The Impact of Child Obesity News on Household Food Expenditure in the United Kingdom

Andres Silva*
Marian Garcia*
Alastair Bailey**

***Kent Business School, University of Kent, Canterbury,
CT2 7PE, United Kingdom.
Email: asilvam@uc.cl**

****School of Economics, University of Kent, Canterbury,
CT2 7NP, United Kingdom.**

***Selected Paper prepared for presentation at the Food Environment Symposium
AAEA & EAAE Joint Meeting, Boston, Massachusetts, May 30-31, 2012***

Abstract

The United Kingdom (UK) has one of the highest obesity levels in the world (Mazzocchi *et al.*, 2009). As indicated by the National Health Service (2010), 25% of adults and 17% of children are obese in the UK. This last statistic represents an increase of four points in comparison to 1995. The Government Office for Science (2010) estimated that by 2050, half of the UK population would be obese, with a consequent direct annual cost of £10 billion and an indirect annual cost of £50 billion at today's prices.

This research aims to contribute to the debate on how health-related information impacts household food expenditure and whether this impact varies across income groups and household composition. This study specifically measures the impact of child obesity news on household food expenditure in the UK. To this end, the study calculated a set of elasticities for different income groups (high vs. low) and family composition (families with and without children). This set of elasticities gives us a measure of responsiveness, to change in terms of price, income and news.

The results indicate that child obesity news causes different impacts on households according to their income level and household composition. Low-income households without children are not significantly impacted by child obesity news. Low-income households with children change their food expenditure composition to a healthier diet without changing the overall food expenditure. High-income households without children decrease their overall food expenditure, mainly changing red meat for dairy products. Finally, high-income households with children increase their overall food expenditure and move on to a healthier diet. Therefore, in three out of four household cases, child obesity news causes a different and positive impact on diet.

Low-income households with children in default-mode spend the smallest proportion of their income on fruit and vegetables; which is even less than low-income households without children. More importantly, low-income households with children influence the nutritional habits of their children. This research shows that low-income households with children respond to child obesity news and move on to a healthier diet without causing undesirable income redistribution.

The Impact of Child Obesity News on Household Food Expenditure in the United Kingdom

1. Introduction

Public authorities around the world are concerned about increasing levels of obesity in the population. In a context of insufficient physical activity (NHS, 2010), and increasing sugar and fat consumption (MacInnis and Rausser, 2005), more people are becoming obese (Hill *et al.*, 2003). The United Kingdom (UK) in particular has one of the highest obesity levels in the world (Mazzocchi *et al.*, 2009). As indicated by the National Health Service (NHS) (2010), 25% of adults and 17% of children are obese. This last statistic represents an increase of four percentage points in comparison to 1995.

Neoclassical economic theory justifies governmental intervention when an activity generates externalities. An externality occurs when the private assessment is different from the social assessment (Varian, 2002). Consequently, prices do not reflect the social-resource costs of production. In this sense, utility maximisation problem leads to a suboptimal allocation of resources. The market price does not reveal the actual cost or benefit for the society.

Moreover, the Government Office for Science (2010) estimated that by 2050, half of the UK population would be obese, with a consequent direct annual cost of £10 billion and an indirect annual cost of £50 billion at today's prices. In the context of increasing obesity costs, governments have put in place public policies to control obesity costs. Government intervention can, in the first instance, be justified as a way of controlling the high and rapidly-increasing obesity costs (Finkelstein *et al.*, 2010). In countries such as the UK, the public sector is the primary health provider. The NHS is the public agency in charge of supplying a national health service to the population. Therefore, increasing obesity is giving rise to increasing costs for the UK government.

This research aims to contribute to academic discussion with respect to the effect of information policy on diet. Policy interventions are more likely to be implemented if they are correctly justified by academic research. In particular, this study provides empirical evidence of the impact of child obesity news on household food expenditure in different types of households in the UK, in terms of income levels and family composition.

In addition, this study aims to characterise the food decision process. With the exception of Tiffin and Arnoult (2010), no recently published study has calculated household food elasticity in the UK. Some studies such as Tiffin and Tiffin (1999), Burton, Young and Cromb (1999), Duffy (2003), have focused on a particular sector rather than on overall household food consumption. Regardless, most of these publications use data which are over ten years old. By comparison, this study calculates elasticities for households of different income levels and household composition using recent, up-to-date data.

This study is one of the few that distinguish between eating out and food at home expenditure, which is not trivial. Okrent and Alston (2011) shows that studies with aggregated dataset tend to produce smaller elasticity estimation than studies that separate eating out and food at home expenditure. Therefore, many researchers overlook this fact that would have strong implications.

We specifically isolate the impact of child obesity news on UK household expenditure. The empirical model specification and dataset of this study can be used to identify news that can have a significant impact on specific population segments. Therefore, the outcome of this study should be of interest to UK public institutions, in the design of public information campaigns. Information based policies are an alternative means of making more information available to households about their food choices. The UK government can create news to target a predetermined population segment, such as promote events, disseminate program or create any news that can help to form healthy eating habits. Even a small but significant impact, would make it a policy tool which could be used to help build a more balanced diet. For instance, it would be interesting to find the type of news that makes low-income households with children respond. Low-income households with children is the group that spends the smallest proportion of their income on fruit and vegetables, even less than low-income households without children, who are causing a long-term impact on their children.

We have selected child obesity news, since it is an especially relevant issue. Despite the fact that some studies have tried to quantify obesity costs, it is not possible to foresee the full consequences of child obesity (Ehmke *et al.*, 2008). It is clear that an obese child is more likely to become an obese adult (MacInnis and Rausser, 2005). Further, an obese child is at greater risk of poor health in adolescence and in adulthood (OECD, 2010). Therefore an

obese child would need more medical attention than a healthy child. Moreover, childhood obesity would potentially require long-term medical attention, compared to obesity in adulthood. In the UK this medical attention is primarily paid for by the public health system.

Taking into account the increasing child obesity rate, and the fact that children are more receptive to new information and to forming eating habits (OECD, 2010), an early intervention in life is crucial if we are to reduce increasing obesity costs. An early intervention should at the very least consist of providing households with relevant information to enable them to make conscientious food choices.

The current study addresses the problem of how child obesity news impacts food expenditure consumption in the UK. This research problem can be summarised in the following research hypotheses:

(1) taking into account income levels and household composition, child obesity news has a significant impact on overall food expenditure.

(2) taking into account income levels and household composition, child obesity news has a significant impact on specific food groups.

The remainder of this article is organised in the following way: firstly, we select the methodology for measuring the effect of information, and characterises the selected dataset. The methodology is required to be consistent with neoclassical economic theory, and to be flexible enough to incorporate child obesity news in the analysis. Thirdly, we present the estimation results, discuss the findings and make policy recommendations.

2. Methodology

2.1 Model

We use the Almost Ideally Demand System (AIDS). The AIDS model has a key advantage that enables, not just impose symmetry and homogeneity, the testing of the negative semi-definiteness of the Slutsky matrix at each data point, which corresponds to the concavity of the expenditure function condition (Barnett and Seck, 2008). Similar to homogeneity,

symmetry, and adding-up, the concavity of the expenditure function is a desirable economic property in a demand system.

The AIDS model explains budget shares as a function of, at least, prices and income. Assuming *m* groups of products:

$$w_{it} = \Omega_{it} + \sum_{j=1}^{m} \gamma_{ij} \ln P_{jt} + \beta_i(lny_t - lnP_t) + e_{it}$$

w_{it} is the expenditure budget share of product *i* in time *t,* equivalent to $p_{it}q_{it}/y_t$, p_{it} is the price of product *i*, q_{it} is the quantity of product *i,* Ω_{it} is the intercept, γ_{ij} is the change in the *i* product budget share with respect to p_t, holding constant the total expenditure. The term β_i is the change in the budget share with respect to a change in real expenditure, holding price constant, and e_{it} is the error term.
The intercept has the following structure:

$$\Omega_{it} = \alpha_i + \delta MI_i + \sum_{t=1}^{3} \theta_t D_t + \vartheta_i w_{it-1}$$

where, α_i is the new intercept, MI_i is the media index, D_t is a set of quarterly dummy variables to take seasonality into account. The term w_{it-1} is the lagged budget share for group *i*, this last variable is used to model habit patterns. The statistical significance of δ would indicate whether child obesity news index causes a statistically significant impact on expenditure share.

The translog non-linear AIDS price index, P_t, can be linearly approximated using the Stone index. When the Stone index is used instead of the non-linear price index the estimated demand system is known as the 'linear approximate AIDS' or LA/AIDS model. The Stone index is built in the following way:

$$lnP_t = \sum_{i=1}^{m} w_{it} \ln (p_{it})$$

However, the Stone index has been critised that is not independent to the unit of measurement (Asche and Wessells, 1997). Asche and Wessells (1997) suggests using a modified version of the Stone index. This study uses the Paasche-corrected Stone index:

$$lnP_t^S = \sum_{i=1}^{m} w_{it} \ln (p_{it}/p_t^0)$$

P_t^S is the Paasche-corrected Stone Index and (p_{it}/p_t^0) is the normalised price. In this way, the prices become independent of the unit of measurement. The AIDS model also allows for testing the following theoretical constraints:

The adding-up restriction requires that the budget constraint be satisfied over changes in prices and income. In adding-up, the sum of the estimated expenditure on the commodities is equal to the total expenditure in every period *t*:

$$\sum_{i=1}^{m} \alpha_i = 1, \sum_{i=1}^{m} \beta_i = 0, \sum_{i=1}^{m} \gamma_{ij} = 0$$

The homogeneity restriction implies that every demand equation must be homogeneous at degree zero in income and prices. In other words, price and income units have no effect on preferences. In degree-zero homogeneity, the relative prices are held constant as is the expenditure, so budget share would also remain the same (Verbeke and Ward, 2001):

$$\sum_{j=1}^{m} \gamma_{ij} = 0$$

Finally, there are the Slutsky symmetry conditions. The Slutsky equation shows that price derivatives of a demand equation can be decomposed into an income effect and a substitution effect. In Slutsky symmetry, the substitution effect of the product *i* with respect to product *j* is equal to the substitution effect of product *j* with respect to product *i*.

$$\gamma_{ij} = \gamma_{ji}$$

Concavity of the expenditure function can also be empirically tested. Concavity in prices of the expenditure function implies a negative semi-definite Hessian (Michalek and Keyzer, 1992). The Hessian is the Slutsky, `*S*', matrix of compensated price responses, also known as the substitution matrix. Non-positive diagonal elements, negative compensated own-price elasticities, are a necessary condition for a negative semi-definite Hessian (Deaton and Muellbauer, 1980). Non-positive eigenvalues are a necessary and sufficient condition for a

negative semi-definite Hessian (Dietrich, 2008, Moschini, 1998, Deaton and Muellbauer, 1980b). The Hessian matrix is composed in the following way:

$$S = \frac{\partial^2 E}{\partial p_i \partial p_j}$$

$$S_{IJ} = \frac{\partial h_i(p,u)}{\partial p_j} = \frac{y}{p_i p_j}\left(\gamma_{ij} + \beta_i \beta_j \log\frac{x}{P} + w_i w_j - \delta_{ij} w_i\right)$$

where *E* is the expenditure function, *y* is the total expenditure, p_i and p_j are the prices, β_i, β_i and γ_{ij} are parameters of the cost function, w_i and w_j are the budget shares and δ_{ij} is the Kronecker delta. The Kronecker delta is equal to "0" if *I=J*, and one otherwise. According to Michalek and Keyzer (1992), the *`k'* elements of the matrix *`S*" can be calculated in the following way:

$$k_{ij} = \gamma_{ij} + \beta_i \beta_j \log\frac{y}{P} + w_i w_j - \delta_{ij} w_i$$

Commonly, concavity is tested only at the sample mean. However, theoretical consistency of the estimated function should ideally be tested at each data point (Sauer, 2006). Following the procedure presented by Baum and Linz (2009) that uses the above expression to calculate each element of the Hessian matrix, this study tests concavity at each point of the sample space, which means calculating a set of eigenvalues at each point.

The system of equations is estimated using a Seemingly Unrelated Regression (SUR) model, which calculates the parameters assuming that the error terms are correlated. These parameters are used to calculate elasticities. Green and Alston (1990) presented how to calculate the elasticities in the LA/AIDS model. Using simulated data, these elasticity expressions were tested empirically by Alston, Foster and Green (1994). The authors found that LA/AIDS can produce accurate elasticity estimations. However, these expressions are for a single stage.

Since they are observable, for policy analysis purposes unconditional elasticities are more informative than conditional elasticities (Rickertsen *et al.*, 2003). Consequently, we need to calculate the unconditional elasticities in the second stage using food budget shares and

unconditional elasticities from the first stage. Carpentier and Guyomard (2001) derived the following expressions for the second stage unconditional elasticities:

$$E_i = E_{(G)i} E_G$$

$$\Sigma_{ij} = e_{ij} + w_{(G)j}\left(\frac{1}{E_{(G)j}} + \Sigma_{GG}\right) E_{(G)i} E_{(G)j} + w_{(G)j} w_G E_G E_{(G)i}(E_{(G)j} - 1)$$

where, *i* is fresh or processed produce, E_i is the unconditional produce expenditure elasticity, $E_{(G)i}$ is the conditional specific food group expenditure elasticity from the second stage, E_G is food expenditure elasticity from the first stage. Σ_{ij} is the unconditional uncompensated food group own-price elasticity from the first stage, e_{ij} is the conditional specific food group price elasticity from the second stage, $w_{(G)j}$ is the specific food group expenditure share from the second stage, Σ_{GG} is food own-price elasticity and w_G is food expenditure share from the first stage.

The compensated price elasticities, known as Hicksian, correspond to $\varepsilon^*_{ij} = \varepsilon_{ij} + w_j E_i$. The term ε_{ii} must be less than "0" because of the law of demand. If $\varepsilon_{ij} < 0$, the *i*th good is a gross complement of the *j*th product. If $\varepsilon_{ij} > 0$, the *i*th good is a gross substitute of the *j*th product. If $E_i > 0$, the *i*th good is classified as normal, and inferior if $E_i < 0$. Also, if $E_i > 1$, the *i*th good is classified as a luxury; and as a necessity, if $E_i < 1$.

Each of the LA/AIDS models is estimated as a system of equations, where each equation corresponds to a expenditure group. Adding-up and symmetry restrictions imply conditions across equations, which explain why the equations need to be estimated as a system (Barten, 1977). The simultaneous estimation method requires a non-singular covariance matrix for the disturbance of the equation system. To avoid matrix singularity, it is necessary to omit an equation, which parameters are recovered post-estimation through the adding-up restriction.

2.2 Data Description

We use the Living Costs and Food Survey that is a continuous survey of household expenditure that includes food and non-food items, income sources and demographics. The

survey is commissioned by the Social Survey Division of the Office for National Statistics and by the DEFRA. Annually, a stratified random sample of around six thousand households is selected across the UK. By regularly changing the surveyed households, information is obtained continuously throughout the year, except for a break at Christmas.

The Living Costs and Food Survey collects data through three questionnaires: the household questionnaire, the income questionnaire, and expenditure diaries. The household questionnaire gathers information about people at home, and general household characteristics. The householder responds on behalf of the household as a whole. It includes questions about family relationships, ethnicity, employment, payments and one-time purchasing, such as vehicles, package holidays and home improvements.

The dataset contains general expenditures, food quantities and food expenditures. The ratio between food expenditure and food quantity provides a food price index. Therefore, we need a general expenditure price index. The Consumer Price Index (CPI) has been used in the past as a price index of an expenditure group. Okrent and Alston (2011) made a list of publications that used a CPI index as a price index. In this study, the CPI was provided by the Office for National Statistics.

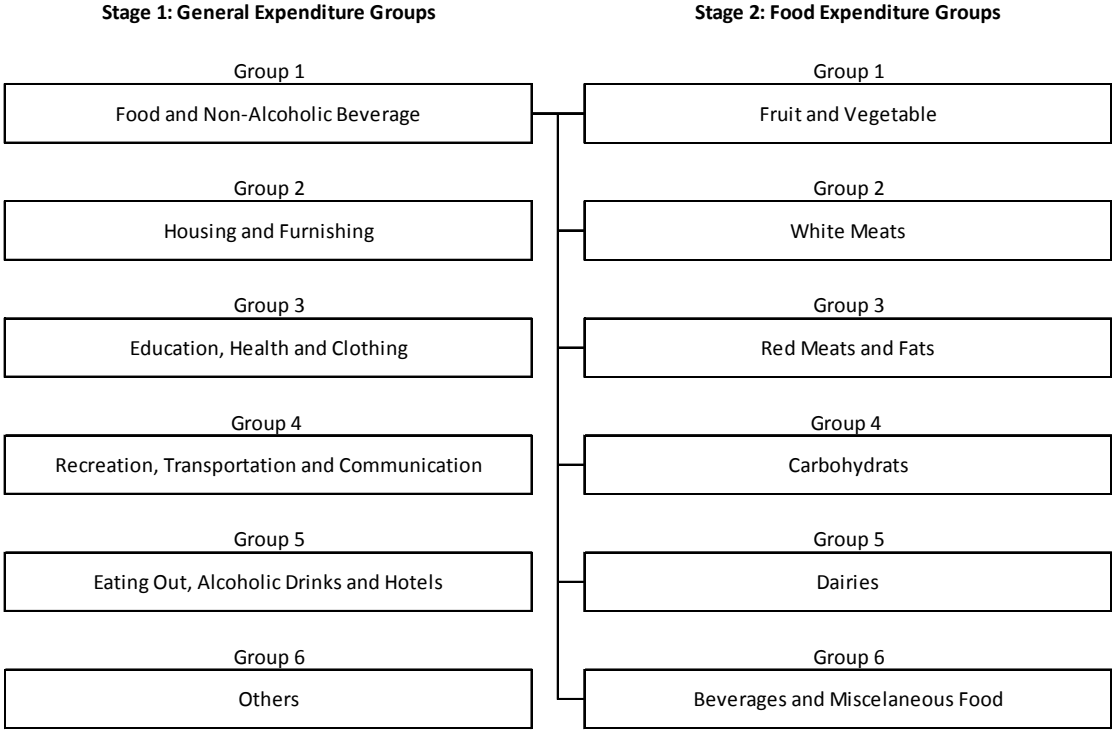
The general expenditure dataset used to be collected by the British Family Expenditure Survey. This survey has been used in seminal articles in applied microeconomics, including the work done by Banks, Blundell et al. (1997) where the quadratic almost ideal demand system is introduced: Blundell, Pashardes et al. (1993) on the discussion of the use of micro data, Atkinson and Stern (1980) and Pollak and Wales (1978). However, all this work was done within a single-stage framework. The food and general expenditure dataset were assembled recently. Therefore, by using a dataset with heritage, this is the first time that general and food expenditures could be studied together in the UK.

Using SAS 9.2 and Stata 11, the dataset is transformed from numerous general and food expenditure products and services into six general and food expenditure groups to be used in the demand system. Figure 1 shows the list of the six general and food expenditure groups. Each one of these expenditure groups contains a number of products and services. The aggregation into six categories is not a trivial task. Deaton and Zaidi (2002) suggest using the

Laspeyres index to approximate the cost-of-living index, which is a measure of the price changes between two periods.

Per capita data is used to create food group budget shares by month, which corresponds to the total food group expenditure divided by total food expenditure. In this way, the data series corresponds to the weekly average expenditure per month from April 2001 to December 2009, equivalent to 105 data points. A data point corresponds to the average per capita weekly expenditure that specific month. All reported monetary tables and values have been adjusted to December 2009 base values.

Figure 1: Expenditure Groups



Finally, this study requires a proxy to reflect the amount of information that UK households are exposed to on a regular basis. The information proxy would be included in the demand system specification to measure the impact of information on consumer behaviour.

Nexis, a search engine for media information, gives the number of times that a specific combination of keywords appears over a given period of time, by media source. Nexis requires the specifying of key words, political region, type of media and dates. The types of

media can vary with political region and type of news publication, such as national newspaper, regional newspaper, and blog.

The current study creates a monthly media index using the key words: infant or child AND nutrition OR diet OR obesity OR overweight. The words correspond to words commonly used in press media to refer to child obesity news.

The dataset has several household expenditure categories. Therefore, this study makes use of a two-stage AIDS model. In the first stage, the impact of child obesity information in broader expenditure categories is measured. In the second stage, the impact of child obesity information in food categories is measured. The first stage calculates the predicted food expenditure share used in the second stage. Consequently, the food expenditure is herein determined endogenously. Therefore, different than most demand studies, we use directly income instead of total expenditure as proxy of income.

Moreover, we assume weak separability. Weak separability is a necessary and sufficient condition for a two-stage demand system (Deaton and Muellbauer, 1980). Weak separability is assumed since it is often rejected (Eales and Unnevehr, 1988). Moreover, the current study uses the food group classification based on Appendix E of the Family Food Report 2009 by DEFRA (2011).

With the purpose of detecting demographic differences, the full aggregated dataset is used to construct four mutually exclusive samples: lower-income households without children (case 1), lower-income households with children (case 2), higher-income households without children (case 3) and higher-income households with children (case 4). A lower-income household, known as high-income household from this point, is defined as a household whose income is below the sample annual average of £199.30 for the full dataset. A higher-income household, known as high-income household from this point, is defined as a household with an income that is above the sample annual average. According to the definition of ‘child’ from the Living Cost and Food survey, a household without children corresponds to a household containing no person under eighteen years old. The household with children corresponds to a household with one or more persons under eighteen years old. Using these definitions, we create complete series for each case, where each case has its

weekly expenditure average per month calculated from April, 2001 to December, 2009. Table 1 corresponds to these four mutually exclusive cases:

Table 1: Dataset Cases by Demographics

Case	Description	Households in 2009
1	Low-income households without children	2,302
2	Low-income households with children	609
3	High-income households without children	1,757
4	High-income households with children	1,154

As is presented in Table 1, some subsamples comprise more households than others. For instance, in 2009, out of a total of 5,822 households, 2,302 households are classified as low income and without children, 609 households as low income with children, 1,757 households as high income and without children and 1,154 households as high income with children. Low-income households with children constitute the smallest number of households is a recurrent one. In 2007 and 2008, low-income households without children were 617 and 666, respectively. Despite being the smallest group of households (10.5% of the total number of households within the survey), low-income households with children make 15.4% of the people in the survey. Using these subsamples, we test the following hypotheses:

(1) taking into account income levels and household composition, child obesity news has a significant impact on overall food expenditure.

H_0: $\delta_{low\ income}^{without\ child} = 0,\ \delta_{low\ income}^{with\ child} = 0,\ \delta_{high\ income}^{without\ child} = 0,\ \delta_{high\ income}^{with\ child} = 0$

The dataset is divided in terms of income and household compositions. Then, the first stage child obesity news index is tested to see if it is statistically significantly different from zero.

(2) taking into account income levels and household composition, child obesity news has a significant on specific food groups.

H_0: $\delta_{low\ income}^{without\ child} = 0,\ \delta_{low\ income}^{with\ child} = 0,\ \delta_{high\ income}^{without\ child} = 0,\ \delta_{high\ income}^{with\ child} = 0$

The dataset is divided in terms of income and household compositions. Then, the second stage child obesity news index is tested to see if it is statistically significantly different from zero.

Therefore, we test the impact of child obesity news on overall food expenditure and specific food expenditure per type of household. Moreover, the current study therefore reports the own-price, cross-price, media and income/expenditure elasticities. In the first stage, this study presents unconditional uncompensated elasticities of the general expenditure. In the second stage, using the unconditional food elasticity from the first stage, this study calculates uncompensated unconditional elasticities for specific food groups.

3. Results and Discussion

With the purpose of gaining familiarity with the data, Table 2 presents some basic sample statistics. In the first stage, this study uses the general expenditure dataset. Taking into account that the sample is stratified and random, we can assume that the statistics correspond closely with those of the population. In fact the UK Government uses the survey data employed here to generate many of its national statistics.

Headey and Fan (2010), in line with past research, explain that poor families spend a large portion of their budget on food. In keeping with this observation, our results show that low-income households spend a larger proportion of their income on satisfying basic needs, such as food and housing, than do high-income households. Low-income households, both with/without children, spend 13.32% and 14.32% of their income on food respectively, while high-income households again with and without children, spend 8.50% and 9.81% of their income on food. Since high-income households already cover their basic needs, they can allocate the remaining income into more luxurious group expenditures. In this sense, high-income households spend a larger proportion of their income on recreation.

Moreover, households with children spend a larger proportion of their income on food and education. This happens in the low income as well as the high income household cases. This is as we would expect, households with children will need to allocate a larger proportion of their income to educate and feed their children.

Table 2: Stage-1 Basic Statistic

		Low Income/No Child		Low Income/Child		High Income/No Child		High Income/Child	
Variable	n	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Expenditure Shares									
Food	105	13.32%	0.94%	14.32%	1.35%	8.50%	0.77%	9.81%	0.82%
Housing	105	21.82%	1.94%	20.38%	3.05%	15.05%	1.41%	13.52%	1.45%
Education	105	6.03%	1.12%	8.95%	1.87%	6.95%	1.07%	8.77%	1.35%
Recreation	105	26.94%	1.95%	26.08%	2.62%	29.93%	1.79%	28.29%	2.14%
Eating Out	105	9.25%	1.04%	9.57%	1.36%	10.30%	1.03%	8.96%	0.97%
Others	105	22.64%	1.87%	20.71%	2.64%	29.26%	2.05%	30.65%	2.27%
Price Index Natural Log									
Food	105	1.02	0.04	1.02	0.04	1.02	0.04	1.02	0.04
Housing	105	1.06	0.06	1.04	0.04	1.03	0.04	1.01	0.03
Education	105	0.82	0.10	0.78	0.11	0.83	0.09	0.97	0.02
Recreation	105	0.97	0.03	0.97	0.03	0.98	0.02	0.98	0.02
Eating Out	105	1.05	0.03	1.05	0.03	1.06	0.03	1.05	0.03
Others	105	1.04	0.02	1.04	0.02	1.03	0.02	1.03	0.02
Income	105	165.00	12.71	94.78	11.01	277.12	20.76	175.69	13.44
News Index									
In levels	105	3.49	2.68	3.49	2.68	3.49	2.68	3.49	2.68
Cumulated	105	168.91	118.02	168.91	118.02	168.91	118.02	168.91	118.02

From March 2001 to December 2009, the combination of keywords appears on average 3.49 articles per month. Twelve months did not register any news with that combination of keywords. In contrast, in December 2008, eleven news articles featured the combination of keywords.

The overall food expenditure can be decomposed on different type of foods. Table 3 presents the food expenditure budget shares, natural logarithmic of prices or, more precisely, unit values, and per capita food expenditure. As an example, of the data presented in Table 3, one can note that high-income households with children have an average fruit and vegetable expenditure of 16.32% of their real total food expenditure, and a standard deviation of 1.53%. In comparison to low-income households, high-income households spend a larger proportion of their income on fruit and vegetables.

Table 3: Stage-2 Basic Statistic

		Low Income/No Child		Low Income/Child		High Income/No Child		High Income/Child	
Variable	n	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Expenditure Shares									
fruit & veg	105	18.10%	1.65%	13.33%	1.73%	19.93%	1.80%	16.32%	1.53%
white meat	105	9.75%	0.57%	8.12%	0.97%	10.33%	0.67%	8.84%	0.66%
red meat	105	22.38%	1.02%	20.41%	1.47%	21.64%	1.20%	20.41%	1.07%
carbohydrate	105	25.80%	1.86%	31.41%	1.91%	24.75%	1.70%	29.56%	1.74%
dairy	105	13.08%	0.76%	13.84%	1.13%	11.86%	0.72%	12.90%	0.81%
others	105	8.98%	0.52%	11.14%	0.89%	9.59%	0.61%	10.33%	0.66%
Price Index Natural Log									
fruit & veg	105	2.34	0.04	2.32	0.06	2.30	0.04	2.31	0.05
white meat	105	2.42	0.05	2.32	0.09	2.34	0.04	2.42	0.06
red meat	105	2.32	0.04	2.38	0.05	2.35	0.04	2.36	0.04
carbohydrate	105	2.36	0.04	2.40	0.05	2.34	0.03	2.34	0.03
dairy	105	2.34	0.05	2.36	0.05	2.35	0.04	2.33	0.05
others	105	2.34	0.04	2.304	0.06	2.29	0.03	2.31	0.04
food expenditure	105	23.13	2.25	14.98	1.52	25.41	2.41	18.85	1.88

A similar phenomenon to that found in the general expenditure dataset, food per capita expenditure is also lower for households with children, as opposed to households without children. Although children do not contribute towards income, they increase the number of people in the household for a per capita comparison.

Table 2 shows that high-income households with children spend 1-2 points more income on food than high-income households without children. Therefore, households with children allocate more income to food expenditure. Table 3 shows that households with children spend less on fruit and vegetables and white meats and more on carbohydrates. Fruit and vegetables are fundamental to a healthy diet. However, in both levels of income, households with children spend a smaller proportion of their total food expenditure on fruit and vegetables. This may suggest that households with children still need to be better-informed with respect to the desirability of including plenty of fruit and vegetable in their household diets.

Here, we consider whether the appropriate information index is either cumulative – that is, it has an immediate and lasting impact – or whether information has a lagged or even weighted distributed lag structure. We found that the cumulative news index has the highest system r-squared in the first and second stages. It suggests that households remember past news. Table 4 shows that the system r-squared is on average 0.88, which means that the system is able to explain 88% of the data variability.

Table 4: System R-Squared

	Stage 1	*Stage 2*
Low Income/No Child	0.88	0.92
Low Income/Child	0.85	0.81
High Income/No Child	0.88	0.91
High Income/Child	0.87	0.91

The completed SUR outputs are presented in the appendix. Following the work done by Dharmasena and Capps (2011), this study checks for serial correlation using the autocorrelation and partial autocorrelation functions. Table 5 shows the results in the first lag. The complete output is available upon request, where there is not significant autocorrelation using twelve lags.

Table 5: Serial Correlation Test

	Low Income/No Child		*Low Income/Child*		*High Income/No Child*		*High Income/Child*	
Stage 1	Q*	Prob>Q	Q*	Prob>Q	Q*	Prob>Q	Q*	Prob>Q
food	0.39	0.53	0.20	0.66	0.27	0.60	0.06	0.81
housing	0.02	0.89	0.44	0.51	0.01	0.93	0.74	0.39
education	0.09	0.77	0.12	0.73	0.10	0.75	0.57	0.45
recreation	0.01	0.92	1.53	0.22	0.49	0.48	0.02	0.89
eating out	0.10	0.75	0.31	0.58	0.15	0.70	0.20	0.65
Stage 2								
fruit & veg	0.72	0.40	1.20	0.27	0.20	0.65	0.67	0.41
white meat	1.35	0.24	0.17	0.68	0.10	0.75	2.62	0.11
red meat	0.0005	0.98	0.05	0.83	0.01	0.92	0.47	0.49
carbohydrate	0.81	0.37	0.61	0.43	1.17	0.28	2.32	0.13
dairy	2.34	0.13	0.54	0.46	0.21	0.64	0.43	0.51

Note: (*) Results in the first lag.

Finally, we tested for concavity of the expenditure function at each point. In the first stage, two out five eigenvalues are negative. It suggests that the general expenditure groups contain some products and services that are durables or that could involve pre-committed expenditure. For instance, in most cases a household would buy a new refrigerator when he/she needs it, rather than when it is cheaper. Also, once a pupil is at school, he/she would be relatively indifferent to changes in tuition fees. In these two examples, the law of demand, stating that when price rises the quantity demanded falls, is unlikely to hold. Therefore, concavity of the general expenditure function may also not hold.

Since the commodities considered within this second stage model do not include durable goods, we expected that households would be able to adapt their food consumption basket to new market conditions faster and be able to make substitutions between goods. We also

expected that the degree of substitution with and between the food groups considered would be large enough to permit some degree of price mitigation as household alter their consumption bundles around well behaved indifference curves. In the second stage, four out five eigenvalues are negative. Therefore, the expenditure functions can be considered as locally concave.

Table 6 shows the own price, cross price, income and news elasticities for general expenditure groups. The compensated elasticities correspond to the changed in quantity demanded changes after a price change, keeping utility constant. In a similar way, the uncompensated elasticities correspond to how quantity demanded changes after a price change, keeping expenditure constant. This study presents the uncompensated elasticities because, unlike compensated demands, they are observables. Consequently, uncompensated elasticities are more interesting from a public policy point of view.

On average, the own price elasticity is -0.37 for food expenditure, -1.13 for housing and furnishing expenditure, -1.46 for education, health and clothing expenditure, -0.77 for recreation, transportation and communication expenditure and 0.72 for eating out expenditure. Own price elasticities, in most of the household cases, have the expected negative sign. Some expenditure groups have positive own-price elasticity, which is likely to be associated with the rejection of concavity of the expenditure function. Despite this, in each case the food own-price elasticity is negative and classified food as inelastic. Food own-price elasticity is the only own-price elasticity that is relevant for the second estimation stage. In each household case, the food own-price elasticity tends to be the most inelastic expenditure group.

The average income elasticity is 0.67 for food expenditure, 0.88 for housing and furnishing expenditure, 0.91 for education, health and clothing expenditure, 1.14 for recreation, transportation and communication expenditure and 0.78 for eating-out. The income elasticities have the expected positive sign. In this sense, it is not expect that a general expenditure group has negative income elasticity, which corresponds to an inferior good. It will be unlikely that a complete group can be considered as an inferior good.

Food, housing, education, and eating-out have income elasticities are less than one, so, they are classified as normal goods. Since they satisfy the more fundamental needs, we expect

food, housing and education to have the lowest income elasticity. In contrast, recreation has income elasticities greater than one, so, it is classified as luxury good. In this sense, households would first satisfy their food, housing and education needs, and only thereafter would they spend on recreation.

With respect to the household cases, high-income households have lower food income elasticity than low-income households. In addition, households with children tend to have lower food income elasticity than households without children. In other words, high-income households and households with children respond less to changes in income. Therefore, after an income change, of all household cases high-income households with children appear less willing to change their overall food expenditure.

Table 6: General Expenditure Unconditional Elasticities

Low Income/No Child

	food	housing	education	recreation	eating out	others	income	news
food	**-0.46**	**0.90**	-0.32	0.57	-0.42	**-1.01**	**0.74**	-0.05
housing	**0.57**	**-1.30**	0.34	**-1.05**	0.40	0.47	**0.57**	0.07
education	-0.71	1.17	**-1.73**	**2.24**	-0.78	-1.00	0.81	-0.07
recreation	0.17	**-1.07**	0.46	-1.20	0.018	0.06	**1.56**	0.09
eating out	-0.56	0.97	-0.49	0.36	3.21	**-3.91**	0.41	-0.21
others	**-0.65**	0.32	-0.29	0.17	**-1.67**	0.93	**1.19**	-0.04

Low Income/Child

	food	housing	education	recreation	eating out	others	income	news
food	-0.15	-0.85	0.19	0.28	-0.10	-0.11	**0.74**	0.002
housing	-0.60	-0.04	0.05	0.18	**1.18**	-1.50	**0.72**	0.003
education	0.33	0.14	**-2.13**	0.18	**-1.67**	**2.56**	**0.58**	-0.01
recreation	0.10	0.06	0.01	-1.55	0.559	-0.31	**1.13**	-0.002
eating out	-0.17	**2.48**	**-1.59**	1.59	0.33	-3.52	**0.89**	**-0.01**
others	-0.19	**-1.63**	**1.02**	-0.49	-1.69	1.46	**1.52**	**0.01**

High Income/No Child

	food	housing	education	recreation	eating out	others	income	news
food	-0.40	**1.08**	**-1.16**	**1.22**	0.05	**-1.41**	**0.63**	**-0.002**
housing	**0.56**	**-1.92**	0.34	**-2.10**	0.52	1.43	**1.17**	-0.00004
education	**-1.41**	0.82	0.03	1.38	-0.80	-0.59	**0.58**	0.004
recreation	**0.32**	**-1.03**	0.29	0.71	0.40	**-1.65**	**0.96**	**0.003**
eating out	0.02	0.81	-0.56	1.18	**-3.59**	1.25	**0.89**	-0.001
others	**-0.46**	0.73	-0.18	**-1.76**	0.41	0.06	**1.20**	**-0.003**

High Income/Child

	food	housing	education	recreation	eating out	others	income	news
food	-0.47	0.33	0.23	**1.54**	0.25	**-2.43**	**0.56**	**0.002**
housing	0.19	-1.25	0.72	**-2.05**	0.80	0.54	**1.05**	-0.002
education	0.15	1.03	**-1.99**	-1.11	-0.97	1.23	**1.67**	**-0.002**
recreation	**0.50**	**-0.96**	-0.27	-1.04	0.29	0.59	**0.89**	-0.001
eating out	0.23	1.22	-0.88	0.89	2.93	**-5.34**	**0.95**	-0.001
others	**-0.83**	0.24	0.41	0.50	**-1.57**	0.20	**1.05**	**0.001**

Note: Bold numbers are significant at 5% significance level

With respect to the testable hypothesis, using 5% significance level, child obesity news does cause a significant impact on the overall food expenditure in high-income households. In contrast, child obesity news does not cause a significant impact on the overall food expenditure in low-income households. After reading child obesity news, high-income households without children spend less on overall the categories of food, while high-income with children spend more on overall food. It suggests that child obesity news causes high-income households with children to move to a more expensive diet, while high-income households without children reallocate expenditure to other general expenditure groups. Now, it would be interesting to see if child obesity news impacts specific food categories. For instance, it could be the case that in low-income households child obesity news does cause a change in the food expenditure composition, which does not change overall food expenditure.

Table 7 shows the uncompensated own-price elasticities for specific food groups. These elasticities have the expected negative sign. The only exception is the carbohydrate expenditure group for low-income households without children. However, this unexpected positive value is not significantly different from zero. Fruit and vegetable, red meat, carbohydrate and dairy groups have an own-price elasticity which is less than one, therefore they are classified as inelastic products. The white meat expenditure group has an own-price elasticity which is less than minus one, thus this demand function could be considered as elastic. Moreover, low-income households respond more to a change in the price of fruit and vegetable than do high-income households. Therefore, the fruit and vegetable diet of low-income households may be more susceptible to fluctuations than that of high-income households.

Food expenditure groups behave as complements. This suggests that households prefer a diversified expenditure basket. However, complementarity between expenditure groups cannot be extrapolated in the same way to each product in the group. It could be the case that a specific product in a group is a complement or substitute of another product in the same or another expenditure group.

The computed expenditure elasticities have a relatively narrow range, and they are more than zero and less than one. Consequently, all the food groups can be classified as necessity goods. High-income households have smaller food expenditure elasticity than low-income households. In addition, households with children tend to have smaller food expenditure elasticity than households without children. In other words, high-income households and households with children, tend to respond less to changes in food expenditure. Therefore, after a food expenditure change, high-income households with children are the least willing to change their food basket compared to any other cases of households.

Fruit and vegetables demand is estimated to have one of the highest expenditure elasticities of the groups considered here. For low-income households the expenditure elasticity varies from 0.82 to 0.83, while for high-income households vary from 0.51 to 0.68. As is discussed later, Tiffin and Arnoult (2010) also found that fruit and vegetables have a high expenditure elasticity. This trend was expected, low-income households may consider fruits and vegetable closer to luxury goods than do other households. After a change in food expenditure, low-

income households might change their fruit and vegetable expenditure in a larger proportion than high-income households. Moreover, Table 7 shows that low-income households have a larger own-price elasticity for fruit and vegetable own-price elasticity than high-income households. Plus, as was presented in Table 3, high-income households spend a larger proportion of food expenditure on fruit and vegetables. This suggests that, especially in a time of economic crisis, the public authorities might consider paying attention to protect the diet of low-income households, since they spend less on fruit and vegetables and are more likely to reduce their expenditure.

As expected, households with children have smaller expenditure elasticities for dairy products than households without children. In this sense, households with children change less their quantity demanded of dairy products after a change in food expenditure. Consequently, households with children appear to make a significant effort to maintain their diary expenditure. Since milk, an important component of this group, contains large quantities of dietary calcium, important for physiological development of the child, this is somewhat reassuring.

Table 7: Food Expenditure Unconditional Elasticities

Low Income/No Child

	f & v	w-meat	r-meat	carbs	dairy	others	expenditure	news
fruit & veg	**-0.52**	**-0.84**	**-1.11**	**-1.54**	**-1.10**	**-1.02**	**0.83**	0.01
white meat	**-0.66**	**-1.09**	**-1.27**	**-1.14**	**-1.01**	**-0.87**	**0.77**	0.01
red meat	**-1.00**	**-1.06**	**-0.66**	**-1.21**	**-0.91**	**-0.93**	**0.61**	-0.02
carbohydrate	**-1.37**	**-1.06**	**-1.25**	0.22	**-1.35**	**-1.25**	**0.77**	0.01
dairy	**-1.10**	**-1.01**	**-0.94**	**-1.67**	**-0.29**	**-1.01**	**0.76**	0.01
others	**-0.99**	**-0.85**	**-0.95**	**-1.68**	**-1.02**	**-0.53**	**0.75**	-0.02

Low Income/Child

	f & v	w-meat	r-meat	carbs	dairy	others	expenditure	news
fruit & veg	**-0.71**	**-1.05**	**-0.79**	**-1.54**	**-1.08**	**-0.92**	**0.82**	**0.08**
white meat	**-1.07**	**-1.00**	**-0.90**	**-1.09**	**-0.91**	**-1.09**	**0.83**	**0.03**
red meat	**-0.88**	**-0.98**	**-0.84**	**-1.26**	**-1.15**	**-1.04**	**0.83**	**-0.02**
carbohydrate	**-1.19**	**-1.00**	**-1.11**	**-0.69**	**-0.94**	**-1.00**	**0.71**	**-0.03**
dairy	**-1.01**	**-0.90**	**-1.11**	**-0.84**	**-0.94**	**-1.08**	**0.63**	**0.03**
others	**-0.84**	**-1.02**	**-0.96**	**-0.97**	**-1.11**	**-1.00**	**0.62**	**-0.04**

High Income/No Child

	f & v	w-meat	r-meat	carbs	dairy	others	expenditure	news
fruit & veg	**-0.51**	**-0.91**	**-1.00**	**-1.41**	**-1.29**	**-0.99**	**0.68**	0.01
white meat	**-0.81**	**-0.63**	**-1.25**	**-1.30**	**-1.11**	**-0.99**	**0.72**	0.01
red meat	**-0.96**	**-1.10**	**-0.38**	**-1.38**	**-0.96**	**-1.18**	**0.61**	**-0.03**
carbohydrate	**-1.28**	**-1.09**	**-1.31**	-0.02	**-1.17**	**-1.02**	**0.58**	0.01
dairy	**-1.43**	**-1.06**	**-0.93**	**-1.38**	-0.18	**-0.96**	**0.58**	**0.02**
others	**-0.95**	**-0.97**	**-1.43**	**-1.11**	**-0.98**	**-0.59**	**0.66**	-0.02

High Income/Child

	f & v	w-meat	r-meat	carbs	dairy	others	expenditure	news
fruit & veg	-0.22	**-1.09**	**-1.00**	**-1.28**	**-1.30**	**-1.03**	0.51	**0.06**
white meat	**-1.21**	**-0.94**	**-0.90**	**-1.10**	**-1.18**	**-0.73**	0.61	**0.04**
red meat	**-1.06**	**-0.98**	**-0.69**	**-1.46**	**-0.93**	**-1.05**	0.63	**-0.04**
carbohydrate	**-1.18**	**-1.03**	**-1.29**	-0.20	**-1.143**	**-1.19**	0.57	**-0.02**
dairy	**-1.34**	**-1.06**	**-0.77**	**-1.23**	-0.25	**-1.15**	0.41	0.01
others	**-1.10**	**-0.77**	**-1.05**	**-1.56**	**-1.26**	-0.31	0.60	**-0.02**

Note: Bold numbers are significant at 5% significance level

Finally, to address the testable hypothesis, using 5% significance level, child obesity news does cause a significant impact on specific food expenditure groups in households with children. In contrast, households without children do not exhibit a significant impact in most specific food expenditure groups. After receiving child obesity news, households with children spend more on fruit and vegetable and white meats, while they also spend less on red meat and carbohydrates. This suggests that child obesity news causes a positive effect on the diet of households with children.

Taking into account the results from the first and second stages, child obesity news causes different impact on households according to their income level and household composition. Low-income households without children are not significant impacted by child obesity news. Low-income households with children change their food expenditure composition to a

healthier diet without changing the overall food expenditure. High-income households without children decrease their overall food expenditure, mainly substituting red meat with dairy products. Finally, high-income households with children increase their overall food expenditure and move on to a healthier diet. In summary, in three out of four household cases, child obesity news causes a different and positive impact on diet.

4. Conclusions

Following a worldwide trend, the UK is experiencing an increasing obesity rate. The increasing obesity rate is associated with an increasing consumption of high calorific food. Obesity would not be such an important problem if people were able to burn all of these calories. However this is not the case, people find it difficult to do physical exercise on a regular basis. Therefore they are becoming increasingly obese.

To make information to households available, governmental policies can directly provide information, through an information campaign or by indirectly establishing regulations that assure a minimum information level, such as food labelling. In this sense, measuring the impact of an information campaign would help to justify its application, but it would also help to identify the most effective information message to improve diet habits.

The challenge is how to measure the effect of information upon food choices. People constantly receive information from a variety of channels while they make hundreds of food choices a day. In addition, the short information effect can differ from the long-term information effect. Consequently, the selected approach needs to take market conditions into account, such as prices and income, and to also isolate a specific information channel and take potential dynamic elements into account. This study aimed to contribute to the debate of how information impacts household food expenditure.

This study chose to use the AIDS model, because it permits to test/impose adding-up, homogeneity, symmetry and concavity of the expenditure function. The Living Cost and Food Survey was the selected dataset, and the information variable corresponded to the number of articles with respect to child obesity in the UK. Using this dataset and the AIDS model, this study calculated a set of elasticities on four mutually exclusive subsamples of households, in terms of income level (low and high) and household composition

(with/without children). In each subsample, the study used the demand system to measure the impact of child obesity news on the overall food expenditure, and in specific food categories.

To recapitulate, the current study presents empirical evidence that child obesity news does not cause a significant impact on overall food expenditure in low-income households without children. However, the estimated results show that low-income households with children and high-income households with and without children change their food expenditure to a healthier diet. Specially, households with children increase white meat and fruit and vegetable expenditures and decrease red meat and carbohydrate expenditures. This finding implies that child obesity news gives the incentive for a movement towards a healthier diet, increasing the quality of the diet.

According to Table 3, low-income households with children spend the smallest proportion of their income on fruit and vegetables (13.33%); this is even less than low-income households without children (18.10%). More importantly, low-income households with children influence the nutritional habits of their children. This finding is consistent with Tiffin and Arnoult (2010), whose study found a smaller per capita expenditure on fruit and vegetables in households with children.

This study found that households with children react positively to child obesity news. They increase their expenditure budget share on fruit and vegetables and white-meat, while they decrease their expenditure budget share on red meats and carbohydrates in the light of increased media coverage of child obesity issues. In this sense, low-income households with children seem a target that historically is the biggest challenge.

This study has made a number of empirical contributions to the literature on the effectiveness of information provision upon healthy dietary choice. Some of these empirical contributions relate to the elasticity estimation. From our search in the literature only one study has calculated own-price, cross-price and income/expenditure elasticity in the UK. Other empirical contribution relates to the use of a media index to measure the information impact. In the past few studies in the UK have used a media index.

We calculated a set of demand elasticities for four mutually exclusive groups of households, according to income level and household composition. Own price and income/expenditure

elasticities are informative in regards to consumer behaviour. Moreover, most studies have focused on a particular subset of narrowly defined foods, rather than on the overall household food consumption; and publications today use data that is over five years old.

This article is the first attempt to combine overall household expenditure and food expenditure in the UK. This work is possible because the Living and Food Cost Survey is available, which provides data about general and food expenditures. Thus this study is able to provide a larger picture than ever before of the impact of information on household behaviour.

In this study the child obesity news elasticity varies between -0.05 and 0.002, on the overall food expenditure from the first stage. Within specific food groups, child obesity news elasticity is estimated to take values between -0.04 and 0.08 in the second stage. It suggests that information has a larger impact on specific food expenditure groups, than it has on the overall food expenditure.

Few studies in the UK have included an information index to measure the impact of food related information on consumer behaviour. Exceptions include those studies conducted by Burton and Young (1996), and Burton, Young and Cromb (1999); which consider the case of Bovine Spongiform Encephalopathy (BSE) on the demand of meat in the UK. The studies by Burton found that BSE information had a negative impact on beef and a positive impact on other types of meats. However, these studies measure the impact of information of a media event, while the work of this article refers to news about a topic that is not linked with a media event. Despite little research in the UK which uses an information index in a demand analysis context, information can play a significant role in achieving the objective of leading the consumer to follow a healthy diet.

In studies outside the UK most of the empirical studies found small but significant information elasticities. Some of these studies are conducted on the impact of advertising, which can be taught as a specific type of information. For instance, for non-alcoholic beverages, Brown and Lee (1993) found advertising elasticities to range from -0.001 to 0.02. Piggott and Marsh (2004) calculated media elasticities as falling between -0.04 and 0.02. In this sense, in this study the estimated news elasticities are larger than those indicated in the literature; it may suggest that overall population can be affected in a small amount by

information. In contrast, specific population segments can be more impacted by information than the overall sample. This finding highlights the relevance of taking demographics into account on the study of household behaviour.

When comparing information and own price elasticities within studies, Brester and Schroeder (1995) while using the Rotterdam model in the meat sector, found that own advertising elasticities are seven to nine times smaller than own price elasticities. This finding is consistent with the research done by Burton and Young (1996), and Piggott and Marsh (2004), that news causes an effect that is much smaller than the effect of a change in price. In other words, a small change in price can produce an effect similar to that of a much larger increase in advertising or news. Consistent with past research, our media index elasticities are in general, at least ten times smaller in magnitude compared to price and income elasticities.

Considering that news elasticities are consistently many times smaller than price elasticities, information policies can be considered as being less effective; in the sense that people would respond less to changes in information, than to changes in prices. However, as discussed by Green, Carman and McManus (1991) regarding the case of generic advertising, the magnitude of media impact does not necessarily relate to potential returns. For this reason, a complete economic feasibility analysis needs to take more elements into account, such as campaign costs and current information levels. From a health policy perspective a small but significant media impact may indicate a tool for shifting eating habits, and consequently increased social welfare.

Even when price policies such as specific food taxes, can be more effective than information in having an impact on household expenditure, price policies need to be considered with care. In the US there has been a substantial amount of debate concerning the imposition of a tax on sugary soda. Soda consumption is one of the main source of calorie intake (Block, 2004). One of the reasons for the increasing consumption is the low price at which these drinks retail to consumers, and in the last 20 years the price of soda has declined as much as 48% (Block and Willett, 2011). In this sense, effective price policies may need to be continually adapted to the long-term price trend, and the portion of a potential specific tax that is reflected into market price.

Moreover, a specific tax associated with unhealthy food would cause not just a change in relative prices, but also undesirable income redistribution. Table 3 shows the basic statistics of food expenditure across different types of households; low-income households spend a larger proportion of their income on red meats and carbohydrates, and a smaller proportion on white-meat and fruit and vegetables. It is therefore likely that a specific tax on unhealthy food would have regressive consequences. Low-income households, at least relative to their income, would pay more tax than high-income households, unless they are able to make substantial substitutions across food groups. However, the estimated cross price elasticities for the household type presented here suggest that changes of the magnitude needed to move households back to a fairly neutral income position, post tax, are unlikely to be made. Therefore, a specific tax levied on unhealthy food may need to be countered by means to return some tax revenues to these low-income households in particular.

Finally, a key difference with price policies is that information policies do not change relative prices, so they do not have an income redistribution effect. However, the measure of economic impacts of information policies are complex, as while it is easy to measure the economic costs, it has been far more difficult to assess the economic benefits these policies produce. In this sense, this research pursues to contribute to the debate, to measure the informational effect on household expenditure.

5. References

Alston, J. M., K. A. Foster, and R. D. Green. 1994. "Estimating Elasticities with the Linear Approximate Almost Ideal Demand System: Some Monte Carlo Results." *The Review of Economics and Statistics* 76, no. 2: 351-356.

Asche, F., and C. R. Wessells. 1997. "On Price Indices in the Almost Ideal Demand System." *American Journal of Agricultural Economics* 79, no. 4: 1182-1185.

Atkinson, A. B., and N. H. Stern. 1980. "On the Switch from Direct to Indirect Taxation." *Journal of Public Economics* 14, no. 2: 195-224.

Banks, J., R. Blundell, and A. Lewbel. 1997. "Quadratic Engel Curves and Consumer Demand." *The Review of Economics and Statistics* 79, no. 4: 527-539.

Barnett, W. A., and O. Seck. 2008. "Rotterdam Model versus Almost Ideal Demand System: Will the Best Specification Please Stand Up?" *Journal of Applied Econometrics* 23, no. 6: 795-824.

Barten, A. P. 1977. "The Systems of Consumer Demand Functions Approach: A Review." *Econometrica* 45, no. 1: 23-51.

Baum, C. F., and T. Linz. 2009. "Evaluating Concavity for Production and Cost Functions." *Stata Journal* 9, no. 1: 161-165.

Block, G. 2004. "Foods Contributing to Energy Intake in the US: Data from NHANES III and NHANES 1999–2000." *Journal of Food Composition and Analysis* 17, no. 3-4: 439-447.

Block, J. P., and W. C. Willett. "Can Taxing Sugary Soda Influence Consumption and Avoid Unanticipated Consequences?" *Choices*.

Blundell, R., P. Pashardes, and G. Weber. 1993. "What do we Learn About Consumer Demand Patterns from Micro Data?" *The American Economic Review* 83, no. 3: 570-597.

Brester, G. W., and T. C. Schroeder. 1995. "The Impacts of Brand and Generic Advertising on Meat Demand." *American Journal of Agricultural Economics* 77, no. 4: 969-979.

Brown, M. G., and J.-Y. Lee. 1993. "Alternative Specifications of Advertising in the Rotterdam Model." *European Review Agricultural Economics* 20, no. 4: 419-436.

Burton, M., and T. Young. 1996. "The Impact of BSE on the Demand for Beef and Other Meats in Great Britain." *Applied Economics* 28, no. 6: 687-693.

Burton, M., T. Young, and R. Cromb. 1999. "Meat Consumer's Long-Term Response to Perceived Risk Associated with BSE in Great Britain." *Cahiers d'Economie et Sociologie Rurales* 507-19.

Carpentier, A., and H. Guyomard. 2001. "Unconditional Elasticities in Two-Stage Demand Systems: An Approximate Solution." *American Journal of Agricultural Economics* 83, no. 1: 222-229.

Deaton, A., and J. Muellbauer. 1980. *Economics and Consumer Behavior*. New York: Cambridge University Press

Deaton, A., and S. Zaidi. 2002. "Guidelines for Constructing Consumption Aggregates for Welfare Analysis." The World Bank. Available online at. Accessed Month Day, 2002.

DEFRA. 2011. "Family Food: A Report on the 2009 Family Food Module of the Living Costs and Food Survey." National Statistics and Department for Environment, Food and Rural Affairs. Available online at. Accessed Month Day, 2011.

Dharmasena, S., and O. J. Capps. 2011. "Intended and Unintended Consequences of a Proposed National Tax on Sugar-Sweetened Beverages to Combat the U.S. Obesity Problem." *Health Economics*.

Duffy, M. 2003. "Advertising and Food, Drink and Tobacco Consumption in the United Kingdom: A Dynamic Demand System." *Agricultural Economics* 28, no. 1: 51-70.

Eales, J. S., and L. J. Unnevehr. 1988. "Demand for Beef and Chicken Products: Separability and Structural Change." *American Journal of Agricultural Economics* 70, no. 3: 521-532.

Ehmke, M. D. T., T. Warziniack, C. Schroeter, and K. Morgan. 2008. "Applying Experimental Economics to Obesity in the Family Household." *Journal of Agricultural and Applied Economics* 40, no. 2: 539–549.

Finkelstein, E. A., K. L. Strombotne, and B. M. Popkin. "The Cost of Obesity and Implications for Policy Makers." *Choices*, 3-9.

Green, R., and J. M. Alston. 1990. "Elasticities in AIDS Models." *American Journal of Agricultural Economics* 72, no. 2: 442-445.

Green, R. D., H. F. Carman, and K. McManus. 1991. "Some Empirical Methods Of Estimating Advertising Effects In Demand Systems: An Application To Dried Fruits." *Western Journal of Agricultural Economics* 16, no. 1: 63-71.

Headey, D., and S. Fan. 2010. "Reflections on the Global Food Crisis." International Food Policy Research Institute. Available online at. Accessed Month Day, 2010.

Hill, J. O., H. R. Wyatt, G. W. Reed, and J. C. Peters. 2003. "Obesity and the Environment: Where Do We Go from Here?" *Science 7* 299, no. 5608: 853-855.

MacInnis, B., and G. Rausser. 2005. "Does Food Processing Contribute to Childhood Obesity Disparities?" *American Journal of Agricultural Economics* 87, no. 5: 1154-1158.

Mazzocchi, M., W. B. Traill, and J. F. Shogren. 2009. *Fat Economics: Nutrition, Health, and Economic Policy*. New York: Oxford University Press

Michalek, J., and M. A. Keyzer. 1992. "Estimation of a Two-Stage LES-AIDS Consumer Demand System for Eight EC Countries." *European Review of Agricultural Economics* 19, no. 2: 137-163.

NHS. 2010. "Statistics on Obesity, Physical Activity and Diet: England, 2010." The NHS Information Centre, Lifestyles Statistics. Available online at: http://www.ic.nhs.uk/pubs/opad10. Accessed Month Day, 2010.

OECD. 2010. "Health at a Glance: Europe 2010." Available online at: http://dx.doi.org/10.1787/health_glance-2010-en. Accessed Month Day, 2010.

Okrent, A. M., and J. M. Alston. 2011. The Demand for Disaggregated Food-Away-from-Home Products. Pittsburgh, Pennsylvania, pp. 1-40.

Okrent, A. M., and J. M. Alston. 2011. "Demand for Food in the United States." University of California, Agriculture and Natural Resources. Available online at. Accessed Month Day, 2011.

Piggott, N. E., and T. L. Marsh. 2004. "Does Food Safety Information Impact U.S. Meat Demand?" *American Journal of Agricultural Economics* 86, no. 1: 154-174.

Pollak, R. A., and T. J. Wales. 1978. "Estimation of Complete Demand Systems from Household Budget Data: The Linear and Quadratic Expenditure Systems." *The American Economic Review* 68, no. 3: 348-359.

Rickertsen, K., D. Kristofersson, and S. Lothe. 2003. "Effects of Health Information on Nordic Meat and Fish Demand." *Empirical Economics* 28, no. 2: 249-273.

Sauer, J. 2006. "Economic Theory and Economic Practice: Parametric Efficiency Analysis." *Empirical Economics* 311061-1087.

Science, G. O. f. 2010. "Tackling Obesities: Future Choices –Project Report." Government Office for Science. Available online at. Accessed Month Day, 2010.

Tiffin, A., and R. Tiffin. 1999. "Estimates of Food Demand Elasticities for Great Britain: 1972-1994." *Journal of Agricultural Economics* 50, no. 1: 140-147.

Tiffin, R., and M. Arnoult. 2010. "The Demand for a Healthy Diet: Estimating the Almost Ideal Demand System with Infrequency of Purchase." *European Review of Agricultural Economics* 37, no. 4: 501-521.

Varian, H. R. 2002. *Microeconomics Analysis*. Third ed. New York: W.W. Norton & Company, Inc.

Verbeke, W., and R. W. Ward. 2001. "A Fresh Meat Almost Ideal Demand System Incorporating Negative TV Press and Advertising Impact." *Agricultural Economics* 25, no. 2-3: 359-374.

6. Appendix

Table 8: General Expenditure SUR Model Estimation

	Low Income/No Child		*Low Income/Child*		*High Income/No Child*		*High Income/Child*	
food	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.
Lagged w	-0.08	0.09	0.02	0.09	-0.13	0.09	**-0.19**	0.09
Ln Price index								
food	**0.07**	0.03	**0.12**	0.05	0.05	0.03	0.05	0.03
housing	**0.11**	0.05	-0.13	0.08	**0.09**	0.04	0.03	0.05
education	-0.04	0.03	0.02	0.04	**-0.10**	0.02	0.02	0.03
recreation	0.07	0.05	0.03	0.08	**0.09**	0.04	**0.14**	0.05
eating out	-0.06	0.04	-0.02	0.07	0.001	0.04	0.02	0.05
others	**-0.14**	0.06	-0.02	0.09	**-0.13**	0.06	**-0.25**	0.06
income	-0.03	0.02	**-0.04**	0.02	-0.03	0.01	**-0.04**	0.01
Seasonal dummies								
jan-mar	-0.0011	0.002	**0.01**	0.004	-0.001	0.002	**0.004**	0.002
apr-jun	-0.005	0.002	**0.01**	0.003	**-0.003**	0.001	0.001	0.002
jul-sep	**-0.01**	0.002	0.00	0.003	**-0.01**	0.002	**-0.01**	0.002
News index	-0.00004	0.00004	0.0001	0.0001	**-0.0001**	0.00003	**0.0001**	0.00002
Constant	**0.32**	0.11	**0.29**	0.08	**0.27**	0.05	**0.34**	0.05
education								
Lagged w	-0.04	0.08	-0.07	0.09	-0.02	0.09	-0.03	0.08
Ln Price index								
food	**0.11**	0.05	-0.13	0.08	**0.09**	0.04	0.03	0.05
housing	-0.086	0.13	0.18	0.20	-0.13	0.11	-0.03	0.12
education	0.07	0.06	0.005	0.09	0.05	0.06	0.10	0.06
recreation	**-0.26**	0.11	0.02	0.15	**-0.31**	0.09	-0.27	0.10
eating out	0.08	0.07	**0.23**	0.12	0.08	0.08	0.11	0.08
others	0.08	0.12	**-0.32**	0.16	**0.22**	0.12	0.07	0.12
income	**-0.09**	0.05	-0.06	0.04	0.03	0.02	0.01	0.02
Seasonal dummies								
jan-mar	**0.01**	0.005	0.01	0.007	0.001	0.004	**0.01**	0.004
apr-jun	0.01	0.004	0.01	0.007	0.004	0.004	0.01	0.004
jul-sep	0.01	0.005	0.01	0.007	0.005	0.004	0.001	0.004
News index	0.0001	0.0001	0.0002	0.0002	-0.000002	0.0001	-0.0001	0.00004
Constant	**0.67**	0.24	**0.42**	0.16	-0.001	0.12	0.10	0.10
housing								
Lagged w	0.08	0.09	0.01	0.08	-0.09	0.09	0.10	0.08
Ln Price Index								
food	-0.04	0.03	0.02	0.04	**-0.10**	0.02	0.02	0.03
housing	0.07	0.06	0.005	0.09	0.05	0.06	0.10	0.06
education	-0.04	0.05	-0.10	0.08	0.07	0.05	-0.08	0.06
recreation	**0.13**	0.07	0.01	0.09	0.09	0.06	-0.08	0.07
eating out	-0.05	0.04	**-0.15**	0.06	-0.06	0.05	-0.08	0.05
others	-0.06	0.07	**0.22**	0.09	-0.05	0.07	0.13	0.08
income	-0.01	0.03	-0.04	0.03	**-0.03**	0.01	**0.06**	0.02
Seasonal dummies								
jan-mar	**-0.01**	0.003	**-0.02**	0.01	**-0.01**	0.003	**-0.01**	0.003
apr-jun	**-0.01**	0.003	**-0.01**	0.00	**-0.01**	0.003	**-0.01**	0.003
jul-sep	**-0.01**	0.003	**-0.01**	0.01	**-0.01**	0.003	**-0.01**	0.004
News index	-0.00003	0.0001	-0.0002	0.0001	0.0001	0.0001	**-0.0001**	0.00003
Constant	0.12	0.14	**0.26**	0.11	**0.26**	0.09	**-0.21**	0.08

	Low Income/No Child		*Low Income/Child*		*High Income/No Child*		*High Income/Child*	
recreation	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.
Lagged w	**-0.19**	0.08	-0.11	0.07	-0.05	0.09	-0.01	0.08
Ln Price Index								
food	0.07	0.05	0.03	0.08	**0.09**	0.04	0.14	0.05
housing	**-0.26**	0.11	0.02	0.15	**-0.31**	0.09	**-0.27**	0.10
education	**0.13**	0.07	0.01	0.09	0.09	0.06	-0.08	0.07
recreation	-0.01	0.17	-0.13	0.22	**0.51**	0.16	-0.02	0.18
eating out	0.02	0.09	0.15	0.13	0.12	0.09	0.08	0.08
others	0.05	0.13	-0.07	0.17	**-0.50**	0.15	0.16	0.16
income	-0.19	0.08	-0.11	0.07	-0.05	0.09	-0.01	0.08
Seasonal dummies								
jan-mar	-0.001	0.005	**-0.02**	0.01	0.01	0.005	**-0.02**	0.006
apr-jun	0.001	0.005	**-0.02**	0.01	-0.01	0.004	**-0.01**	0.006
jul-sep	0.002	0.005	**-0.02**	0.01	0.00	0.005	-0.001	0.006
News index	0.0001	0.0001	-0.0001	0.0002	**0.0002**	0.0001	-0.0001	0.0001
Constant	-0.42	0.26	0.17	0.15	**0.38**	0.15	**0.46**	0.15
eating out								
Lagged w	-0.04	0.08	-0.0210	0.089	-0.08	0.09	0.04	0.09
Ln Price Index								
food	-0.06	0.04	-0.02	0.07	0.001	0.04	0.02	0.05
housing	0.08	0.07	**0.23**	0.12	0.08	0.08	0.11	0.08
education	-0.05	0.04	**-0.15**	0.06	-0.06	0.05	-0.08	0.05
recreation	0.02	0.09	0.15	0.13	0.12	0.09	0.08	0.08
eating out	**0.38**	0.16	0.13	0.24	-0.27	0.16	**0.35**	0.14
others	**-0.37**	0.15	-0.34	0.22	0.13	0.16	**-0.48**	0.14
income	-0.0001	0.0001	**-0.0002**	0.0001	-0.00002	0.0001	-0.00001	0.00003
Seasonal dummies								
jan-mar	**-0.005**	0.002	0.00004	0.004	**-0.009**	0.003	**-0.005**	0.003
apr-jun	-0.003	0.002	**0.01**	0.003	0.002	0.002	0.002	0.002
jul-sep	**0.01**	0.002	0.004	0.004	**0.006**	0.003	**0.006**	0.003
News index	-0.0001	0.0001	**-0.0002**	0.0001	-0.00002	0.0001	-0.00001	0.00003
Constant	**0.37**	0.12	0.14	0.08	**0.18**	0.09	0.11	0.06
Others								
Lagged w	0.27	0.21	0.17	0.22	0.36	0.21	0.09	0.20
Ln Price Index								
food	**-0.14**	0.06	-0.02	0.09	**-0.13**	0.06	-0.25	0.06
housing	0.08	0.12	**-0.32**	0.16	**0.22**	0.12	0.07	0.12
education	-0.06	0.07	**0.22**	0.09	-0.05	0.07	0.13	0.08
recreation	0.05	0.13	-0.07	0.17	**-0.50**	0.15	0.16	0.16
eating out	**-0.37**	0.15	-0.34	0.22	0.13	0.16	**-0.48**	0.14
others	**0.45**	0.21	**0.53**	0.27	0.33	0.24	0.37	0.23
income	0.04	0.05	**0.11**	0.04	0.06	0.03	0.01	0.03
Seasonal dummies								
jan-mar	0.009	0.005	0.01	0.007	0.011	0.006	**0.03**	0.01
apr-jun	**0.012**	0.005	0.01	0.007	**0.014**	0.005	**0.01**	0.01
jul-sep	0.004	0.005	**0.01**	0.007	**0.015**	0.006	0.011	0.01
News index	-0.00005	0.0001	**0.0003**	0.0001	**-0.0002**	0.0001	**0.0001**	0.0001
Constant	-0.06	0.27	-0.30	0.16	-0.09	0.19	0.21	0.16

Note: Bold numbers are significant at 5% significance level

Table 9: Food Expenditure SUR Model Estimation

	Low Income/No Child		*Low Income/Child*		*High Income/No Child*		*High Income/Child*	
fruit & veg	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.
Lagged w	**0.15**	0.06	0.02	0.06	**0.20**	0.06	**0.18**	0.06
Ln Price index								
fruit & veg	**0.09**	0.03	0.04	0.03	**0.10**	0.04	**0.13**	0.03
white meat	**0.03**	0.01	-0.01	0.01	0.02	0.02	-0.02	0.01
red meat	-0.01	0.02	0.03	0.02	0.00	0.03	0.00	0.03
carbohydrate	**-0.10**	0.03	**-0.07**	0.03	**-0.08**	0.03	-0.05	0.03
dairy	-0.01	0.01	-0.01	0.02	**-0.05**	0.01	**-0.05**	0.02
others	0.0004	0.01	0.01	0.02	0.005	0.02	-0.009	0.02
expenditure	0.02	0.01	0.02	0.01	0.02	0.02	-0.01	0.01
Seasonal dummies								
jan-mar	**0.01**	0.003	0.01	0.004	**0.01**	0.003	**0.01**	0.003
apr-jun	**0.02**	0.003	**0.01**	0.004	**0.02**	0.003	**0.02**	0.003
jul-sep	**0.03**	0.003	**0.01**	0.004	**0.03**	0.004	**0.01**	0.003
News index	0.00001	0.00001	**0.0001**	0.00001	0.00002	0.00001	**0.0001**	0.00001
Constant	**0.12**	0.02	**0.11**	0.01	**0.13**	0.02	**0.13**	0.01
white meat								
Lagged w	-0.05	0.08	0.03	0.08	-0.06	0.07	0.11	0.07
Ln Price index								
fruit & veg	**0.03**	0.01	-0.01	0.01	0.02	0.02	-0.02	0.01
white meat	-0.01	0.01	0.00005	0.01	**0.04**	0.02	0.01	0.01
red meat	-0.02	0.02	0.01	0.01	-0.02	0.02	0.01	0.02
carbohydrate	-0.01	0.02	-0.01	0.02	-0.03	0.02	-0.01	0.02
dairy	0.00	0.01	0.01	0.01	-0.01	0.01	-0.01	0.01
others	0.01	0.01	-0.005	0.01	0.002	0.01	**0.02**	0.01
expenditure	0.003	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Seasonal dummies								
jan-mar	**0.004**	0.002	-0.002	0.003	-0.001	0.002	0.003	0.002
apr-jun	0.002	0.002	-0.001	0.003	0.002	0.002	0.001	0.002
jul-sep	0.001	0.002	-0.005	0.003	0.003	0.002	-0.002	0.002
News index	0.000004	0.00001	**0.00002**	0.00001	0.00001	0.00001	**0.00002**	0.00001
Constant	**0.10**	0.01	**0.07**	0.01	**0.10**	0.01	**0.07**	0.01
red meat								
Lagged w	-0.02	0.06	0.08	0.06	0.01	0.06	**0.13**	0.06
Ln Price Index								
fruit & veg	-0.01	0.02	0.03	0.02	0.005	0.03	0.00	0.03
white meat	-0.02	0.02	0.01	0.01	-0.02	0.02	0.01	0.02
red meat	0.07	0.04	0.03	0.03	**0.13**	0.04	0.07	0.04
carbohydrate	-0.06	0.03	-0.05	0.03	**-0.08**	0.03	**-0.09**	0.03
dairy	0.01	0.02	-0.02	0.02	0.01	0.02	0.02	0.02
others	0.01	0.02	0.00	0.02	**-0.04**	0.02	-0.01	0.02
expenditure	**-0.04**	0.01	**0.03**	0.01	-0.01	0.01	**0.03**	0.01
Seasonal dummies								
jan-mar	-0.002	0.003	**-0.01**	0.004	0.00	0.003	0.00	0.003
apr-jun	**-0.01**	0.003	**-0.02**	0.004	**-0.01**	0.003	0.00	0.003
jul-sep	**-0.01**	0.003	-0.005	0.003	**-0.01**	0.003	0.00	0.003
News index	**-0.00002**	0.00001	**-0.00003**	0.00001	**-0.00004**	0.00001	**-0.00004**	0.00001
Constant	**0.27**	0.02	**0.20**	0.01	**0.23**	0.02	**0.17**	0.01

carbohydrate								
Lagged w	0.05	0.05	0.02	0.06	**0.14**	0.05	0.07	0.05
Ln Price Index								
fruit & veg	**-0.10**	0.03	**-0.07**	0.03	**-0.08**	0.03	-0.05	0.03
white meat	-0.01	0.02	-0.01	0.02	-0.03	0.02	-0.01	0.02
red meat	-0.06	0.03	-0.05	0.03	**-0.08**	0.03	**-0.09**	0.03
carbohydrate	**0.31**	0.05	**0.10**	0.04	**0.24**	0.05	**0.24**	0.05
dairy	**-0.09**	0.02	0.02	0.02	**-0.04**	0.02	-0.03	0.02
others	**-0.06**	0.02	0.002	0.02	-0.01	0.02	**-0.06**	0.02
expenditure	0.05	0.05	0.02	0.06	**0.14**	0.05	0.07	0.05
Seasonal dummies								
jan-mar	**-0.02**	0.003	-0.002	0.004	**-0.01**	0.003	**-0.01**	0.003
apr-jun	**-0.02**	0.003	**-0.01**	0.004	**-0.02**	0.003	**-0.02**	0.003
jul-sep	**-0.03**	0.003	**-0.02**	0.004	**-0.03**	0.003	**-0.02**	0.003
News index	0.00001	0.00001	**-0.0001**	0.00001	0.00002	0.00001	**-0.00003**	0.00001
Constant	**0.25**	0.02	**0.32**	0.02	**0.24**	0.02	**0.29**	0.02

dairy								
Lagged w	0.05	0.07	0.09	0.07	0.09	0.06	0.05	0.06
Ln Price Index								
fruit & veg	-0.01	0.01	-0.01	0.02	**-0.05**	0.01	**-0.05**	0.02
white meat	-0.001	0.01	0.010	0.01	-0.009	0.01	-0.013	0.01
red meat	0.01	0.02	-0.02	0.02	0.01	0.02	0.02	0.02
carbohydrate	**-0.09**	0.02	0.02	0.02	**-0.04**	0.02	-0.03	0.02
dairy	**0.09**	0.02	0.01	0.02	**0.10**	0.02	**0.09**	0.02
others	-0.002	0.01	-0.012	0.01	0.003	0.01	-0.024	0.01
expenditure	0.00001	0.00001	**0.00002**	0.00001	**0.00001**	0.00001	0.00001	0.00001
Seasonal dummies								
jan-mar	**0.01**	0.002	**0.01**	0.003	**0.004**	0.001	**0.005**	0.002
apr-jun	**0.01**	0.002	**0.01**	0.003	**0.01**	0.001	**0.01**	0.002
jul-sep	**0.01**	0.002	**0.01**	0.002	0.002	0.002	**0.005**	0.002
News index	0.00001	0.00001	**0.00002**	0.00001	**0.00001**	0.00001	0.00001	0.00001
Constant	**0.11**	0.01	**0.12**	0.01	**0.11**	0.01	**0.13**	0.01

Others								
Lagged w	-0.19	0.20	-0.25	0.22	**-0.39**	0.20	**-0.54**	0.19
Ln Price Index								
fruit & veg	0.0004	0.01	0.0147	0.02	0.005	0.02	-0.009	0.02
white meat	0.01	0.01	0.00	0.01	0.002	0.01	**0.024**	0.01
red meat	0.01	0.02	0.00	0.02	**-0.04**	0.02	-0.01	0.02
carbohydrate	**-0.06**	0.02	0.00	0.02	-0.01	0.02	**-0.06**	0.02
dairy	-0.002	0.01	-0.012	0.01	0.003	0.01	-0.02	0.01
others	**0.04**	0.02	0.00	0.02	0.04	0.02	**0.07**	0.02
expenditure	0.001	0.01	**-0.018**	0.01	0.005	0.01	0.008	0.01
Seasonal dummies								
jan-mar	**-0.005**	0.002	-0.001	0.002	-0.001	0.002	**-0.003**	0.002
apr-jun	-0.002	0.002	-0.001	0.003	0.002	0.002	0.001	0.002
jul-sep	-0.0002	0.002	0.0046	0.002	0.002	0.002	0.002	0.002
News index	-0.00001	0.0000	**-0.00002**	0.0000	-0.00001	0.00001	**-0.00001**	0.00001
Constant	**0.15**	0.04	**0.18**	0.04	**0.20**	0.04	**0.21**	0.03

Note: Bold numbers are significant at 5% significance level