table 1). Specifically,

[10] Note that the removal treatment is, in a sense, hypothetical in that participants in the experiments may still purchase the dirty alternative after completing the study. Nevertheless, it provides an interesting alternative to the price-related substitution pattern.

Table 3: Consumption patterns by product/instrument

		Info	Subsidy	Price	Removal
Cola	Purchases	62	64	63	76
	Clean t	23	20	17	35
	Clean $t+1$	36	32	44	66
	Changes	13	12	27	31
Spread	Purchases	83	71	82	84
	Clean t	42	40	32	42
	Clean $t+1$	52	45	42	75
	Changes	10	5	10	33
Meat	Purchases	56	63	69	56
	Clean t	7	13	15	14
	Clean $t+1$	18	19	23	44
	Changes	11	6	8	30
Milk	Purchases	162	147	168	175
	Skimmed t	23	9	14	24
	Skimmed $t+1$	35	16	24	95
	Changes	12	7	10	71
	Semi-skimmed t	84	79	97	85
	Semi-skimmed $t+1$	83	77	99	0
	Changes	-1	-2	2	-40
	Whole t	55	59	57	66
	Whole $t+1$	44	54	45	0
	Changes	-11	-5	-12	-31

Notes: For the "removal" treatment respondents who did not chose the clean alternative exited the market by choosing not to purchase any of the remaining clean alternatives.

the information label is coded as the absolute difference of the carbon footprint associated with clean and the dirty versions of each product, measured in kilograms of CO_2. In the case of milk, where the carbon footprint differs for whole, semi-skimmed and skimmed milk, the label treat-

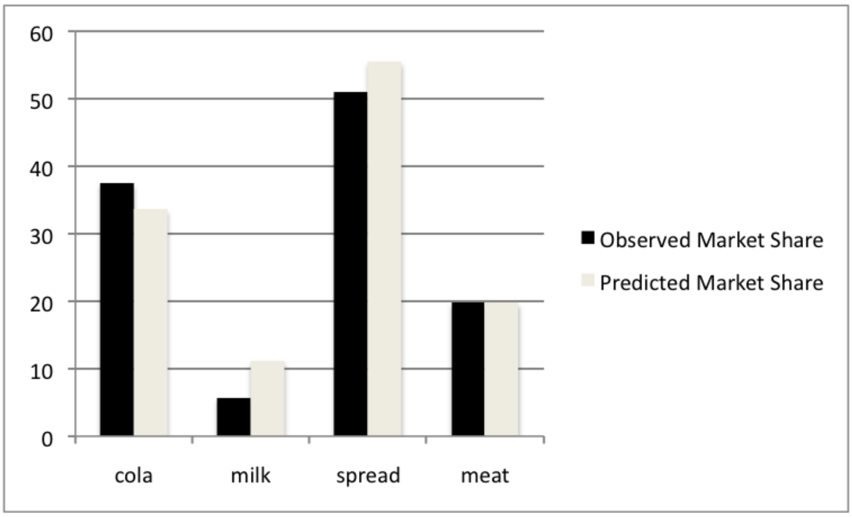


Figure 1: Predicted and observed market shares of clean products (%)

ment variable captures the difference with the footprint of the 'dirtiest' option (i.e. whole milk). The monetary treatments – subsidy ('subs') and neutral price change ('dprice') – are coded in GBP cents. The coefficients for the labeling treatment should thus be interpreted as the impact of a given difference in kilogram of CO_2 footprint between the clean and the dirty version, and of a given GBP cent of monetary instrument. Finally, the removal treatment offers respondents the possibility to exit the market in their second choice. These treatments are coded as categorical variables, and the utility of the 'outside' good is captured by an additional dummy variable ('remove outside').

The coefficients on attributes 1 and 2 inform us about preferences for products with a high carbon footprint. Consistent with initial market shares reported in Table 3, they have a positive impact on choice probabilities. Furthermore, most variables capturing preferences for products' attribute are statistically significant at conventional levels, suggesting that the model provides a good account of observed choices. This is confirmed by comparing the predicted market shares of clean products with the initial market shares observed from our sample (Figure 1).

Results confirm that most treatments have a statistically significant impact on the probability of choosing clean vs. dirty options, with the expected sign: treatments increase the market share of the clean options. The only exceptions for which variables associated with each treatment are not statistically significantly different from zero are the labeling treatment for meat products and the neutral price change for spreads. Treatments for skimmed milk are more effective than

Table 4: Estimation results – Multinomial logit model

	Cola (1)	Milk (2)	Spread (3)	Meat (4)
Info label	1.67***	.948***	.050**	.024
	(.427)	(.184)	(.022)	(.023)
Subs	.135***	.108**	.012**	.024*
	(.049)	(.026)	(.005)	(.013)
Dprice	.303***	.227***	.0004	.031***
	(.056)	(.039)	(.005)	(.012)
Removal	-19.07***	-20.61***	-17.09***	-17.85***
	(.157)	(.110)	(.150)	(.230)
Remove outside	.552	-.172	3.546***	3.985***
	(.380)	(.152)	(.619)	(.616)
Price	.0005		-.017***	-.001
	(.001)		(.003)	(.0004)
Attribute 1	.602***	1.877***	.998**	1.21***
(DIRTY VS CLEAN)	(.232)	(.031)	(.489)	(.190)
Attribute 2		2.190***		
(DIRTY VS CLEAN)		(.104)		
Attribute 3	1.71***		2.11***	.129***
	(.146)		(.347)	(.016)
Attribute 4	-.677***		-2.24**	-6.77***
	(.119)		(.521)	(1.25)
Attribute 5	-1.69***		.140	.221***
	(.173)		(.303)	(.020)
Attribute 6			.221	
			(.225)	
Attribute 7			-5.78**	
			(2.33)	
Attribute 8			.751	
			(1.50)	
Attribute 9			-1.88	
			(2.02)	
Attribute 10			.321	
			(.538)	
Respondents	333	809	396	312
Wald chi^2	50559.61	132556.82	48777.62	35191.07
Prob > chi^2	0.00	0.00	0.00	0.00
Pseudo R^2	0.2414	0.3098	0.1642	0.2491

Notes: Standard errors in parenthesis, clustered at the respondent level. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Policy instruments are coded in kg of CO_2 and in GBP cents. The list of attributes can be found in Table 2.

for semi-skimmed milk because respondents could move directly from whole milk to skimmed. We discuss the implication of these results in Section 4.4 below.

As robustness check, we estimate a mixed logit model as described in equation (6). Results are reported in Appendix C. We use random coefficients for product attributes only and treat treatment variables as fixed because we only observe one choice in the presence of the treatment.[11] While we find evidence of preference heterogeneity, as demonstrated by the standard deviations parameters in the MXL specification, results for the treatment variables are very close to those from the MNL model, suggesting that our estimates are robust to IIA.

4.3 Measures of substitutability

We now calculate our two measures of substitutability from the estimates in Table 4, namely the price elasticity and the impact of the product removal treatment. Table 5 reports elasticity estimates and odds ratio for the purchasing probabilities in the top and bottom panels respectively.[12]

Starting with the measure of price elasticity, measured by the impact of the neutral price treatment, recall that a large effect would reflect high substitutability between the clean and the dirty versions. In the case of cola products, a change in the price of 1 percent is translated in an increase in purchasing probability of 1.40 percent, 0.77 percent for milk, 0.56 percent for meat and 0.01 percent for spread. For the associated odds ratios, an increase of one GBP cent results in a change in the ratio of choice probability of 1.354 for cola, 1.255 for milk, 1.032 for meat and 1.000 for spread (i.e. no impact). These results suggest that the substitutability between clean and dirty alternative is highest for the cola category, followed by milk, fresh meat and finally by spread, where the impact of a change in relative price is close to none.

Results for our second measure of substitutability, resulting from the share of respondents not purchasing any good when their preferred dirty alternative is removed from the choice set, are by and large consistent with evidence from the neutral price change. Recall that the

[11] For more general specifications we encountered issues with the convergences of the simulated maximum likelihood procedure, so that the number of number of standard deviation parameters that can be estimated from the data is limited. Therefore our main results are derived from the MNL model.

[12] Recalling equation (9), an odds ratio higher than one (between zero and one) means that the covariate increases (decreases) the probability of choice.

Table 5: Measures of Substitutability of Clean vs. Dirty Versions

	Cola	Milk	Spread	Meat
Coefficients as Odds Ratio				
Price elasticity	1.354***	1.255***	1.000	1.032***
	(.076)	(.049)	(.005)	(.012)
Removal - outside option	1.736	.842	34.67***	53.77***
	(.659)	(.127)	(21.45)	(33.11)
Elasticities of Purchasing Probabilities				
Price elasticity	1.399***	.7657***	.0148	.560***
	(.056)	(.039)	(.005)	(.012)
Removal - outside option	.510	-.1289	3.223***	3.415***
	(.380)	(.152)	(.619)	(.616)
Respondents	333	809	403	312

Notes: Standard errors in parenthesis, clustered at the respondent level. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Price elasticity is based on the estimate for the neutral price change treatment coded in GBP cent and calculated at the mean of prices. The estimate for the outside option is based on the coefficient on the outside option measured as a categorical variable.

interpretation for this treatment is opposite: a high value of the elasticity / odds ratio would imply a high value of the outside option, reflecting a large share of consumer opting out the market. This would suggest that consumers do not perceive the remaining clean alternatives as sufficiently close substitute to the dirty products.

We find that consumers are more likely to opt out of the market in the case of fresh meat and spread, the non-substitutable product categories, than for cola and milk. For the two latter product categories the coefficients on the outside option becomes statistically insignificant.[13] Furthermore, the removal treatment suggests that substitutability between clean and dirty options is higher for cola product than for milk, although results from the neutral price change treatment suggest the opposite. The interpretation is that consumers are more likely to purchase a less-preferred version if the product is more important in the food basket, as in the

[13] Note that the magnitude of the odds ratio for the non-substitutable product categories is very high, which reflects the fact the initial market share of the outside option is close to zero by definition.

case of milk, as opposed to cola products. A similar effect is observed for non-substitutable product categories: spread products are found to be more essential than fresh meat products, presumably due the high number of end-uses associated with spreads.

4.4 Effectiveness of Policy instruments

Having identified substitution possibilities for each product category, in this section we explore whether the availability of close substitutes translates into higher effectiveness of the carbon footprint policies. In order to assess the behavioral impact of the carbon footprint label and Pigovian subsidy both within and across products we use two alternative measures derived from the RUM framework. With the first our aim is to compare the impact of instruments across product categories and identity how the availability of clean substitute influence the impact of instruments. As previously, because differences in effectiveness across product categories could be triggered by differences in the level of externality rather than in the availability of substitutes, treatments are coded according to the level of externality: the information label is coded in kilograms of CO_2 – the difference of CO_2 footprint between the clean and the dirty version – and the monetary instruments in GBP cents. In the second specification we compare policy instruments within each product category, and they are thus coded as categorical variables. This will allow us to quantify potential crowding out effects.

The results are provided in Table 6. In the top panel we report odds ratios to compare instruments across products.[14] Important differences across products are evident: instruments are more effective for product categories where clean versions were identified as close substitutes, namely cola and milk, than for spread and fresh meat. All else equal, a carbon footprint label and a subsidy on cleaner options perform better when the cost of switching in terms of private preferences is low. Similarly, a subsidy (in GBP cents) has a larger behavioral impact for cola and milk than for spread and meat. While these results accord with expectations, the differences are economically significant. For meat products we find almost no impact of the policy treatments on choice probabilities, while for cola products the probability of choosing a clean alternative is

[14] Figures in Specification 1 are to be interpreted as the impact of label and the subsidy, in kilogram of CO_2 and GBP cent respectively, on the relative choice probabilities.

Table 6: Effectiveness of Policy Instruments

		Cola	Milk	Spread	Meat
Specification 1 - Comparison of instruments across product categories					
Info	OR	5.313***	2.580***	1.051**	1.024
		(2.27)	(.290)	(.023)	(.023)
Subsidy	OR	1.145***	1.113***	1.012**	1.024*
		(.056)	(.030)	(.005)	(.013)
Specification 2 - Comparison of instruments within product categories					
Info	Coeff.	1.01***		.491**	.677**
		(.247)		(.213)	(.294)
Infosemi	Coeff.		.362**		
			(.173)		
Infoskim	Coeff.		1.96***		
			(.207)		
Subsidy	Coeff.	.683***		.512**	.570**
		(.488)		(.229)	(.261)
Subs. semi	Coeff.		.082		
			(.163)		
Subs. skim	Coeff.		.970***		
			(.272)		
Respondents		333	809	403	312

Notes: Standard errors in parenthesis, clustered at the respondent level. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. In specification 1, instruments are coded in kilograms of $C0_2$ and GBP cents. In specification 2, treatments are coded as categorical (dummy) variables. Thus in specification 1 the magnitude of coefficients can be compared *across* products, while in specification 2 it can be compared *within* products.

multiplied by a factor of five.

In the bottom panel of Table 6 we compare instrument within each product category to assess the effectiveness of different types of incentives. Here the label and the subsidy treatments refer to the same level of externality.[15] As mentioned previously, the subsidy treatment combines

[15] Note that within product comparison can be done directly on the basis of the marginal utility estimates. In the case of milk, because the treatment is continuous, 2 dummies had to be added.

a monetary incentive with information about the public good content of products, and can thus expected to have a greater impact than an information label alone. However, for 3 out of 4 products, the labeling treatment has a higher impact on the purchasing probability of clean goods than a subsidy calibrated on the same level of externality. This is consistent with Perino et al. (2014) and can be interpreted as motivation crowding: the monetary incentive in the subsidy treatment tends to reduce the impact of information working through intrinsic motivation.[16]

More interestingly, differences between the behavioral impact of the label and the subsidy is greater for cola and milk, i.e. where clean and dirty alternatives are perceived to be close substitutes. In other words, motivation crowding increases if the private cost of switching from the preferred dirty alternative towards the clean option is low. Importantly, when consumers have strong preferences for the private attributes of the goods, both instruments are relatively ineffective in affecting market shares. This translates first into low effectiveness of policies for those product categories, but it also lowers motivation crowding effects.

In sum, when consumers consider that the clean and dirty alternatives are not good substitutes preferences over the private attributes of the goods are the main determinant of choices. Conversely when there is no strong preferences for the private attribute associated with the externality, so that clean and dirty alternatives are good substitutes, market shares are responsive to policy interventions but also subject to motivation crowding.

5 Conclusion

While there is an increasing amount of evidence about the impact of environmental policies on consumer choices, comparisons between alternative policy instruments in a "real" consumption choice setting remains scarce. In addition, there is little evidence about how similar policy instruments influence consumption choices across different products, and in particular how the existence of 'clean' substitutes will impact the effectiveness of alternative policy instruments. Against this background our study has allowed to analyze and compare a label and a Pigovian subsidy to internalize the carbon footprint of products, and evaluate how the instruments

[16] Note that Perino et al. (2014) do not distinguish between the impacts of different goods but rather focus on aggregated motivation crowding patterns.

performed across a range of frequently-purchased products.

Our results suggest that, on average, information labels and monetary incentives increase the market share of clean alternatives. However, differences across products were found to be important. Using two empirical measures of substitutability between clean and dirty alternatives – namely a price elasticity and a measure of the propensity of consumers not to purchase anything when their preferred alternative is removed form the choice set – we established that substitutability is associated with a higher effectiveness of both policy treatments. If there exists strong preferences for the private attribute of the dirty products, monetary instruments and information provision are found to be less effective. Substitutability between alternatives was also found to alter motivation crowding mechanisms. Indeed for products where close substitutes were available the impact of the labeling treatment is significantly larger than that of the subsidy treatment.

We close by highlighting two potential limitations to the conclusions of our work. First, purchases for the categories of goods we consider tend to be carried out by habits (Ouellette and Wood, 1998). This is associated with a tendency to devote less time and effort to the decision process (Verplanken et al., 1997), so that consumers may be less sensitive to new attributes entering the decision process. Therefore, the impact of policy instruments could be lower than that observed through experimental treatments. From this perspective, our work provides an interesting complement to studies using non-experimental consumption behavior such as Teisl et al. (2002) and Bjorner et al. (2004), as these have shown that labels have an impact on market shares in a setting closer to day-to-day transactions. Second, the regulation we consider focus on carbon emissions, which are associated with a pure public good. However many environmental labels tend to combine both private good and public good components. For example, organic products have public good component such as using less pesticides, but these are also associated with private benefits such as being more healthy for consumers (e.g. Bougherara and Combris, 2009). Therefore, while focusing on a pure public good has afforded a clearer understanding of the impact of policy interventions, whether our results carry over to a setting that mixes public and private incentives remains an important research question.

Appendix A Screenshots of the experiment for cola products

Figure A1: Screenshot for the initial purchase of cola products

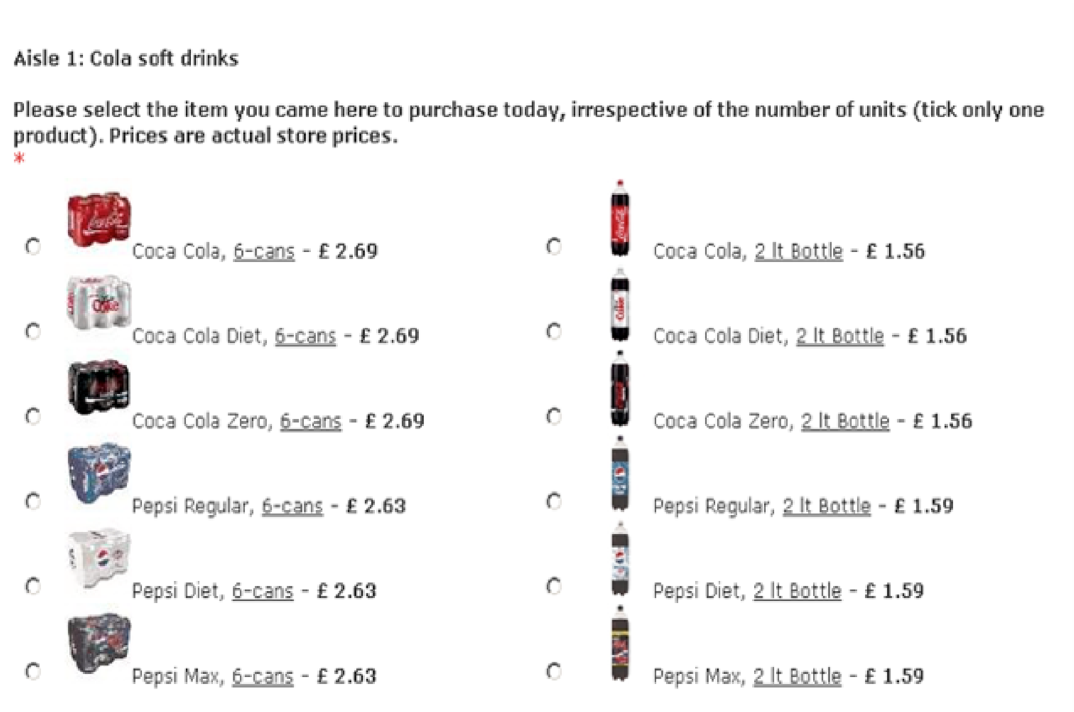
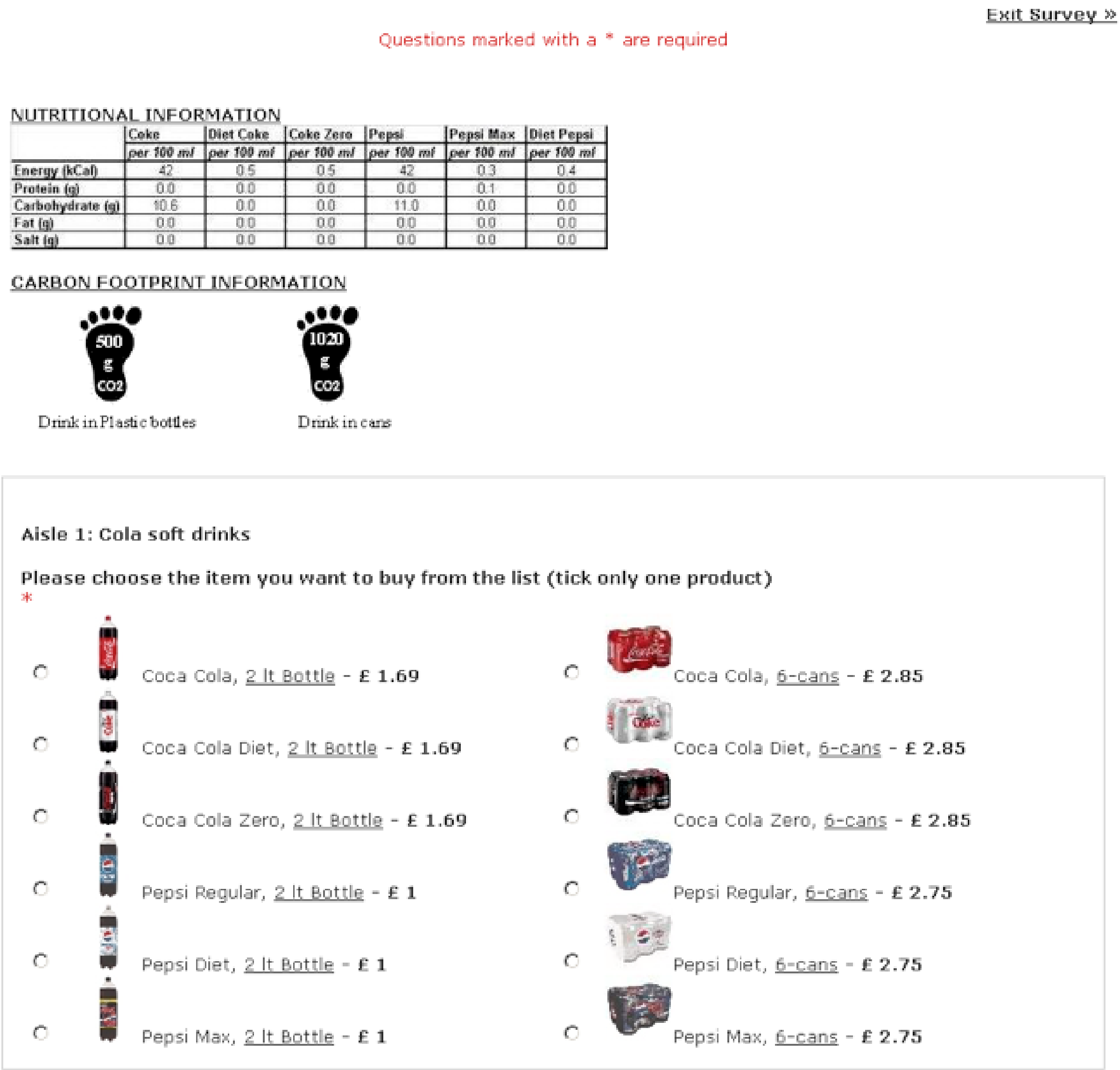


Figure A2: Screenshot for the labeling treatment



Exit Survey »

Questions marked with a * are required

NUTRITIONAL INFORMATION

	Coke	Diet Coke	Coke Zero	Pepsi	Pepsi Max	Diet Pepsi
	per 100 ml	*per 100 ml*	*per 100 ml*	*per 100 ml*	*per 100 ml*	*per 100 ml*
Energy (kCal)	42	0.5	0.5	42	0.3	0.4
Protein (g)	0.0	0.0	0.0	0.0	0.1	0.0
Carbohydrate (g)	10.6	0.0	0.0	11.0	0.0	0.0
Fat (g)	0.0	0.0	0.0	0.0	0.0	0.0
Salt (g)	0.0	0.0	0.0	0.0	0.0	0.0

CARBON FOOTPRINT INFORMATION

500 g CO2

Drink in Plastic bottles

1020 g CO2

Drink in cans

Aisle 1: Cola soft drinks

Please choose the item you want to buy from the list (tick only one product)
*

- Coca Cola, 2 lt Bottle - £ 1.69
- Coca Cola, 6-cans - £ 2.85
- Coca Cola Diet, 2 lt Bottle - £ 1.69
- Coca Cola Diet, 6-cans - £ 2.85
- Coca Cola Zero, 2 lt Bottle - £ 1.69
- Coca Cola Zero, 6-cans - £ 2.85
- Pepsi Regular, 2 lt Bottle - £ 1
- Pepsi Regular, 6-cans - £ 2.75
- Pepsi Diet, 2 lt Bottle - £ 1
- Pepsi Diet, 6-cans - £ 2.75
- Pepsi Max, 2 lt Bottle - £ 1
- Pepsi Max, 6-cans - £ 2.75

Figure A3: Screenshot for the Pigovian subsidy treatment

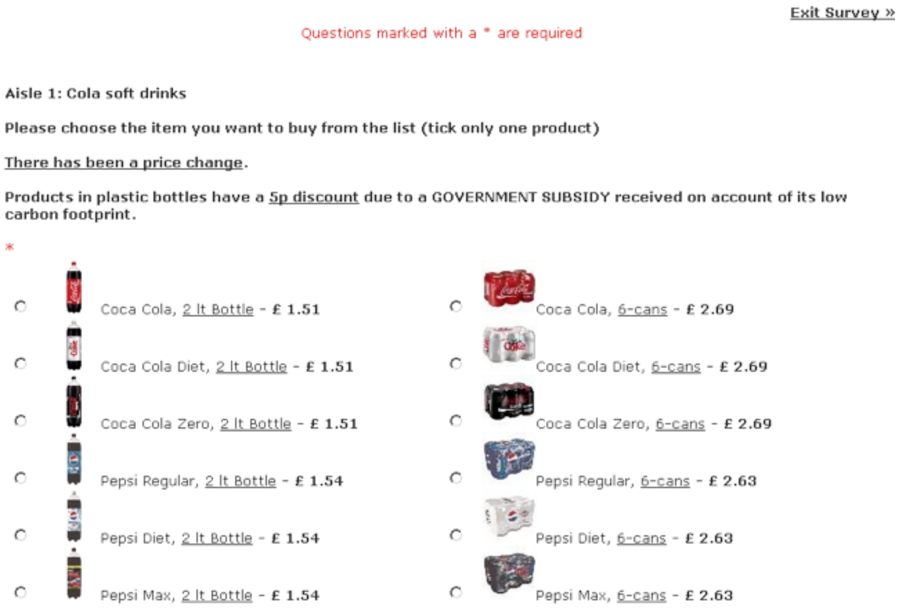


Figure A4: Neutral price change treatment

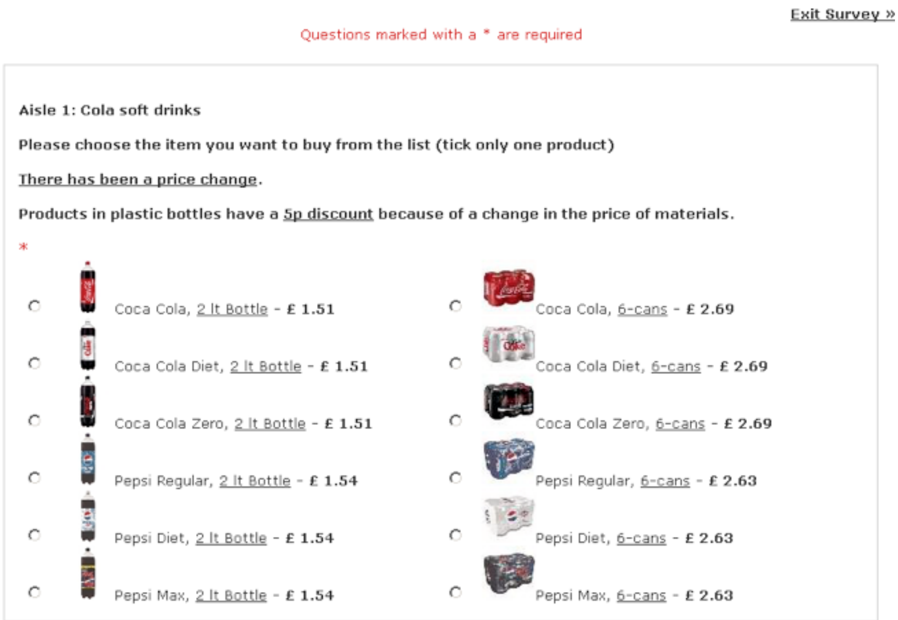
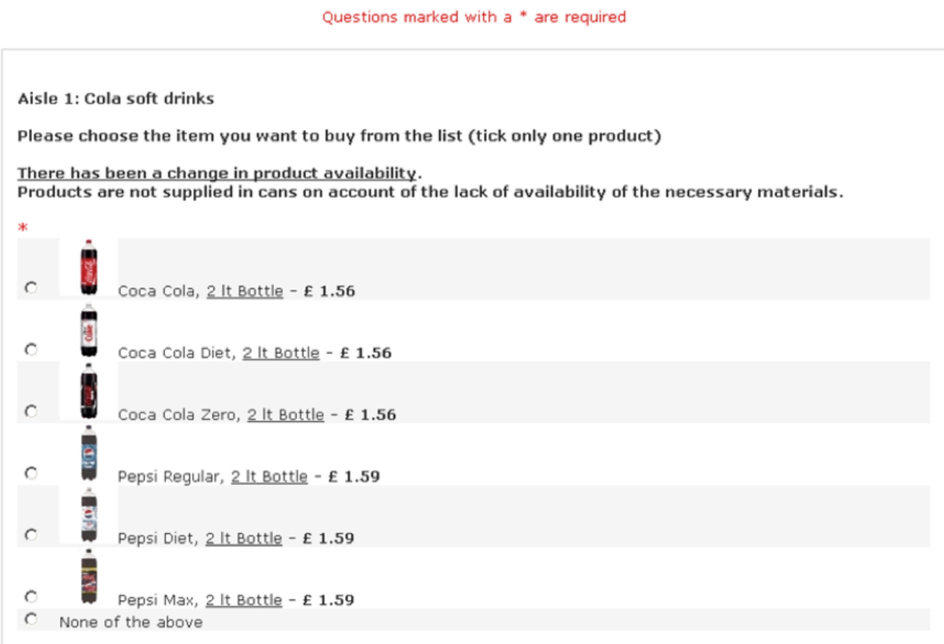


Figure A5: Neutral product removal treatment


Questions marked with a * are required

Aisle 1: Cola soft drinks

Please choose the item you want to buy from the list (tick only one product)

There has been a change in product availability.
Products are not supplied in cans on account of the lack of availability of the necessary materials.

*

- Coca Cola, 2 lt Bottle - **£ 1.56**
- Coca Cola Diet, 2 lt Bottle - **£ 1.56**
- Coca Cola Zero, 2 lt Bottle - **£ 1.56**
- Pepsi Regular, 2 lt Bottle - **£ 1.59**
- Pepsi Diet, 2 lt Bottle - **£ 1.59**
- Pepsi Max, 2 lt Bottle - **£ 1.59**
- None of the above

Appendix B Demographic variables by product subsample

Variable	Mean	Std. Dev.	Min	Max
Cola subsample (N=346)				
Male dummy	0.439	0.497	0	1
Age (in years)	33.62	11.6	18	72
Education[a]	1.766	0.765	1	3
Income categories[b]	3.9	2.763	1	9
Children in the Household	.630	1.036	0	6
Non-white dummy	0.451	.50	0	1
Milk subsample (N=825)				
Male dummy	.358	.480	0	1
Age (in years)	37.07	12.03	18	80
Education[a]	1.802	.733	1	3
Income categories[b]	4.024	2.792	1	9
Children in the Household	.632	1.00	0	6
Non-white dummy	.360	.48	0	1
Spread subsample (N=431)				
Male dummy	.336	.473	0	1
Age (in years)	38.26	12.24	18	79
Education[a]	1.789	.747	1	3
Income categories[b]	3.807	2.684	1	9
Children in the Household	.649	1.011	0	6
Non-white	.379	.49	0	1
Meat subsample (N=322)				
Male dummy	.373	.484	0	1
Age (in years)	38.39	12.22	18	79
Education[a]	1.748	.729	1	3
Income categories[b]	3.901	2.641	1	9
Children in the Household	.540	1.01	0	6
Non-white	.27	.45	0	1

Notes: [a]Education is coded as: 1 – Non-university education or equivalent; 2 – Graduate level (including current undergraduate students) - and any other university diploma; and 3 – Post-graduate level (including current postgraduate students). [b]Income is coded from 1–8, from 15'000 to 75'000 pounds annually.

Appendix C Estimation results – Mixed logit model

	Cola (1)		Milk (2)		Spread (3)		Meat (4)	
	Coeff.	S.D.	Coeff.	S.D.	Coeff.	S.D.	Coeff.	S.D.
Info label	1.64***		.934***		.052**		.028	
	(.433)		(.107)		(.024)		(.025)	
Subs	.132***		.149***		.014**		.029**	
	(.050)		(.025)		(.006)		(.014)	
Dprice	.302***		.215***		.005		.044***	
	(.056)		(.022)		(.006)		(.014)	
Removal	-25.9***		-24.9***		-24.6***		-24.0 ***	
	(.158)		(.112)		(.767)		(.354)	
Remov. outside	.981*		-.131		7.71***		3.69***	
	(.564)		(.152)		(1.93)		(.464)	
Price	-.0006				-.031***		-.000	
	(.001)				(.006)		(.000)	
Attribute 1	.695***		.206***	-0.01	-.666		1.22***	
	(.239)		(.009)	(.050)	(1.013)		(.224)	
Attribute 2	3.40***	3.02***			1.606	-5.76**	.105***	.000
	(.428)	(.470)			(1.029)	(1.045)	(.015)	(.005)
Attribute 3	-2.99***	6.05***			-6.747	-5.88*	-5.90***	3.24
	(.618)	(1.07)			(4.472)	(3.28)	(1.42)	(2.15)
Attribute 4	-7.24***	6.16***			-2.19***	5.61***	.222***	.17***
	(1.45)	(1.04)			(.790)	(.944)	(.021)	(.022)
Attribute 5					-.331	.009***		
					(.343)	(.002)		
Attribute 6					-.485			
					(4.52)			
Attribute 7					-1.33			
					(1.84)			
Attribute 8					3.19			
					(3.08)			
Attribute 9					2.82**			
					(1.15)			
AIC	2281.1		3600.4		2819.6		1799.3	
BIC	2370.7		3651.5		2945.0		1878.6	
Wald chi2	92362.8		193432.0		14761.9		14761.8	
Prob> chi2	0.00		0.00		0.00		0.00	

Notes: Standard errors in parenthesis, clustered at the respondent level. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Instruments are coded in kg of CO_2 and in GBP cents. Random coefficients are attributes of products except price variable and Attribute 1. For butter, some additional attributes (prot, carb, fat, salt) are treated as non-random variables to ensure convergence.

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