The Impact of Child Obesity News on UK Household Food Expenditure

A thesis submited to
The University of Kent
In the subject of Management Science
For the degree
Of Doctor of Philosophy

By
Andres Silva
February 2012

Abstract

The United Kingdom (UK) has one of the highest obesity levels in the world (Mazzocchi, Traill and Shogren, 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.

Governments have the role of ensuring that households have the most complete information possible about their food choices (Mazzocchi, Traill and Shogren, 2009). With this objective, the UK government has conducted information campaigns such as nutritional food labelling and the 'Change 4 Life' campaign, in order to increase nutritional awareness. Despite government efforts, obesity has been steadily increasing in the UK.

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.

This study uses an augmented two-stage budgeting demand system. Demand systems combine price, income and news index data into a well-supported economic framework. The empirical analysis includes testing for homogeneity, symmetry, concavity and the time series properties of the data and the residuals. In the UK, no recent study has measured the impact of news on household food expenditure. Moreover, few empirical demand studies use structural approaches that are consistent with the time series properties of the data.

The results indicate that child obesity news do not have a significant impact on overall food expenditure. However, child obesity news causes a significant expenditure change in high-income households with children, with a significant increase in fruit and vegetable expenditure and white-meat expenditure, coupled with a significant reduction in red-meat expenditure and carbohydrate expenditure. This finding implies that child obesity news gives the incentive for a movement towards a healthier diet only to high income households with children. In contrast to this, low-income households and high-income households without children do not experience a significant impact on their diets.

This study also finds that, on average, households respond above ten times more to changes in prices, than changes in news. Moreover, the news effect on food group expenditure lasts a month, which implies that child obesity news needs to be recurrent for it to have a long-term impact. Therefore, price policies can be more effective in having an impact on household expenditure. Nevertheless, price policy would affect relative prices and impact on real household income.

The outcomes 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 empirical model specification and dataset employed can be used in this study to identify news that can have a significant impact on specific population segments. 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 spend the smallest proportion of their income on fruit and vegetables, even less than low-income households without children.

Table of contents

Table of contents v

List of tables viii

List of figures ix

1. Introduction 10

1.1. Background 10

1.2. Proposed Research 14

1.3. Research Problem and Hypotheses 16

1.4. Outline of the Report 16

1.5. Summary 17

2. Literature Review 18

2.1. Introduction 18

2.2. Experimental Studies 18

2.3. Single Equation 22

2.4. Demand Systems 23

2.4.1. Linear Expenditure System 26

2.4.2. The Rotterdam Model 28

2.4.3. Almost Ideal Demand System 30

2.5. Information in Demand Systems 33

2.6. Habits 37

2.7. Cointegration 39

2.8. Demographics 42

2.9. Endogeneity 43

2.10. Summary 45

3. Methodology 46

3.1. Introduction 46

3.2. Empirical Model 47

3.3. Data Description 51

3.4. The Living Costs and Food Survey ... 52
3.5. Media Index ... 53
3.6. Data Construction ... 55
3.7. General and Food Expenditure Groups ... 61
3.8. Summary ... 65

4. Estimation Strategy ... 67

5. Data Analysis ... 76

5.1. Introduction ... 76
5.2. First Stage Estimation ... 77
5.2.1. Basic Statistics ... 77
5.2.2. Unit Root Tests ... 83
5.2.3. Media Index ... 87
5.2.4. Seemingly Unrelated Regression Model ... 88
5.2.5. Residual Tests ... 93
5.2.6. Economic Constraint Tests ... 96
5.2.7. Elasticities ... 97
5.3. Second Stage Estimation ... 101
5.3.1. Basic Statistics ... 101
5.3.2. Unit Root Tests ... 106
5.3.3. Media Index ... 108
5.3.4. Seemingly Unrelated Regression Model ... 110
5.3.5. Residual Tests ... 114
5.3.6. Economic Constraint Tests ... 117
5.3.7. Elasticities ... 119
5.4. Hypothesis Testing ... 123
5.5. Summary ... 124

6. Discussion and Conclusions ... 127

6.1. Introduction ... 127
6.2. Contributions ... 132
6.3. Limitations ... 137

6.4. Future Research 139

Bibliography 141

7. Appendix 150

List of tables

Table 3.1 General Expenditure Group Composition 64
Table 3.2 Food Expenditure Group Composition 65
Table 5.1 Dataset Cases by Demographics 77
Table 5.2 General Expenditure Basic Statistics 80
Table 5.3 General Expenditure Series Order 86
Table 5.4 Media Index Selection 88
Table 5.5 Summary of the General Expenditure SUR Model 89
Table 5.6 General Expenditure SUR Model Estimation 91
Table 5.7 General Expenditure Residual Correlation Tests 93
Table 5.8 General Expenditure Residual Unit Root Tests 94
Table 5.9 General Expenditure Residual Distribution Tests 95
Table 5.10 General Expenditure Homogeneity and Symmetry Tests 96
Table 5.11 General Expenditure Unconditional Elasticities 99
Table 5.12 Food Expenditure Basic Statistics 104
Table 5.13 Food Expenditure Series Order 108
Table 5.14 Media Index Selection 109
Table 5.15 Summary of Food Expenditure SUR Model 110
Table 5.16 Food Expenditure SUR Model Estimation 113
Table 5.17 Food Expenditure Residual Correlation Tests 115
Table 5.18 Food Expenditure Residual Unit Root Tests 116
Table 5.19 Food Expenditure Residual Distribution Tests 117
Table 5.20 Food Expenditure Homogeneity and Symmetry Tests 118
Table 5.21 Food Expenditure Unconditional Elasticities 122
Table 7.1 General Expenditure Concavity Tests 158
Table 7.2 Food Expenditure Concavity Tests 168
Table 7.3 Conditional Food Expenditure Elasticities 170

List of figures

Figure 3.1 Media Index Plots 54
Figure 3.2 Expenditure Groups 63
Figure 5.1 Per Capita Total Expenditure Plots 78
Figure 5.2 Food Expenditure Share Plots 81
Figure 5.3 Food Expenditure Price Index Plot 82
Figure 5.4 Per Capita Food Expenditure Plots 102
Figure 5.5 Food Expenditure Share Plots 105
Figure 5.6 Fruit & Vegetable Expenditure Price Index Plots 106
Figure 7.1 Case 1: General Expenditure Budget Shares Plots 150
Figure 7.2 Case 1: General Expenditure Price Index Plots 151
Figure 7.3 Case 2: General Expenditure Budget Shares Plots 152
Figure 7.4 Case 2: General Expenditure Price Index Plots 153
Figure 7.5 Case 3: General Expenditure Budget Shares Plots 154
Figure 7.6 Case 3: General Expenditure Price Index Plots 155
Figure 7.7 Case 4: General Expenditure Budget Shares Plots 156
Figure 7.8 Case 4: General Expenditure Price Index Plots 157
Figure 7.9 Case 1: Food Expenditure Budget Shares Plots 160
Figure 7.10 Case 1: Food Expenditure Price Index Plots 161
Figure 7.11 Case 2: Food Expenditure Budget Shares Plots 162
Figure 7.12 Case 2: Food Expenditure Price Index Plots 163
Figure 7.13 Case 3: Food Expenditure Budget Shares Plots 164
Figure 7.14 Case 3: Food Expenditure Price Index Plots 165
Figure 7.15 Case 4: Food Expenditure Budget Shares Plots 166
Figure 7.16 Case 4: Food Expenditure Price Index Plots 167

Chapter 1

Introduction

1.1. Background

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, Traill and Shogren, 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.

Obesity is associated with the over-consumption of calories relative to need (DEFRA, 2010). On the one hand the vast majority of people do not practise physical activities on a regular basis. Most people do not have the time to undertake physical activities that are in accordance with government guidance. According to the National Health System (NHS) (2010), the UK public health agency, only 39% of men and 29% of women over sixteen years old meet the government's recommendations of thirty minutes of physical activity five times a week. Among children, a higher proportion of boys (32%) than girls (24%) practise the recommended daily hour of physical activity.

On the other hand there is an increased demand for convenience food (Ehmke *et al.*, 2008). Convenience food in general requires little preparation, contains additives, and a high sugar and fat content. According to the UK Department for Environmental and Rural Affairs (DEFRA) (2010), in order to achieve a healthy diet people should eat more fruit and vegetables and starchy foods, and fewer dairy products and foods with high sugar or fat content. Yet under a third of adults and a fifth of children had met the recommended fresh fruit and vegetable intake (NHS, 2010).

Obesity has multiple consequences, viewed from both a private and a public perspective. It can reduce the quality of life and lead to social stigmatisation, discrimination and difficulties in finding employment (Muth, 2010). Obesity is also a major risk factor for illness and may lead to premature death (NHS, 2010). Some illnesses commonly linked to obesity are hypertension, strokes, and diabetes. Thus we can say that obesity costs money not only to the individual but also to society both directly and indirectly.

Obesity costs can be classified as direct and indirect costs (Muth, 2010). Direct costs are directly linked to obesity, such as healthcare utilisation and medication expenditure. According to Thompson *et al.* (2001), obese adults have 48% more inpatient days per year and 1.8 times more pharmaceuticals dispensed to them in comparison to non-obese adults. Indirect costs are linked to lost productivity, which can be due to absenteeism – sick worker at home, or presenteeism – sick worker at work. Finkelstein *et al.* (2010) estimated the increased loss due to absenteeism for obese men as 0.5 to 5.9 days per year, whilst presenteeism was estimated to be 2.3 to 21.9 days per year, depending on the obesity level. Moreover, the obese population makes more frequent and more expensive disability and workers' compensation claims (Trogdon *et al.*, 2008).

Overall, the National Audit Office in England (2001) estimated that obesity causes £500 million direct costs and £2 billion indirect costs. 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, Strombotne and Popkin, 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.

Interventions to reduce obesity are also justified from an economic theory perspective. Neoclassical economic theory assumes perfect information. Perfect information means that everyone is aware of all the alternatives and information in the market. However, the perfect information assumption is not likely to be true in the real world. Tiffin, Traill and Mortimer (2006) took into account errors in perception. Errors in perception occur when individuals do not fully understand the short and long-term consequences of their food choices. Households tend to make suboptimal choices as a result of having only incomplete or misleading information available to them.

An important governmental role is to ensure that households have the most complete information possible about their food choices (Mazzocchi, Traill and Shogren, 2009). In 2009, the UK government launched the 'Change 4 Life' campaign to increase nutritional awareness. This campaign promotes eating more than five portions of fruit and vegetables a day, decreasing the consumption of saturated fats and increasing physical activity. Consumption of five portions of fruit and vegetables, 400 grams excluding potatoes, is associated with a reduced risk of cardiovascular disease and of some types of cancers (DEFRA, 2011).

Furthermore, the UK government has made efforts to increase information by improving food label regulations. Since 1996, the authorities have been continually improving the information displayed on food labels. For example, the traffic-light system applied to food labels aims to inform consumers better by summarising nutritional information using colours (Roosen and Marette, 2011). Additionally, Drichoutis, Lazaridis and Nayga (2009) found that consumers are willing to pay for nutritional information to be displayed on the label. Research supports the notion that labels can be used to inform consumers about product attributes. It is to be expected, that an informed consumer is more likely to make food choices that would help to reduce obesity.

Neoclassical economic theory also 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.

A negative externality occurs when the social cost is greater than the private cost. For example, in cases of smoking and unhealthy eating, social costs are consequently greater than private costs. Conversely, a positive externality occurs when the social benefit exceeds the private benefit, such as engaging in physical activities on a regular basis (Just, Hueth and Schmitz, 2004). Research has proposed the implementation of a specific tax on unhealthy food, as a way to internalise the obesity-externality. For example, Andreyeva, Chaloupka and Brownell (2011) discussed taxation of sugar sweetened beverages, while Lacanilao, Cash and Adamowicz (2011) studied the impact of a snack tax.

Tiffin, Traill and Mortimer (2006) stated that constraints on the choices available can also justify policy interventions in food markets. Constraint on the choices available occurs when healthy food is not available or affordable. For instance, low-income households cannot afford some of the healthy food choices. Taking this into account, the food stamp programs help low-income households by increasing nutrient availability (Devaney and Moffitt, 1991).

A reduction in the obesity trend would control direct obesity costs for the NHS; it would reduce loss of productivity and increase population welfare. The UK Government Office for Science (2010) recommended a substantial degree of intervention, to generate an impact on the rising trend in obesity. Amongst the policy alternatives available, information policies have a key role to play in helping people make conscientious food choices (Shimshack, Ward and Beatty, 2007). In this sense, food choices can be described as being private decisions with public impacts.

1.2. Proposed Research

The objective of this study is to generate empirical evidence of the impact of child obesity on household expenditure. Child obesity news is treated as a specific information message that is received by households. In more general terms, information refers to any indicators that consumers receive from the outside. Even prices are information, in the sense that prices are the product of the interaction between supply and demand (Mazzocchi, Traill and Shogren, 2009).

Households receive information from a variety of sources and through a variety of channels. Householders can be influenced by information, such as advertising, to explicitly pursue a specific purchase action. Advertising is unlikely to be seen as objective information, because its objective is clearly to increase sales (Burton and Young, 1996). Households can also be affected by information in the media regarding food products, such as food safety crises. Chang and Kinnucan (1991) argued that people are more likely to trust more neutral sources, like newspapers, rather than advertising. Finally, households can also receive nutritional information from food packaging. In this sense, advertising, news and labelling content are all sources of information that potentially affect household behaviour.

Some researchers who have looked at the impact of information on consumer demand in the UK, are Burton and Young (1996) on food incidents, and Duffy (2003) on advertising. They stated that information significantly impacts food expenditure. Burton and Young argued that the Bovine Spongiform Encephalopathy (BSE) crisis caused a shift of expenditure to substitutes, and Duffy argued that generic advertising is less effective than brand advertising for promoting a product. Nevertheless, taking into account the increasing obesity rate, the debate is centred on the issue of how to use information in order to encourage people to shift to a healthier diet.

In terms of UK studies, this research is closest to that of Burton and Young (1996), in that it involves a methodology that allows for imposing neoclassical economic theory. However, Burton and Young (1996) do not include a discussion on the role of habits in food expenditure and the study's application relates to food safety crises rather than child obesity. Consequently, there is still ample work to be done on measuring information impact.

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 specifically isolates 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.

1.3. Research Problem and Hypotheses

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.

1.4. Outline of the Report

The remainder of this document is organised in the following way:

Chapter 2 reviews methodologies, to measure the effect of information in the context of household food decisions. These methodologies include experimental economics and demand systems. The demand system combines price, income and information effects, within a framework consistent with neoclassical economic theory. This study singles out three popular demand systems for discussion.

Chapter 3 selects 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. This study explains how the raw data, household expenditure and child obesity news data is converted into the variables necessary to estimate the empirical model.

Chapter 4 justifies some econometric choices. It reviews some of the past research in this area, in order to justify each one of these empirical choices. Chapter 5 presents the estimation results. Chapter 6 discusses the findings, compares their implications with past research, makes policy recommendations, identifies some limitations and highlights some areas for future research.

1.5. Summary

Increasing obesity, especially in children, is of high public concern in the UK. Policy interventions can be justified in order to correct a market failure or to reduce increasing obesity costs. Information-based policy is an alternative policy intervention. However, there has not until now been any empirical evidence produced regarding the impact of child obesity news at household level in the UK.

In this context, this document aims to help identify effective information-policies which would provide an incentive for making healthy food choices at a household level. This methodology can be applied to other types of information messages. In undertaking this exercise, this methodology could help us to identify which households are more susceptible to a specific message.

Chapter 2

Literature Review

2.1. Introduction

In neoclassical economic theory, consumers maximise their utility by consuming goods subject to a budget constraint based on a given set of prices and assuming perfect information. Information is assumed to be costless and fully available. The quantity demanded depends exclusively on prices and income. However, perfect information is a theoretical assumption that is unlikely to hold in reality. Studies have found that information is of particular relevance in understanding consumers' behaviour (i.e. Brown and Schrader, 1990).

This chapter describes how past research has measured the impact of information, and reviews some of advantages and disadvantages of different approaches. In particular, this chapter focuses on experimental studies and demand systems. Concerning the demand system, this study covers in particular: the Linear Expenditure Systems, the Rotterdam Model and the Almost Ideal Demand System.

Experimental economics relies on primary data, while the demand system relies on secondary data. The coming section starts describing the type of data and the characteristics of each of these two approaches to measure informational effects.

2.2. Experimental Studies

Experimental economic studies have been used to measure information impacts. In experimental economic studies, people are called "subjects" and recruited to perform a protocol or set of tasks. Depending on the objective of the study, subjects may receive payment and be required to fill demographic, attitude and/or consumption questionnaires.

Experimental economic studies have been performed in a range of controlled conditions (Harrison, 2011). In a more controlled environment, such as a laboratory setting, it is possible to conduct long protocols due to the greater likelihood of holding subjects' attention for a longer period of time. However, subjects may be faced with conditions that are too artificial and this could bias their responses.

By contrast, in a less controlled environment, such as a field studies, subjects are in a more natural and familiar environment (Roosen and Marette, 2011). However, subjects tend to be less available for long protocols, and external random events can influence their responses. For instance, List (2001) elicited sport cards using alternative levels of information. The author explained that a field experiment allows for a wide range of demographic characteristics. Lusk and Hudson (2004) added that lower compensatory fees are necessary, with a more natural availability of complement and substitute goods, and a greater ability to target the population of interest.

Some experimental studies have directly elicited the value of information. For instance, Fox, Hayes and Shogren (2002) compared the effects of favourable and unfavourable information on the Willingness to Pay (WTP) for a pork sandwich irradiated to control *Trichinella.* They found that subjects were more influenced by a negative description, even when the information is derived from a questionable source.

Moreover, information has also contributed towards the increased realism of experimental study settings and, therefore, to the increased reliability of WTP estimates. There is a general acknowledgement that people in hypothetical situations behave differently, when compared to those in real situations. For instance, Blumenschein *et al.* (2001) found that 38% of subjects stated that they would buy a specific asthma-management program, but only 12% of the subjects actually bought it.

In hypothetical WTP studies in particular, subjects tend to overstate their actual WTP, also known as hypothetical bias (Cummings, Harrison and Rutstrom, 1995). In the hypothetical WTP studies, where the subject is not directly exposed to the product, contingent valuation (CV) and conjoint analysis (CA) have been widely used (Green, Krieger and Wind, 2001, Carson, Flores and Meade, 2001). Evidence of this hypothetical bias is widespread in CV studies (Neill et al., 1994, Cummings, Harrison and Rutstrom, 1995, List and Gallet, 2001, Loomis et al., 1997) and is less frequent in CA (see Ding, Grewal and Liechty, 2005).

Information can help to minimise hypothetical bias. Cummings and Taylor (1999) introduced the concept of "cheap talk" as a non-binding communication of actions before a hypothetical commitment. This communication specifically included information about the hypothetical bias problem. Cummings and Taylor (1999) tested two alternative script versions. In the first version, they included a discussion of the numerical results of a similar hypothetical task. In the second version, the same results were discussed without reference to numerical statistics. The cheap talk scripts were successful in reducing hypothetical bias. Both scripts made explicit reference to the expected direction of the bias.

After Cummings and Taylor (1999), many researchers have used information, in the form of cheap talk scripts, to generate more reliable WTP estimations. However, empirical evidence may be contradictory in a number of cases. The effectiveness of the cheap talk script in mitigating hypothetical bias depends, at a basic level, on the script length, payment level and subject's background (Murphy, Stevens and Weatherhead, 2005). Loomis *et al.* (1996) and Brummett, Nayga and Wu (2007) found that a short cheap talk script was ineffective to remove hypothetical bias. In contrast, Aadland and Caplan (2003) and Carlsson, Frykblom, and Lagerkvist (2005) found that a short cheap talk script was effective in reducing hypothetical bias. However, Cummings and Taylor (1999), Murphy, Stevens and Weatherhead (2005), and Landry and List (2007) consistently found that a long script was an effective means to reduce hypothetical bias. Consequently, the empirical evidence tends to show that long scripts tend to be more effective than short scripts in the mitigation of hypothetical bias.

Brown, Ajzen and Hrubes (2003) and Murphy, Stevens and Weatherhead (2005) found that cheap talk scripts were effective only with high-level payment. Moreover, List (2001) and Lusk (2003) found that the cheap talk script was able to remove the hypothetical bias only where inexperienced/uninformed subjects were concerned. Therefore, experimental studies show that information plays a significant role in consumer behaviour. Subjects are willing to pay for increasing levels of information and information can also help to mitigate hypothetical bias. However, the impact of information would depend on, at a basic level, the information itself, the level of commitment of the subjects, and the previous information level.

Critiques of experimental economic studies have focused on their lack of external validity, likely selection bias, and relatively small sample size. External validity refers to how easily laboratory findings may be extrapolated to a real world situation. Selection bias is associated with the way that subjects are selected to participate in a protocol. In general, experimental economic studies do not use random samples. In fact, it is common for researchers to use classroom students. Finally, because of logistic or budget constraints, it is rare to find a sample size larger than a few hundred subjects.

Recently, Dillaway *et al.*(2011) conducted the only experimental study that measures the long and short-term impact of food safety media information. The study expanded previous research because it conducted a follow up WTP valuation after a week and seven weeks. Doing this, it is possible to test how the WTP valuation changes over time. The data were analysed using double bounded Tobit. Results showed that subjects are willing to change their food choices based on food safety information. Subjects avoided unsafe products even if they need to switch to more unknown brands. Moreover, negative information effect last longer than positive information effect.

Another way to analyse information impact is by using secondary data. Secondary data corresponds to data already collected by a third party. Single equation and a system of equations can be used to model secondary data.

2.3. Single Equation

In a single equation, the dependent variable is explained by a set of independent variables. In a single equation time series, the right hand side commonly corresponds to lagged values of the dependent variable. For instance, event studies have been used to measure information effect, such as the impact of food safety incidents. Event studies use historical time series data to generate predictions from a number of days before and after the event. Then, the difference between predicted and real data is quantified using a measure such as the mean cumulative prediction error. Thomsen and McKenzie (2001) found a 1.5% to 3% negative return when a food recall involves serious a food hazard to consumer health. Using the same approach, Salin and Hooker (2001) analysed the stock market reaction using four food recalls. Finally, Schlenker and Villas-Boas (2009) used event studies with scanner data and future prices to analyse the impact of BSE events in the meat market.

In some time series, as is frequently the case in financial data, large and small residuals come in clusters. In this sense, the variance of an error may depend on the size of the preceding error. Engle (1982) introduced the conditional variance or volatility model that can also be used to measure the impact of information. AutoRegressive Conditional Heteroskedasticity (ARCH) and Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) models explain the variance, thus relaxing the unlikely assumption of constant stock return variance. A basic conditional variance model has a mean equation and a variance equation. The residuals of the mean equation are used in the variance equation. The mean equation can also include exogenous variables. In the ARCH model, the variance is the function of the square of previous residuals and a constant. The constant represents the long-term volatility. The GARCH includes the ARCH components in addition to previous variance terms.

A food-safety event can be treated as new information that would be reflected in the stock returns. Wang *et al.* (2002), using five stock return, calculated the impact of food bacterial contamination on stock returns. The authors found that the stock conditional variance changed over time, so, it was appropriate to use a GARCH model. Moreover, compared with an event study, the GARCH model is more informative with respect to the level of the stock return series as well as variance of the stock return series. The GARCH equations were augmented with dummy variables to measure the daily impact on returns and variance. The authors found that food-safety events decreased stock returns, while increasing volatility at the company and industry levels. However, subsequent food-safety events have a reduced impact, which can be interpreted as indication that the market had already taken into account a higher food safety risk in these stocks.

With a more general specification, single equation regression allows for two or more variables in the analysis. In a single equation regression, the dependent variable is the consumed food quantity and explanatory variables are factors that influence consumption. Explanatory variables can include own product price, complementary and substitute product price, *per capita* income, region, gender, trends and seasonal variables. For instance, Shimshack, Ward and Beatty (2007) conducted a study to measure the effect of heavy metal information in canned fish purchased. The model specification is equivalent to a Heckman two-step procedure with a Probit in the first step and a single regression in the second step. The Probit model explains the purchase decision as a binary outcome, buy or not buy, and the simple regression explains the quantity purchased decision as a continuous outcome. The authors included a set of interaction variables, such as child and reader. The results show that access to information, newspaper readership, ability to assimilate information, and education, play a significant role in consumer behaviour. However, a single regression equation fails to include the economic theory that it is desirable to reflect in a model. By contrast, as will later be shown, some demand systems make use of economic theory.

2.4. Demand Systems

Demand systems are composed of a set of equations, where each equation represents a demand equation for an expenditure group, such as food, transport and recreation. The sum of group expenditures equals the total expenditure. Without considering savings or debts, the total expenditure is equal to the income that is equivalent to the budget constraint. The system is estimated jointly. Due to the large number of parameters that are calculated, a large sample size is required, and this approach provides a more complete understanding of the consumers' decision process.

As indicated by Deaton and Muellbauer (1980b), early developments in demand analysis are associated with the calculation of demand elasticities. Elasticity is a measure of the responsiveness of the dependent variable to a change in an independent variable. In demand analysis, own-price, cross-price, and expenditure or income elasticities are frequently calculated. Own price elasticity, also known as price elasticity, measures the percentage change in quantity demanded after a one-percent change in price (Sloman and Hinde, 2007). Considering the law of demand, price elasticity is expected to be negative. A product is inelastic (elastic) if its price elasticity is less (more) than one in absolute value. Cross-price elasticity measures the percentage change in quantity demanded after a percentage change in the price of a complementary or substitute product. Expenditure elasticity measures the percentage change in quantity demanded after a percentage change in expenditure. Cross-price and expenditure elasticities can bear any sign, which is informative with regard to characterising the type of product and its relations to other products. A product can be classified based on the expenditure elasticity sign and its magnitude. A product is called "inferior" if its income elasticity is negative. A product is called "normal" if its income elasticity is positive and "luxury" if its income elasticity is larger than one (Sloman and Hinde, 2007). These elasticity definitions are used in commenting on the results of the current study.

The negative sign of price elasticity is associated with income and substitution effects. After a price change, the consumer would experience simultaneously the income and substitution effects. The income effect is the change in the quantity demanded due to change in real income, which causes a shift to another indifference curve (Sloman and Hinde, 2007). For instance, if the price rises, the consumer would be worse off since he would be able to buy fewer products than before, consequently, the consumer moves to an indifference curve to the left.

The substitution effect is the change on the quantity demanded due to the relative price change, which causes a movement along the indifference curve (Sloman and

Hinde, 2007). For instance, if the price rises, the consumer would switch consumption to alternative products, consequently, the consumer moves along his indifference curve.

Economic theory predicts that own-price substitution effect is negative because of the law of demand. If the price of a product goes up, it is expected that the quantity demanded for that product would go down. However, income effect has an ambiguous sign. Income and substitution effects are represented in the Slutsky equation (Deaton and Muellbauer, 1980b):

$$S_{IJ} = \frac{\partial h_i(p,u)}{\partial p_J} = \frac{\partial g_i}{\partial x} q_j + \frac{\partial g_i}{\partial p_j} \qquad [1]$$

where $h_i(p,u)$ is the Hicksian demand for product i, p_J is the price of product j, g_i is the Marshallian demand and x is expenditure. The term $\frac{\partial h_i(p,u)}{\partial p_J}$ is the substitution effect and $\frac{\partial g_i}{\partial x} q_j$ is the income effect. Marshallian demand, or uncompensated demand, is derived from the utility maximisation problem. Marshallian demand is observable and shows how the quantity demanded changes after a price change, keeping expenditure constant. In a similar way, the Hicksian demand, or compensated demand, is derived from the cost minimisation problem. Hicksian demands are not directly observable, and show how the quantity demanded changes after a price change, keeping utility constant (Deaton and Muellbauer, 1980b). The current study uses these concepts to characterise alternative demand systems. Moreover, Chapter 5 presents the uncompensated elasticities, which would help to better understand the impact of information in consumers' decision-making processes.

The demand system has numerous advantages. Taking into account that it is a system of equations that simultaneously estimate more than one demand equation, a demand system allows for testing cross-equation constraints. In this regard, Zheng and Kaiser (2008) argued that demand systems, rather than any single equation, are more adequate to evaluate spillover effects. A spillover effect occurs when non-target groups benefit from information aimed at a different target group. In particular in this research, as it is presented later on, spillover effects would be important to measure the actual information effect.

Moreover, economic properties can be included in demand systems. In some demand systems, it is possible to recover the complete Slutsky matrix, which contains the compensated own-price and cross-price elasticities. Nevertheless, demand systems offer some empirical challenges, as will be discussed in Chapter 4. In the following subsection, the current study reviews three well-known demand system specifications and the empirical contributions associated with each of them: Linear Expenditure System, Rotterdam Model, and the Almost Ideal Demand System (AIDS).

2.4.1. Linear Expenditure System

The Linear Expenditure System (LES) was developed by Stone (1954). In the LES, the expenditure on each good is a linear function of price and category total expenditure in the following way:

$$p_i q_i = p_i \gamma_i + \beta_i [x - \sum p_k \gamma_k] \qquad [2]$$

where p_i is the price of product *i*, q_i is the quantity of product *i*, *x* is the expenditure, β_i is the subsistence or precommitted quantity of the product *i*, and β_i is the proportion of the supernumerary expenditure, such as, $0 < \beta_i < 1$ and $\sum_i \beta_i = 1$. Firstly, the consumer satisfies his/her required minimum $(p_i \gamma_i)$, and then, the residual expenditure or supernumerary level $(x - \sum p_k \gamma_k)$ is allocated in a fixed proportion β_i. As presented by Pollak and Wales (1992), $x > \sum p_k \gamma_k$, therefore, $q_i > \gamma_i$. In other words, since the total expenditure is bigger than the sum of expenditure on other products, excluding product *i*, the subsistence quantity is lower than the total consumed quantity of product *i*.

The LES is quite restrictive and its results need to be considered with caution (Deaton and Muellbauer, 1980b). For instance, β_i is fixed and nonnegative. Non-negativity eliminates the possibility of inferior goods. Fixed β_i, known as the linear Engle curve, means linear consumption expansion after successive increases of income. In other words, β_i is constant over different income levels. Non-existence of inferior goods is not likely to hold in reality, since, as income rises, it is likely that households would shift expenditure from more basic to more sophisticated products.

Numerous researchers have used LES by itself or in combination with other demand systems. Using a two-stage LES-AIDS demand system, Han and Wahl (1998) estimated household demand in rural China. In the first stage, the expenditure is allocated into five broad groups. In the second stage, the food group is divided into ten food subgroups. The authors found that the demand for fruit and vegetables is linked with high levels of income.

Also using a two-stage LES-AIDS demand system, Richards, Ispelen and Kagan (1997) measured the impact of promotion in exportation programmes for US apples. In the first stage, the model included broader import categories. In the second stage, the apple imports are divided by country of origin. The analysis is repeated for Singapore and the UK. The results showed that promotion has increased the consumption of apples in both countries. However, only in the UK did the US promotion lead to a larger US apples share. This fact suggests that other apple-producing countries are gaining benefits from US apple-promotion programs.

Another piece of research using a two-stage LES-AIDS demand system, Michalek and Keyzer (1992) estimated a demand system for eight European countries. In the first stage, the expenditure is distributed into four broader categories. In the second stage, the food expenditure is divided into ten food subcategories. The analysis is done for 1970 and 1985. The authors found a larger difference in elasticity across countries than over time. Consequently, despite the highly restrictive non-existence-of-inferior-product assumption, LES has numerous applications. In the following demand specification, the assumption of non-existence of inferior goods is relaxed.

2.4.2. The Rotterdam Model

The Rotterdam model was initially derived from consumer demand theory by Barten (1964) and Theil (1965). The Rotterdam model is estimated as a system of equations – the dependent variables are the budget expenditure shares in log form – and allows for the imposition of theoretical restrictions. The demand equations can be calculated in the following form:

$$\bar{w}_i \Delta q_i = b_i[\Delta y - \sum_k w_k \Delta p_k] + \sum_j c_{ij} \Delta p_j \qquad [3]$$

where,

$$\Delta q_i = \log\left(\frac{q_i}{q_{it-1}}\right)$$

$$\Delta p_j = \log\left(\frac{p_j}{p_{jt-1}}\right)$$

$$\Delta y = \log\left(\frac{y}{y_{t-1}}\right)$$

$$\bar{w}_i = \frac{w_i + w_{it-1}}{2}$$

where, w_i is the expenditure budget share of product *i,* equivalent to ${p_i q_i}/_{x}$, p_i is the price of product *i*, q_i is the quantity of product *i*, b_i is the marginal propensity to spend on the *i*th good, c_{ij} is the *(i,j)*th term of the Slustky matrix. The term$c_{ij} = w_i \varepsilon_{ij}^*$, where, ε_{ij}^* is the compensated cross-price elasticity.

The Rotterdam model allows for testing and/or imposing some economic theory. The homogeneity restriction, also known as 'absence of money illusion', implies that every demand equation must be homogeneous of degree zero in income and prices. In other words, if relative prices and income are multiplied by the same positive constant, preferences must remain the same. Deaton and Muellbauer (1980b) explain that the price and income units have no effect on purchases. The adding-up restriction, also known as the Engle Aggregation condition, 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*. As a consequence, the marginal propensity to spend on each product must amount to one, and a price change has zero net effect on the budget constraint (Deaton and Muellbauer, 1980b). Finally, there are the Slutsky symmetry conditions. At the beginning of the discussion on the demand system, the current study mentions the Slutsky equation, which corresponds to equation 1. The Slutsky equation shows that price derivatives of a demand equation can be decomposed into an income effect and a substitution effect.

The Slutsky matrix of compensated price responses, or substitution matrix, is symmetric and negative semi-definite. Symmetric given that 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. Negative semi-definiteness takes into account that the diagonal elements are negative (own substitution effects). The sign of each non-diagonal element would depend on the relations between products in terms of substitutes, complements and independents. Chapter 4 discusses how to calculate the Slutsky matrix. The Slutsky matrix is used to test for concavity of the expenditure function, which is discussed in Chapter 4.

A set of demand functions satisfies integrability conditions if it fulfils adding-up, homogeneity and symmetry conditions. Moreover, if it also satisfies the negative semi-definiteness condition, it is considered rational (Lewbel, 1996).

Compared with the LES model, the Rotterdam model has the advantages of imposing economic restrictions and recovering the complete Slutsky substitution matrix (Deaton and Muellbauer, 1980b). The Rotterdam model has numerous applications. Capps and Schmitz (1991), using the data set from Brown and Schrader (1990), measured the impact of scientific cholesterol information on meat consumption. The authors found that cholesterol information has impacted poultry and fish consumption positively, and pork consumption negatively.

Brown and Lee (1993) studied alternative ways to include the advertising effect in the Rotterdam model. Using scanner data of three types of fruit juices, the authors found that own-price elasticity was consistently negative. The advertising effect was smaller than own-price elasticity and did not have a consistent sign across model specifications. However, it is not possible to state something about advertising effectiveness without first obtaining advertising cost information.

Brester and Schroeder (1995) used the Rotterdam model to compare generic and branded advertising effects on meat demand. In most cases, the generic advertising effect was not significantly different from zero. However, the brand advertising effect tended to be significant, which effects went beyond the substitution between meats. Brand advertising, in some cases, increased the total meat consumption.

Marsh, Schroeder and Mintert (2004) estimated the impact of food recall events in the same sector (meat consumption). The authors used an augmented Rotterdam model that included newspaper and recall indexes. The results showed that the recall index had a significant impact. In contrast, the newspaper index did not have a significant effect. The authors inferred from this that consumers could rely more on the actual recall than on the related newspaper information. Moreover, any positive demand effects on meat substitutes for a recall is offset by a more general negative effect on meat demand. In the following section, the current study discusses the AIDS model, which also allows for the imposition of theoretical restriction, while fulfilling the integrability condition.

2.4.3. Almost Ideal Demand System

In this chapter, this study introduces the most general AIDS specification, with a view to reviewing some past research applications. Chapter 3 describes the general AIDS model, and the general AIDS model is modified to test the hypotheses. The AIDS model was introduced by Deaton and Muellbauer (1980b). The AIDS specifies a system of budget shares equations in the following way:

$$w_i = \alpha_i + \sum_{j=1}^{m} \gamma_{ij} \, ln \, P_j + \beta_i ln(lnx - lnP) + \, e_i \qquad [4]$$

where α_i is the intercept, γ_{ij} is the change in the budget share of i with respect to p holding constant the total expenditure, β_i is the change in the budget share with respect to a change in real expenditure holding price constant. The term α_i comprises the budget shares for households at subsistence levels of expenditure. The term $\beta_i > 0$ means a luxury good and $\beta_i < 0$ indicates necessities (Deaton and Muellbauer, 1980b). Finally, e_i is the error term and P is a price index which takes the following non-linear form:

$$lnP = \alpha_0 + \sum_{i=1}^{m} \alpha_i \, lnp_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \gamma_{ij} \, lnp_i ln\, p_j \qquad [5]$$

The AIDS model has numerous applications. For example, Green, Carman and McManus (1991) compared two alternative AIDS model specifications using dried fruit data in California. The authors developed two AIDS specifications that included advertising variables in the income term rather than as an intercept shifter. The results showed a weak generic advertising effect. Piggott and Chalfant (1996) compared a single regression to the AIDS model in the case of generic advertising in the Australian meat market. The results showed that the advertising effects were not very sensitive to the functional forms, an observation which does not seem applicable to other cases. Pofahl, Capps and Love (2006) used an AIDS model to show the price effect of merger in the ready-to-eat cereals industry. The authors found that high-income price zones are more affected by post-merger prices than low-income zones. In Chapter 3 and Chapter 4, the current study reviews more AIDS model applications to support empirical choices.

The AIDS model and the Rotterdam models are two of the most popular demand systems. These demand systems are second-order locally flexible functional forms, and both have the same data requirements and the same number of parameters, and can be linear in parameters (Alston and Chalfant, 1993). Moreover, since these models are specified as a system of equations, it allows the testing of cross-effects, which would not be possible with a single equation (Zheng and Kaiser, 2008).

Since the AIDS and the Rotterdam models have different forms of dependent variables, it is not clear how to choose the most appropriate model for a particular dataset, which may lead to different results (Alston and Chalfant, 1993). On account of this, in general the demand system is chosen arbitrarily. Few cases present both model estimations, as Zheng and Kaiser (2008) do. However, identifying the most appropriate estimate of elasticities is not a straightforward matter.

Up to this point, the current study has reviewed three popular demand systems and highlighted some desirable theoretical constraints, such as homogeneity, symmetry and adding-up. However, these model specifications are static. By contrast, a dynamic model specification includes lagged dependent and/or independent variables as explanatory variables. In this sense, a dynamic specification would help to explain how a variable impacts through time.

The importance of dynamic elements in demand systems is well-documented. In an LES model, Pollak and Wales (1969) highlighted the importance of including dynamic specification. Chen and Veeman (1991) stated that the main limitation of the static AIDS model, as well as other static demand systems, is the lack of dynamic elements to explain consumer behaviour.

Not only could the lack of dynamic elements lead to misleading results – it has furthermore been identified as the cause of over-reject theoretical constraints. Empirically, Gang, Haiyan and Stephen (2004) found that not only does dynamic AIDS specification fulfil theoretical constraints, it also has better forecast accuracy.

Food expenditure and information are likely to have an effect that lasts longer than the contemporaneous period. Consequently, the current study takes into account habit and information as dynamic elements. With regard to this point, in the following section this study introduces the topic of information in demand systems. Moreover, we also include discussion on habits, co-integration, demographics and endogeneity, which are aspects that we take into account in Chapter 4 and Chapter 5.

2.5. Information in Demand Systems

Information explains some variability in the consumer demand (Brown and Schrader, 1990). Because of this, information variables are included as explanatory variables. Since it is expected that information would cause a continuous change, it is more appropriate to use continuous information variables (Burton and Young, 1996).

Continuous information variables have been created using data of advertising expenditure or coverage (Baye, Jansen and Lee, 1992), the size of product recall (Marsh, Schroeder and Mintert, 2004), and the number of news (Verbeke and Ward, 2001) or academic articles (Capps and Schmitz, 1991) with a combination of keywords. These keywords can be related to a broad topic or a food event like a specific food-safety crisis from a particular region, within a specific period of time.

In the case of news articles, the information index – also known as the media index – may allow for positive and negative media news. For instance, Smith, Ravenswaay and Thompson (1988) explained that after a food-safety incident it is likely that authorities would use the media to counteract negative information. The authors created a media index using the two major newspapers over the period under study. Each article was classified separately as either negative or positive media. Verbeke and Ward (2001) also distinguished between positive and negative news. The authors argued that most news has a negative content and total news is highly correlated with negative news. Therefore, a media index using total news or the difference between negative and positive news should generate similar results. However, as indicated by Mazzocchi (2006), the classification into positive and negative news can be a highly subjective matter.

In addition to news, the information index can aggregate the number of appearances of a particular combination of keywords in a scientific online search engine. In the US, Brown and Schrader (1990) created a scientific information index based on the articles in Medline, which is an academic online search engine. Capps and Schmitz (1991) used the data set from Brown and Schrader (1990) to take into account the impact of scientific cholesterol information on egg consumption. However, even when performing relatively well historically, it is debatable how easily the academic information may be transferred to the consumer level (Verbeke and Ward, 2001). In this respect, it is unclear how scientific publications would increase consumer awareness.

Also using a scientific cholesterol information index, Rickertsen, Kristofersson and Lothe (2003) measured the impact on meat consumption in Nordic countries. In most Nordic countries, cholesterol information had a positive effect on chicken consumption. In addition, meat own-price elasticities were less than one in absolute value. Therefore, the authors suggested using information combined with taxes as an incentive for the consumption of healthier types of meat.

Burton and Young (1996) used a specific food-safety media event index to measure the impact of BSE information effects on beef demand in the UK. The study found that the BSE crisis had a significantly negative impact on beef-consumption in both the short and the long run. In the long run, the authors found that the beef market share was reduced by 4.5%.

Alternatively, an information index can contain advertising expenditure or coverage data to measure the impact of a marketing campaign. Green, Carman and McManus (1991) compared a double-log demand system to the AIDS model specifications using data from the dried fruit sector. The double-log demand system explains the log of quantity demanded as a function of the log of prices, log of advertising and log of expenditure. The authors found that generic advertising has a weaker effect on the demand than price and total expenditure do. The finding is consistent with the work done by Brester and Schroeder (1995) in relation to demand for meat.

Few studies consider more than a single information effect in the same model. Yen *et al.* (2004) combined many information sources in a single variable. Therefore, a single variable contained information sources such as newspapers, TV, radio and labels. The authors found that information and advertising campaigns can effectively minimise the substitution between soft drinks and milk. However, the results cannot identify the impact of a single source.

Verbeke and Ward (2001) included a media index of TV coverage and advertising expenditure, as two separate variables, to measure the impact of BSE information in Belgium. The results showed that brand and generic advertising effect caused a minor positive impact, as compared with the negative TV media impact.

Piggott and Marsh (2004) built separate media indexes for beef, poultry and pork. The separate media index allowed for testing cross-effects, such as the impact of food-safety information about beef on the demand for poultry. The authors found that food-safety information causes a statistically significant own- and cross-information effect, which is small in magnitude.

Using an advertising and a scientific information index, and building upon the work done by Brown and Schrader (1990), Chang and Kinnucan (1991) used a system of semi-logarithmic equations to estimate the impact of advertising and scientific information on the Canadian butter market. In this system, the quantity demanded was explained as a function of the log of prices, log of expenditure and log of cholesterol information.

Chang and Kinnucan (1991) found that, in absolute terms, the scientific information elasticity was larger than the advertising elasticity. The larger information effect is consistent with findings by Verbeke and Ward (2001) for the meat market in Belgium. Marsh, Schroeder and Mintert (2004) found that product recall, as opposed to media product recall, significantly impacted consumer behaviours. Consequently, consumers tend to be more influenced by scientific information than by advertising. At the same time, an actual recall seems to be more significant than the related news.

An information index can be included in demand system in level or cumulative specification forms. Moreover, the information index can include both weighted and lagged structures. Cumulative informational indexes are used to take into account the summative effect (Burton and Young, 1996), which can also be interpreted as a gradual change in consumer behaviour (Brown and Schrader, 1990).

A weight structure would give more importance to some types of information or specific period. For example, Swartz and Strand (1981) selected four major newspapers and assigned them a value from one to zero, with respect to the likelihood of generating a negative consumption reaction across the population. A value of one is associated with a predicted very negative reaction and a value of zero is neutral. This value is weighted by the probability of being read, which was estimated by referring to the newspaper market share and the price of advertising space. The authors found that the media index is statistically significant in explaining the demand contraction. Arbitrary weights are difficult to justify – a possible reason for the infrequency of its application.

Chang and Kinnucan (1991) estimated a scientific information index as the weighted sum of negative information values. Each weight corresponds to the ratio between the number of scientific articles with negative information divided by the total number of articles that month. Using this same procedure to calculate weights, Kinnucan *et al.* (1997) created a health information index using cumulative series. The authors, studying the effect of meat-related generic advertising in the US, found that health information elasticity is, in absolute values, larger than price elasticity. This means that a one percent change in the information led to a larger change in the quantity demanded, than in price change.

Piggott *et al.* (1996) and Rickertsen, Kristofersson and Lothe (2003) used a free-form-lag specification. Free-form-lag specification means including lagged index variables without imposing a weight structure. In this sense, it is data-driven and does not impose any prior information. Marsh, Schroeder and Mintert (2004) argued that free-form-lag specification is an unrestricted specification, affording room to freely interpret the information impact across products and over time.

Baye, Jansen and Lee (1992) wanted to quantify the advertising effect on consumer expenditure using the AIDS model, and assumed that consumers give more importance to contemporaneous media than past media. The authors used a geometrical weight structure which imposes the use of decreasing weights. According to Baye, Jansen and Lee (1992), a dynamic advertising specification can help to attain greater consistency with neoclassical economic theory. The dynamic AIDS specification did not reject homogeneity or symmetry using a 1% significance level.

Brown and Schrader (1990), Brester and Schroeder (1995) and Larivière, Larue and Chalfant (2000) studied the information effect on demand using a polynomial distributed lag structure (PDL), also known as the Almon distributed lag. Lag weights are specified by a continuous function and approximated by a polynomial function. The lag length and the degree of the polynomial need to be specified. The calculations are simplified imposing endpoint restrictions. An endpoint restriction assumes zero weight for the first and/or last lag periods.

2.6. Habits

Habits are formed when the consumption in one period increases the consumption in subsequent periods (Nicholson, 2005). In this sense, consumers may have some persistent consumption patterns due to contractual fixed commitments, ignorance of further consumption bundles and/or habit effect (Pollak, 1970).

The literature recognises mainly two types of habit patterns (Alessie and Teppa, 2010): firstly, myopic habits, or backward looking, are when current consumption depends only on past consumption. The concept of myopic habits was initially introduced by Pollak (1970). Myopic habits allow for using two-stage budgeting, where in the first stage the consumer decides the consumption expenditure of broader categories, such as food, housing and personal expenditure, and in the second stage the consumer allocates his pre-determined food budget to specific product groups, such as fresh and processed fruit and vegetables. Secondly, rational habits are described when current consumption depends upon past and expected consumption, as was presented by Spinnewyn (1981). In the case of rational habits, since the first stage would depend on the second stage, it is not appropriate to use a two-stage budgeting system.

Richards and Patterson (2006) explained that alcohol, cigarettes and caffeine consumption have been historically characterised as rational habits. Policy interventions that increase expected future price would be effective to deter consumption. Conversely, food consumption is characterised by myopic habits. In myopic habits, the pre-existing condition, such as genetic predisposition, plays a significant role and policy interventions that increase future prices would be less effective unless specifically targeting unhealthy food.

The inclusion of habits in a demand system makes the empirical model more realistic and can help solve potential autocorrelation. Autocorrelation happens when error terms are correlated across different periods, which would represent a violation of the independence assumption of linear regression. Autocorrelation keeps the estimated coefficients unbiased, however, it artificially increases standard error estimation. As a consequence, the hypothesis testing can fail to reject that some estimated coefficients are equal to zero, when in fact, these coefficients are truly different from zero. Moreover, serial correlation would cause artificial large forecast confidence intervals. Consequently, as is explained by Klonaris and Hallam (2003), autocorrelation can be interpreted as a sign of dynamic misspecification of a static demand system specification.

In order to include habit in a demand system, Blanciforti and Green (1983) proposed the lagged dependent variables as explanatory variables. Including own lagged share expenditure as an explanatory variable or a lagged demanded quantity, the authors recognised that past consumption explains current consumption and corrected for autocorrelation. This specification has numerous applications such as Chen and Veeman (1991), Holt and Goodwin (1997) and Larivière, Larue and Chalfant (2000).

Another possible way to correct for habits in a demand system is to include autoregressive terms in order to restrict possible autocorrelation patterns. Autoregressive terms are lagged error term values. Zheng and Kaiser (2008) included autoregressive terms directly the demand equations. Berndt and Savin (1975) imposed alternative restrictions to the first order correlation matrix. The first order correlation matrix is composed of first-order autoregressive error terms. The restriction can then be zero matrix, diagonal matrix and full matrix. Null matrix means that all the elements are restricted to zero, also known as 'no autocorrelation'. Diagonal matrix means that the diagonal elements are restricted to the identical; and the non-diagonal elements are zero. Full-matrix means that all the elements need to be non-zero. The work undertaken by Piggott *et al.* (1996) and Piggott and Marsh (2004) follows this approach. The empirical estimation presents results for each one of the correlation matrix restriction.

Finally, habits can also suggest that consumers take time to adjust to long-term equilibrium. In this sense, a price change would not cause an immediate full change in demand. Co-integrated models have the flexibility to differentiate between short-term adjustment, and long-term equilibrium.

2.7. Cointegration

A variable series is characterised by its integrated order or the number of times that a series needs to be differentiated to make it stationary. A stationary series has a constant variance and a zero mean. In contrast, a non-stationary series would have a mean and variance that change over time. To determine the order of the integration of each series is the equivalent of testing for the presence of unit roots. A stochastic process is non-stationary if it has a unit root. To follow the conventional nomenclature, a non-stationary series is integrated into order d, known as $I(d)$, if after differencing d times it becomes stationary (Kennedy, 1998).

The time series properties would affect the estimation results. If the regression variables have a different integrated order, then it is possible that residuals, also known as innovations in time series, would have a unit root. The results would seem to be highly significant, with a high R-squared, when in fact they are not. A unit root in the residuals of an estimation would make for spurious results (Lewbel and Ng, 2005) since the variance changes over time (Kennedy, 1998).

In addition, the integrated order of a series would help in predicting its behaviour after a shock. A stationary covariance series would revert to the original values. However, a series with a unit root would change the long-term equilibrium level. To sum up, the time series properties of the data are important to ensure meaningful results and predict the behaviour of the series.

In order to avoid spurious results, the model needs a balanced model design in terms of integrated order. A balanced design implies that dependent variables and independent variables have the same order of integrated series (Granger, 1981). However, alongside having a balanced design, it is also important to take into account possible co-integration.

Co-integration is so-called when a linear combination of two non-stationary series generates a stationary series. Using the nomenclature, two or more *I(1)* series are co-integrated if a linear combination of them is *I(0)* (Kennedy, 1998). A necessary condition for a relationship of cointegration is that the series has the same order have (Dawson and Dey, 2002, Mushtaq and Dawson, 2002).

A co-integrated model, in contrast to the static version, has the flexibility of allowing for different short- and long-run behaviours. A co-integrated model can be appropriate since food consumption is expected to have different short- and long-run behaviours. Besides this, ignoring this short-run disequilibrium leads to the rejection of theoretical constraints (Duffy, 2002). Duffy (2003) argued that in the short run, consumers can be "out of equilibrium" due to an incomplete process of adjustment. This consumption adjustment may be associated with habits, imperfect information or adjustment costs (Gang, Haiyan and Stephen, 2004). In this sense, it is to be expected that long-term elasticities be larger than short-term elasticities.

Engle and Granger (1987) developed a two-step procedure to take into account co-integration in demand systems. Initially, the co-integrating equation is estimated, and then error terms are used as explanatory variables in the respective AIDS equation. The estimated coefficient associated with the error term is expected to have a negative sign and to be less than one in absolute value. Consequently, if the budget share is above the long-term equilibrium, the error correction term would make the budget decrease, and vice versa. The estimated coefficient associated with the error term needs to be less than one for the short-run model moves to a long-run solution (Harris and Sollis, 2003).

Engle and Granger's two-step procedure has been used in food demand systems. Karagiannis, Katranidis and Velentzas (2000) used Greek annual meat data for the period 1950-1993. Short-run demand elasticities were smaller than long-run demand elasticities in absolute value. Eakins and Gallagher (2003), using Irish annual alcohol data from 1960 to 1998, also found that short-term demand elasticities were smaller than long-term demand elasticities. As is expected, own-price response is larger in the long run than in the short run.

Karagiannis, Katranidis and Velentzas (2000) found that homogeneity and symmetry failed to be rejected. Karagiannis and Mergos (2002), using Greek annual food data for the period 1950-1993, found that homogeneity failed to be rejected if the model specification did not include a deterministic trend. In this sense, co-integration can help to improve the theoretical consistency of demand systems.

Some authors have augmented demand systems with exogenous variables to study the impact of information on consumers' choices. For example, Duffy (2003) used alcoholic beverage data from 1963 to 1996 in the UK. The author specified an error-correction AIDS model with advertising variables. The data was consistent with homogeneity and symmetry. The results also showed that price, rather than advertising, impacted the demand for alcoholic products.

A final alternative is leaving the coefficient to change over time. Mazzocchi, Delle Monache and Lobb (2006) modelled multiple and resurgent meat scares in Italy. The authors specified an error-correction AIDS model for the period 1986 to 2003. The model, without using a media index, was flexible enough to separate the impacts of long- and short-run food scares.

Consequently, the time series properties of the data play a key role in obtaining meaningful results. From them it can be inferred that co-integration is a dynamic element in a demand system that helps to improve theoretical consistency, and recognises that elasticities can differ in the short run and in the long run. Few empirical models or authors have considered combining information and co-integration.

2.8. Demographics

Demographics are statistical characteristics of a population. Demographics were initially introduced into demand systems by Barten (1964). Since then, demographic variables have played a major role in the analysis of household consumption (Pollak and Wales, 1992). In particular: age, education, gender of the household head, income and household composition are the demographic characteristics most frequently used in demand studies (see Bernard and Bernard, 2009, Krishna and Qaim, 2008, Huang, 1993, Posri, Shankar and Chadbunchachai, 2007, Akgüngör, Miran and Abay, 2001). In the most recent demand study in the UK, Tiffin and Arnoult (2010) found that income, household composition, age and region cause a significant impact on food expenditure household behaviour.

Demographics are especially helpful for explaining the change in consumer behaviour with respect to food choices. Bertail and Caillavet (2008) argued that income is one of the main determinants of food consumption and expenditure. It has been confirmed that rising income has highly impacted food choices (Blaylock *et al.*, 1999). People spend half as much time cooking as was the case in the sixties, with an increasing proportion of food preparation taking place outside the home, transferred to factories, retailers and food services (Cutler, Glaeser and Shapiro, 2003). Moreover, past research has found consistent evidence that rising income has increased the eating-out expenditure, while its effect on the demand for particular nutritional content in food products remains ambiguous (Blaylock *et al.*, 1999).

Pollak and Wales (1992) have described alternative ways of including demographics in demand systems. Basically, the dataset can be subdivided based on demographics or incorporate demographic variables in the model. As an example of the latter, demographics can be incorporated as intercept shifters in a demand system. Arnoult, Tiffin and Traill (2008), using an AIDS model, incorporated variables such as children, administrative region, income, household size, householder gender, and householder age. However, demographic variables can significantly reduce the degree of freedom.

2.9. Endogeneity

A model has endogenous and exogenous variables. Endogenous variables are determined by the model, while exogenous variables are predetermined or independent (Varian, 2002, pg. 202). In a demand system, price and expenditure can sometimes be assumed to be exogenous when in fact they are endogenous. LaFrance (1998) and Dhar, Chavas and Gould (2003) empirically showed the importance of taking endogeneity into account.

Duffy (2003) argued that price can be classified as exogenous since it may have some sources of rigidity such as menu costs, price contracts or imperfect market conditions. These rigidities would cause prices to require an adjustment period before reaching their long-term equilibrium. Consequently, it is common for consumers to be assumed to be price-takers (Dhar, Chavas and Gould, 2003). However, expenditure is more likely to be endogenous.

If endogeneity is detected, it can be resolved in at least three ways. Using a multistage demand system, expenditure is determined at a previous stage. However, at some higher level of the budgeting demand system, the expenditure may be treated as exogenous. Consequently, endogeneity may displace the problem rather than solve it (Thompson, 2004).

Larivière, Larue and Chalfant (2000) used a two-stage demand system augmented with an advertising expenditure variable. In the first stage, an equation is specified to endogenise group expenditure. In the second stage, the expenditure is allocated between alcoholic beverages. The first stage allowed for analysing the overall alcoholic expenditure, and the second stage the advertising impact on specific type of alcoholic drinks. The authors found that advertising does not significantly affect overall alcoholic expenditure. However, advertising significantly impacts own- and cross-product expenditure.

In further examples of a two-stage demand system, Fan, Wailes and Cramer (1995) calculated demand elasticities for China using a dataset spanning from 1982 to 1990.

Gao, Wailes and Cramer (1996) used a modified LES/AIDS model version and analysed the elasticities at different income levels. Richards, Ispelen and Kagan (1997) determined the effectiveness of export advertising programs for US apples. Michalek and Keyzer (1992) calculated demand elasticities for eight EU countries in 1970 and 1985 and Han and Wahl (1998) expanded the elasticity analysis with respect to different levels of income. The major contribution of these articles lies in the empirical results, which are presented as references in the discussion section of this study. In general, own-price elasticities would vary by up to ten times depending on the income level. Moreover, in the same group, individual products can have very different own-price and expenditure elasticities.

In other cases, authors have included a censored model as the first step to take into account non-consumption. For instance, Gao, Wailes and Cramer (1995) used a Tobit model in the first stage of a two-step budgeting demand system to study alcohol consumption. It was important to consider the non-consumption alternative since some people do not consume alcohol, and the demand system only includes alcoholic beverages (low aggregation level). More aggregated groups in demand systems tend to have fewer censored observations; however, more aggregated groups lose some richness of the data.

Multistage demand systems, in general, fall into two stages. In some cases authors have expanded this to three stages. Using a three-stage AIDS model, Jiang and Davis (2007) characterised food consumption in rural China. In the first stage, households divided their expenditure between food and non-food expenditures. Then, the food expenditure was distributed across four food categories: grain, vegetables, animal products and others. In the third stage, the animal products were subdivided into meats, aquatic products and eggs. Thus, the larger number of stages allows for more disaggregation regarding consumption.

Another way to correct for endogeneity is to use a proxy to replace the endogenous variable. This proxy variable, also known as an instrumental variable, needs to be highly correlated with the original variable and uncorrelated with the error terms. The proxy can be another variable or can be predicted values of an auxiliary regression. For instance, Haden (1990) analysed cigarette demand in Japan using an auxiliary regression. The auxiliary regression corresponds to a linear equation of per capita cigarette expenditure as a function of prices, income, a lagged dependent variable and a time trend. Then, the AIDS model aggregates cigarettes according to their origin in the US, Japan, and others. Both stages consider a lagged dependent variable to take into account potential habits. However, in the second stage, the habit variables were not significantly different from zero. Also using an auxiliary regression, Bertail and Caillavet (2008) analysed fruit and vegetable consumption in France. The independent variable corresponded to potential endogenous expenditure and the explanatory variables were income, prices and household characteristics. The residuals were independent from the expenditure and had a constant variance.

2.10. Summary

Information can be measured using an experimental approach and demand systems, such as the LES model, the Rotterdam model and/or the AIDS model. A demand system allows the imposition of economic theory and enables the processing of a large amount of data. Information indexes are used to include media, advertising or scientific information in a demand system. Moreover, using a demand system to model food expenditure, it is important to take into account habits, co-integration, demographics, and potential variable endogeneity.

Chapter 3

Methodology

3.1. Introduction

The purpose of this chapter is to introduce a methodological framework, testable hypothesis and dataset to measure the impact of child obesity news on household expenditure. The methodological framework provides a structure for combining price, expenditure and child obesity news in a way that is compatible with neoclassical economic theory. This study identifies expressions in the methodological framework that can be validated by empirical data, also known as testable hypotheses. Finally, this chapter describes the original dataset and how the raw data is converted into variables to be used in the empirical model.

To begin with, consumers need to make consumption decisions, such as those pertaining to food, clothing and transportation. According to economic theory, consumers maximise utility subject to their disposable income, and assuming constant tastes and preferences and perfect information. In the dual cost minimisation problem, the consumer minimises his/her expenditure to reach a predetermined utility level. In this regard, the expenditure function shows the minimum amount of money necessary to achieve a predetermined utility level given a set of prices.

In perfectly competitive markets, consumers have perfect information on products. However, perfect information is not likely to hold in reality. Capps and Schmitz (1991) and Piggott and Marsh (2004) explained that consumption would normally depend on information. Our objective is to measure the impact of child obesity news, a specific type of information, on household expenditure. Starting from the expenditure function, the following section develops an empirical model that combines prices and information to explain consumer demand.

3.2. Empirical Model

Chapter 2 discuses three popular demand systems, the LES, the Rotterdam and AIDS models. The Rotterdam and AIDS models have a key advantage over the LES model, in that they allow a test to be performed, and impose symmetry and homogeneity. However, the AIDS model, unlike the Rotterdam model, enables 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. Concavity of the expenditure function means that if a price rises, holding other prices and utility constant, the total cost would increase less than linearly (Deaton and Muellbauer, 1980b). After a price rises, since the consumer minimises cost, he/she would rearrange purchases to compensate for the changes in the price structure.

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.

The two-stage AIDS model consists of an individual AIDS model per stage. The individual AIDS model is derived in the following way:

The expenditure function gives the minimum level of expenditure to reach a predeterminated utility level u , given prices $p_{1,\dots}p_n$:

$$e(u, p_{1,\dots}p_n) \qquad [6]$$

Specifically, according to Deaton and Muellbauer (1980a), the Price Independent Generalised Logarithmic cost function (PIGLOG) associated with the AIDS model is:

$$lnc(u,p) = (1-u)lna(p) + ulnb(p) \qquad [7]$$

where p are prices, $a(p)$ and $b(p)$ are positive linear homogeneous functions, and can be interpreted as the cost of subsistence and satisfaction respectively. For instance,

$$lna(p) = \alpha_0 + \sum_k \alpha_k lnp_k + \frac{1}{2}\sum_k \sum_j \gamma_{kj}^* lnp_k lnp_j \qquad [8]$$

$$lnb(p) = lna(p) + \beta_0 \prod_k p_k^{\beta_k} \qquad [9]$$

so,

$$lnc(u,p) = \alpha_0 + \sum_k \alpha_k lnp_k + \frac{1}{2}\sum_k \sum_j \gamma_{kj}^* lnp_k lnp_j + u\beta_0 \prod_k p_k^{\beta_k} \; [10]$$

where α_i, β_i and γ_{kj}^* are parameters of the cost function. The demand functions can be obtained by applying Sheppard's Lemma, $\frac{\partial c(u,p)}{\partial p_i} = q_i$. The budget shares can be derived by multiplying both sides of Sheppard's Lemma by $p_i/c(u,p)$:

$$\frac{p_i q_i}{c(u,p)} = w_i = \frac{\partial lnc(u,p)}{\partial lnp_i} \qquad [11]$$

w_i is the expenditure budget share of product i. Consequently, equation 10 can be logarithmically differentiated with respect to lnp_i to obtain w_i, in the following way:

$$\frac{\partial lnc(u,p)}{\partial lnp_i} = w_i = \alpha_i + \sum_j \gamma_{ij} lnp_j + \beta_i u \beta_0 \prod p_k^{\beta_k} \qquad [12]$$

where, $\gamma_{ij} = \frac{1}{2}(\gamma_{ij}^* + \gamma_{ji}^*)$. The term $c(u,p)$ equals the total expenditure (y), thus the indirect utility function, u in terms of p and y, can obtained isolating u in equation 12.

$$u = \frac{lny - \left(\alpha_0 + \sum_k \alpha_k lnp_k + \frac{1}{2}\sum_k \sum_j \gamma_{kj}^* lnp_k lnp_j\right)}{\beta_0 \prod_k p_k^{\beta_k}} \qquad [13]$$

Equation 13 is used to replace u in equation 10. The denominator of equation 13 cancels out with the numerator of equation 10. The term in parenthesis in equation 13 is the translog non-linear price index, P_t. Therefore, assuming m groups of products:

$$w_{it} = \Omega_{it} + \sum_{j=1}^{m} \gamma_{ij} \, ln \, P_{jt} + \beta_i(lny_t - lnP_t) + e_{it} \qquad [14]$$

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. Equation 14 can be estimated empirically.

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:

$$lnP_t = \sum_{i=1}^{m} w_i \ln (p_{it}) \qquad [15]$$

The AIDS model also allows for testing the theoretical constraints introduced in Chapter 2. The theoretical conditions are the following:

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*:

$$\sum_{i=1}^{m} \alpha_i = 1, \sum_{i=1}^{m} \beta_i = 0, \sum_{i=1}^{m} \gamma_{ij} = 0 \qquad [16]$$

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):

$$\sum_{j=1}^{m} \gamma_{ij} = 0 \qquad [17]$$

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*.

$$\gamma_{ij} = \gamma_{ji} \qquad [18]$$

The intercept has the following structure:

$$\Omega_{it} = \alpha_i + \delta MI_i + \sum_{t=1}^{3} \theta_t D_t + \vartheta_i q_{it-1} \qquad [19]$$

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 q_{it-1} is the lagged quantity demanded for group *i*, this last variable is used to model habit patterns.

Thus far, this chapter has derived the AIDS model and modified the intercept to take into account information, seasonal effects and potential habits. This study addresses the problem of how media information impacts household expenditure choices. This study specifically focuses on child obesity news in relation to food expenditure in the UK. Using equation 14, it is also possible to derive the testable hypothesis to measure the impact of child obesity news on household expenditure. The statistical significance of δ would indicate whether child obesity news index causes a statistically significant impact on expenditure share. The hypotheses are the following:

(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.

H₀: $\delta_{low\ income}^{without\ child} = 0,\ \delta_{low\ income}^{with\ child} = 0,\ \delta_{high\ income}^{without\ child} = 0,\ \delta_{high\ income}^{with\ child} = 0$

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.

3.3. Data Description

A two-stage demand system can give a more complete idea of household behaviour. However, it is data-demanding. In order to answer the research questions, the current study needs detailed household expenditure data where price, quantity and demographics are concerned. In the first stage, this study requires data on overall household expenditure. In the second stage, this study requires data on food expenditure.

In 1940, the National Food Survey from the Office for National Statistics started collecting expenditure household data in urban areas in the UK. Since then, the survey has increased its coverage and sample size, and modified its categories. For instance, since 1983, the database used to select households changed from the Electoral Register to the Postcode Address File. In 1992, the survey started including data on food bought and consumed at home, such as soft drinks, sweets and alcoholic beverages. In 1994, the survey was extended to include eating-out expenditure. In 1996, the survey incorporated Northern Ireland.

In April 2001, the Expenditure and Food Survey replaced both the National Food Survey and the Family Expenditure Survey. The Expenditure and Food Survey included the Family Expenditure Survey questionnaire, as well as a selection of questions from the National Food Survey. In addition, the Expenditure and Food Survey underwent a major reclassification change, to bring it in line with the United Nations Statistical Commission's Classification of Individual Consumption by Purpose. Finally, the Expenditure and Food Survey extended the data collection time from a week to two weeks per household.

In 2008, the Expenditure and Food Survey was renamed the Living Costs and Food Survey, and it became part of the Integrated Household Survey. This study uses data gathered between April 2001 and December 2009. April 2001 is the month the survey last underwent large structural change, while December 2009 is the most recent month available at this moment.

3.4. The Living Costs and Food Survey

The Living Costs and Food Survey 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.

By way of example to show the extent of coverage, we could note that in 2008 the survey involved 13,890 people equivalent to 5,845 households that classified their expenditure into 250 household food groups and 250 eating-out food groups: this corresponds to a total of 343,298 observations. The response rates were 51% in Great Britain and 54% in Northern Ireland.

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 income questionnaire collects information about each adult individually and the household as a unit, covering income from employment, benefits and assets such as salary, money sent abroad, and received and paid interests.

Finally, the expenditure diaries are kept for each person over 16 years old in the household. Households are required to keep records of daily food in terms of weight or volume and expenditure over two weeks.

Using the three questionnaires, the data is collected at household, individual (person), and item levels. Due to confidentiality reasons, the raw diary data is not made publicly available. The results of the Living Costs and Food Survey are presented as general expenditure and food expenditure datasets. The general expenditure dataset includes weekly expenditure per household on food and non-food products and services. The food expenditure dataset includes the household daily food data, where it is possible to find each food item with its quantity and associated expenditure per household.

3.5. Media Index

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.

Figure 3.1 shows the monthly newspaper and the cumulated media indexes. The figure 3.1 on the left corresponds to the number of news items with the combination of keywords or the plot in levels of the child obesity index. 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 figure 3.1 on the right corresponds to the number of cumulated news articles with the combination of keywords or the plot in levels of the cumulated child obesity index. The index is cumulative because it adds the number of news articles per month from the beginning of the child obesity index series.

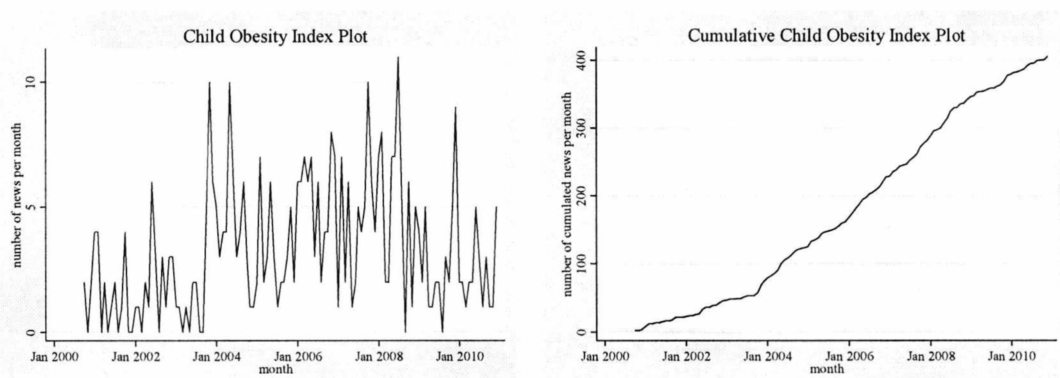

Figure 3.1 Media Index Plots

In this study, a media index is combined with general and food expenditure data in a demand system. However, in most cases, the raw data cannot be entered directly into the demand system. For instance, data needs to be aggregated into a few categories, deflated into real terms, and some missing values completed where appropriate. The coming section describes the process by which the data made available by the Office for National Statistics is converted into variables in the demand system.

3.6. Data Construction

The Living Costs and Food Survey raw data files needed to be manipulated in order to conduct the demand analysis. This manipulation needs to be data-driven to minimise any change in the properties of the original dataset. In this sense, we want to facilitate the emergence and visibility of patterns in the data. Care must be had to avoid artificial manipulation which could bias the results. For instance, manipulations should not alter the total food expenditure per year in real terms.

The original dataset of the Living Costs and Food Survey is annually made publicly available as general expenditure and food expenditure files. The Survey was conducted on a financial year basis from 2001 to 2006. In 2006, the survey shifted to a calendar-year basis. This means that the complete dataset has an overlapping period from January to March 2006. The overlapped period January to March 2006 was used to double-check data aggregation consistency.

The raw data is transformed into aggregated time series data. Few publications explain how to manipulate variables before a demand analysis. The current study follows some of the guidelines proposed by DEFRA (2000) and Deaton and Zaidi (2002). General and Food expenditure categories need to be aggregated into groups, keeping the expenditure the same and creating a monthly price index per group.

This study follows a similar procedure for the general and food expenditure datasets, considered separately. SAS and Stata are econometric software packages that help to manipulate the data and conduct later analysis. SAS allows the manipulation of large volumes of data. Stata has numerous econometric functions, and offers the flexibility to write codes for specific tests.

The overall objective of the data codes is to have the data on a sorted and comparable basis. In a demand system products need to be aggregated into groups in order to reduce the number of parameters which need to be estimated, and to concentrate them into fewer groups of more particular interest. For computational reasons, it is not feasible to have more than six to eight groups, considering that the number of own-price and cross-price elasticities of demand increases with the square of the number of groups.

To create the general expenditure dataset, original datasets from the Living Costs and Food Survey are imported to SAS, which corresponds to a file per year. The file contains data from the household and income questionnaires per household. A file is created with selected variables from the original dataset. The included variables are household I.D., month, income and number of people, number of children and the twelve general expenditure categories set by the Office for National Statistics, which are the following: (1) food and non-alcoholic beverages, (2) alcoholic beverages, tobacco and narcotics, (3) clothing and footwear, (4) housing, water, electricity, gas and other fuels, (5) furnishings, household equipment and routine maintenance of the house, (6) health, (7) transport, (8) communication, (9) recreation, (10) education, (11) restaurants and hotels, (12) miscellaneous goods and services. After this, using the income variable, an indicator variable is created, which value equals zero if the household is under the average income, and one if the household is above the average income. Using the number of children variable, an indicator variable is created, which value equals zero if the household has no child, and one if the household has a child or more. A set of commands allows for creating different subsamples of data based on income level and household child composition.

Up to this point, the file contains data per household. Now, the data per month is added. The dataset is thus reduced to a single aggregated value per month. The year variable remains the same, and the number of people per household becomes the number of people per month. The file is thereafter merged with the nominal inflation rate data from the Office of National Statistics. The expenditure corresponds to nominal values, and needs to be converted to real values using a nominal rate. In order to do this, May 2005 is used as the inflation base month. The resultant file is saved with a different name that identifies the year.

The same process is repeated for each year from 2001 to 2009. At the end of the SAS code, the annual data files are compiled into a single file. This file contains year, month, nominal inflation rate, total number of people and the twelve general expenditure categories afore-specified. Each one of the twelve general expenditure categories corresponds to the total sum expenditure of households for that month. The aggregated general expenditure values remain the same.

The SAS file is imported into Stata. Then, using the month and year variables, a time variable is created that identifies month and year in a single cell. Since there was a change within the data collection period, January to March of 2006 appears in two datasets. At this time, the overlapped period in the dataset 2005/06 was deleted. The helpdesk from the Living Costs and Food Survey suggested deleting these months.

After this, the data is declared as a time series in Stata. Expenditure data is divided by the number of people, and the nominal expenditure values are deflated into real expenditure values using a monthly nominal inflation rate from the Office of National Statistics. Real per capita data is used to create food group budget shares by month, which corresponds to the food group expenditure divided by total food expenditure.

The group price index is imported from the Office for National Statistics. These price indexes are deflated into a real price index using a monthly nominal inflation rate from the same institution. The media index data is merged with the above.

This study uses an index to aggregate categories, as presented in Figure 3.2. In other words, the general expenditure categories need to be reduced from twelve in the Living Cost and Food Survey to six groups in the demand system. Deaton and Muellbauer (1980b) explained that the true-cost-living index is the ratio of minimum expenditures to reach a referential indifference curve given two sets of prices. Therefore, the cost-of-living index would indicate how price changes between two periods. The cost-of living price index would normally be approximated by the Laspeyres index (Deaton and Zaidi, 2002). Taking this into account, this study used the Laspeyres index to aggregate similar general expenditure categories into a single price index.

Finally, some additional variables are created, such as a set of seasonal dummy variables, a linear trend, while the general expenditure price indexes are converted into their log forms to be included in the demand system. The variables are thereupon ready to be used in the first stage in the AIDS demand system.

To create the food expenditure dataset, original datasets from the Living Costs and Food Survey are imported to SAS, which corresponds to a Microsoft Access file per year. Each Access file contains ten tables. Each table corresponds to a food expenditure database or code.

In the Access file, the food expenditure dataset classifies expenditure from food and non-alcoholic beverages and alcoholic beverages, tobacco and narcotics – general expenditure categories – into the following food expenditure categories: (1) food and drink brought home, (2) takeaways brought home, (3) eating-out, and (4) home-grown and wild food. Food and drink brought home and eating-out categories are the largest, with close on 250 food products in each one.

The food expenditure data construction starts with the same initial file as the general expenditure dataset. The file contains data from the household and income questionnaires per household. A file is created with selected variables from the original dataset. The included variables are household I.D., month, year, income and number of people, number of children. After this, using the income variable, an indicator variable is created, which value equals zero if the household is under the average income, and one if the household is above the average income. Using the number of children variable, an indicator variable is created, which value equals zero if the household has no child and one if the household has a child or more. A set of commands allows for creating different subsamples of data based on income level and household child composition.

Using the household-I.D. variable, the file with the demographic data is merged with the table in the Access file containing the food expenditure data. This file is again merged with the table in the Access file containing food expenditure categories and food group names. In this manner, the merged file comes to link demographics, food category, food group, food product and food expenditure, and price or quantity.

Up to this point, the file has contained data per household, which can contain expenditure and price or quantity data. Now, the data per month and food category is added, and grouped into 250 food products. Consequently, the dataset is reduced to a single aggregated value per month and food product. The year variable remains the same, and the number of people per household becomes the number of people per month. The file is then merged with nominal inflation rate data from the Office of National Statistics. The food expenditure corresponds to nominal values, and needs to be converted to real values using a nominal rate. In order to do this, May 2005 is used as the inflation base month. The resultant file is saved with a different name that identifies the year.

The same process is repeated for each year from 2001 to 2009. At the end of the SAS code, the annual data files are compiled into a single file. This file contains year, month, nominal inflation rate, total number of people, food category names and food expenditure, and price or quantity. Each food expenditure value corresponds to the sum of food expenditure from all the households in a specific food category and month. The aggregated food expenditure values remain the same.

The SAS file is imported into Stata. Then, using the month and year variables, a time variable is created that identifies month and year in a single cell. The food products are associated with a unique food group.

Since prices are not available in the dataset, unit values are used as proxies. For each food product, this study calculates unit values as the ratio between aggregated product expenditure and aggregated product quantity per specific month. The nominal expenditure values are deflated into real expenditure values using a monthly nominal inflation rate from the Office of National Statistics.

Home-grown food products have quantity values but they do not have expenditure values. Since home-grown food implies some effort, the current study assumes that the household values the product at least at its market price. Market price is therefore used as the proxy for home-grown price.

Free-food products have quantity values but they do not have expenditure values. Free-food can be any food product that the household has received for free. This study takes into account free food eating at home in the same way as home-grown food. The prices for free food products are recoverable from the market price that specific month. Free-food, home-grown and regular-food products are aggregated as a single food quantity and expenditure. Thus, each of the 250 food categories has a monthly price, or unit value, and quantity.

Quantity and expenditure are divided by the number of people, by two and by a hundred. It is divided by the number of people since where household data is concerned, working with per capita data is recommended (Carpentier and Guyomard, 2001). Alternatively, we could work with household level data; however, this would be ignoring the fact that households may vary in size. It is also divided by two and a hundred because the food expenditure dataset reports two weeks of expenditure data in pence, while the general expenditure data reports expenditure per week in pounds. Doing this makes it easier to check the consistency between general and food expenditure datasets and present data plots.

Households do not spend on each food category over the year, or there may be missing values. The incomplete series are aggregated into a single series per food group. Following the work done by Gao and Wailes (1996), the current study creates a weighted average price using expenditure as weight. The aggregated series corresponds to the weighted sum, using expenditure as weight of prices. Total expenditure values remain the same. As a result, the dataset contains a complete series of prices and quantities of food categories, which are linked to food groups and demographic information. Thirty-three of two hundred and fifty food categories constitute an incomplete series. In the UK, each person spends close on £20.92 per week. £0.63 of this corresponds to incomplete series.

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 figures, tables and values have been adjusted to December 2009 base values.

Following the same procedure as that for the general expenditure dataset, the current study uses an index to aggregate categories, as presented in Figure 3.2. In other words, the 250 food expenditure categories in the Living Cost and Food Survey need to be reduced to six food expenditure groups in the demand system. Taking this into account, this study used the Laspeyres index to aggregate similar food expenditure unit values into a single price index. After this, the data is declared as a time series in Stata.

Finally, additional variables are imported from the general expenditure Stata file. These variables consist in a set of seasonal dummy variables, a linear trend, cumulated and contemporaneous child obesity news indexes, and the predicted food expenditure share. This last variable connects the first and second AIDS stages. The food price indexes are converted into their log forms in order to be included in the demand system. Henceforth, the variables are ready to be used in the second stage in the AIDS demand system.

3.7. General and Food Expenditure Groups

The Living Cost and Food Survey lists numerous general and food expenditure products that need to be aggregated into fewer groups. Aggregation can effectively reduce the groups to be used in a demand system (Capps and Love, 2002). The objective of aggregation is to concentrate on the groups of interest and thus facilitate the computational estimation.

Empirical demand studies commonly rely on separability conditions to justify an aggregation level (Eales and Unnevehr, 1988). It is expected that separable products in an expenditure group tend to interact closely while products between separable groups do not.

From an economic point of view, separability implies that the marginal rate of substitution between products must be functionally independent of the quantities of certain other products (Nayga and Capps, 1994). Specifically, weak separability means that a change in the price of a product in a group would affect the demand of products in other group in the same way (Edgerton, 1997).

As a more formal definition, weak separability implies that intergroup off-diagonal terms in the Slutsky substitution matrix need to be proportional to the corresponding income derivatives of the two separable goods (Goldman and Uzawa, 1964). Consequently, separability implies that between-group responses follow a specific pattern, which does not condition the magnitude of the rate of substitution (Nayga and Capps, 1994). Therefore, it is reasonable to impose separability to closely related products (Nayga and Capps, 1994). Moreover, weak separability is a necessary and sufficient condition for two-stage budgeting (Deaton and Muellbauer, 1980b).

In past literature, weak separability is often rejected (Eales and Unnevehr, 1988), which may explain why it is more commonly assumed, as it is in this study, than tested (i.e. Green, Carman and McManus, 1991, Piggott *et al.*, 1996, Gracia, Gil and Angulo, 1998, Verbeke and Ward, 2001). In the case of the AIDS model, the weak separability condition depends on the variables, so the results are local. In general, the results are reported at the mean share. The results at the same mean do not necessary hold for the complete dataset.

As is presented in Figure 3.2, the current study organises the data in two stages, with six groups in each one. The first stage corresponds to broader general expenditure categories. One of these general expenditure groups is food and non-alcoholic beverages expenditure. The second stage corresponds specifically to food and non-alcoholic beverages expenditure groups.

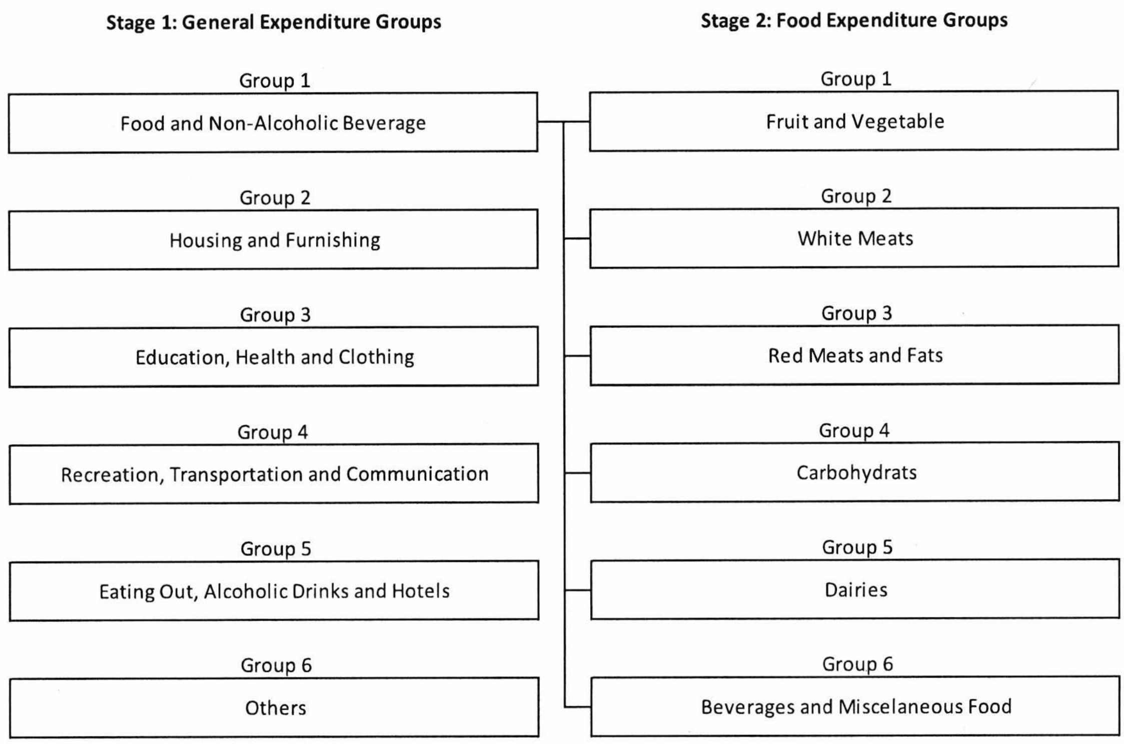

Figure 3.2 Expenditure Groups

Table 3.1 shows the list of the six general expenditure groups. Each one of these general expenditure groups contains a number of general expenditure products and services. With the SAS and Stata codes already described above, the general dataset is transformed from numerous general expenditure products and services into six general expenditure groups that would be used in the demand system.

Table 3.1 General Expenditure Group Composition

Group	Group Name	Main Categories
1	Food and non-alcoholic beverage expenditure	Food at home
		Take away
		Homegrown food
		Non-alcoholic beverages
2	Housing and furnishing	Actual rentals for housing
		Water supply, gas and electricity
		Furniture and furnishings
3	Education, health and clothing expenditure	Education fees
		Clothing & footwear
		Medical products, appliances and equipment
4	Recreation, Transportation and communication	Audio accessories e.g. tapes, headphones
		Package holidays
		Purchase of vehicles
		Operation of personal transport
		Transport services
		Postal services, telephone and telefax equipment
5	Eating out, alcoholic drinks and hotels	Alcoholic drink, tobacco & narcotics
		Catering services
		Accommodation services
6	Miscellaneous goods and services	Personal care
		Social protection
		Insurance

Table 3.2 shows the list of the six food expenditure groups. Each one of these food expenditure groups contains a number of food products. Since there are close to 250 food products, there is no unique way to aggregate food products into food groups. This study used the classification in Appendix E of the Family Food Report 2009 by DEFRA (2011). With the SAS and Stata codes described above, the food dataset is transformed from numerous food expenditure products into six food expenditure groups that would be used in the demand system.

Table 3.2 Food Expenditure Group Composition

Group	Group Name	Food Category DEFRA Report
1	Fruits and vegetable	Fresh and processed vegetables, excluding potatoes
		Fresh and processed fruit
2	White Meats	Fish
		Poultry
3	Red Meats	Carcase meat
		Non-carcase meat and meat products
		Eggs
		Fats
4	Carbohydrats	Sugar and preserves
		Fresh and processed potatoes
		Bread
		Flour
		Cakes, buns and pastries
		Biscuits and crispbreads
		Confectionery
		Other cereals and cereal products
5	Dairies	Milk and milk products excluding cheese
		Cheese
6	Beverages and Miscellaneous foods	Non-alcoholic beverages
		Soft drinks
		Spices
		Sauces, soups and description salad dressings

In the Food Category "Other Food and Drinks", DEFRA mainly includes mineral or spring water, soups, sauces, salad dressings, ice creams and condiments. This study reclassifies mineral water or spring water as beverages, and ice creams as dairy products. Since for computational reasons is not feasible to analyse more than six food groups, it is debatable whether to have an "others" food group, of which the elasticity estimation would be less informative than that of a well-defined group, such as fruit and vegetables. However, an "others" food group helps by providing an alternative option, and therefore making it unnecessary to force food categories into groups with which they have only a tenuous connection.

3.8. Summary

We presented a modified version of the LA/AIDS model that contains a modified intercept to take into account potential habits, seasonal patterns and child obesity news. Drawing upon the derivation of the demand system, the testable hypotheses are presented, keeping in mind that the overall objective is to isolate the impact of child obesity news on household expenditure. Finally, the dataset is described, presenting how the raw variables are converted into variables that can be used in the demand system.

The dataset is divided into a general and a food expenditure stage. Each of the two datasets combines data from the Living Costs and Food Survey and a media index from Nexis. The raw data is deflated, completed, and finally, aggregated using the Laspayres index. The resulting dataset is comprised of six expenditure groups per stage. Each expenditure group corresponds to a series of weekly expenditure – unit values and quantity – per month, from March 2001 to December 2009.

Chapter 4

Estimation Strategy

Before applying the empirical model, there are some empirical choices that need to be made. The objective of this chapter is to discuss them, and justify our choices based on past research and dataset characteristics.

This study proposes a two-stage LA/AIDS model to measure the impact of child obesity news on UK household expenditure. The variables correspond to monthly average expenditure per week from March, 2001 to December, 2009. The child obesity news index is a proxy of the number of news articles in a particular month.

The AIDS model gives a framework for combining prices, expenditure and the child obesity media index. The LA/AIDS is a linearised version of the AIDS model. It is linearised because it uses a log linear approximation of per capita income/expenditure. Taking into account that the time series dataset is relatively small, consisting of 105 observations and 15 parameters, this study uses this linear approximation of per capita income/expenditure. Banks, Blundell and Lewbel (1997) found that the UK food sector is well-characterised by the linear expenditure specification.

A dynamic version of the AIDS model would better explain the food decision process. In this sense, autocorrelation and over-rejection of theoretical properties have been indicated as a sign of lack of dynamic elements in a demand system. Moreover, a desirable empirical model would also allow for short- and long-run behaviours that take into account possible non-stationary variables. Therefore, we need begin analysing the time series properties of the data.

From a time-series point of view, we need to start testing the presence of unit roots in each series. However, series order is sensitive to structural breaks. Therefore, at the time of testing for unit roots, we need to take into account possible structural breaks.

A structural break is a consequence of a change to the underlying utility function which is not directly observable (Capps and Schmitz, 1991).

Following the work by Dawson and Dey (2002), the Augmented Dickey Fuller and Zivot and Andrew tests are conducted to test for unit roots. The Augmented Dickey Fuller test is highly popular. The Zivot and Andrew test takes into account a potential structural break, which does not require us to know the possible break-points *a priori*. Then, if there is more than one *I(1)* series, the Engle-Granger 2-step procedure would be used to take co-integration into account.

In addition, in demand analysis, Moschini and Moro (1996) argued that structural change can be tested using nonparametric or parametric methods. Nonparametric methods rely on 'revealed preference' theory. However, as presented in the following chapter, the average household expenditure has experienced a decline especially in the last years. Therefore, it may be difficult to compare bundles after a large change in income/expenditure (Moschini and Moro, 1996).

With respect to parametric methods, CUSUM and Chow tests have been used to test for structural breaks. Moschini and Moro (1996) argued that CUSUM and Chow tests are tests for parameter stability and structural break is one of the possible sources of instability. Moreover, parametric methods rely on functional form selection.

After identifying the structural breaks, this information needs to be included in the demand system. To take into account structural breaks in the AIDS model, that had not been captured by the remaining variables, Mazzocchi (2003) identified four possible approaches: firstly, using a linear trend as intercept shifter (McGuirk *et al.*, 1995, Marsh, Schroeder and Mintert, 2004). A time variable is used as a black box for structural changes, since it recognises structural change without being able to identify the cause (Brown and Schrader, 1990, Moschini and Moro, 1996). To know the cause of a structural break can be more informative. Despite that, a time variable as intercept shift is quite commonly used (Burton and Young, 1996).

Secondly, it more explicitly allows for a linear trend in all the variables; for instance, Moschini and Meilke (1989) and Rickertsen (1996) applied a switching parameter

AIDS model, with the inconvenience that the structural change period needs to be specified *a priori*.

Thirdly, stochastic AIDS approaches: Mazzocchi (2003) developed a time-varying coefficient AIDS model, which is not required to specify the period of the structural change. It allows non-linear trends, and its only requirement is that income and price are explanatory variables. Despite the advantages with respect to the simple trend specification, Mazzocchi (2003) argued that time-variant specification does not identify the cause of the structural break.

Fourthly, the model can include explanatory variables such as advertising and media indexes. Despite being data-demanding, this approach explicitly isolates the source of structural change, which can help to support policy recommendations. Direct modelling of preference-shifters is preferred to a generic trend (Moschini and Moro, 1996).

The current study includes a media index to explain the variability associated with child obesity news, and a linear trend to capture unknown remaining patterns. The media index can take several possible empirical specifications in terms of number of lags and weights. The number of lags can play a significant role, since it is expected that information would affect consumer behaviour beyond the current period. Moreover, weights can be used to include prior information in the lagged structure.

Drawing upon the work done by Marsh, Schroeder and Mintert (2004), we chose to retain the unrestricted specification to freely interpret the media impact across group expenditures and over time. However, we still needed a selection criterion to choose the appropriate number of lags. Brown and Schrader (1990) used Akaike information criteria (AIC) and Schwarz information criteria (SIC) in lag selection, to create an index for scientific cholesterol information in a supply and demand system. Gracia, Gil and Angulo (1998) calculated the system R-squared using the following expression:

$$R^2 = 1 - \frac{1}{1+2*(LL_u - LL_b)*\frac{1}{T}*(N-1)} \qquad [20]$$

where, LL_u is the likelihood of the unrestricted model, LL_b is the likelihood of the base model, only intercepts, T is the number of observations, and N the number of equations of the system. AIC and SIC include a penalty factor associated with the number of variables, they are preferred to R-squared. It is desirable to have a penalty factor to avoid including unnecessary variables. In this sense, a parsimonious model would have the minimum number of variables that explain the data in the best way. In the following chapter, we use AIC, SIC and R-squared to perform a lag media index selection.

Taking advantage of the large number of expenditure categories in the dataset, the current study uses a two-stage demand system to give a more complete idea of household expenditure behaviour. At the same time, a two-stage demand system helps to address endogeneity concerns. The first stage predetermines per capita food expenditure that is used in the second stage. The first stage uses a disposable income variable. The disposable income variable comes directly from the raw data. Consequently, disposable income is exogenous.

Besides this, a two-stage demand system is compatible with myopic habits (Alessie and Teppa, 2010). As is presented by Richards and Patterson (2006), we expect UK food expenditure to be characterised by myopic habits. In the empirical model, the myopic habits are included using lagged quantity variables.

In addition to minimising a possible endogeneity bias, and being compatible with myopic habits, a two-stage demand system gives us more insights into the consumer decision process, and allows for processing a larger number of variables. In a demand system, it is very difficult to handle more than six groups. The current study uses six groups per stage, or twelve groups in total. In so doing, this study analyses overall food expenditure, and then, food expenditure in specific food expenditure groups.

This study assumes weak separability in order to calculate a two-stage demand system. Weak separability is a necessary and sufficient condition for a two-stage demand system (Deaton and Muellbauer, 1980b). Weak separability is assumed since it is often rejected (Eales and Unnevehr, 1988) and, in the AIDS model, its test is restricted to a single point. Moreover, the current study uses the food group classification based on Appendix E of the Family Food Report 2009 by DEFRA (2011). In this Appendix, food groups are divided into food categories. This aggregation level would facilitate comparison with past studies.

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.

The system of equations is estimated using a Seemingly Unrelated Regression (SUR) model, which calculates the parameters assuming that the error terms are correlated. In this sense, homogeneity and symmetry can be directly tested from the empirical specification. However, in order to be consistent with the utility maximisation theory, a demand system also needs to fulfil concavity of the expenditure function (Kaabia and Gil, 2001).

Concavity of the expenditure function means that if a price rises, holding other prices and utility constant, the total cost would increase less than linearly (Deaton and Muellbauer, 1980b). After a price rises, since the consumer minimises cost, he/she would rearrange purchases to take advantage of the changes in the price structure. Non-concavity of the expenditure function means that subjects buy more at higher prices. Empirical rejection of concavity can be a sign of model misspecification (Baum and Linz, 2009) and can lead to improper policy recommendations (Sauer, 2006).

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, 1980b). 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:

$$S = \frac{\partial^2 E}{\partial p_i \partial p_j} \qquad [21]$$

$$S_{IJ} = \frac{\partial h_i(p,u)}{\partial p_j} = \frac{y}{p_i p_j}\left(\gamma_{ij} + \beta_i \beta_j \log\frac{x}{P} + w_i w_j - \delta_{ij} w_i\right) \qquad [22]$$

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 (see equation 10), 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:

$$k_{ij} = \gamma_{ij} + \beta_i \beta_j \log\frac{y}{P} + w_i w_j - \delta_{ij} w_i \qquad [23]$$

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.

Finally, we want to explicate how the parameters are converted into elasticities. In the first stage, the media index shows the impact of child obesity news on the distribution of food expenditure and other broader expenditure groups. In the second stage, the media index shows the impact of child obesity news on specific food expenditure groups. The elasticities in the second stage are, then, conditional on the food group elasticity in the first stage.

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 and do not take into account potential habits.

Larivière, Larue and Chalfant (2000) adapted the elasticity expression to include habits in a two-stage framework. Therefore, in the first stage, the unconditional price elasticity, ε_{ij}, and expenditure, E_i, elasticities are given by:

$$\varepsilon_{ii} = \frac{\gamma_{ii} - w_i - (\beta_i w_i)}{w_i - (\vartheta_i q_i)} \quad [24]$$

$$\varepsilon_{ij} = \frac{\gamma_{ij} - (\beta_i w_i)}{w_i - (\vartheta_i q_i)} \quad [25]$$

$$E_i = \frac{\beta_i + w_i}{w_i - (\vartheta_i q_i)} \quad [26]$$

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 $E_i < 1$.

With respect to the media elasticity (I_i), the expression to calculate the elasticity would vary if the media index is in levels or in logarithmic form. Some examples can be found in the work done by Larivière, Larue and Chalfant (2000) and Duffy (2003). The media elasticity expressions are calculated in the following way:

For a media index in levels:

$$I_i = \frac{\Omega_i}{w_i} * MI \quad [27]$$

For a logarithmic media index:

$$I_i = \frac{\Omega_i}{w_i} \quad [28]$$

where, I_i is the media elasticity, Ω_i is the estimated coefficient from the information variable, MI is the information variable and w_i is the expenditure budget share for the group i.

Since they are observable, for policy analysis purposes unconditional elasticities are more informative than conditional elasticities (Rickertsen, Kristofersson and Lothe, 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:

$$E_i = E_{(G)i}E_G \quad [29]$$

$$\Sigma_{ij} = e_{ij} + w_{(G)j}\left(\frac{1}{E_{(G)j}} + \Sigma_{GG}\right)E_{(G)i}E_{(G)j} + w_{(G)j}w_G E_G E_{(G)i}(E_{(G)j} - 1) \quad [30]$$

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 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.

To sum up, assuming weak separability, the current study calculates a two-stage linearised AIDS model. The intercept is modified to include habits, seasonality and the child obesity media index. The elasticity expressions take into account the two-stage nature of the demand system. Using them, this study reports the own-price, cross-price, media and income/expenditure elasticities that characterise UK households behaviour. In past research, some AIDS model specifications have involved the impact of media (see Verbeke and Ward, 2001, Piggott and Marsh, 2004, Burton and Young, 1996) and advertising (Piggott *et al.*, 1996). However, these studies are a single-stage specification.

Although it seems intuitive to include information index and habit formation variables in food demand systems, few studies have used them. Amongst these, Larivière, Larue and Chalfant (2000) conducted a demand study using the AIDS model with polynomial distributed lag for advertising and lagged quantity variables for alcohol consumption in Canada. Rickertsen, Kristofersson and Lothe (2003) studied the demand for meat and fish in Nordic countries. The authors used two-stage budgeting, with two information indexes and allowing for habit formation.

To the best of our knowledge, Rickertsen, Kristofersson and Lothe (2003) is the only demand specification that allowed for information index and habits in a two-stage budgeting procedure. It is to be expected that news and habits would impact on consumer behaviour. Moreover, the current study also tests for, instead of assuming, concavity, and for the consistency of series order with the time series properties.

Chapter 5

Data Analysis

5.1. Introduction

This chapter presents the results of the empirical analysis of the two-stage demand system approach outlined in Chapter 3. In the first stage, an AIDS model is estimated using the general expenditure data which includes expenditure shares equations for food, housing, education, recreation, eating out and other miscellaneous items. In the second stage, a further AIDS model is estimated including share equations for more disaggregated food expenditure. In this second stage, the expenditure shares for fruit and vegetables, white meats, red meats, carbohydrates, dairy products and other foods are considered. At both stages, the child obesity news index was used to detect whether consumers adjust their purchasing patterns in response to information regarding the potential health impacts. These results will be used to test the research hypotheses at the end of this chapter. Extensive use is made of tabulated results here, but the interested reader will, throughout, be referred to further tables reproduced in the Appendix to this thesis.

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 5.1 corresponds to these four mutually exclusive cases:

Table 5.1 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 5.1, 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.

5.2. First Stage Estimation

5.2.1. Basic Statistics

With the purpose of gaining familiarity with the data, we present 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 sample averages 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. Therefore, we can infer that, in the UK, the average person spent £149.61 on all goods in total per week, with a standard deviation of £9.04, a minimum of £130.39, and a maximum of £177.44. For comparison purposes, a household spent in average £356.67, with a standard deviation of £22.43, a minimum of £317.81, and a maximum of £433.38. Therefore, on average, a households has 2.38 people, from which, 0.24 correspond to children.

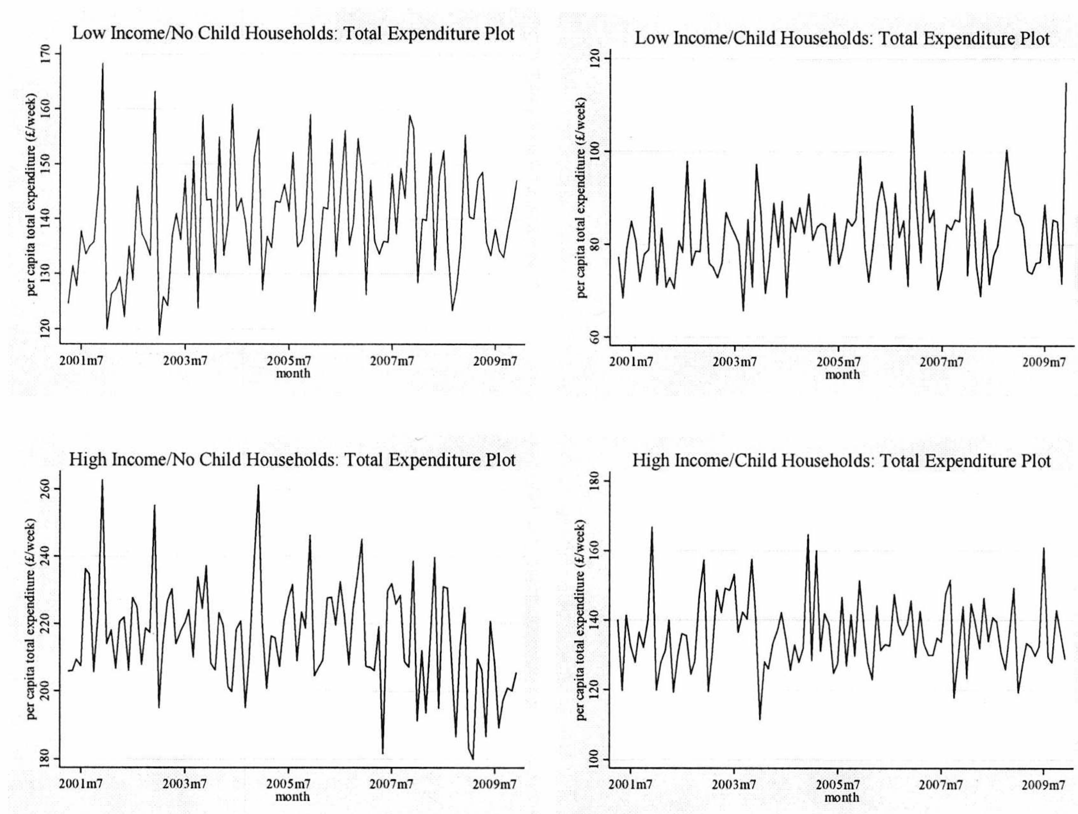

Figure 5.1 Per Capita Total Expenditure Plots

Figure 5.1 corresponds to the plot of the real per capita general expenditure. In the last decade, the average real terms expenditure has experienced a decline of close upon 0.2% per year. Nevertheless, due to the post 2008 economic crisis, the decline had accelerated reaching a rate of 3.2% in 2009. Therefore, households could be seen to be reducing the overall expenditure. The overall per capita expenditure is lower in households with a child, than in households without a child. Children do not contribute income, while they increase the number of people in the household for a per capita comparison.

Table 5.2 presents the general expenditure budget shares. A budget share corresponds to the fraction of the total income that is allocated to an item within a specific general expenditure group. As an example of the results contained in Table 5.2, we can note that households of low income and with children spend on average 15.72% of their total expenditure on food, with a 1.00% standard deviation. The natural logarithmic of food price index is 0.02, with a standard deviation of 0.04.

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 15.72% and 16.52% of their income on food respectively, while high-income households again with and without children, spend 10.90% and 12.67% 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 and eating out.

Low-income households with (without) children spend 7.12% (10.32%) of their income on education, health and clothing, while high-income households with (without) children spend 8.91% (11.32%) of their income on education, health and clothing. High-income households appear to spend a larger proportion of their income on education, health and clothing, which in some circumstances can be considered a basic need, is of course misleading. For some higher income households fashion purchases likely form an important part of cloths expenditure. Likewise, this apparent contradiction can be explained since education and health expenditure can be divided into basic and superior-quality expenditure, and this is particularly so in the UK. Basic education and health is provided by the state as a public service at no- or low-cost to all households. Low-income households mostly rely on public education and health. However, some high-income households spend post tax income on higher-quality education and health. For instance, children can attend private schools, with, at least perceived, higher educational standards and for a greater number of years. In addition, high-income households may purchase health related services that may be of higher quality or be provided in a more timely way than that provided by the public health system. Of course, some of these services may not be provided by the state and services such as, plastic surgery or state of the art hair lost treatments may be included here.

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 5.2 General Expenditure Basic Statistics

		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	15.72%	1.00%	16.52%	1.47%	10.90%	0.91%	12.67%	1.01%
Housing	105	25.77%	2.18%	23.50%	3.32%	19.29%	1.78%	17.45%	1.90%
Education	105	7.12%	1.30%	10.32%	2.13%	8.91%	1.32%	11.32%	1.71%
Recreation	105	31.82%	2.28%	30.10%	3.05%	38.36%	2.10%	36.50%	2.27%
Eating Out	105	10.92%	1.21%	11.04%	1.56%	13.21%	1.27%	11.56%	1.18%
Others	105	8.64%	0.81%	8.52%	1.41%	9.34%	0.94%	10.51%	1.16%
Price Index Natural Log									
Food	105	0.02	0.04	0.02	0.04	0.02	0.04	0.02	0.04
Housing	105	0.02	0.05	0.02	0.06	0.02	0.05	0.02	0.05
Education	105	-0.02	0.14	-0.02	0.17	-0.004	0.07	0.009	0.07
Recreation	105	-0.01	0.04	-0.01	0.03	-0.01	0.03	-0.01	0.02
Eating Out	105	-0.002	0.02	-0.002	0.02	-0.003	0.03	-0.003	0.03
Others	105	-0.01	0.03	-0.01	0.03	-0.01	0.03	-0.01	0.03
Income	105	5.02	0.05	4.29	0.08	5.80	0.06	5.23	0.07
News Index									
In levels	105	3.49	2.68	3.49	2.68	3.49	2.68	3.49	2.68
Cumulated	105	4.76	0.98	4.76	0.98	4.76	0.98	4.76	0.98

The media index used is the same for each household case (low income/no child, low income/child, high income/no child and high income/child), and the basic statistics for this series is reported in Table 5.2. The natural logs of the price indexes are very similar for the four household cases but, of course, they are not all identical. The price indexes for each sub aggregate commodity within an expenditure type are taken from the Office for National Statistics without taking into account the type of household. Therefore, the price index is the same for each household case only when no aggregation is required. The aggregation process involves a weighted sum, using the Laspeyres index, which would causes variability across cases whenever 2 or more commodities are aggregated. For instance, food price index is not combined with any other group, so, it has the same price index for each household case. In contrast, education is combined with health and clothing, therefore, the price index would vary across cases.

Figure 5.2 corresponds to the plot of the general expenditure budget shares. Overall, budget shares tend to be relatively stable, with some variability over the year. The range of values of budget shares is relatively narrow. This relatively narrow range suggests that households might substitute between goods within expenditure groups more than between expenditure groups in response to changing prices.

Taking into account that low-income households have a larger range than high-income households, it suggests that low-income households may be already consuming (close to) the cheapest product, so, after a price shock, low-income households may feel forced to increase their overall food expenditure and have little latitude to mitigate by adjusting their consumption bundle. In other hand, high-income households may have a larger set of cheaper substitute products to enable them to avoid rising prices.

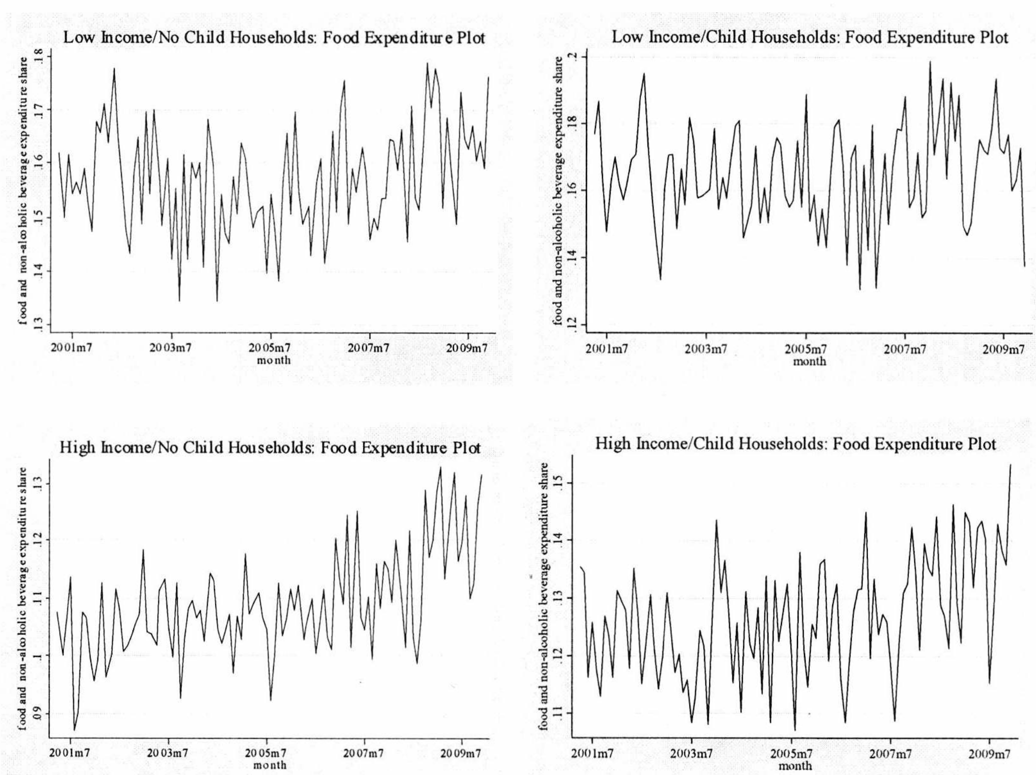

Figure 5.2 Food Expenditure Share Plots

The six general expenditure shares and the natural logarithm of the price indexes for each type of household are presented in the Appendix. Figure 7.1 and Figure 7.2 correspond to low-income households without children. Figure 7.4 and Figure 7.4 Case 2: General Expenditure Price Index Plots

represent low-income households with children. Figure 7.5 and Figure 7.6 correspond to high-income households without children. Finally, Figure 7.7 and Figure 7.8 represent high-income households with children.

As was presented in Chapter 3, the group price indexes were imported from the Office for National Statistics. For example, Figure 5.3 corresponds to the plot of the natural logarithm of the food price index of any household case:

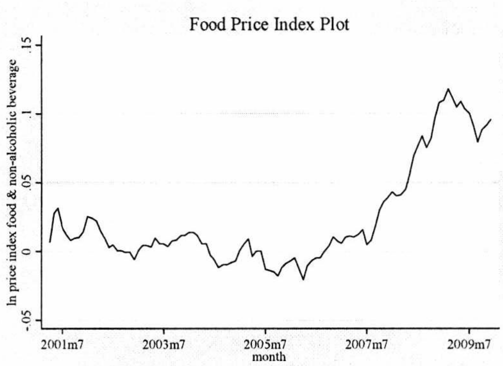

Figure 5.3 Food Expenditure Price Index Plot

The food price index series seems less stationary than food expenditure budget shares. In the last decade, the food price index declined up to mid-2007. Then, the prices increased until the beginning of 2009, when the peak for the decade occurs. Richards and Pofahl (2009) explained that, in the last portion of the past decade, commodity prices rose at unprecedented rates. There has been some controversy surrounding the causes of the high commodity prices. Some studies, such as that conducted by the Overseas Development Institute (2008), blame directly as a consequence of high oil prices. The high oil prices would impact the food market, since they have increased the cost of fertilisers, machine operation and transport. These high oil prices are caused by growing incomes in countries such as China and India, which have increased the demand for meat. Headey and Fan (2010), from the International Food

Policy Research Institute, argued that Chinese and Indian demand for meat is not directly linked to the spike in food prices. The growing Chinese and Indian demand may thus have caused a long-term price increase, rather than a spike. Among others factors, Headey and Fan (2010) found that speculation and low interest rates contributed to the spike in prices. The Overseas Development Institute and International Food Policy Research Institute agree that rising oil prices have supplied an incentive for grain production to be converted into ethanol rather than food. In addition, some production areas had also suffered adverse weather, with a final result of smaller inventory shocks.

Combining graphical information, Figure 5.1 shows that overall expenditure decreased to some extent from 2006 to 2009. Figure 5.3 shows that food prices increased after mid-2007. Figure 5.2 shows that the food expenditure share increases after mid-2007. Consequently, within a context of a small contraction in the overall UK household expenditure, the higher food prices are increasing food budget shares. As expected, in a time of economic contraction, households tend to adjust other expenditure groups more than food. As a result, food expenditure increases its budget share.

It was not so clear before doing the plot that overall food expenditure have a seasonal pattern. A seasonal component is more expected on individual food items, in the sense, that households may prefer to consume some fresh food items when they are in harvest season. Therefore, this seasonal, and also possible a linear trend, component would be taking into consideration in the empirical model specification.

5.2.2. Unit Root Tests

Table 5.3 shows the results of the Augmented Dickey Fuller and Zivot and Andrews tests for the order of integration of each series. Depending on the series, it would be appropriate to use a specific version of the Augmented Dickey Fuller test. A stationary series would tend to return to a constant mean. Therefore, the intuition behind the Dickey Fuller test is that a negative (positive) change in the series would be followed by a positive (negative) change. In this sense, the lagged value of a series, with a negative sign, is a good predictor of the current period change. A positive (negative) value would precede a negative (positive) change. The Augmented version of the Dickey Fuller test also includes as explanatory variable the first difference of a series, and depending on the model specification, a constant and/or a trend. This study uses the criterion of minimising AIC to select the most appropriate model. However, as we already discussed, Dickey Fuller test has been criticised because it does not take into account potential structural breaks.

The Zivot and Andrews test is employed here because it allows for a structural break in the series without specifying the break point *a priori*. The critical values also depend on the model specification, which in its most general specification allows for a break in the intercept and trend. Since the visual inspection of the data suggests the presence of some seasonal variation the Augmented Dickey Fuller and Zivot and Andrews tests, applied here will include up to twelve lags and the optimal lag will be selected using the AIC.

The Augmented Dickey Fuller and Zivot and Andrews test results suggest that the first stage budget shares are consistently stationary in levels. Moreover, the Zivot and Andrews test does not provide evidence of a structural break. However, as can be seen in Table 5.3, the results are more mixed for the logged price indexes, disposable income and the media index. Logged price indexes tend to be *I(1)*, however, some series are *I(0)*, or even, *I(2)*. In the case of high-income households without children, the price index are consistently *I(0)*. In the remaining three household cases, the Augmented Dickey Fuller test shows that the education, health and clothing price index is *I(2)*, while the Zivot and Andrews test indicates *I(0)*. Structural breaks may cause this dissimilar behaviour, where the Augmented Dickey Fuller test needs to be differenced twice to make the series stationary.

Since the dependent variables in the LA/AIDS model (budget shares) are consistently *I(0)*, the AIDS share equation model will not have a balanced order design. A balanced design is a necessary condition for a cointegration relationship. In the empirical model, dependent variables *I(0)* would be explained mostly by independent variables *I(1)*. Therefore, we would see if even being stationary in levels, some of the budget share variability can be explained by income and prices. We also acknowledge that the issue of estimating a demand system using non stationary prices is controversial. This tension in the empirical literature has been recognized by Tiffin and Balcombe (2005) and Lewbel and Ng (2005).

Therefore, the current study proceeds to apply the LA/AIDS model in levels using seemingly unrelated regression (SUR). Subsequent to estimation, the share equation residuals are tested for stationarity, normality and white noise in order to ensure consistency and to rule out obviously spurious estimation.

Table 5.3 General Expenditure Series Order

	Low Income/No Child							*Low Income/Child*						
	Augmented Dickey Fuller Test				**Zivot-Andrews Test**			**Augmented Dickey Fuller Test**				**Zivot-Andrews Test**		
	Model	Order	Lag*	Stat	Order	Lag*	t-Stat	Model	Order	Lag*	Stat	Order	Lag*	t-Stat
Expenditure Shares														
Food	w/trend	I(0)	0	-8.93	I(0)	3	-5.66	w/constant	I(0)	0	-8.49	I(0)	0	-9.21
Housing	w/trend	I(0)	0	-9.69	I(0)	0	-10.76	w/trend	I(0)	0	-9.95	I(0)	0	-10.35
Education	w/constant	I(0)	0	-7.86	I(0)	0	-8.44	w/trend	I(0)	0	-8.92	I(0)	0	-9.68
Recreation	w/trend	I(0)	0	-11.15	I(0)	1	-7.29	w/trend	I(0)	0	-9.64	I(0)	0	-9.87
Eating Out	w/trend	I(0)	0	-8.34	I(0)	0	-8.67	w/trend	I(0)	0	-8.39	I(0)	0	-8.83
Others	w/trend	I(0)	0	-10.62	I(0)	0	-11.34	w/constant	I(0)	0	-10.30	I(0)	2	-8.23
Price Index Natural Log														
Food	wo/constant	I(1)	0	-8.33	I(1)	0	-9.25	wo/constant	I(1)	0	-8.33	I(1)	0	-9.25
Housing	w/trend	I(1)	0	-8.36	I(1)	3	-6.41	w/trend	I(1)	0	-7.57	I(1)	0	-8.38
Education	wo/constant	I(2)	10	-11.97	I(0)	2	-6.36	wo/constant	I(2)	10	-11.95	I(0)	2	-6.37
Recreation	w/trend	I(1)	0	-7.86	I(1)	1	-8.15	wo/constant	I(1)	0	-7.93	I(1)	0	-8.74
Eating Out	w/trend	I(1)	0	-12.94	I(1)	2	-5.95	w/constant	I(1)	0	-12.70	I(1)	2	-5.92
Others	w/trend	I(1)	0	-12.24	I(1)	1	-9.64	wo/constant	I(0)	0	-2.16	I(1)	1	-9.64
Income	w/trend	I(0)	1	-4.97	I(1)	3	-8.31	w/trend	I(0)	1	-6.58	I(0)	0	-9.21

	High Income/No Child							*High Income/Child*						
	Augmented Dickey Fuller Test				**Zivot-Andrews Test**			**Augmented Dickey Fuller Test**				**Zivot-Andrews Test**		
	Model	Order	Lag*	Stat	Order	Lag*	t-Stat	Model	Order	Lag*	Stat	Order	Lag*	t-Stat
Expenditure Shares														
Food	wo/constant	I(0)	1	-14.38	I(0)	2	-10.16	w/trend	I(0)	0	-8.97	I(0)	0	-9.76
Housing	wo/constant	I(0)	3	-8.86	I(0)	3	-8.93	w/trend	I(0)	0	-9.95	I(0)	0	-10.13
Education	w/trend	I(0)	0	-17.51	I(0)	3	-7.81	w/trend	I(0)	0	-9.64	I(0)	0	-9.94
Recreation	wo/constant	I(0)	2	-10.13	I(0)	3	-8.90	w/trend	I(0)	0	-9.67	I(0)	1	-8.70
Eating Out	w/trend	I(0)	0	-17.53	I(0)	0	-17.42	w/constant	I(0)	0	-7.33	I(0)	0	-7.61
Others	w/trend	I(0)	0	-17.97	I(0)	3	-8.88	w/constant	I(0)	0	-8.26	I(0)	0	-8.49
Price Index Natural Log														
Food	wo/constant	I(0)	0	-8.33	I(0)	0	-9.25	wo/constant	I(1)	0	-8.33	I(1)	0	-9.25
Housing	w/constant	I(0)	0	-9.27	I(0)	3	-6.60	w/constant	I(1)	0	-9.51	I(1)	3	-6.64
Education	wo/constant	I(0)	10	-13.31	I(0)	3	-12.24	wo/constant	I(2)	10	-16.61	I(0)	2	-6.05
Recreation	wo/constant	I(0)	0	-7.89	I(0)	0	-8.66	w/trend	I(0)	1	-3.57	I(1)	0	-8.70
Eating Out	w/trend	I(0)	1	-10.40	I(0)	0	-10.90	w/constant	I(1)	0	-12.94	I(1)	2	-6.31
Others	w/trend	I(0)	0	-12.24	I(0)	1	-9.64	w/constant	I(1)	0	-11.83	I(1)	1	-9.64
News Index														
In Levels	w/trend	I(0)	1	-5.53	I(0)	0	-8.42							
Cumulated	w/constant	I(0)	2	-4.71	I(1)	0	-9.91							
Income	wo/constant	I(0)	4	-8.12	I(0)	3	-8.90	w/constant	I(0)	0	-9.83	I(0)	0	-10.24
Critical values		**1%**	**5%**	**10%**	**1%**	**5%**	**10%**		**1%**	**5%**	**10%**	**1%**	**5%**	**10%**
	wo/constant	-2.60	-1.95	-1.61				wo/constant	-2.60	-1.95	-1.61			
	w/constant	-3.51	-2.89	-2.58	-5.57	-5.08	-4.82	w/constant	-3.51	-2.89	-2.58	-5.57	-5.08	-4.82
	w/trend	-4.04	-3.45	-3.15				w/trend	-4.04	-3.45	-3.15			

Note: (*) Optimum lag

The Augmented Dickey Fuller test has three versions: without constant (wo/constant), with constant (w/constant) and trend & constant (w/trend). The Zivot and Andrews test corresponds to the version that allows structural breaks in intercept and trend.

In Table 5.3, the Augmented Dickey Fuller test shows that the cumulated media index variable is *I(0)*. However, the Zivot and Andrews test indicates *I(1)*. Consequently, at this point, it is still uncertain whether that media index needs to be entered in levels or as first difference in the LA/AIDS model. If the most appropriate media index is *I(0)* means that households are more affected by the current level of news than for an increase or decrease of the level of news.

5.2.3. Media Index

Since prior to estimation it is unclear exactly how households will assimilate and respond to news signals, it is necessary to empirically test the appropriate specification of the news index within the demand system framework used here. This will allow us assess whether new information has an immediate or even a lasting effect on the expenditure and, therefore, consumption behaviour of households. 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. Chapter 3 already discussed geometrical weights, polynomial distributed lags and free-form specification. Following the work done by Rickertsen, Kristofersson and Lothe (2003), this study adopts a free form lag specification. The free form lag specification is the most data-driven and there is no *a priori* information available to justify weights.

After deciding the use of the free form lag, it is needed to decide the media index specification. Table 5.4 compares seven alternative media indexes, four free form specifications, and three cumulated forms. The free form specification does not show a significant effect after only one or two months. Thus, three months were used as a maximum number of lags. The free form specification corresponds to zero, one, two and three lags. The news index series used starts in January, 2001. By starting the news index three months before the household datasets, we avoid losing the initial observations in the lag media index specifications.

Table 5.4 considers the cumulated newspaper variables in terms of levels and first differences. In addition, it considers the media index with and without the logarithmic transformations. The cumulated media index in first differences is the same as free form specification in those levels without lag.

Table 5.4 Media Index Selection

	Low Income/No Child			*Low Income/Child*		
News Index Specification	AIC	BIC	System R2	AIC	BIC	System R2
Free form in levels (0 lag)	-3225	-3093	0.319	-2760	-2628	0.522
Free form in levels (1 lag)	-3219	-3073	0.348	-2753	-2608	0.529
Free form in levels (2 lags)	-3186	-3028	0.353	-2716	-2558	0.535
Free form in levels (3 lags)	-3141	-2971	0.370	-2684	-2513	0.533
Cumulated newspaper Index in levels	-3224	-3092	0.469	**-2765**	**-2633**	**0.555**
Log cumulated newspaper Index in levels	**-3227**	**-3095**	**0.286**	-2762	-2630	0.524
Log cumulated newspaper Index in first differences	-3224	-3092	0.358	-2764	-2631	0.510

	High Income/No Child			*High Income/Child*		
News Index Specification	AIC	BIC	System R2	AIC	BIC	System R2
Free form in levels (0 lag)	-3245	-3113	0.562	**-3119**	**-2974**	**0.438**
Free form in levels (1 lag)	-3243	-3097	0.558	-3112	-2953	0.447
Free form in levels (2 lags)	-3201	-3043	0.568	-3077	-2906	0.432
Free form in levels (3 lags)	-3158	-2987	0.587	-3036	-2852	0.483
Cumulated newspaper Index in levels	**-3251**	**-3119**	**0.532**	-3114	-2968	0.432
Log cumulated newspaper Index in levels	-3247	-3115	0.564	-3113	-2968	0.400
Log cumulated newspaper Index in first differences	-3248	-3115	0.550	-3114	-2968	0.441

Model specification without lags consistently has the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC). In the case of high-income households with children, the data supports the deduction that expenditure is impacted by contemporaneous news. These households would not have a memory effect. In this sense, they need to be constantly reminded about child obesity. However, in the other three cases, a cumulated specification better fits the data. This finding suggests that these three types of households are influenced by news in the cumulated form. In the sense, monthly news would increase the cumulated news, therefore, the effect would become permanently.

Consequently, this study tested for seven alternative media indexes. From which, the cumulated version was the most appropriate one in three out of four household cases. The door is opened for alternative media index specification that can do a better job than the cumulative media index.

5.2.4. Seemingly Unrelated Regression Model

Table 5.5 and Table 5.6 correspond to the SUR estimation with restrictions imposed to account for homogeneity and symmetry assumptions, which correspond to equation 14 to 19. As is presented in Table 5.5, the SUR model is more effective at explaining food expenditure in high-income households than in low-income households. Testing for all the parameters to be equal to zero per equation, the results show that each equation has parameters significantly different from zero.

Table 5.5 Summary of the General Expenditure SUR Model

	Low Income/No Child			*Low Income/Child*			*High Income/No Child*			*High Income/Child*		
Equation	"R-sq"	chi2	p-value	"R-sq"	chi2	p-value	"R-sq"	chi2	p-value	"R-sq"	chi2	p-value
food	0.35	54.56	0.00	0.25	31.71	0.00	0.54	130.09	0.00	0.50	107.3	0.00
housing	0.39	68.97	0.00	0.42	82.47	0.00	0.21	32.69	0.00	0.17	26.93	0.01
education	0.30	47.82	0.00	0.22	36.76	0.00	0.29	53.39	0.00	0.35	59.23	0.00
recreation	0.25	38.31	0.00	0.15	23.69	0.01	0.23	37.08	0.00	0.17	30.59	0.00
eating out	0.41	75.53	0.00	0.30	44.99	0.00	0.35	62.13	0.00	0.33	53.22	0.00

Table 5.6 shows that the autoregressive terms in each of the general expenditure group share equations are insignificantly different from zero. This suggests that the influence of habit, that which is formed from previous consumption patterns, here is undetectable. In each case, at least one out of three seasonal dummy variables is significantly different from zero and confirms our initial suspicions that seasonal patterns in household expenditure are important. In food expenditure, the seasonal component is stronger in households with children. A possible explanation is that it could be the case that households with children rely more on fresh seasonal products than do households without children. It also could be case that households with children adapt their food expenditure to external events, such as holiday season and school time.

Using a 5% significance level, the child obesity news index does not have a significant impact on food expenditure at this level of aggregation. However, we should note that this result reveals little about the nature of the impact of information on specific food categories. This result does, however, suggest that households appear not to react to this type of news by increasing, or otherwise, their expenditure on food and, therefore, by altering the overall quality of food that they purchase. In the second stage of the estimation, we should be able to test the child obesity news impact on the balance of specific food group expenditures. Moreover, the empirical evidence suggests that child obesity news does not cause a significant spillover over other general expenditure categories.

The remaining parameters correspond to price index variables that are used to calculate the own price, income and news elasticities. At the end of this section, we present and comment on the elasticity estimation.

Table 5.6 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 quantity	-0.00004	0.0005	0.001	0.001	-0.0002	0.0003	-0.001	0.001
Ln Price index								
food	0.03	0.04	0.12**	0.06	0.05	0.03	0.10***	0.04
housing	0.07	0.05	-0.13*	0.08	0.07	0.05	-0.05	0.05
education	-0.04**	0.02	0.03	0.04	-0.13***	0.04	0.01	0.04
recreation	0.08	0.05	-0.02	0.09	0.06	0.06	0.03	0.05
eating out	-0.08	0.05	-0.01	0.08	0.03	0.05	-0.05	0.06
others	-0.03	0.05	0.04	0.07	-0.05	0.05	0.01	0.05
income	-0.03	0.02	-0.03	0.02	-0.03***	0.01	-0.05***	0.01
Seasonal dummies								
jan-mar	-0.0002	0.002	0.01***	0.004	0.001	0.002	0.01***	0.002
apr-jun	-0.004	0.002	0.01***	0.004	-0.002	0.002	0.003	0.002
jul-sep	-0.01***	0.002	0.01*	0.004	-0.01***	0.002	-0.01***	0.003
Linear trend							0.0002*	0.0001
News index	-0.001*	0.0003	0.0001	0.0001	-0.0001	0.00004	-0.0002	0.0003
Constant	0.32**	0.12	0.25***	0.08	0.28***	0.06	0.37***	0.06
education								
Lagged quantity	0.0001	0.0004	-0.0001	0.001	0.0002	0.0002	0.0001	0.0003
Ln Price index								
food	-0.04**	0.02	0.03	0.04	0.07	0.05	-0.05	0.05
housing	0.005	0.04	0.01	0.09	-0.03	0.13	0.08	0.12
education	-0.04*	0.03	-0.08	0.08	0.08	0.08	0.12	0.08
recreation	0.12**	0.06	0.11	0.10	-0.36***	0.11	-0.17*	0.10
eating out	-0.02	0.04	-0.14**	0.06	0.06	0.08	0.09	0.08
others	0.02	0.04	0.13**	0.06	0.14*	0.08	-0.08	0.08
income	-0.04	0.03	-0.06**	0.03	0.05*	0.03	0.01	0.02
Seasonal dummies								
jan-mar	-0.02***	0.003	-0.02***	0.006	0.05*	0.03	0.01***	0.005
apr-jun	-0.01***	0.003	-0.01**	0.006	0.01	0.005	0.01*	0.005
jul-sep	-0.02***	0.003	-0.01**	0.006	0.01**	0.004	0.0001	0.01
Linear trend					0.01**	0.005	0.0002	0.0003
News index	-0.0005	0.0004	-0.0001	0.0001	-0.00002	0.0001	-0.001	0.001
Constant	0.30*	0.16	0.37***	0.12	-0.10	0.15	0.11	0.13
housing								
Lagged quantity	-0.0001	0.0003	0.0002	0.0006	-0.0001	0.0003	-0.0001	0.0003
Ln Price Index								
food	0.07	0.05	-0.13*	0.08	-0.13***	0.04	0.01	0.04
housing	0.05	0.09	0.09	0.19	0.08	0.08	0.12	0.08
education	0.00	0.04	0.01	0.09	0.09	0.08	-0.09	0.09
recreation	-0.18**	0.09	-0.08	0.16	0.08	0.08	-0.12	0.09
eating out	-0.01	0.08	0.19	0.12	-0.02	0.07	-0.06	0.07
others	0.14*	0.08	-0.04	0.11	-0.05	0.06	0.06	0.06
income	-0.07	0.05	-0.04	0.04	-0.04**	0.02	0.08***	0.02
Seasonal dummies								
jan-mar	0.02***	0.005	0.02	0.01	-0.01**	0.003	-0.02***	0.004
apr-jun	0.01***	0.005	0.01	0.01	-0.01***	0.003	-0.02***	0.004
jul-sep	0.01**	0.005	0.01*	0.01	-0.02***	0.004	-0.01*	0.005
Linear trend							-0.001**	0.0003
News index	0.0001	0.0007	0.0001	0.0002	0.0001	0.0001	0.002***	0.001
Constant	0.60**	0.26	0.35**	0.17	0.32***	0.11	-0.26***	0.10

recreation								
Lagged quantity	-0.0001	0.0002	-0.0003	0.0003	-0.0001	0.0001	-0.0001	0.0002
Ln Price Index								
food	0.08	0.05	-0.02	0.09	0.06	0.06	0.03	0.05
housing	-0.18**	0.09	-0.08	0.16	-0.36***	0.11	-0.17*	0.10
education	0.12**	0.06	0.11	0.10	0.08	0.08	-0.12	0.09
recreation	-0.23*	0.14	-0.18	0.25	0.29*	0.17	-0.08	0.15
eating out	0.11	0.10	0.18	0.16	0.05	0.11	0.12	0.11
others	-0.10	0.09	-0.07	0.13	-0.13	0.09	0.24***	0.10
income	0.20***	0.06	0.06	0.04	0.01	0.03	-0.04	0.03
Seasonal dummies								
jan-mar	0.0004	0.006	-0.02**	0.01	0.01**	0.01	-0.02***	0.006
apr-jun	0.01	0.005	-0.02**	0.01	0.002	0.01	-0.01	0.006
jul-sep	0.01	0.006	-0.01	0.01	0.01	0.01	0.00	0.007
Linear trend							-0.0005	0.0003
News index	0.001	0.001	0.00002	0.0002	0.0002*	0.0001	-0.001	0.001
Constant	-0.69**	0.30	0.06	0.18	0.28	0.18	0.59***	0.16
eating out								
Lagged quantity	0.00001	0.0004	0.0002	0.001	-0.0001	0.0002	0.0002	0.0005
Ln Price Index								
food	-0.08	0.05	-0.01	0.08	0.03	0.05	-0.05	0.06
housing	-0.01	0.08	0.19	0.12	0.06	0.08	0.09	0.08
education	-0.02	0.04	-0.14**	0.06	-0.02	0.07	-0.06	0.07
recreation	0.11	0.10	0.18	0.16	0.05	0.11	0.12	0.11
eating out	0.15	0.16	-0.03	0.24	-0.37**	0.15	0.07	0.19
others	-0.09	0.10	-0.18	0.15	0.25**	0.11	-0.19	0.12
income	-0.06**	0.03	-0.002	0.02	0.002	0.02	0.002	0.01
Seasonal dummies								
jan-mar	-0.003	0.003	0.001	0.004	-0.01***	0.003	-0.003	0.003
apr-jun	-0.001	0.003	0.01**	0.004	0.01***	0.003	0.01*	0.003
jul-sep	0.01***	0.003	0.01	0.004	0.01***	0.003	0.01**	0.004
Linear trend							-0.00004	0.0003
News index	-0.0002	0.0004	-0.0002**	0.0001	-0.000005	0.0001	-0.001	0.0004
Constant	0.39***	0.15	0.15	0.09	0.12	0.10	0.10	0.08

Single, double and triple asterisks (*) denote statistical significance at the 10%, 5% and 1% level.

Concerning the food price index parameters, the food expenditure equation has the only price index parameter with a positive sign across all households. When food prices rise the households increase their food expenditure budget shares. After a food price increase, households experience a loss in purchasing power and may focus more on satisfying their basic needs, such as food, than more luxury needs, such as, recreation. This idea is consistent with the discussion on the basic statistic in Table 5.2, where low-income households spend a larger proportion of their income in food.

With respect to income index parameters, the food expenditure equation has only income index parameter with a positive sign across all households. This is also consistent with the paragraph above. When income rises, households decrease their food budget shares since they allocate more income to satisfy more sophisticated needs.

5.2.5. Residual Tests

The expenditure in different groups is highly linked. Households make simultaneous decisions regarding how to allocate their income across categories, where the income that is allocated to a particular category cannot be reallocated (at least in this empirical model). Therefore, it is expected that the residuals be correlated across equations, which is also a testable assumption in the SUR. Table 5.7 shows the results of the Breusch-Pagan test and finds, as expected, that the residuals are correlated across equations.

Table 5.7 General Expenditure Residual Correlation Tests

	Low Income/No Child					*Low Income/Child*				
Residuals	food	housing	education	recreation	eating out	food	housing	education	recreation	eating out
food	1					1				
housing	-0.07	1				0.05	1			
education	-0.20	-0.24	1			-0.22	-0.37	1		
recreation	-0.29	-0.62	-0.15	1		-0.36	-0.48	-0.24	1	
eating out	0.14	-0.12	-0.05	-0.39	1	0.13	-0.23	0.01	-0.29	1
Breusch-Pagan test: chi2(10) = 81.811, Pr = 0.0000						Breusch-Pagan test: chi2(10) = 79.004 , Pr = 0.0000				

	High Income/No Child					*High Income/Child*				
Residuals	food	housing	education	recreation	eating out	food	housing	education	recreation	eating out
food	1					1				
housing	-0.11	1				-0.08	1			
education	0.02	-0.26	1			0.02	-0.21	1		
recreation	-0.39	-0.50	-0.18	1		-0.28	-0.49	-0.43	1	
eating out	0.15	-0.14	-0.21	-0.37	1	0.02	-0.19	-0.15	-0.16	1
Breusch-Pagan test: chi2(10) =76.613, Pr = 0.0000						Breusch-Pagan test: chi2(10) = 66.170, Pr = 0.0000				

Table 5.8 shows that the residuals are *I(0)*. The Augmented Dickey Fuller Test shows consistently that the residuals are *I(0)*. The Augmented Dickey Fuller test with the lowest AIC corresponds to the specification without constant and no lags. This should be case since any remaining mean should be removed by the constant in the empirical model. Finally, if the residuals were not *I(0),* this would be a sign of model misspecification resulting in spurious results.

Table 5.8 General Expenditure Residual Unit Root Tests

	Low Income/No Child				*Low Income/Child*			
	Augmented Dickey Fuller Test				**Augmented Dickey Fuller Test**			
	Model	Order	Lag*	t-stat	Model	Order	Lag*	t-stat
food	wo/constant	I(0)	0	-11.56	wo/constant	I(0)	0	-10.50
housing	wo/constant	I(0)	0	-10.89	wo/constant	I(0)	0	-9.96
education	wo/constant	I(0)	0	-9.85	wo/constant	I(0)	0	-10.04
recreation	wo/constant	I(0)	0	-12.07	wo/constant	I(0)	0	-9.04
eating out	wo/constant	I(0)	0	-10.50	wo/constant	I(0)	0	-9.56

	High Income/No Child				*High Income/Child*			
	Augmented Dickey Fuller Test				**Augmented Dickey Fuller Test**			
	Model	Order	Lag*	t-stat	Model	Order	Lag*	t-stat
food	wo/constant	I(0)	0	-11.57	wo/constant	I(0)	0	-10.56
housing	wo/constant	I(0)	0	-10.32	wo/constant	I(0)	0	-11.18
education	wo/constant	I(0)	0	-11.35	wo/constant	I(0)	0	-10.01
recreation	wo/constant	I(0)	0	-9.06	wo/constant	I(0)	0	-10.35
eating out	wo/constant	I(0)	0	-11.07	wo/constant	I(0)	0	-9.95

Note: (*) Optimum lag

SUR residuals also need to be normally-distributed and white noise. Normally-distributed residuals are a testable assumption. A white-noise residual pattern occurs if the residuals do not retain relevant information and contemporaneous residuals are not correlated with past residuals from the same equations.

Table 5.9 General Expenditure Residual Distribution Tests

Low Income/No Child

	Normality				**White noise**	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
food	0.03	0.49	0.24	0.89	1.88	0.17
housing	1.72	0.04	5.33	0.07	0.64	0.43
education	1.78	0.04	5.85	0.05	0.01	0.94
recreation	1.62	0.05	7.92	0.02	3.29	0.07
eating out	0.84	0.20	2.49	0.29	0.14	0.71

Low Income/Child

	Normality				**White noise**	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
food	-0.67	0.75	0.77	0.68	0.31	0.58
housing	1.20	0.12	2.92	0.23	0.04	0.85
education	0.58	0.28	3.08	0.21	0.01	0.92
recreation	-0.24	0.60	0.64	0.72	1.29	0.26
eating out	2.56	0.01	10.67	0.00	0.002	0.97

High Income/No Child

	Normality				**White noise**	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
food	-1.81	0.97	0.12	0.94	1.95	0.16
housing	-1.48	0.93	0.49	0.78	0.05	0.83
education	0.41	0.34	2.51	0.29	1.54	0.21
recreation	1.01	0.16	3.71	0.16	1.25	0.26
eating out	0.07	0.47	2.66	0.26	0.91	0.34

High Income/Child

	Normality				**White noise**	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
food	-0.98	0.84	1.64	0.44	0.31	0.58
housing	0.27	0.39	2.16	0.34	0.93	0.34
education	1.36	0.09	3.65	0.16	0.005	0.94
recreation	2.39	0.01	9.40	0.01	0.04	0.84
eating out	-0.78	0.78	0.42	0.81	0.02	0.88

Note: (*) results in the first lag.

As is shown in Table 5.9, the Shapiro-Francia and Skewness/Kurtosis test results, in most of the cases, generally fail to reject normality. The rejection of normality happens mainly in households cases of low-income and without children. It is not surprising, it tends to be more complicated to explain the expenditure decision of households without children since they may be able to expend their money without so many nutritional concerns that leads to more irregular expenditure patterns. At the same time, low-income households have fewer choices in their diet. Therefore, low-income households may be more constrained by their budget to adapt their diet to their affordable options.

In all cases, a white-noise test has also failed to reject it. The Portmanteau test was conducted from lag 1 to 10 in each residual series. Table 5.9 shows the Portmanteau test using the first lag. Consequently, the residuals are *I(0)*, white noise and mostly normally distributed, which provide evidence that the relations are not spurious.

5.2.6. Economic Constraint Tests

The first stage LA/AIDS model is run twice. In order to test key theoretical assumptions the LA/AIDS model is first run unconstrained and a second run is conducted with homogeneity and symmetry imposed. Table 5.10 shows the results of testing for homogeneity and symmetry constraints. Using a 5% significance level, in the case of low-income households with children and high-income households without children, this study jointly rejected homogeneity and symmetry.

Education, health and clothing group and recreation, transportation and communication group are the expenditure groups that most commonly reject these two economic properties. In both these expenditure groups, it is likely the prices are rigid (e.g. contracts) and may not adjust quickly to changes in demand conditions. Even where they were often empirically rejected, we imposed these two theoretical constraints.

Table 5.10 General Expenditure Homogeneity and Symmetry Tests

	Low Income/No Child		Low Income/Child		High Income/No Child		High Income/Child	
Restriction	Wald Stat	p-value	Wald Stat	p-value	Wald Stat	p-value	Wald Stat	p-value
Homogeneity for equation:								
food	0.14	0.71	0.40	0.71	3.30	0.07	0.80	0.37
housing	0.57	0.45	0.26	0.61	0.09	0.76	1.36	0.24
education	0.03	0.86	2.93	0.09	7.25	0.01	0.65	0.42
recreation	0.37	0.54	6.20	0.01	1.48	0.22	0.50	0.48
eating out	0.17	0.68	3.49	0.16	4.58	0.03	2.18	0.14
Joinly	1.22	0.94	11.9	0.04	18.20	0.00	4.60	0.47
Symmetry for price parameter:								
food and housing	0.01	0.91	0.03	0.85	0.97	0.32	1.64	0.20
food and education	0.08	0.77	3.94	0.05	1.51	0.22	1.70	0.19
food and recreation	0.07	0.79	0.75	0.39	3.39	0.07	0.31	0.58
food and eat-out	1.49	0.22	3.88	0.05	4.72	0.03	1.42	0.23
housing and education	0.03	0.87	2.48	0.12	4.16	0.04	0.26	0.61
housing and recreation	0.93	0.33	4.16	0.04	0.33	0.57	0.03	0.86
housing and eat-out	0.36	0.55	0.49	0.48	0.10	0.75	3.25	0.07
edu and recreation	0.27	0.60	3.91	0.05	8.35	0.00	0.93	0.34
education and eat-out	0.00	0.97	0.59	0.44	8.61	0.00	0.03	0.85
recreation and eat-out	0.33	0.57	2.68	0.10	0.66	0.42	0.89	0.35
Joinly	4.94	0.90	30.59	0.00	23.3	0.01	13.69	0.19

This study also tests for concavity of the expenditure function. The results of that test can be found in the Table 7.1 of the Appendix. In three out of four household cases, three out of five eigenvalues are negative. Consequently, concavity is mostly rejected. Only in the case of households with high-income and child, are four of five eigenvalues negative, therefore, the expenditure function is locally concave.

The concavity of the expenditure function was mostly rejected. It suggests that the general expenditure groups contain some products and services that are durables or that can 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 expenditure function may also not hold.

5.2.7. Elasticities

As was presented in Chapter 2, 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. The uncompensated own-price elasticity combines own-budget share, own-price and lagged-quantity parameters. The cross price elasticity uses the cross-price parameter instead of the own-price parameter. Finally, the expenditure elasticity uses the expenditure parameter instead of a price parameter. The exact expressions correspond to equations 24 to 30 in Chapter 4.

Table 5.11 corresponds to price, income and news uncompensated elasticities for the general expenditure groups. On average, the own price elasticity is -0.48 for food expenditure, -0.49 for education, health and clothing expenditure, -0.84 for housing and furnishing expenditure, -1.17 for recreation, transportation and communication expenditure and -2.05 for eating out expenditure. Therefore, we classified food, housing and furnishing and education, health and clothing as inelastic. As expected, households respond less to change in food prices, education, health and clothing and housing and furnishing than they do to changes related to recreation, transportation and communication and eating out.

Own price elasticities, in most of the household cases, have the expected negative sign. A few 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. 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. Having a child in the household causes a more inelastic response to a change in the price of food. From this, it may be inferred that households with a child are less willing to alter their food expenditure after a change in food prices.

Moreover, high-income households have a more inelastic response to a change in food prices, when compared to low-income households. As expected, high-income households respond less to changes in overall food prices. It would appear that high-income households are more willing to continue food expenditure level even if the food price increases.

Table 5.11 General Expenditure Unconditional Elasticities

Low Income/No Child	food	housing	education	recreation	eating out	others	income	news
food	-0.75	0.48	-0.25	0.58	-0.50	-0.15	0.79	-0.01
housing	0.30	-0.72	0.04	-0.61	-0.003	0.55	0.72	0.002
education	-0.51	0.23	-1.61	1.97	-0.28	0.41	0.40	-0.02
recreation	0.16	-0.73	0.33	-1.90	0.28	-0.37	1.61	0.01
eating out	-0.68	0.06	-0.18	1.21	0.41	-0.77	0.48	-0.01
others	-0.33	1.60	0.23	-1.24	-1.17	-0.28	1.19	0.003

Low Income/Child	food	housing	education	recreation	eating out	others	income	news
food	-0.25	-0.82	0.20	-0.06	-0.05	0.26	0.88	0.09
housing	-0.56	-0.59	0.05	-0.29	0.84	-0.15	0.86	0.10
education	0.37	0.21	-1.72	1.22	-1.33	1.36	0.44	-0.23
recreation	-0.09	-0.29	0.33	-1.61	0.55	-0.25	1.17	0.01
eating out	-0.09	1.75	-1.31	1.65	-1.29	-1.68	1.00	-0.39
others	0.35	-0.57	1.47	-1.06	-2.26	0.38	1.68	0.24

High Income/No Child	food	housing	education	recreation	eating out	others	income	news
food	-0.50	0.33	-1.37	0.15	0.24	-0.59	0.73	-0.08
housing	0.64	-1.24	0.95	-0.94	0.43	1.53	1.30	-0.02
education	-1.12	0.40	0.06	0.19	-0.18	-0.57	0.53	0.12
recreation	0.62	-2.06	1.01	-0.26	0.40	-1.36	1.02	0.08
eating out	0.32	0.28	-0.21	0.14	-3.70	2.54	0.98	-0.01
others	-0.47	0.72	-0.53	-0.33	1.82	-2.64	1.09	-0.30

High Income/Child	food	housing	education	recreation	eating out	others	income	news
food	-0.15	-0.31	0.10	0.33	-0.29	0.10	0.56	-0.01
housing	-0.31	-0.54	0.68	-1.00	0.53	-0.46	1.06	-0.01
education	-0.01	0.92	-1.83	-1.28	-0.59	0.41	1.68	0.05
recreation	0.09	-0.44	-0.30	-1.16	0.35	0.67	0.89	-0.01
eating out	-0.42	0.81	-0.52	1.11	-0.36	-1.70	1.05	-0.02
others	0.06	-0.75	0.52	2.30	-1.88	-1.27	1.02	0.01

The average income elasticity is 0.66 for food expenditure, 0.96 for housing and furnishing expenditure, 1.06 for education, health and clothing expenditure, 1.08 for recreation, transportation and communication expenditure and 1.16 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 and housing have income elasticities are less than one, so, they are classified as normal goods. Since they satisfy the most fundamental needs, we expect food and housing to have the lowest income elasticity. In contrast, education, recreation and eating-out have income elasticities greater than one, so, they are classified as luxury goods. In this sense, households would first satisfy their food and housing needs, and only thereafter would they spend on education, recreation and eating-out.

With respect to the household cases, high-income households have lower food income elasticity than low-income households. In addition, households with children 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.

Finally, in most of the cases, food expenditure is a substitute for eating out, while complementary with education, health and clothing expenditure and recreation, transportation and communication expenditure. It is not surprising that food expenditure for home consumption and eating out behave as substitutes since households need to choose between one of them in order to satisfy similar, but not identical, needs. Home food expenditure does include take-away and other prepared meals that are consumed at home. Moreover, households that spend more on food at home also spend more on education, health and clothing group and recreation, transportation and communication group. In other words, high-income households seem to spend more on food as absolute value but, according to the basic statistics, this still represents a smaller proportion of their income compare to low-income households.

Using 5% significance level, this study found that child obesity news does not cause a significant impact on overall food expenditure. Now, it would be interesting to see if child obesity news impact specific food categories. It could be the case that child obesity does cause a change in the food expenditure composition that does not change the overall food expenditure.

5.3. Second Stage Estimation

5.3.1. Basic Statistics

What follows presents the estimated food group demand system and associated parameter and elasticity estimates, derived from the second stage of the households two stage budgeting problem. Here, data extracted from the expenditure diary questionnaires of the Living Cost and Food Survey are employed to derive food expenditure shares and unit values, which we assume correspond closely to prices. However, unlike the case of a simple single stage budgeting problem, here the fitted values for the food expenditure group are used to construct the total food expenditure data that enters each of the second stage share equations in the system. Again, the data used is aggregated from the level of individual household to the level of the four household cases, high with, high without, low with and low without children, thus generating four distinct demographic time series. Further, while the survey data contains entries on some 250 products eating at home, we aggregate across products in order to generate data on six food groups. The choice of grouping reflects the focus of this research on diet and health. Like the work of the first stage reported above, each share equation is augmented with this addition of our media index in order to take account of the potential impact of information on obesity related dietary news, particularly that relating to child health.

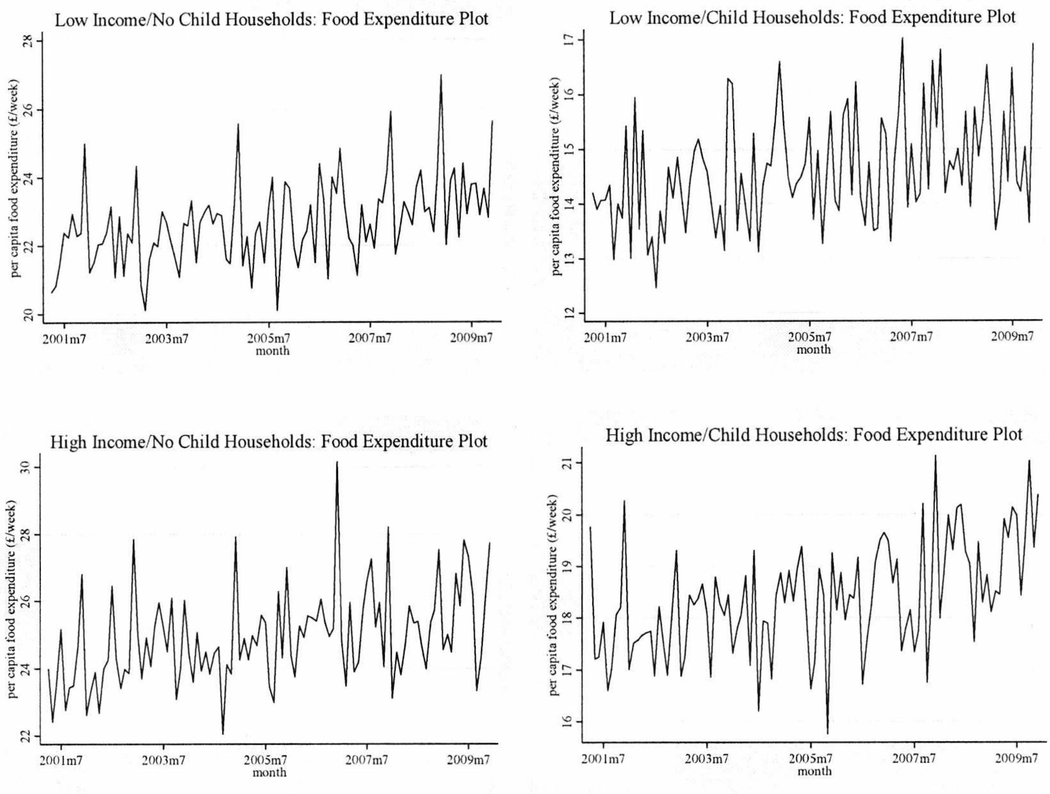

Figure 5.4 Per Capita Food Expenditure Plots

Considering that the sample is stratified and random, we can infer that in the UK, each person spends on average £20.92 per week on food; with a standard deviation of £1.10, a minimum of £18.61 and a maximum of £24.51. In contrast with the first stage, where the total real household expenditure contract slightly over the sample period, over the last decade food-at-home and non-alcoholic beverage expenditures have increased on average and in real terms by 1.01% per year.

Figure 5.4 corresponds to the plots of the per capita food expenditure across each of our four demographic groups of households. In the four household cases, the series plot suggests increasing per capita food expenditure. If the food expenditure is decomposed into price and quantity, we would be able to see if the increasing expenditure is price related or quantity related. In other words, if the households are eating more quantity or they are paying more for what they eat. The plot per type of food expenditure suggests that the increasing food expenditure is caused by increasing food prices, which peak is reached late 2008. At this time, as we already discussed, food price reached historical high prices. The price plots correspond to Figure 7.10, Figure 7.12, Figure 7.14 and Figure 7.16 in the Appendix.

The increasing food expenditure is more pronounced in low-income households and households with children. It is expected that low-income households would have less available choices to avoid the rising food prices. Therefore, they may be forced to reallocate income from other less essential expenditure groups to food expenditure. In addition, households with children may be more likely to be concerned about the nutritional requirements to rise children, and consequently, to stay in a less flexible basket of food.

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. However, at the household level, low-income households with children spend 35% more than low-income households without children. Also, high-income households with children spend 43% more income than high-income households without children. Therefore, households with children allocate more income to food expenditure. This finding goes in the same line than the basic statistic in Table 5.2, where households with children spend a higher proportion of their per capita income on food.

The overall food expenditure can be decomposed on different type of foods. Table 5.12 presents the food expenditure budget shares, and natural logarithmic of prices or, more precisely, unit values. As an example, of the data presented in Table 5.12, one can note that high-income households with children have an average fruit and vegetable expenditure of 16.98% of their real total food expenditure, and a standard deviation of 1.49%. In comparison to low-income households, high-income households spend a larger proportion of their income on fruit and vegetables.

With respect to children, households with children spend a larger proportion of food expenditure on carbohydrates, dairy products and a smaller proportion of their food budget on fruit and vegetables. Fruit and vegetables are fundamental for 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 household with children still need to be more informed in respect to the relevance of including plenty fruit and vegetable in their household diets.

Table 5.12 Food Expenditure Basic Statistics

		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	18.53%	1.57%	13.78%	1.75%	20.63%	1.79%	16.98%	1.49%
white meat	105	9.99%	0.67%	8.29%	1.03%	10.66%	0.75%	9.04%	0.69%
red meat	105	22.60%	1.07%	20.73%	1.54%	21.87%	1.30%	20.71%	1.13%
carbohydrate	105	26.29%	1.16%	31.53%	1.64%	24.91%	1.17%	29.36%	1.32%
dairy	105	13.47%	0.66%	14.36%	1.10%	12.24%	0.70%	13.42%	0.77%
others	105	9.13%	0.54%	11.30%	0.89%	9.68%	0.62%	10.48%	0.65%
Price Index Natural Log									
fruit & veg	105	0.03	0.04	0.02	0.06	-0.01	0.04	0.002	0.05
white meat	105	0.12	0.05	0.02	0.09	0.03	0.04	0.11	0.06
red meat	105	0.02	0.04	0.08	0.06	0.05	0.04	0.06	0.04
carbohydrate	105	0.03	0.04	0.09	0.05	0.01	0.03	0.02	0.04
dairy	105	0.04	0.05	0.05	0.05	0.05	0.04	0.03	0.05
others	105	0.04	0.06	0.003	0.06	-0.001	0.03	0.01	0.04
expenditure	105	3.05	0.07	2.54	0.08	3.14	0.06	2.81	0.06
News Index									
In levels	105	3.49	2.68	3.49	2.68	3.49	2.68	3.49	2.68
Cumulated	105	4.76	0.98	4.76	0.98	4.76	0.98	4.76	0.98

Figure 5.5 corresponds to the plot of food expenditure budget shares. In households without children, fruit and vegetable budget shares tend to be relatively stable (no clear trend), with some variability over the year. Households without children have a peak in fruit and vegetable expenditure, around the summer time every year. In contrast, households with children have multiple peaks over the year. Fruit and vegetable expenditure share fluctuates more over the year, it suggests that households with children have a more rigid food and vegetable basket. Therefore, they reallocate expenditure from other food groups to keep buying the same, or close to the same, fruit and vegetable basket.

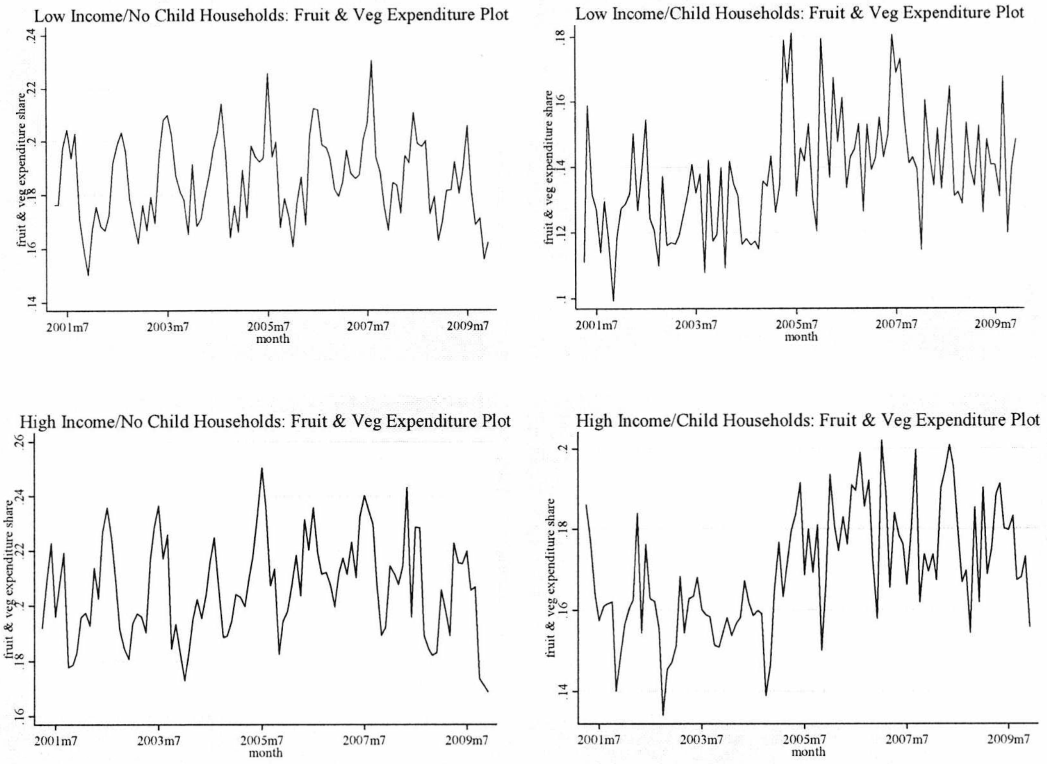

Figure 5.5 Food Expenditure Share Plots

In the Appendix, Figure 7.10, Figure 7.12, Figure 7.14 and Figure 7.16 correspond to the plot of the natural logarithm of the price indexes per type of household. As an example, Figure 5.6 corresponds to the plot of the natural logarithm of the fruit and vegetable price index, per household case:

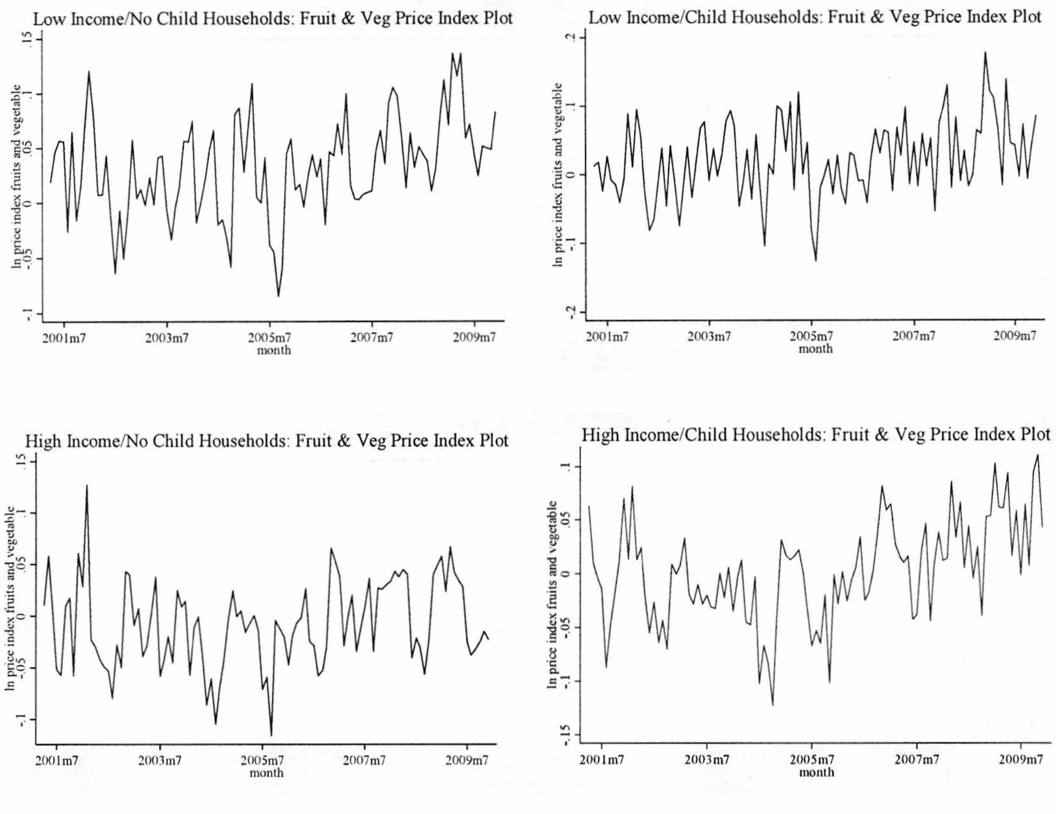

Figure 5.6 Fruit & Vegetable Expenditure Price Index Plots

Towards the end of the last decade, the fruit and vegetables price index shows a tendency to increase. However, the fruit and vegetables price increase is marked less than the overall food price increase. As presented in the plot in the Appendix, Figure 7.10, Figure 7.12, Figure 7.14 and Figure 7.16, the groups that are a product of animal origin (meat and dairy), have experienced a significant increasing trend. The high commodity prices are likely responsible for this by pushing up the price of animal feed, which are more likely passed on into poultry, red-meat and dairy product retail prices.

5.3.2. Unit Root Tests

Table 5.13 shows the results of the Augmented Dickey Fuller test and Zivot and Andrews tests that were presented in the first stage. Both the Augmented Dickey Fuller test and Zivot and Andrews tests results lend strong support for the hypothesis that budget shares are stationary in levels. In some price index, both tests show different series order results. Since Augmented Dickey Fuller test does not take structural breaks into account, it is expected that Augmented Dickey Fuller test can lead to higher series than Zivot and Andrews test. Nevertheless, this case is the inverse situation. Zivot and Andrews test shows that some price indexes are *I(1)* while the Augmented Dickey Fuller test shows *I(0)*. It could be that the statistics are in the rejection limit. Even though some price index are estimated to be *I(1)*, cointegration requires that the dependent and independent variables in the LA/AIDS model are integrated of the same order and, therefore, in this case, the model would not accommodate cointegration.

Therefore, the current study proceeds to apply the LA/AIDS model in levels using seemingly unrelated regression. Subsequently, the analysis of residuals in terms of stationarity, normality and white noise, would help to support the estimation.

Table 5.13 Food Expenditure Series Order

	Low Income/No Child							*Low Income/Child*						
	Augmented Dickey Fuller Test				**Zivot-Andrews Test**			**Augmented Dickey Fuller Test**				**Zivot-Andrews Test**		
	Model	Order	Lag*	Stat	Order	Lag*	t-Stat	Model	Order	Lag*	Stat	Order	Lag*	t-Stat
Expenditure Shares														
fruit & veg	w/constant	I(0)	0	-5.26	I(0)	3	-6.93	w/trend	I(0)	0	-8.40	I(0)	1	-7.10
white meat	w/constant	I(0)	0	-9.80	I(0)	0	-10.12	w/trend	I(0)	0	-9.38	I(0)	0	-10.15
red meat	w/trend	I(0)	0	-7.19	I(0)	0	-7.79	w/trend	I(0)	0	-7.77	I(0)	0	-8.18
carbohydrate	w/constant	I(0)	0	-7.89	I(0)	4	-8.44	w/trend	I(0)	0	-9.84	I(0)	0	-10.64
dairy	w/trend	I(0)	0	-7.49	I(0)	0	-7.95	w/trend	I(0)	0	-8.77	I(0)	0	-9.32
others	w/trend	I(0)	0	-9.42	I(0)	0	-11.19	w/trend	I(0)	0	-9.11	I(0)	0	-9.66
Price Index Natural Log														
fruit & veg	w/trend	I(0)	0	-6.26	I(0)	1	-6.81	w/trend	I(0)	1	-5.54	I(0)	2	-6.45
white meat	w/trend	I(0)	1	-8.52	I(0)	0	-11.99	w/trend	I(0)	1	-7.95	I(0)	0	-10.68
red meat	w/trend	I(0)	1	-5.18	I(1)	2	10.62	w/trend	I(0)	1	-5.72	I(0)	0	-9.01
carbohydrate	w/trend	I(0)	1	-6.33	I(1)	3	-9.34	w/trend	I(0)	1	-7.24	I(0)	0	-10.12
dairy	w/trend	I(0)	1	-3.68	I(1)	1	-11.37	w/trend	I(0)	1	-4.67	I(0)	1	-6.44
others	w/constant	I(0)	0	-9.47	I(0)	1	-8.42	w/trend	I(0)	1	-8.06	I(0)	1	-9.25
expenditure	w/trend	I(0)	0	-10.93	I(0)	2	-7.59	w/trend	I(0)	0	-12.15	I(0)	0	-12.37

	High Income/No Child							*High Income/Child*						
	Augmented Dickey Fuller Test				**Zivot-Andrews Test**			**Augmented Dickey Fuller Test**				**Zivot-Andrews Test**		
	Model	Order	Lag*	Stat	Order	Lag*	t-Stat	Model	Order	Lag*	Stat	Order	Lag*	t-Stat
Expenditure Shares														
fruit & veg	w/constant	I(0)	0	-4.88	I(0)	3	-6.54	w/trend	I(0)	0	-6.80	I(0)	1	-6.20
white meat	w/trend	I(0)	0	-9.50	I(0)	1	-9.50	w/trend	I(0)	0	-9.40	I(0)	0	-10.15
red meat	w/trend	I(0)	0	-6.81	I(0)	0	-7.41	w/trend	I(0)	0	-8.58	I(0)	1	-6.81
carbohydrate	w/constant	I(0)	0	-6.36	I(0)	0	-7.83	w/trend	I(0)	0	-7.83	I(0)	0	-8.39
dairy	w/trend	I(0)	0	-7.49	I(0)	0	-8.93	w/trend	I(0)	0	-7.44	I(0)	0	-8.98
others	w/trend	I(0)	0	-8.99	I(0)	0	-9.67	w/trend	I(0)	0	-7.90	I(0)	0	-9.17
Price Index Natural Log														
fruit & veg	wo/constan	I(0)	0	-5.98	I(0)	2	-6.19	w/trend	I(0)	1	-4.21	I(1)	0	-16.59
white meat	w/trend	I(0)	1	-6.93	I(0)	3	-7.16	w/trend	I(0)	1	-5.68	I(0)	0	-9.73
red meat	w/trend	I(0)	1	-4.44	I(0)	1	-5.65	w/trend	I(0)	1	-5.45	I(0)	1	-7.84
carbohydrate	w/trend	I(0)	1	-5.59	I(1)	2	-11.24	w/trend	I(0)	1	-5.43	I(0)	1	-7.50
dairy	w/trend	I(0)	1	-3.87	I(0)	2	-5.81	wo/constant	I(1)	0	-21.58	I(1)	2	-10.17
others	w/trend	I(0)	1	-8.16	I(0)	2	-6.86	w/constant	I(0)	0	-10.25	I(0)	0	-11.29
expenditure	w/trend	I(0)	0	-9.89	I(0)	1	-8.57	w/trend	I(0)	0	-9.91	I(0)	0	-10.95

Critical values		1%	5%	10%	1%	5%	10%		1%	5%	10%	1%	5%	10%
	wo/constan	-2.60	-1.95	-1.61				wo/constant	-2.60	-1.95	-1.61			
	w/constant	-3.51	-2.89	-2.58	-5.57	-5.08	-4.82	w/constant	-3.51	-2.89	-2.58	-5.57	-5.08	-4.82
	w/trend	-4.04	-3.45	-3.15				w/trend	-4.04	-3.45	-3.15			

Note: (*) Optimum lag

The Augmented Dickey Fuller test has three versions: without constant (wo/constant), with constant (w/constant) and trend & constant (w/trend). The Zivot and Andrews test corresponds to the version that allows structural breaks in intercept and trend.

5.3.3. Media Index

As reported in section 5.2.3 prior to estimation of first stage of the household budgeting problem, it is necessary to consider here the appropriate form in which the child obesity news index enters the second stage of food demand system.

In both stages we use the same child obesity news index. From the first stage estimation, Table 5.3 reports the Augmented Dickey Fuller test performed on the cumulated media index variable and suggests that this variable is *I(0)*. However, the Zivot and Andrews test indicates, also reported in that table, that the cumulated media index is *I(1)*. Consequently, it is uncertain whether the media index needs to be entered in levels or as first difference in the LA/AIDS model.

Seven alternative media indexes specifications, four free form specifications, and three cumulated forms are again considered. Some of these alternative specifications are *I(0)*, and some of them *I(1)*. The free form specification corresponds to zero, one, two and three lags. The media index series starts in January 2001 some three months before the household datasets, to avoid losing the initial observations when lagging media index itself.

Table 5.14 reports the calculated selection criteria obtained following separate estimation of the four demand systems for each of the seven tested information forms considered. The forms considered are the cumulated media index, in terms of levels and with/without the logarithmic transformations. In addition, it considers the news index in first differences. The cumulated news index in first differences is the same as free form specification in those levels without lag.

Table 5.14 Media Index Selection

	Low Income/No Child			*Low Income/Child*		
News Index Specification	AIC	BIC	System R2	AIC	BIC	System R2
Free form in levels (0 lag)	-3676	-3506	0.767	-3224	-3079	0.304
Free form in levels (1 lag)	-3683	-3499	0.772	-3231	-3073	0.316
Free form in levels (2 lags)	-3641	-3445	0.773	-3200	-3029	0.334
Free form in levels (3 lags)	-3596	-3387	0.780	-3165	-2981	0.365
Cumulated newspaper Index in levels	-3686	-3515	0.766	-3222	-3077	0.328
Log cumulated newspaper Index in levels	**-3763**	**-3618**	**0.573**	**-3234**	**-3088**	**0.361**
Log cumulated newspaper Index in first differences	-3674	-3503	0.769	-3221	-3076	0.321

	High Income/No Child			*High Income/Child*		
News Index Specification	AIC	BIC	System R2	AIC	BIC	System R2
Free form in levels (0 lag)	-3664	-3519	0.460	-3633	-3501	0.668
Free form in levels (1 lag)	-3664	-3506	0.478	-3632	-3486	0.679
Free form in levels (2 lags)	-3623	-3452	0.475	-3587	-3429	0.687
Free form in levels (3 lags)	-3584	-3401	0.468	-3546	-3375	0.690
Cumulated newspaper Index in levels	-3665	-3520	0.472	-3686	-3554	0.467
Log cumulated newspaper Index in levels	**-3674**	**-3528**	**0.487**	**-3690**	**-3558**	**0.543**
Log cumulated newspaper Index in first differences	-3669	-3524	0.447	-3634	-3502	0.661

The results are more consistent than in the first stage. In the first stage, the most appropriate media index specification was not the same for all the household cases. In contrast, in the second stage, the model's with the log of the cumulated news index consistently has the lowest AIC and BIC. Therefore, this news index better fits the data specification for all household cases.

The cumulated news index better fits the data, which can be interpreted that previous news make households more susceptible to respond to contemporaneous additional child obesity news. This result suggests that households have long memories in relation to this health related information. It would appear that the purchasing patterns of households are conditioned by, not only the appearance of news in the current period, but that the past history of information also has an important baring on their current food bundle.

5.3.4. Seemingly Unrelated Regression Model

Table 5.15 and Table 5.16 correspond to the SUR estimation of the 2nd stage LA AIDS model with restrictions to account for homogeneity and symmetry assumptions imposed. As presented in Table 5.15, in most of the equations, the SUR model can satisfactorily explain the food expenditure. Testing for all the parameters to be equal to zero per equation, the results show that most equations have parameters significantly different from zero. Only in two household cases, the white-meat equation is not significantly different from zero. As presented in Table 5.14, the system R-squared for each household type group ranges from 0.36 to 0.57, where 0.36 corresponds to low-income households with children and 0.57 corresponds to low-income households without children. Overall, it would seem than that this model explains a reasonable proportion of the variation in food expenditure shares for each of the 4 cases.

Table 5.15 Summary of Food Expenditure SUR Model

	Low Income/No Child			*Low Income/Child*			*High Income/No Child*			*High Income/Child*		
Equation	"R-sq"	chi2	p-value	"R-sq"	chi2	p-value	"R-sq"	chi2	p-value	"R-sq"	chi2	p-value
fruit & veg	0.57	146.65	0.00	0.30	51.81	0.00	0.65	202.71	0.00	0.62	180.47	0.00
white meat	0.28	42.96	0.00	0.12	15.61	0.21	0.18	22.72	0.05	0.27	35.36	0.00
red meat	0.47	102.87	0.00	0.36	62.11	0.00	0.47	100.65	0.00	0.30	65.21	0.00
carbohydrate	0.50	109.58	0.00	0.26	39.31	0.00	0.47	101.50	0.00	0.54	124.50	0.00
dairy	0.55	149.52	0.00	0.33	59.06	0.00	0.48	99.55	0.00	0.45	85.46	0.00

Table 5.16 shows that, for only fruit and vegetable expenditure, and only in the two cases of households without children, does the lagged dependent variable appear to be significantly different from zero. This suggests that, while some degree of habitual consumption of fruit and vegetables, based on past consumption experience, appear to be present, for all other food groups no evidence exists.

Fruit and vegetable, carbohydrates and dairy are the only food aggregates estimated to have consistent positive own-price parameters across all household types. In other words, a price increase would lead to an increase in the budget shares of these foods in each of the household types considered. A price change would cause income and substitution effects. As revised in Chapter 2, the income effect is due to change in real income and substitution effect is due to the relative price change. The basic statistic presented in Table 5.12 shows that low-income households spend a higher proportion of their expenditure on carbohydrates and dairy, while they spend a smaller proportion on fruit and vegetable. Therefore, after a price increase, the income effect is estimated to be the stronger effect in the case of carbohydrates and dairy, while the substitution effect appears to be the stronger in the case of fruit and vegetables.

The white-meat expenditure parameter is the only one consistently positive across all type of households. In this sense, an increase in the allocation of income to total food expenditure would lead to an increase in the white-meat expenditure budget share. This appears to be consistent with the basic statistics in Table 5.12. In this sense, high-income households spend a larger proportion of their food expenditure, and any increase in that expenditure, on white meats than low-income households.

Food group expenditure, and especially fruit and vegetables, also appears to exhibit a high seasonal pattern. With the exception of white-meat expenditure, most expenditure groups have at least two out of three seasonal dummy variables that are estimated to be significantly different from zero. This highly seasonal component in household expenditure is consistent with the plots in the Appendix, which correspond to Figure 7.9, Figure 7.11, Figure 7.13 and Figure 7.15.

Using a 5% significance level, the first stage had already established that the news index does not have a significant impact on overall food expenditure. However, this finding does not say anything about the effect of media information on the expenditure on individual food groups. In this second stage the results suggest that the news index has a significant impact on four out of five food expenditure groups but that this only applies in the case of high-income households with children. An increase in the number of news articles addressing childhood obesity issues is estimated to generate an increase in the share of expenditure committed to fruit and vegetable and white-meat expenditures, while it also leads to a decrease in red-meat and carbohydrate expenditures.

Using a 10% significance level, the child obesity news index is estimated to lead to a rather ambiguous effect on the diet in low-income households with children. Additional news concerning childhood obesity issues appears to decreases the fruit and vegetable expenditure share, whilst increasing the proportion of the food budget spent on white-meat and carbohydrate. However, the results do suggest a negative impact on red-meat consumption which is likely to have a positive effect on diets.

Two out of four household cases include autoregressive error terms to eliminate serial correlation patterns. Serial correlation, frequently encountered in the analysis of time series data, happens when the contemporaneous residuals are correlated with previous residuals. It suggests that there may be some remaining pattern in the residuals. Some of this remaining pattern can be linked with a variable that is not being considered in the model, such as, a more sophisticated habit variable. The model already includes the lagged of quantity to account for habit. Nevertheless, it may be possible more sophisticated habit patterns do exist.

Table 5.16 Food Expenditure SUR Model Estimation

	Low Income/No Child		*Low Income/Child*		*High Income/No Child*		*High Income/Child*	
fruit and vegetable	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.
Lagged quantity	0.01**	0.002	-0.002	0.003	0.003**	0.001	-0.0004	0.003
Ln price index								
fruit & veg	0.06*	0.03	0.04	0.03	0.06*	0.03	0.15***	0.03
white meat	0.02	0.01	-0.01	0.01	0.03**	0.02	-0.005	0.01
red meat	-0.004	0.02	0.03	0.02	0.012	0.03	-0.02	0.03
carbohydrate	-0.05**	0.02	-0.06***	0.02	-0.03	0.03	-0.03	0.03
dairy	-0.01	0.01	-0.01	0.02	-0.05***	0.01	-0.06***	0.02
others	-0.02*	0.01	0.00	0.02	-0.04*	0.02	0.01	0.02
expenditure	0.01	0.01	0.01	0.02	0.01	0.02	-0.04***	0.02
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	0.02***	0.004	0.03***	0.003	0.02***	0.003
jul-sep	0.03***	0.003	0.01**	0.004	0.03***	0.004	0.01***	0.003
Linear trend	0.001*	0.0003	0.00001	0.0002	0.003**	0.001		
Quadratic trend					-0.00001***	5E-06		
News index	-0.0001*	0.000	0.01	0.006	-0.04*	0.019	0.01***	0.001
AR(1)	-0.11	0.07					0.07	0.10
AR(2)	-0.07	0.06					0.15**	0.07
Constant	0.10**	0.04	0.07*	0.04	0.23***	0.07	0.23***	0.04
white meat								
Lagged quantity	0.005	0.004	-0.0001	0.004	-0.001	0.00	0.005	0.004
Ln price index								
fruit & veg	0.02	0.01	-0.01	0.01	0.04**	0.02	-0.005	0.01
white meat	-0.01	0.01	-0.0004	0.01	0.02	0.02	-0.009	0.01
red meat	-0.02	0.02	0.004	0.01	-0.02	0.02	0.01	0.02
carbohydrate	0.01	0.02	-0.01	0.01	-0.03	0.02	-0.003	0.02
dairy	-0.01	0.01	0.01	0.01	-0.01	0.01	-0.01	0.01
others	0.002	0.01	-0.01	0.01	-0.01	0.01	0.01	0.01
expenditure	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Seasonal dummies								
jan-mar	0.003	0.002	-0.002	0.003	-0.004*	0.002	0.003	0.002
apr-jun	-0.0007	0.002	-0.002	0.003	-0.002	0.002	-0.0001	0.002
jul-sep	-0.003	0.002	-0.007***	0.003	-0.001	0.002	-0.003	0.002
Linear trend	-0.0003*	0.0002	0.0002	0.0001	0.0003	0.0007		
Quadratic trend					-2E-06	3E-06		
News index	0.0001*	0.00004	-0.004	0.004	0.00	0.012	0.003***	0.001
AR(1)	-0.26***	0.11					-0.20*	0.10
AR(2)	-0.25***	0.08					-0.13*	0.08
Constant	0.08***	0.03	0.06**	0.03	0.07	0.05	0.04	0.03
red meat								
Lagged quantity	-0.004	0.002	0.0001	0.00	-0.001	0.001	0.01**	0.004
Ln price index								
fruit & veg	-0.004	0.02	0.03	0.02	0.012	0.03	-0.02	0.03
white meat	-0.02	0.02	0.00	0.01	-0.02	0.02	0.01	0.02
red meat	0.05	0.03	0.04*	0.02	0.12***	0.03	0.06	0.04
carbohydrate	-0.02	0.03	-0.04*	0.02	-0.07***	0.03	-0.10***	0.03
dairy	0.002	0.02	-0.03**	0.01	-0.01	0.02	0.05**	0.02
others	0.03***	0.01	-0.03*	0.02	-0.04**	0.02	-0.05**	0.02
expenditure	-0.04***	0.01	0.02*	0.01	0.01	0.01	0.05***	0.02
Seasonal dummies								
jan-mar	-0.01**	0.002	-0.01***	0.004	0.00	0.003	-0.001	0.003
apr-jun	-0.02***	0.002	-0.02***	0.004	-0.01***	0.003	-0.01***	0.003
jul-sep	-0.02***	0.002	-0.01**	0.003	-0.01***	0.003	0.0002	0.003
Linear trend	0.0001	0.0002	-0.0003*	0.0002	-0.002*	0.001		
Quadratic trend					0.00001*	5E-06		
News index	-0.0001	0.0001	0.006	0.005	0.02	0.02	-0.01***	0.001
AR(1)	-0.04	0.08					-0.10	0.11
AR(2)	-0.18***	0.06					-0.09	0.07
Constant	0.38***	0.04	0.15***	0.04	0.14**	0.07	0.07	0.05

carbohydrate								
Lagged quantity	-0.001	0.002	-0.003	0.002	0.0001	0.002	-0.006*	0.003
Ln price index								
fruit & veg	-0.05**	0.02	-0.06***	0.02	-0.03	0.03	-0.03	0.03
white meat	0.01	0.02	-0.01	0.01	-0.03*	0.02	0.00	0.02
red meat	-0.02	0.03	-0.04*	0.02	-0.07***	0.03	-0.10***	0.03
carbohydrate	0.13***	0.04	0.08***	0.03	0.13***	0.04	0.17***	0.04
dairy	-0.07***	0.02	0.03	0.02	-0.02	0.02	-0.01	0.02
others	-0.01	0.01	0.01	0.02	0.04*	0.02	-0.04**	0.02
expenditure	0.01	0.01	-0.01	0.02	-0.01	0.01	0.02	0.02
Seasonal dummies								
jan-mar	-0.01***	0.003	0.002	0.004	-0.01***	0.003	-0.01***	0.003
apr-jun	-0.01***	0.002	-0.004	0.004	-0.02***	0.003	-0.02***	0.003
jul-sep	-0.02***	0.003	-0.01**	0.004	-0.02***	0.003	-0.01***	0.003
Linear trend	-0.001**	0.0002	0.0000	0.0002	-0.0005	0.0009		
Quadratic trend					4E-06	4E-06		
News index	0.0001**	0.0001	-0.01	0.006	0.002	0.015	-0.01***	0.001
AR(1)	0.01	0.08					0.01	0.08
AR(2)	-0.07	0.07					-0.10	0.07
Constant	0.25***	0.04	0.40***	0.04	0.29***	0.06	0.32***	0.05
dairy								
Lagged quantity	0.003	0.003	0.001	0.003	-0.003	0.002	0.001	0.004
Ln price index								
fruit & veg	-0.01	0.01	-0.01	0.02	-0.05***	0.01	-0.06***	0.02
white meat	-0.01	0.01	0.01	0.01	-0.01	0.01	-0.01	0.01
red meat	0.002	0.02	-0.03**	0.01	-0.01	0.02	0.05**	0.02
carbohydrate	-0.07***	0.02	0.03	0.02	-0.02	0.02	-0.01	0.02
dairy	0.09***	0.02	0.01	0.02	0.09***	0.02	0.07***	0.02
others	-0.02**	0.01	0.001	0.01	0.01	0.01	0.01	0.01
expenditure	0.01	0.01	-0.02*	0.01	-0.01*	0.01	-0.05***	0.01
Seasonal dummies								
jan-mar	0.01***	0.001	0.01***	0.003	0.003*	0.002	0.004**	0.002
apr-jun	0.01***	0.001	0.01***	0.003	0.01***	0.002	0.01***	0.002
jul-sep	0.01***	0.001	0.01***	0.003	0.001	0.002	0.002	0.002
Linear trend	0.00004	0.0001	0.0004***	0.0001	-0.0001	0.0005		
Quadratic trend					1E-06	3E-06		
News index	0.000002	0.00003	-0.01**	0.004	0.0005	0.009	0.001	0.001
AR(1)	-0.22**	0.11					-0.06	0.10
AR(2)	-0.17**	0.08					-0.07	0.08
Constant	0.09***	0.02	0.20***	0.03	0.17***	0.04	0.26***	0.03

Single, double and triple asterisks (*) denote statistical significance at the 10%, 5% and 1% level.

5.3.5. Residual Tests

The decision to allocate shares of expenditure among one food groups will be highly linked, both by definition and due to the predetermined nature of overall food expenditure. As a result, it is expected that the residuals across equations would be correlated. This, of course, makes it highly appropriate to use SUR estimation techniques and, itself, leads us to estimate the demand equations simultaneously as a system.

The correlation of the residuals is a testable assumption. Indeed as is expected, Table 5.17 shows the Breusch-Pagan test, where the residuals as correlated across equations. If this were not the case, it would suggest that is not an advantage of estimating the equations as part of a system since the food expenditure decision in a group is independent from other food expenditure groups.

Table 5.17 Food Expenditure Residual Correlation Tests

	Low Income/No Child					*Low Income/Child*				
Residuals	f&v	w-meat	r-meat	carb	dairy	f&v	w-meat	r-meat	carb	dairy
fruits & veg	1					1				
white meat	-0.04	1				0.01	1			
red meat	-0.41	-0.22	1			-0.38	-0.08	1		
carbohydrate	-0.61	-0.22	-0.14	1		-0.43	-0.34	-0.25	1	
dairy	-0.16	-0.20	-0.33	0.23	1	-0.06	-0.26	-0.24	-0.20	1
	Breusch-Pagan test: chi2(10) =90.204 , Pr = 0.0000					Breusch-Pagan test: chi2(10) = 70.549, Pr = 0.0000				

	High Income/No Child					*High Income/Child*				
Residuals	f&v	w-meat	r-meat	carb	dairy	f&v	w-meat	r-meat	carb	dairy
fruits & veg	1					1				
white meat	-0.01	1				0.14	1			
red meat	-0.43	-0.22	1			-0.52	-0.20	1		
carbohydrate	-0.52	-0.33	-0.09	1		-0.45	-0.48	-0.09	1	
dairy	-0.08	-0.24	-0.39	0.02	1	0.02	-0.19	-0.39	-0.08	1
	Breusch-Pagan test: chi2(10) = 85.951 , Pr = 0.0000					Breusch-Pagan test: chi2(10) = 95.720, Pr = 0.0000				

Table 5.18 shows the Augmented Dickey Fuller Test to ascertain the series order of the residuals from each of the five estimated share equations across the four demographic group share equations systems suggest that are all *I(0)* or stationary. Even more, the Augmented Dickey Fuller Test without intercept has the lowest AIC. In this sense, the residual series are stationary with zero mean. As is expected, any residual mean would be captured by the model intercept.

This result suggests that, even though these time series regressions are performed using data which is estimated to follow both stationary and non-stationary time series processes, the linear combination of these data as described by each share equation estimated does at least not appear to represent a spurious relationship.

Table 5.18 Food Expenditure Residual Unit Root Tests

	Low Income/No Child				*Low Income/Child*			
	Augmented Dickey Fuller Test				**Augmented Dickey Fuller Test**			
	Model	Order	Lag*	t-statistic	Model	Order	Lag*	t-statistic
fruits & veg	wo/intercept	I(0)	0	-8.80	wo/constant	I(0)	0	-9.19
white meat	wo/intercept	I(0)	0	-12.07	wo/constant	I(0)	0	-10.61
red meat	wo/intercept	I(0)	0	-8.39	wo/constant	I(0)	0	-9.49
carbohydrate	wo/intercept	I(0)	0	-10.16	wo/constant	I(0)	0	-10.46
dairy	wo/intercept	I(0)	0	-11.26	wo/constant	I(0)	0	-10.24

	High Income/No Child				*High Income/Child*			
	Augmented Dickey Fuller Test				**Augmented Dickey Fuller Test**			
	Model	Order	Lag*	t-statistic	Model	Order	Lag*	t-statistic
fruits & veg	wo/constant	I(0)	0	-10.23	wo/constant	I(0)	0	-8.95
white meat	wo/constant	I(0)	0	-10.46	wo/constant	I(0)	0	-10.53
red meat	wo/constant	I(0)	0	-9.67	wo/constant	I(0)	0	-9.95
carbohydrate	wo/constant	I(0)	0	-10.97	wo/constant	I(0)	0	-9.55
dairy	wo/constant	I(0)	0	-9.49	wo/constant	I(0)	0	-8.44

Note: (*) Optimum lag

As in the first stage, we also test whether or not the estimated SUR residuals from our four demand systems are normally distributed and can be considered as white noise. Table 5.19 shows the results of the Shapiro-Francia and Skewness/Kurtosis tests. White-meat expenditure of low-income households without children is the only case where consistently both tests reject normality clearly. In the other three cases, the tests provides different results or their statistics are in the rejection limit.

Table 5.19 Food Expenditure Residual Distribution Tests

Low Income/No Child

	Normality				White noise	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
fruits & veg	0.98	0.16	4.20	0.12	1.63	0.20
white meat	2.36	0.01	11.90	0.00	3.60	0.06
red meat	-0.85	0.80	0.38	0.83	2.12	0.15
carbohydrate	1.20	0.11	0.91	0.64	0.01	0.93
dairy	0.27	0.39	1.46	0.48	1.69	0.19

High Income/No Child

	Normality				White noise	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
fruits & veg	1.85	0.40	0.53	0.30	0.00	0.86
white meat	2.52	0.28	0.44	0.33	0.18	0.72
red meat	7.85	0.02	0.69	0.25	0.26	0.77
carbohydrate	0.62	0.73	-1.28	0.90	0.64	0.44
dairy	4.55	0.10	1.47	0.07	0.19	0.65

Low Income/Child

	Normality				White noise	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
fruits & veg	0.17	0.43	2.66	0.26	1.39	0.24
white meat	1.71	0.04	6.20	0.05	0.20	0.65
red meat	1.38	0.08	0.66	0.72	0.51	0.48
carbohydrate	-0.48	0.69	2.02	0.36	0.10	0.75
dairy	0.07	0.47	0.97	0.62	0.114	0.74

High Income/Child

	Normality				White noise	
	Shapiro-Francia		Skewness/Kurtosis tests		Portmanteau test*	
Residuals	Statistic	p-value	Statistic	p-value	Q Statistic	p-value
fruits & veg	2.47	0.01	6.31	0.04	0.84	0.36
white meat	-0.19	0.57	2.14	0.34	0.38	0.54
red meat	-1.02	0.84	0.16	0.92	0.028	0.87
carbohydrate	0.52	0.30	2.53	0.28	0.13	0.71
dairy	1.23	0.11	5.43	0.07	2.74	0.10

Note: (*) results in the first lag.

Table 5.19 shows the Portmanteau test using one lag. However, the Portmanteau test was conducted from lags one to ten in each residual series, to test for white noise patterns in the residuals. The residuals of fruit and vegetables, white meats, red-meat and dairy equations have a p-value larger than 5% in each lag. However, the carbohydrate equation presents some serial correlation after seven lags. Consequently in each case, residuals are *I(0)*, mostly white noise, and normally distributed; which provides evidence that the relations are not spurious.

5.3.6. Economic Constraint Tests

The second stage LA/AIDS model is also run twice. In the beginning the model is run unconstrained, which allow for testing homogeneity and symmetry. After that, the

LA/AIDS model is run imposing homogeneity and symmetry. Table 5.20 shows the results of testing for homogeneity and symmetry constraints. Using a 5% significance level, in the case of households with high-income, this study jointly rejects homogeneity. As is discussed in Chapter 2, the homogeneity restriction implies that every demand equation must be homogeneous at degree zero in income and prices. The economic meaning of this assumption is that, the representative households, as consumers, do not suffer from money illusion. That is, if relative prices and income are multiplied by the same positive constant, preferences must remain the same. In this case, fruit and vegetable and white-meat are the equations that more commonly reject homogeneity, which are the expenditure groups that are assumed to have a significant impact on dietary quality. Therefore, some households may have suffered some money illusion at some point over the last decade. Even though these assumptions are empirically rejected, as is that is the case in a significant part of the literature, this study continues to impose these two theoretical constraints in the work that follows to ensure that the model is constrained to behave in a theoretically consistent manner.

Table 5.20 Food Expenditure Homogeneity and Symmetry Tests

	Low Income/No Child		Low Income/Child		High Income/No Child		High Income/Child	
Restriction	Wald Stat	p-value	Wald Stat	p-value	Wald Stat	p-value	Wald Stat	p-value
Homogeneity for equation:								
fruits & vegetable	0.01	0.91	1.01	0.32	9.09	0.00	4.94	0.03
white meat	8.55	0.00	0.41	0.52	6.64	0.01	5.67	0.02
red meat	0.16	0.69	2.01	0.16	3.47	0.06	12.22	0.00
carbohydrate	1.24	0.27	2.71	0.10	8.46	0.00	0.69	0.41
dairy	1.81	0.18	0.43	0.51	0.07	0.79	3.53	0.06
Joinly	9.63	0.09	7.20	0.21	19.87	0.00	19.99	0.00
Symmetry for price parameters:								
f&v and w-meat	0.28	0.60	0.25	0.62	1.97	0.16	0.00	0.96
f&v and r-meat	0.44	0.51	0.54	0.46	0.13	0.71	0.11	0.74
f&v and carb	0.00	0.95	1.98	0.16	5.88	0.02	4.18	0.04
f&v and dairy	4.28	0.04	1.75	0.19	0.01	0.94	5.31	0.02
w-meat and r-meat	0.04	0.85	0.41	0.52	0.60	0.44	0.18	0.67
w-meat and carb	0.02	0.88	0.01	0.92	0.30	0.58	0.52	0.47
w-meat and dairy	1.04	0.31	0.32	0.57	0.03	0.86	0.02	0.89
r-meat and carb	0.08	0.78	0.52	0.47	0.00	0.99	0.05	0.82
r-meat and dairy	1.17	0.28	0.00	0.99	0.17	0.68	5.29	0.02
carb and dairy	4.37	0.04	0.80	0.37	0.56	0.45	0.11	0.75
Joinly	16.97	0.08	8.23	0.61	13.54	0.20	12.75	0.24

This study also tests for concavity of the second stage expenditure function. The concavity of the expenditure function means that, following food price increase, households would increase their food expenditure in a smaller proportion since they are able to mitigate some of the effect of the price rise by substituting between food products in their basket. Since the commodities considered within this second stage model do not include durable goods, we expect 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 would also expect 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. The results of the test correspond to Table 7.2 in the Appendix. In the two low-income household cases, all the eigenvalues are negative, and so, their expenditure functions are globally concave. However, in the case of both high-income households, only four out of five eigenvalues are negative; therefore the expenditure functions can be considered as locally concave.

5.3.7. Elasticities

The conditional uncompensated own price, cross price and expenditure elasticities calculated using the estimates presented in Table 5.16 are presented in Table 7.3 of the Appendix. These conditional uncompensated elasticities are used as input, along with the predicted budget share from the first stage, to calculate the unconditional uncompensated elasticities in presented in Table 5.21. Chapter 2 already discussed the meaning of uncompensated and compensated elasticities. Moreover, the expressions used to calculate the uncompensated elasticities correspond to the equations 24 to 30 in Chapter 4.

On average for the four household cases, uncompensated own-price elasticities, derived only from the second stage results, have the expected negative sign and all have point estimate values of less than one, thus these demand functions can be considered as inelastic. In absolute value, white-meat has the largest own price elasticity, which is close to one; then follows fruit and vegetables, red-meat, dairy and carbohydrates. Moreover, low-income households respond more to a change in the price of fruit and vegetable than high-income households. Therefore, low-income households may have a more susceptible fruit and vegetable diet than high-income households.

The cross price relations change depending on the household case. On average, fruit and vegetables are complements to carbohydrate and dairy, while fruit and vegetables are substitutes with white and red meats. These computed elasticities suggest that all household types do substitute meat expenditure with fruit and vegetable expenditure. In contrast, a complementary relation is suggested between carbohydrate and dairy for households without children.

Both red and white meat groups behave as substitutes with all other food expenditure groups. The only exception to this is that red-meat that appears to be a complement of carbohydrate. It is surprising that meat is a substitute for most of food expenditure groups.

With respect to dairy products, they are a complement only for fruit and vegetable. For all the remaining food expenditure groups, dairy is a substitute. However, the overall pattern changes importantly case by case. In this sense, it is not surprising that households use dairy products to replace meats.

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 have smaller food expenditure elasticity than households without children. In other words, high-income households and households with children, 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 0.91 to 0.95, while for high-income households vary from 0.43 to 0.84. As is discussed on the following chapter, 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, as we already saw, 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 5.12, 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.

With respect to meat expenditure, white-meat expenditure elasticities fluctuate between 0.68 and 1.03, while red-meat expenditure elasticity goes from 0.60 to 0.99. Low-income households with children have the highest expenditure elasticities for red and white meats. Households seem to be less willing to change their red-meat expenditure than their white-meat expenditure. At the same time, meats contain many essential elements which contribute to a child's physical development and although these can be found in other foods, may be more conveniently sourced from meats. Therefore, from a policy point of view, it is relevant to keep monitoring low-income households with children since these are the household estimated to be most responsive to changes in food 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, cantaines large quantities of dietary calcium, important for physiological development of the child, this is somewhat reassuring.

Table 5.21 Food Expenditure Unconditional Elasticities

	Low Income/No Child							
	f&v	w-meat	r-meat	carb	dairy	others	exp	news
fruit & veg	-0.81	0.17	0.06	-0.22	-0.08	-0.10	0.95	-0.13
white meat	0.28	-1.15	-0.10	0.10	-0.06	0.06	0.87	0.12
red meat	0.03	-0.04	-0.61	0.02	0.05	0.16	0.60	-0.05
carbohydrate	-0.15	0.03	0.02	-0.50	-0.21	-0.01	0.81	0.10
dairy	-0.11	-0.04	0.12	-0.42	-0.35	-0.09	0.90	-0.01
others	-0.19	0.07	0.39	-0.01	-0.12	-0.73	0.62	-0.01

	Low Income/Child							
	f&v	w-meat	r-meat	carb	dairy	others	exp	news
fruit & veg	-0.60	0.02	0.35	-0.21	0.05	0.08	0.91	0.07
white meat	0.02	-0.95	0.19	0.10	0.25	-0.07	1.03	-0.05
red meat	0.24	0.08	-0.66	0.04	-0.03	-0.06	0.99	0.03
carbohydrate	-0.09	0.03	0.03	-0.48	0.19	0.13	0.81	-0.02
dairy	0.06	0.15	-0.04	0.44	-0.80	0.10	0.79	-0.06
others	0.09	-0.08	-0.14	0.38	0.13	-0.64	0.88	0.05

	High Income/No Child							
	f&v	w-meat	r-meat	carb	dairy	others	exp	news
fruit & veg	-0.73	0.21	0.13	-0.07	-0.19	-0.15	0.84	-0.17
white meat	0.35	-0.74	-0.14	-0.25	-0.04	-0.05	0.82	-0.01
red meat	0.09	-0.07	-0.37	-0.26	-0.02	-0.15	0.77	0.11
carbohydrate	-0.06	-0.11	-0.23	-0.39	-0.01	0.18	0.72	0.01
dairy	-0.28	-0.03	-0.03	-0.04	-0.23	0.14	0.62	0.004
others	-0.35	-0.05	-0.31	0.48	0.18	-0.58	0.67	0.10

	High Income/Child							
	f&v	w-meat	r-meat	carb	dairy	others	exp	news
fruit & veg	0.01	0.05	0.06	0.06	-0.22	0.14	0.43	0.06
white meat	0.10	-1.11	0.31	0.22	-0.01	0.19	0.68	0.03
red meat	0.05	0.14	-0.65	-0.29	0.41	-0.16	0.80	-0.03
carbohydrate	0.03	0.06	-0.16	-0.15	0.06	-0.04	0.54	-0.02
dairy	-0.28	-0.001	0.57	0.17	-0.36	0.17	0.36	0.005
others	0.24	0.17	-0.31	-0.10	0.21	-0.34	0.50	-0.02

Finally, we want to compare some tendencies across both the first and second stages demand functions. In first stage, households with children were estimated to respond less, in terms of their commitment of overall income to food expenditure, to a food price and income changes. In the second stage, however, having a child in the household appears to causes a different response, depending on the food group considered. Fruit and vegetables and carbohydrate groups are estimated to respond less to own price and food expenditure changes than other groups. On the other hand, the presence of a child in the household appears to lead to a larger than average response to a change in red-meat prices and to overall food expenditure.

In both stages, high-income households consistently tend to respond less to a change in prices and food expenditure than low-income households. This corresponds to *a* *priori* expectations that high-income households likely to be less willing to change their expenditure bundle in response to a change in price or overall food expenditure.

5.4. Hypothesis Testing

As stated in section 1.2, the current study aims to address how news articles which convey information regarding child obesity issues impacts upon the expenditure choices made by household. This study employs a two stage theoretically consistent demand system which explicitly incorporates an index of childhood obesity news estimated using Living Cost and Food survey data collected from around six thousands households per year over nine years across the UK. In the following, each of the research problems discussed in Chapter 3 are summarised and addressed:

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

This hypothesis can be addressed by referring to the estimated parameter for the media index within the Food share equation from stage 1 of the households budgeting problem. According to Table 5.6 the news index parameter is estimated to have a value from -0.001 to 0.0001. The t-tests confirm that these estimates are indeed insignificantly different from zero using a 5% significance level. Therefore, this study fails to provide evidence that for the rejection of the null hypothesis of 'no news index effect on total food expenditure' for low- and high-income households whether or not those households include children. In other words, overall household expenditure on food is not significantly impacted by child obesity news.

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

According to Table 5.16, using a 5% significance level, in high-income households with children, the child obesity news index parameter is significant with values of 0.01 for fruit and vegetable expenditure group and 0.003 for white-meat expenditure group. In contrast, the child obesity news index parameter has a significant and negative impact of -0.01 for red-meat expenditure group and -0.01 for carbohydrate expenditure group. This study provides evidence to reject the null hypothesis of 'no news effect' in these four equations. What is more, this news appears to be used by households in such a way that potential dietary improvements result with a reduction in red-meat and carbohydrate consumption associated with a substitution toward white-meat and fruit and vegetable consumption.

5.5. Summary

This research aimed to measure the impact of child obesity news on 1) the overall share of total expenditure committed to food products and 2) on the allocation of food expenditure among specific food expenditure groups. With this objective in mind, the Living Cost and Food Expenditure Survey dataset provided by the Economic Social Research Service in the UK was divided into four mutually exclusive subsamples. The four subsamples are high-income households with and without children, and low-income households with and without children. Income levels and household composition, popular demographic variables, were chosen in this investigation the potential difference in the pattern of response to child obesity news. As a result, each estimated system uses a single aggregated subsample of the micro-data. Each series then includes observations on monthly time series from March 2001 to December 2009.

In the analysis, this study considered the possibility that budget shares can be cointegrated with prices. Even though bounded by zero and one, much of the previous literature has found that budget shares had behaved as *I(1)* series, as found by Balcombe and Davis (1996), Karagiannis, Katranidis and Velentzas (2000) and Kaabia and Gil (2001). However, Karagiannis, Katranidis and Velentzas (2000) created expenditure groups of beef, mutton-lamb, chicken, pork and sausages. Kaabia and Gil (2001) used beef, lamb and poultry. Balcombe and Davis (1996) worked with bread, milk, cheese and meat. It may be the case that less aggregated categories lead to less stationary results. In this sense, aggregation minimises the influence of extreme data points and fluctuations over the year. In high-aggregated groups, households may be able to substitute products within the same group expenditure easier than in low-aggregated groups.

As reviewed, necessary conditions for cointegration are: at least two series *I(1)*, and a balanced design in terms of dependent and independent variables. Table 5.3 and Table 5.13 showed that budget shares in this study, moved in a narrow range of values and behaved as *I(0)*. The results of this study did not support the balanced design necessary for applying cointegration techniques. In addition, we found that SUR residuals were *I(0)*, white noise, and most often normally distributed. The order of the residuals was tested using the Augmented Dickey Fuller, which shows that residuals were *I(0)*. This set of tests provides evidence that the relations are, at least, not spurious. Therefore, by using the variables in levels, this study proceeded to estimate the two-stage AIDS model with a news index and a habit variable.

Using the specified two- stage demand system, this study calculated own-price, cross price, income/expenditure and news elasticities for each household type sub-sample. The elasticities in the first stage only used the general expenditure dataset. The elasticities in the second stage used the food expenditure dataset and, from the first stage, the food budget shares and food elasticities. Doing this, the two-stage estimation measures the child obesity news impact of the overall food expenditure, and then, more detail is revelled in the second stage regarding specific food expenditure groups.

In the first stage, we divided the subsample into six general expenditure groups, where just one group represented food expenditure. We used the LA-AIDS model to test the homogeneity, symmetry and concavity of the expenditure function. The adding-up constraint was used to recover the omitted equation in the demand system. Homogeneity was jointly rejected in two out of four cases, while concavity of the expenditure function is rejected in every household case. It suggests that market changes are not reflected quickly into demand and supply conditions.

Despite these theoretical rejections of several important theoretical constraint, most of own-price elasticities have the expected negative sign. Moreover, since the objective of the first stage is mainly to test the significance of the child obesity index in the food expenditure group and provides a prediction of the budget shares for the second stage, much of this is overlooked here.

In the second stage, using the food expenditure dataset, far fewer economic constraints are rejected. This model appears to be far more consistent with the desirable theoretical properties associated with demand systems. Specifically, our results show that the expenditure functions are, at least, locally concave across household cases. While it is clearly highly desirable that at each stage of estimation that concavity of the expenditure function is supported, it is, for the effort here, far more important that it hold in the second stage. The first stage supplied the food expenditure fitted values that are used in the second stage. However, the second stage produces the most informative results in terms of the scope of this food household expenditure study.

With respect to child obesity news, we used the criteria of minimising the AIC to select the specification of the information index that best fits the data. In the first stage, no single specification consistently has the lowest AIC across all household types. The child obesity media index was, however, not found to cause a significant impact on overall food expenditure. In contrast, in the second stage, the natural logarithmic version of the cumulated child obesity news index consistently minimises the AIC across each of the household cases considered. This finding suggests that households keep a significant recall of past child obesity news and do use this memory in conjunction with contemporaneous news events when they decide upon their household food budget allocation. This child obesity index, however, only has a significant impact on most of the food expenditure categories only in high-income households with children. In this case, the child obesity index has a positive impact on food and vegetable and white-meat expenditure, while, the child obesity index has a negative impact on red-meat and carbohydrates. It suggests that information conveyed within the news media regarding child obesity related health issues can have a permanent, and in some cases positive, impact on the food basket composition of households.

Chapter 6

Discussion and Conclusions

6.1. Introduction

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.

As presented in Chapter 1, the obesity cost goes beyond the private interests. Obesity causes increasing direct and indirect costs that are being paid by the society. In this sense, governmental interventions can be justified as a way to control the increasing obesity costs, or as a way to inform households about the long-term consequences of their food choices.

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.

Chapter 2 reviewed some alternative approaches to measure information effects. Using primary data, experimental economics is able to isolate the effect of information in a laboratory setting. However, due to the artificial conditions and small sample size, it is debatable whether or not these findings can be applied to the real world. Some studies have recently conducted experiments close to the real market situation. Nevertheless, in most of the studies, the small sample size is still a limitation. Using secondary data, a demand system is another alternative to measure information effect. This study chose to use a demand system because it can be used to combine large datasets with information variables in a framework that allows the test of economic theory.

Chapter 3 showed the selected demand system specification and testable hypothesis. 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.

Chapter 4 justified some of the empirical choices that needed to be solved before conducting the estimation. For instance, the thesis presented how to take structural breaks into account, how to convert the AIDS parameters into elasticities and how to calculate a measure of goodness of fit of the overall demand system.

Chapter 5 presented the results of each stage. Each of the research questions were answered in section 5.4. To recapitulate, the current study presents empirical evidence that child obesity news does not cause a significant impact on overall food expenditure, in any of the aggregate household types considered here. However, the estimated results from the second stage of the demand system analysis produced here, suggest that there is a statistically significant relationship between the appearance of additional news regarding child obesity issues, and the expenditure shares households commit to different food groups. In particular, the second stage estimation shows that child obesity news causes a significant expenditure change mostly in some specific food groups in high-income households with children. High-income households with children significantly increase their fruit and vegetables expenditure and white-meat expenditure, whilst they would also significantly reduce their red-meat expenditure and carbohydrate expenditure, in response to increased information on child obesity. This finding implies that child obesity news gives the incentive for a movement towards a healthier diet, increasing the quality of the diet only to high-income households with children. In contrast to this, all low-income households and high-income households without children, do not appear to respond in any significant way in response to increased child obesity information.

As a general trend, Chapter 5 showed that in households with children and households with a larger than average income, the absolute value of the estimated own-price and expenditure elasticities, are estimated to be lower than low-income households or households without children. However, this study still needs to discuss how this elasticity estimation fits, with respect to past studies and its relevance from a policy point of view.

Using data from 2001 to 2009, the thesis calculated the own-price elasticity per type of household. It was found that the estimated own-price elasticity varies from -0.75 to -0.15, for overall food across households. Low-income households without children have the most elastic response, with an own-price elasticity of -0.75 for food. High-income households with children have the most inelastic response, with an own-price elasticity of -0.15 for food. Michalek and Keyzer (1992) compared demand elasticity for eight countries in the EU in 1970 and 1985. In 1985, Michalek and Keyzer (1992) calculated an own-price elasticity of -0.15 for food. In the UK, Tiffin and Tiffin (1999) also used a three stage demand system. The authors used the National Food Survey (former version of The Living Costs and Food Survey) from 1974 to 1994, and found an own-price elasticity of -0.11 for food. Using a co-integrated AIDS model, Duffy (2003) found a food own-price elasticity of -0.12 during 1963-1996.

Tiffin and Arnoult (2010), using Expenditure and Food Survey (former version of The Living Costs and Food Survey) for 2003-2004, calculated a set of elasticities for specific food groups, so, they are not comparable at this stage with our estimates. Therefore, own-price elasticity values from past research are in the lower band of the own-price elasticity values calculated in this study.

In the case of food expenditure elasticities, Michalek and Keyzer (1992) estimated the food income elasticity at 0.02, while Tiffin and Tiffin (1999) calculated their food expenditure elasticity at 0.52, and Duffy (2003) reported a comparable estimate at 0.27.

In this study, the income elasticity goes from 0.56 to 0.79. High-income households with children have an income elasticity of 0.56, while low-income households without children have an income elasticity of 0.79. This study found that the food expenditure elasticity is relatively high for low-income households, compared to high-income households. This finding that high-income households have smaller income elasticity is consistent with past research. In empirical studies, Han and Wahl (1998), and Gao, Wailes and Cramer (1996) found that expenditure elasticity varies by up to ten times depending on the income level. The authors Gao, Wailes and Cramer (1996) explained that in China, pork is considered as a luxury product for low-income households, but a necessity for high-income households. Therefore, after a change in income, a high-income household would not change the overall food expenditure much in comparison to a low-income household. As an additional finding, households without children have higher income food elasticity than households with children. This suggests that households with children would respond less to a change in income, in comparison to households without children.

In specific food groups the different aggregation level makes the comparison less straight forward. Tiffin and Tiffin (1999) found that own-price (expenditure) elasticity was -0.95 (1.59) for meats, -0.31 (0.28) for vegetables and -0.21 (0.03) for fruit. Tiffin and Arnoult (2010) calculated -0.20 (0.72) for dairies, - 0.86 (1.16) for meats, -0.52 (0.92) for carbohydrates and -0.71 (1.04) for fruit and vegetables. The own price (expenditure) elasticity for specific types of fish had a range from -0.67 to -1.04 (0.87-1.32) and fruit and vegetable from -0.69 to -0.98 (0.66-1.15). This thesis showed on average that own-price elasticity (expenditure) is estimated at -0.99 (0.85) for white-meat, -0.57 (0.79) for red meats, -0.38 (0.72) for carbohydrates, -0.44 (0.67) for dairies and -0.53 (0.78) for fruit and vegetables. Therefore, our results are closer to the work presented by Tiffin and Arnoult (2010), which is also the one that use the most recent database. For instance, Tiffin and Tiffin (1999) presented a expenditure elasticity of 0.03 for fruit and 0.28 for vegetables. Later on, Tiffin and Arnoult (2010) calculated an expenditure elasticity of 1.04 for fruit and vegetables. Finally, our study calculated an expenditure elasticity of 0.78 for fruit and vegetables. Therefore, the study conducted by Tiffin and Arnoult (2010) and this thesis found a high expenditure elasticity for fruit and vegetables.

As discussed by Kasteridis, Yen and Fang (2011), high expenditure elasticity suggests that the income support program is likely to be an adequate policy tool to promote food consumption. This thesis found that low-income households have expenditure elasticity close to one of fruit and vegetables. This relatively high expenditure elasticity suggests that income support programs can help increase fruit and vegetable consumption.

The differences between the elasticity estimates from past studies and this study may be associated with sample differences in terms of time or composition. In terms of time, it happens if the differences can be attributed to change over time, of the same population sample. For instance, the food own-price elasticity in the UK in the seventies is not expected to be the same as in the nineties. In the most recent study of the four studies mentioned above that worked with overall food expenditure Duffy (2003) used a dataset from 1963 to 1997, while our study used data from 2001 to 2009. Consequently, there is not an overlap period, and some differences can be attributed to difference in time of the dataset. In addition, except in the work of Tiffin who used former versions of the Living and Cost Food Survey, some of the differences can also be attributed to different sample characteristics. Even more, Tiffin and Arnoult (2010) used a dataset from 2003-04 for more specific food categories, which elasticities estimates are the closest to our estimation.

Therefore, the current study calculated own-price and income elasticities that in most cases are in the lower range of results reported in past studies. This study differs from previous research in that it presents a set of elasticities for four mutually exclusive samples. In this sense, our results shed some light on the different responses of households to variation in income levels and prices across demographic household types. Past studies have worked with a single aggregated sample, making the implicit assumption that demographic variables do not have an impact on key model parameters in the estimated model itself.

6.2. Contributions

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.

This study 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 thesis 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.

With respect to information indexes, most of the studies have been done abroad, and have found a small but significant impact. In this study the child obesity news elasticity varies between -0.02 and -0.08, on the overall food expenditure from the first stage. Specifically within food groups however, child obesity news elasticity is estimated to take values between -0.17 and 0.12 in the second stage. It suggests that information elasticities are larger for specific food expenditure groups, than for 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 thesis 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 five times smaller in magnitude compared to price and income elasticities.

Considering that information elasticities are consistently at least five 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 5.12 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.

This study contributes to the debate on the impact of health related news media information, on the behaviour of households with differing levels of income. As we already stated, high-income households spend a larger share of their budget on fruit and vegetables, and less on carbohydrates. At least in the case of fruit and vegetables, the impact on diet is amplified, considering that high-income households have larger comparative income basis. Our findings are consistent with DEFRA (2010) in the sense that fruit and vegetable consumption increases with income.

As presented in Figure 5.1, since 2008 the overall household expenditure is declining, whilst the food expenditure share is increasing. Consequently household food budget shares are increasing. This is a sign of economic contraction; households spend a greater proportion of their total income on food to satisfy their basic needs. However, the increase in food expenditure does not mean that households have healthier diets. Households are spending more on food simply because of the high aggregate food prices. Food prices declined by around 12% between 1998 and mid 2007, after this food prices climbed until they reached a peak in February 2009, which was higher than that in 1998 (DEFRA, 2010). Commodity prices have experienced historically high prices, and have consequently increased the price of animal products, such as poultry, red-meat and dairy.

Fruit and vegetable prices have however, not experienced such a significant increasing trend. Nevertheless, fruit and vegetable consumption has still declined over the period studied here. As indicated by DEFRA (2010), fruit and vegetable consumption by low-income households (overall) increased from 3.6 (4.0) portions a day in 2001, to 3.8 (4.3) portions a day in 2007. Due to the rise in food prices, fruit and vegetable consumption dropped to 3.3 (4.1) portions a day in 2008. Taking the higher food prices into account and that healthy food tends to be more expensive than unhealthy food, low-income households not only have a less healthy diet than high-income households, but they are also more susceptible to higher food prices, thus moving towards a less healthy diet. It is also expected that food prices would remain high during this decade (Headey and Fan, 2010), and so a reversal of the dietary fortunes of low income households seams less likely to occur soon. Consequently, the UK government faces the challenge at the very least, to counteract the negative effect on diet in an unfavourable price environment. Information may help to make the diets, if not the welfare of households, less susceptible to adverse economical conditions.

This study found that high-income 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. However, low-income households remain to be the biggest challenge. As presented in Table 5.2, low-income households spend less on education, and are those whose diet appears to be the most vulnerable in the face of rising food prices. More importantly, low-income households with children, since these households influence the nutritional habits of their children. According to Table 5.12, low-income households with children spend the smallest proportion of their income on fruit and vegetables (13.78%); which is even less than low-income households without children (18.53%). This finding is consistent with Tiffin and Arnoult (2010) that found a smaller per capita expenditure on fruit and vegetables in households with children. The challenge remains to create an information message, and find the appropriate channel of dissemination to effectively inform and improve their diet habit.

Finally, how government information affects the number of news articles in the written press may be debatable. The government may support research on healthy nutrition, which may itself yield media attention on publications of the research findings in the scholarly press, and subsequently affect the diet of a population. The government research funding contracts through the Research Councils, can stipulate a minimum level of dissemination activity which could include the more popular press outlets. Moreover, the government can support the organisation of health related events and ensure that they have adequate levels of written press coverage. The research conducted here should provide a starting point to a further investigation into media outlets, keywords and phrases that may be more likely to lead to a reaction of household food choices.

6.3. Limitations

The main limitations of the study relate to the dataset characteristics and the use of a specific media index. A dataset may have spatial and temporal variations. Spatial variation is due to household heterogeneity, and temporal variation happens over time after changes in supply or demand conditions.

With respect to spatial variations, this study worked with the mean of an aggregated sample of households. The Living Cost and Food Survey is conducted on a continuous basis, which means that samples of postcodes are drawn several times a year from the sampling frame within each strata; therefore, there should not be a geographical clustering of the observation according to the time of the year.

In relation to temporal variations, on the demand side, tastes and preferences may change over time (Mazzocchi, 2003). On the supply side, as discussed by Capps and Schmitz (1991), aggregated data does not necessarily take product composition changes due to health concerns into account. For instance, fat content in some products may be different at the beginning of 2001 than at the end of 2009. As a result, parameters and then elasticities may vary over time (Capps and Schmitz, 1991, Mazzocchi, 2003). As an empirical test, Gallet and List (1998) employed a gradual switching regression model that allows parameter heterogeneity over time. Using a beer-consumption dataset spanning the 1964-1992 period, the authors found elasticities to have significantly changed over time. Therefore, our elasticity estimation needs to be considered with caution.

In order to cover more than a single year, monthly per capita expenditure averages need to be used to limit the number of demographic variables. Whilst using a panel analysis, Dharmasena, Capps and Clauson (2011) were able to analyse numerous demographics ascertaining the nutritional impact of non-alcoholic beverages in the US. Nevertheless, in our case, since the dataset is randomised several times per year, it is not appropriate build a panel dataset. In the future, it may be possible to build pseudo panels. Despite this demographic limitation, in the study income and household composition is taken into account with the simple expedient of using separate data sets for four different household types. Tiffin and Arnoult (2010) explained that income level and the presence of children are two of the most important, but not only, determinants to take into account to explain household food expenditure behaviour. These authors also found that region and age play a significant role.

The Living Costs and Food Survey collects expenditure data rather than consumption data. Every adult over 16 years of age needs to register food items, expenditure and quantity. However, this data is registered at the moment of purchase. It is not clear how the food is consumed, which can impact its nutritional content. Despite this limitation, the Living Costs and Food Survey is continuously used to make policy recommendations. Even in some reports like the one by Arnoult, Tiffin and Traill (2008), the data in the Living Costs and Food Survey is called household consumption data. When researchers are assuming that the expenditure data is equivalent to the consumption data, it is normal to assume that wastage is zero, and that preparation would not affect the nutritional properties of food. Now, if a higher food expenditure would translate into improved health, it would depend on the nutritional content of food purchased (Meyerhoefer and Yang, 2011). Therefore, this study identified the impact per food expenditure group. However, the final effect on health is not certain. Moreover, the health condition would depend on other lifestyle choices such as regular physical activity. Some households can be spending more on carbohydrates, because they do more physical exercise on a regular basis.

Finally, the Living Costs and Food survey does not provide enough detailed information to include eating out categories in the second stage. The database provides only eating out expenditure. Thus its quantity is not available and its classification into food groups can be controversial. Eating out categories mainly involves prepared food, which is not straightforward in its classification into food groups. For instance, any type of tomatoes can be easily assigned to the fruit and vegetable group. However, in the case of a dish such as chicken curry with vegetables, it is more debatable whether or not it should be assigned to the white-meat group or to the fruit and vegetables group.

6.4. Future Research

At this stage it is possible to see extensions of this study; all these aspects are possible to do at some point. Nevertheless, it could be complicated to try to handle all of them at the same time. Even with that being the case, it is interesting to keep them in mind as an area of future development.

This study calculated a linear version of the AIDS model; it is linear since it assumes linear Engle curves. In other words, as the income increases, the households increase/decrease their expenditure of each group in a constant rate. However, the linearised version can be an oversimplification that imposes an unrealistic assumption. Therefore, it is also possible to calculate the non-linear version of the AIDS model, known as QUAIDS, which includes a quadratic term for real income.

On another aspect for future development, this study discussed that structural breaks can significantly impact the demand system estimation. Bayesian techniques are flexible enough to permit different combinations of explanatory variables in time. By using Bayesian techniques, Koop and Tole (2011) found that models allow changes in explanatory variables to outperform, at least forecasting, time-variant models.

Bayesian techniques can also be used to improve the economic properties of the estimation. In our estimation, the first stage rejects the curvature of the expenditure function. This rejection may be the cause of unexpected elasticity signs. However, as presented by Tiffin and Arnoult (2010), the concavity of the expenditure function can be imposed.

With respect to information sources, this study took only written newspaper information into account. The media variable correspond to a single child obesity newspaper index; nevertheless, consumers received information from several sources such as labels, word of mouth and numerous other media sources, i.e. the radio, television and the internet. The source of food safety information would influence its impact (Mazzocchi *et al.*, 2008). After conducting a survey involving more than two thousand people, the Food Standard Agency (FSA) showed that TV news (42%) and newspapers (35%) are the primary sources of food safety information (FSA, 2008). This study only considers newspapers; which was pursued here because, as Brown and Schrader (1990) state, the printed news media are often considered to be fairly neutral sources of information, and tend to be more credible and trusted than the more commercial sources. Despite the fact that some research has involved more than one source of information, such as that undertaken by Brown and Schrader (1990), the study of isolated effects along with the interaction of different sources is an area that is still being developed.

This work used secondary data to measure the impact of information on households. As we revised in the literature review, primary data can also be used to measure the magnitude an information impacts. More recently, some studies are using primary data to measure how long an information impact lasts. Dillaway *et al.* (2011) conducted four consecutive sessions with follow-up sessions after a week, three weeks and seven weeks; and found that subjects significantly change their willingness to pay. In particular, the authors found evidence that previous experience would have a significant role in the stated willingness to pay. In most of the cases this thesis found that a cumulative media index is more appropriate than a contemporaneous (no-cumulative) media index. This study used free from specification, as it is not available prior information, to justify a weight structure. Using experimental economics it could be possible to understand better how experience can condition the subject's reaction to news. These results can then be used to justify alternative media index specifications, such as a particular weight structure or a non-linear index form.

Bibliography

AADLAND, D. & CAPLAN, A. J. (2003) Willingness to Pay for Curbside Recycling with Detection and Mitigation of Hypothetical Bias. *American Journal of Agricultural Economics,* 85, 492-502.

AKGÜNGÖR, S., MIRAN, B. & ABAY, C. (2001) Consumer Willingness to Pay for Food Safety Labels in Urban Turkey: A Case Study of Pesticide Residues in Tomatoes. *Journal of International Food & Agribusiness Marketing,* 12, 91-107.

ALESSIE, R. & TEPPA, F. (2010) Saving and Habit Formation: Evidence from Dutch Panel Data. *Empirical Economics,* 38, 385-407.

ALSTON, J. M. & CHALFANT, J. A. (1993) The Silence of the Lambdas: A Test of the Almost Ideal and Rotterdam Models. *American Journal of Agricultural Economics,* 75, 304-313.

ALSTON, J. M., FOSTER, K. A. & GREEN, R. D. (1994) Estimating Elasticities with the Linear Approximate Almost Ideal Demand System: Some Monte Carlo Results. *The Review of Economics and Statistics,* 76, 351-356.

ANDREYEVA, T., CHALOUPKA, F. J. & BROWNELL, K. D. (2011) Estimating the Potential of Taxes on Sugar-Sweetened Beverages to Reduce Consumption and Generate Revenue. *Preventive Medicine,* 52, 413-416.

ARNOULT, M. H., TIFFIN, R. & TRAILL, B. (2008) Models of Nutrient Demand, Tax Policy & Public Health Impact. *Implications of a Nutrition Driven Food Policy for Land Use and the Rural Environment.* Reading, The University of Reading.

BALCOMBE, K. & DAVIS, J. R. (1996) An Application of Cointegration Theory in the Estimation of the Almost Ideal Demand System for Food Consumption in Bulgaria. *Agricultural Economics,* 15, 47-60.

BANKS, J., BLUNDELL, R. & LEWBEL, A. (1997) Quadratic Engel Curves and Consumer Demand. *The Review of Economics and Statistics,* 79, 527-539.

BARNETT, W. A. & SECK, O. (2008) Rotterdam Model versus Almost Ideal Demand System: Will the Best Specification Please Stand Up? *Journal of Applied Econometrics,* 23, 795-824.

BARTEN, A. P. (1964) Consumer Demand Functions under Conditions of Almost Additive Preferences. *Econometrica,* 32, 1-38.

BARTEN, A. P. (1977) The Systems of Consumer Demand Functions Approach: A Review. *Econometrica,* 45, 23-51.

BAUM, C. F. & LINZ, T. (2009) Evaluating Concavity for Production and Cost Functions. *Stata Journal,* 9, 161-165.

BAYE, M. R., JANSEN, D. W. & LEE, J.-W. (1992) Advertising Effects in Complete Demand Systems. *Applied Economics,* 24, 1087-1096.

BERNARD, J. C. & BERNARD, D. J. (2009) What Is It About Organic Milk? An Experimental Analysis. *American Journal of Agricultural Economics,* 91, 826-836.

BERNDT, E. R. & SAVIN, N. E. (1975) Estimation and Hypothesis Testing in Singular Equation Systems with Autoregressive Disturbances. *Econometrica,* 43, 937-957.

BERTAIL, P. & CAILLAVET, F. (2008) Fruit and Vegetable Consumption Patterns: A Segmentation Approach. *American Journal of Agricultural Economics,* 90, 827-842.

BLANCIFORTI, L. & GREEN, R. (1983) An Almost Ideal Demand System Incorporating Habits: An Analysis of Expenditures on Food and Aggregate Commodity Groups. *Review of Economics & Statistics,* 65, 511-515.
BLAYLOCK, J., SMALLWOOD, D., KASSEL, K., VARIYAM, J. & ALDRICH, L. (1999) Economics, Food Choices, and Nutrition. *Food Policy,* 24, 269-286.
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, 439-447.
BLOCK, J. P. & WILLETT, W. C. (2011) Can Taxing Sugary Soda Influence Consumption and Avoid Unanticipated Consequences? *Choices.* Agricultural and Applied Economics Association.
BLUMENSCHEIN, K., JOHANNESSON, M., YOKOYAMA, K. K. & FREEMAN, P. R. (2001) Hypothetical versus Real Willingness to Pay in the Health Care Sector: Results from a Field Experiment. *Journal of Health Economics,* 20, 441-457.
BRESTER, G. W. & SCHROEDER, T. C. (1995) The Impacts of Brand and Generic Advertising on Meat Demand. *American Journal of Agricultural Economics,* 77, 969-979.
BROWN, D. J. & SCHRADER, L. F. (1990) Cholesterol Information and Shell Egg Consumption. *American Journal of Agricultural Economics,* 72, 548-555.
BROWN, M. G. & LEE, J.-Y. (1993) Alternative Specifications of Advertising in the Rotterdam Model. *European Review Agricultural Economics,* 20, 419-436.
BROWN, T. C., AJZEN, I. & HRUBES, D. (2003) Further Tests of Entreaties to Avoid Hypothetical Bias in Referendum Contingent Valuation. *Journal of Environmental Economics and Management,* 46, 353-61.
BRUMMETT, R. G., NAYGA, R. M. & WU, X. (2007) On the Use of Cheap Talk in New Product Valuation. *Economics Bulletin,* 2, 1-9.
BURTON, M. & YOUNG, T. (1996) The Impact of BSE on the Demand for Beef and Other Meats in Great Britain. *Applied Economics,* 28, 687-693.
BURTON, M., YOUNG, T. & CROMB, R. (1999) Meat Consumer's Long-Term Response to Perceived Risk Associated with BSE in Great Britain. *Cahiers d'Economie et Sociologie Rurales,* 50, 7-19.
CAPPS, O., JR. & LOVE, H. A. (2002) Econometric Considerations in the Use of Electronic Scanner Data to Conduct Demand Analysis. *American Journal of Agricultural Economics,* 84, 807-816.
CAPPS, O., JR. & SCHMITZ, J. D. (1991) A Recognition Of Health And Nutrition Factors In Food Demand Analysis. *Western Journal of Agricultural Economics,* 16, 21-35.
CARLSSON, F., FRYKBLOM, P. & JOHAN LAGERKVIST, C. (2005) Using Cheap Talk as a Test of Validity in Choice Experiments. *Economics Letters,* 89, 147-152.
CARPENTIER, A. & GUYOMARD, H. (2001) Unconditional Elasticities in Two-Stage Demand Systems: An Approximate Solution. *American Journal of Agricultural Economics,* 83, 222-229.
CARSON, R., FLORES, N. & MEADE, N. (2001) Contingent Valuation: Controversies and Evidence. *Environmental & Resource Economics,* 19, 173-210.
CHANG, H.-S. & KINNUCAN, H. W. (1991) Advertising, Information, and Product Quality: The Case of Butter. *American Journal of Agricultural Economics,* 73, 1195-1203.

CHEN, P. Y. & VEEMAN, M. M. (1991) An Almost Ideal Demand System Analysis for Meats with Habit Formation and Structural Change. *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie,* 39, 223-235.

CUMMINGS, R. G., HARRISON, G. W. & RUTSTROM, E. E. (1995) Homegrown Values and Hypothetical Surveys: Is the Dichotomous Choice Approach Incentive-Compatible? *American Economic Review,* 85, 260-266.

CUMMINGS, R. G. & TAYLOR, L. O. (1999) Unbiased Value Estimates for Environmental Goods: A Cheap Talk Design for the Contingent Valuation Method. *American Economic Review,* 89, 649-665.

CUTLER, D. M., GLAESER, E. L. & SHAPIRO, J. M. (2003) Why Have Americans Become More Obese? *The Journal of Economic Perspectives,* 17, 93-118.

DAWSON, P. J. & DEY, P. K. (2002) Testing for the Law of One Price: Rice Market Integration in Bangladesh. *Journal of International Development,* 14, 473-484.

DEATON, A. & MUELLBAUER, J. (1980a) An Almost Ideal Demand System. *The American Economic Review,* 70, 312-326.

DEATON, A. & MUELLBAUER, J. (1980b) *Economics and Consumer Behavior,* New York, Cambridge University Press.

DEATON, A. & ZAIDI, S. (2002) Guidelines for Constructing Consumption Aggregates for Welfare Analysis. *Living Standards Measurement Study Working Paper No. 135.* Washington D.C, The World Bank.

DEFRA (2000) National Food Survey. Department for Environment, Food and Rural Affairs.

DEFRA (2010) Food Statistics Pocketbook. Department for Environmental, Food and Rural Affaires National Statistics.

DEFRA (2011) Family Food: A Report on the 2009 Family Food Module of the Living Costs and Food Survey. London, National Statistics and Department for Environment, Food and Rural Affairs.

DEVANEY, B. & MOFFITT, R. (1991) Dietary Effects of the Food Stamp Program. *American Journal of Agricultural Economics,* 73, 202-211.

DHAR, T., CHAVAS, J.-P. & GOULD, B. W. (2003) An Empirical Assessment of Endogeneity Issues in Demand Analysis for Differentiated Products. *American Journal of Agricultural Economics,* 85, 605-617.

DHARMASENA, S., CAPPS, O. J. & CLAUSON, A. (2011) Ascertaining the Impact of the 2000 USDA Dietary Guidelines for Americans on the Intake of Calories, Caffeine, Calcium, and Vitamin C from At-Home Consumption of Nonalcoholic Beverages. *Journal of Agricultural and Applied Economics,* 43, 13-27.

DILLAWAY, R., MESSER, K. D., BERNARD, J. C. & KAISER, H. M. (2011) Do Consumer Responses to Media Food Safety Information Last? *Applied Economic Perspectives and Policy,* 33, 363-383.

DING, M., GREWAL, R. & LIECHTY, J. (2005) Incentive-Aligned Conjoint Analysis. *Journal of Marketing Research,* 42, 67-82.

DRICHOUTIS, A. C., LAZARIDIS, P. & NAYGA, R. M. (2009) Would Consumers Value Food-Away-From-Home Products with Nutritional Labels? *Agribusiness,* 25, 550-575.

DUFFY, M. (2002) On the Estimation of an Advertising-Augmented, Cointegrating Demand System. *Economic Modelling,* 20, 181-206.

DUFFY, M. (2003) Advertising and Food, Drink and Tobacco Consumption in the United Kingdom: A Dynamic Demand System. *Agricultural Economics,* 28, 51-70.

EAKINS, J. M. & GALLAGHER, L. A. (2003) Dynamic Almost Ideal Demand Systems: An Empirical Analysis of Alcohol Expenditure in Ireland. *Applied Economics,* 35, 1025-1036.

EALES, J. S. & UNNEVEHR, L. J. (1988) Demand for Beef and Chicken Products: Separability and Structural Change. *American Journal of Agricultural Economics,* 70, 521-532.

EDGERTON, D. L. (1997) Weak Separability and the Estimation of Elasticities in Multistage Demand Systems. *American Journal of Agricultural Economics,* 79, 62-79.

EHMKE, M. D. T., WARZINIACK, T., SCHROETER, C. & MORGAN, K. (2008) Applying Experimental Economics to Obesity in the Family Household. *Journal of Agricultural and Applied Economics,* 40, 539–549.

ENGLE, R. F. (1982) Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* 50, 987-1007.

ENGLE, R. F. & GRANGER, C. W. J. (1987) Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica,* 55, 251-276.

FAN, S., WAILES, E. J. & CRAMER, G. L. (1995) Household Demand in Rural China: A Two-Stage LES-AIDS Model. *American Journal of Agricultural Economics,* 77, 54-62.

FINKELSTEIN, E. A., DIBONAVENTURA, M. D., BURGESS, S. M. & HALE, B. C. (2010) The Costs of Obesity in the Workplace. *Journal of Occupational and Environmental Medicine,* 52, 971-976.

FINKELSTEIN, E. A., STROMBOTNE, K. L. & POPKIN, B. M. (2010) The Cost of Obesity and Implications for Policy Makers. *Choices.* Agricultural & Applied Economics Association.

FOX, J. A., HAYES, D. J. & SHOGREN, J. F. (2002) Consumer Preferences for Food Irradiation: How Favorable and Unfavorable Descriptions Affect Preferences for Irradiated Pork in Experimental Auctions. *Journal of Risk and Uncertainty,* 24, 75-95.

FSA (2008) Consumer Attitudes to Food Standards: Wave 8 Food Standard Agency.

GALLET, C. A. & LIST, J. A. (1998) Elasticities of Beer Demand Revisited. *Economics Letters,* 61, 67-71.

GANG, L., HAIYAN, S. & STEPHEN, F. W. (2004) Modeling Tourism Demand: A Dynamic Linear AIDS Approach. *Journal of Travel Research,* 43, 141-150.

GAO, X. M., WAILES, E. J. & CRAMER, G. L. (1995) A Microeconometric Model Analysis of US Consumer Demand for Alcoholic Beverages. *Applied Economics,* 27, 59-69.

GAO, X. M., WAILES, E. J. & CRAMER, G. L. (1996) A Two-Stage Rural Household Demand Analysis: Microdata Evidence from Jiangsu Province, China. *American Journal of Agricultural Economics,* 78, 604-613.

GOLDMAN, S. M. & UZAWA, H. (1964) A Note on Separability in Demand Analysis. *Econometrica,* 32, 387-398.

GRACIA, A., GIL, J. M. & ANGULO, A. M. (1998) Spanish Food Demand: A Dynamic Approach. *Applied Economics,* 30, 1399-1405.

GRANGER, C. W. J. (1981) Some Properties of Time Series Data and Their Use in Econometric Model Specification. *Journal of Econometrics,* 16, 121-130.

GREEN, P. E., KRIEGER, A. M. & WIND, Y. (2001) Thirty Years of Conjoint Analysis: Reflections and Prospects *Interfaces* 31 56-73.

GREEN, R. & ALSTON, J. M. (1990) Elasticities in AIDS Models. *American Journal of Agricultural Economics,* 72, 442-445.

GREEN, R. D., CARMAN, H. F. & MCMANUS, K. (1991) Some Empirical Methods Of Estimating Advertising Effects In Demand Systems: An Application To Dried Fruits. *Western Journal of Agricultural Economics,* 16, 63-71.

HADEN, K. (1990) The Demand for Cigarettes in Japan. *American Journal of Agricultural Economics,* 72, 446-450.

HAN, T. & WAHL, T. I. (1998) China's Rural Household Demand For Fruit And Vegetables. *Journal of Agricultural and Applied Economics,* 30, 141-150.

HARRIS, R. & SOLLIS, R. (2003) *Applied Times Series Modelling and Forecasting,* Chichester, John Wiley & Sons Ltd.

HARRISON, G. W. (2011) Experimental Methods and the Welfare Evaluation of Policy Lotteries *European Review of Agricultural Economics,* 38, 335-360.

HEADEY, D. & FAN, S. (2010) Reflections on the Global Food Crisis. *Research Monograph.* Washington, D.C., U.S.A., International Food Policy Research Institute.

HILL, J. O., WYATT, H. R., REED, G. W. & PETERS, J. C. (2003) Obesity and the Environment: Where Do We Go from Here? *Science 7,* 299, 853-855.

HOLT, M. T. & GOODWIN, B. K. (1997) Generalized Habit Formation in an Inverse Almost Ideal Demand System: An Application to Meat Expenditures in the U.S. *Empirical Economics,* 22, 293-320.

HUANG, C. L. (1993) Simultaneous-Equation Model for Estimating Consumer Risk Perceptions, Attitudes, and Willingness-to-Pay for Residue-Free Produce. *Journal of Consumer Affairs,* 27, 377-396.

JIANG, B. & DAVIS, J. (2007) Household Food Demand in Rural China. *Applied Economics,* 39, 373-380.

JUST, R. E., HUETH, D. L. & SCHMITZ, A. (2004) *The Welfare Economics of Public Policy,* Cheltenham, Edward Elgar Publishing Limited.

KAABIA, M. B. & GIL, J. M. (2001) Estimation and Inference in Cointegrated Demand Systems: An Application to Tunisian Meat Consumption. *European Review of Agricultural Economics,* 28, 349-370.

KARAGIANNIS, G., KATRANIDIS, S. & VELENTZAS, K. (2000) An Error Correction Almost Ideal Demand System for Meat in Greece. *Agricultural Economics,* 22, 29-35.

KARAGIANNIS, G. & MERGOS, G. J. (2002) Estimating Theoretically Consistent Demand Systems using Cointegration Techniques with Application to Greek Food Data. *Economics Letters,* 74, 137-143.

KASTERIDIS, P., YEN, S. T. & FANG, C. (2011) Bayesian Estimation of a Censored Linear Almost Ideal Demand System: Food Demand in Pakistan. *American Journal of Agricultural Economics,* 93, 1374-1390.

KENNEDY, P. (1998) *A Guide to Econometrics,* Cambridge, Massachusetts, The MIT Press.

KINNUCAN, H. W. & XIAO, H. (1997) Effects of Health Information and Generic Advertising on U.S. *American Journal of Agricultural Economics,* 79, 13-23.

KLONARIS, S. & HALLAM, D. (2003) Conditional and Unconditional Food Demand Elasticities in a Dynamic Multistage Demand System. *Applied Economics,* 35, 503-514.

KOOP, G. & TOLE, L. (2011) Forecasting the European Carbon Market. *Working Paper.* GLASGOW, Department of Economics University of Strathclyde.

KRISHNA, V. V. & QAIM, M. (2008) Consumer Attitudes Toward GM Food and Pesticide Residues in India. *Review of Agricultural Economics,* 30, 233-251.

LACANILAO, R. D., CASH, S. B. & ADAMOWICZ, W. L. (2011) Heterogeneous Consumer Responses to Snack Food Taxes and Warning Labels. *Journal of Consumer Affairs,* 45, 108-122.
LAFRANCE, J. T. (1998) The Silence Bleating! Of the Lambdas: Comment. *American Journal of Agricultural Economics,* 80, 221-230.
LANDRY, C. & LIST, J. A. (2007) Using Ex Ante Approaches to Obtain Credible Signals for Value in Contingent Markets: Evidence from the Field. *American Journal of Agricultural Economics,* 89, 420-29.
LARIVIÈRE, É., LARUE, B. & CHALFANT, J. (2000) Modeling the Demand for Alcoholic Beverages and Advertising Specifications. *Agricultural Economics,* 22, 147-162.
LEWBEL, A. (1996) Aggregation Without Separability: A Generalized Composite Commodity Theorem. *The American Economic Review,* 86, 524-543.
LEWBEL, A. & NG, S. (2005) Demand Systems with Nonstationary Prices. *Review of Economics and Statistics,* 87, 479-494.
LIST, J. A. (2001) Do Explicit Warnings Eliminate the Hypothetical Bias in Elicitation Procedures? Evidence from Field Auctions for Sportscards. *American Economic Review,* 91, 1498-1507.
LOOMIS, J., BROWN, T., LUCERO, B. & PETERSON, G. (1996) Improving Validity Experiments of Contingent Valuation Methods: Results of Efforts to Reduce the Disparity of Hypothetical and Actual Willingness to Pay. *Land Economics,* 72, 450-61.
LUSK, J. L. (2003) Effects of Cheap Talk on Consumer Willingness-to-Pay for Golden Rice. *American Journal of Agricultural Economics,* 85, 840-856.
LUSK, J. L. & HUDSON, D. (2004) Willingness-to-Pay Estimates and Their Relevance to Agribusiness Decision Making. *Review of Agricultural Economics,* 26, 152-69.
MACINNIS, B. & RAUSSER, G. (2005) Does Food Processing Contribute to Childhood Obesity Disparities? *American Journal of Agricultural Economics,* 87, 1154-1158.
MARSH, T. L., SCHROEDER, T. C. & MINTERT, J. (2004) Impacts of Meat Product Recalls on Consumer Demand in the USA. *Applied Economics,* 36, 897-909.
MAZZOCCHI, M. (2003) Time-Varying Coefficients in the Almost Ideal Demand System: An Empirical Appraisal. *European Review of Agricultural Economics,* 30, 241-270.
MAZZOCCHI, M. (2006) No News Is Good News: Stochastic Parameters versus Media Coverage Indices in Demand Models after Food Scares. *American Journal of Agricultural Economics,* 88, 727-741.
MAZZOCCHI, M., DELLE MONACHE, D. & LOBB, A. E. (2006) A Structural Time Series Approach to Modelling Multiple and Resurgent Meat Scares in Italy. *Applied Economics,* 38, 1677-1688.
MAZZOCCHI, M., LOBB, A., TRAILL, W. B. & CAVICCHI, A. (2008) Food Scares and Trust: A European Study. *Journal of Agricultural Economics,* 59, 2-24.
MAZZOCCHI, M., TRAILL, W. B. & SHOGREN, J. F. (2009) *Fat Economics: Nutrition, Health, and Economic Policy,* New York, Oxford University Press.
MEYERHOEFER, C. D. & YANG, M. (2011) The Relationship between Food Assistance and Health: A Review of the Literature and Empirical Strategies

for Identifying Program Effects. *Applied Economic Perspectives and Policy,* 33, 304-344.
MICHALEK, J. & KEYZER, M. A. (1992) Estimation of a Two-Stage LES-AIDS Consumer Demand System for Eight EC Countries. *European Review of Agricultural Economics,* 19, 137-163.
MOSCHINI, G. & MEILKE, K. D. (1989) Modeling the Pattern of Structural Change in U.S. Meat Demand. *American Journal of Agricultural Economics,* 71, 253-261.
MOSCHINI, G. & MORO, D. (1996) Structural Change and Demand Analysis: A Cursory Review. *European Review of Agricultural Economics,* 23, 239-261.
MURPHY, J. J., STEVENS, T. H. & WEATHERHEAD, D. (2005) Is Cheap Talk Effective at Eliminating Hypothetical Bias in a Provision Point Mechanism? *Environmental and Resource Economics,* 30, 327-343.
MUTH, M. (2010) Theme Overview: Addressing the Obesity Challenge. *Choices.* Agricultural & Applied Economics Association.
NATIONAL-AUDIT-OFFICE (2001) Tackling Obesity in England. IN HOUSE-OF-COMMONS (Ed.) *The Stationery Office.* London, National Audit Office.
NAYGA, R. M., JR. & CAPPS, O., JR. (1994) Tests of Weak Separability in Disaggregated Meat Products. *American Journal of Agricultural Economics,* 76, 800-808.
NHS (2010) Statistics on Obesity, Physical Activity and Diet: England, 2010. The NHS Information Centre, Lifestyles Statistics.
NICHOLSON, W. (2005) *Micoreconomic Theory: Basic Principles and Extensions*, Thomson South-Western.
ODI (2008) Rising Food Prices: A Global Crisis. *Briefing Paper.* London, Overseas Development Institute.
OECD (2010) Health at a Glance: Europe 2010. IN PUBLISHING, O. (Ed.).
PIGGOTT, N. E., CHALFANT, J. A., ALSTON, J. M. & GRIFFITH, G. R. (1996) Demand Response to Advertising in the Australian Meat Industry. *American Journal of Agricultural Economics,* 78, 268-279.
PIGGOTT, N. E. & MARSH, T. L. (2004) Does Food Safety Information Impact U.S. Meat Demand? *American Journal of Agricultural Economics,* 86, 154-174.
POFAHL, G. M., CAPPS, O., JR. & LOVE, H. A. (2006) Retail Zone Pricing and Simulated Price Effects of Upstream Mergers. *International Journal of the Economics of Business,* 13, 195-215.
POLLAK, R. A. (1970) Habit Formation and Dynamic Demand Functions. *The Journal of Political Economy,* 78, 745-763.
POLLAK, R. A. & WALES, T. J. (1969) Estimation of the Linear Expenditure System. *Econometrica,* 37, 611-628.
POLLAK, R. A. & WALES, T. J. (1992) *Demand System Specification and Estimation,* New York, Oxford University Press.
POSRI, W., SHANKAR, B. & CHADBUNCHACHAI, S. (2007) Consumer Attitudes Towards and Willingness to Pay for Pesticide Residue Limit Compliant "Safe" Vegetables in Northeast Thailand. *Journal of International Food & Agribusiness Marketing,* 19, 81-101.
RICHARDS, T. J., ISPELEN, P. V. & KAGAN, A. (1997) A Two-Stage Analysis of the Effectiveness of Promotion Programs for U.S. Apples. *American Journal of Agricultural Economics,* 79, 825-837.

RICHARDS, T. J. & PATTERSON, P. M. (2006) Native American Obesity: An Economic Model of the "Thrifty Gene" Theory. *American Journal of Agricultural Economics,* 88, 542-560.
RICHARDS, T. J. & POFAHL, G. M. (2009) Commodity Prices and Food Inflation. *American Journal of Agricultural Economics,* 91, 1450-1455.
RICKERTSEN, K. (1996) Structural Change and the Demand for Meat and Fish in Norway. *European Review of Agricultural Economics,* 23, 316-330.
RICKERTSEN, K., KRISTOFERSSON, D. & LOTHE, S. (2003) Effects of Health Information on Nordic Meat and Fish Demand. *Empirical Economics,* 28, 249-273.
ROOSEN, J. & MARETTE, S. (2011) Making the 'Right' Choice Based on Experiments: Regulatory Decisions for Food and Health. *European Review Agricultural Economics,* 38, 361-381.
SALIN, V. & HOOKER, N. H. (2001) Stock Market Reaction to Food Recalls. *Review of Agricultural Economics,* 23, 33-46.
SAUER, J. (2006) Economic Theory and Economic Practice: Parametric Efficiency Analysis. *Empirical Economics,* 31, 1061-1087.
SCIENCE, G. O. F. (2010) Tackling Obesities: Future Choices –Project Report. Government Office for Science.
SHIMSHACK, J. P., WARD, M. B. & BEATTY, T. K. M. (2007) Mercury Advisories: Information, Education, and Fish Consumption. *Journal of Environmental Economics and Management,* 53, 158-179.
SLOMAN, J. & HINDE, K. (2007) *Economics for Business,* Essex, Pearson Education Limited.
SMITH, M. E., RAVENSWAAY, E. O. V. & THOMPSON, S. R. (1988) Sales Loss Determination in Food Contamination Incidents: An Application to Milk Bans in Hawaii. *American Journal of Agricultural Economics,* 70, 513-520.
SPINNEWYN, F. (1981) Rational Habit Formation. *European Economic Review,* 15, 91-109.
STONE, R. (1954) Linear Expenditure Systems and Demand Analysis: An Application to the Pattern of British Demand. *The Economic Journal,* 64, 511-527.
SWARTZ, D. G. & STRAND, I. E., JR. (1981) Avoidance Costs Associated with Imperfect Information: The Case of Kepone. *Land Economics,* 57, 139-150.
THEIL, H. (1965) The Information Approach to Demand Analysis. *Econometrica,* 33, 67-87.
THOMPSON, D., BROWN, J. B., NICHOLS, G. A., ELMER, P. J. & OSTER, G. (2001) Body Mass Index and Future Healthcare Costs: A Retrospective Cohort Study. *Obesity,* 9, 210-218.
THOMPSON, W. (2004) Using Elasticities from an Almost Ideal Demand System? Watch Out for Group Expenditure! *American Journal of Agricultural Economics,* 86, 1108-1116.
THOMSEN, M. R. & MCKENZIE, A. M. (2001) Market Incentives for Safe Foods: An Examination of Shareholder Losses from Meat and Poultry Recalls. *American Journal of Agricultural Economics,* 83, 526-538.
TIFFIN, A. & TIFFIN, R. (1999) Estimates of Food Demand Elasticities for Great Britain: 1972-1994. *Journal of Agricultural Economics,* 50, 140-147.
TIFFIN, R. & ARNOULT, M. (2010) The Demand for a Healthy Diet: Estimating the Almost Ideal Demand System with Infrequency of Purchase. *European Review of Agricultural Economics,* 37, 501-521.

TIFFIN, R. & BALCOMBE, K. (2005) Testing Symmetry and Homogeneity in the Almost Ideal Demand System with Co-integrated Data using Fully Modified Estimation and the Bootstrap. *Journal of Agricultural Economics,* 56, 253-270.

TIFFIN, R., TRAILL, W. B. & MORTIMER, S. (2006) Food Choice in an Interdisciplinary Context. *Journal of Agricultural Economics,* 57, 213-220.

TROGDON, J. G., FINKELSTEIN, E. A., HYLANDS, T., DELLEA, P. S. & KAMAL-BAHL, S. J. (2008) Indirect Costs of Obesity: A Review of the Current Literature. *Obesity Reviews,* 9, 489-500.

VARIAN, H. R. (2002) *Microeconomics Analysis,* New York, W.W. Norton & Company, Inc.

VERBEKE, W. & WARD, R. W. (2001) A Fresh Meat Almost Ideal Demand System Incorporating Negative TV Press and Advertising Impact. *Agricultural Economics,* 25, 359-374.

WANG, Z., SALIN, V., HOOKER, N. H. & LEATHAM, D. (2002) Stock Market Reaction to Food Recalls: A GARCH Application. *Applied Economics Letters,* 9, 979-987.

YEN, S. T., LIN, B.-H., SMALLWOOD, D. M. & ANDREWS, M. (2004) Demand for Nonalcoholic Beverages: The Case of Low-Income Households. Agribusiness, 20, 309-321.

ZHENG, Y. & KAISER, H. M. (2008) Advertising and U.S. Nonalcoholic Beverage Demand. Agricultural and Resource Economics Review, 37, 147–159.

Chapter 7

Appendix

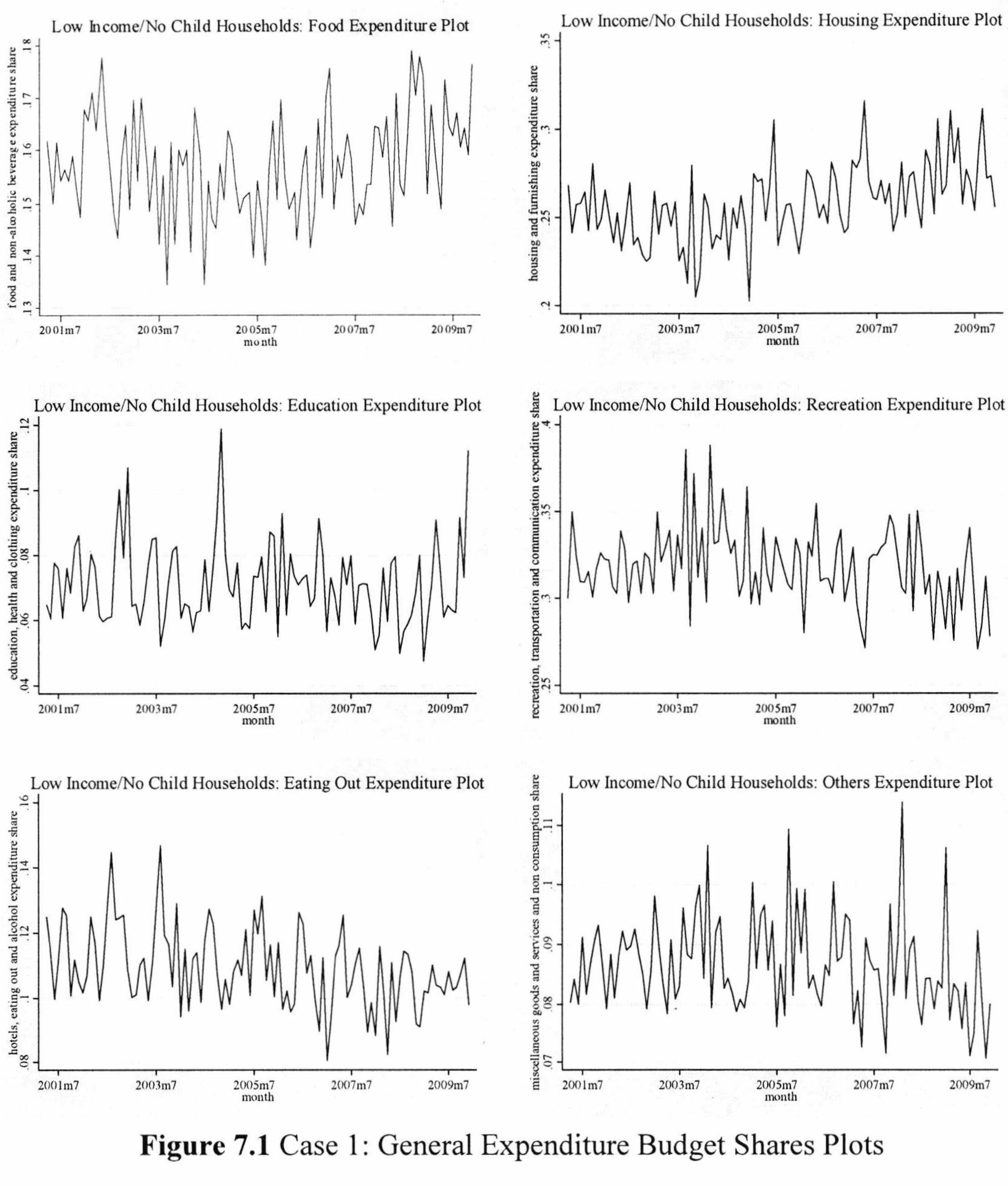

Figure 7.1 Case 1: General Expenditure Budget Shares Plots

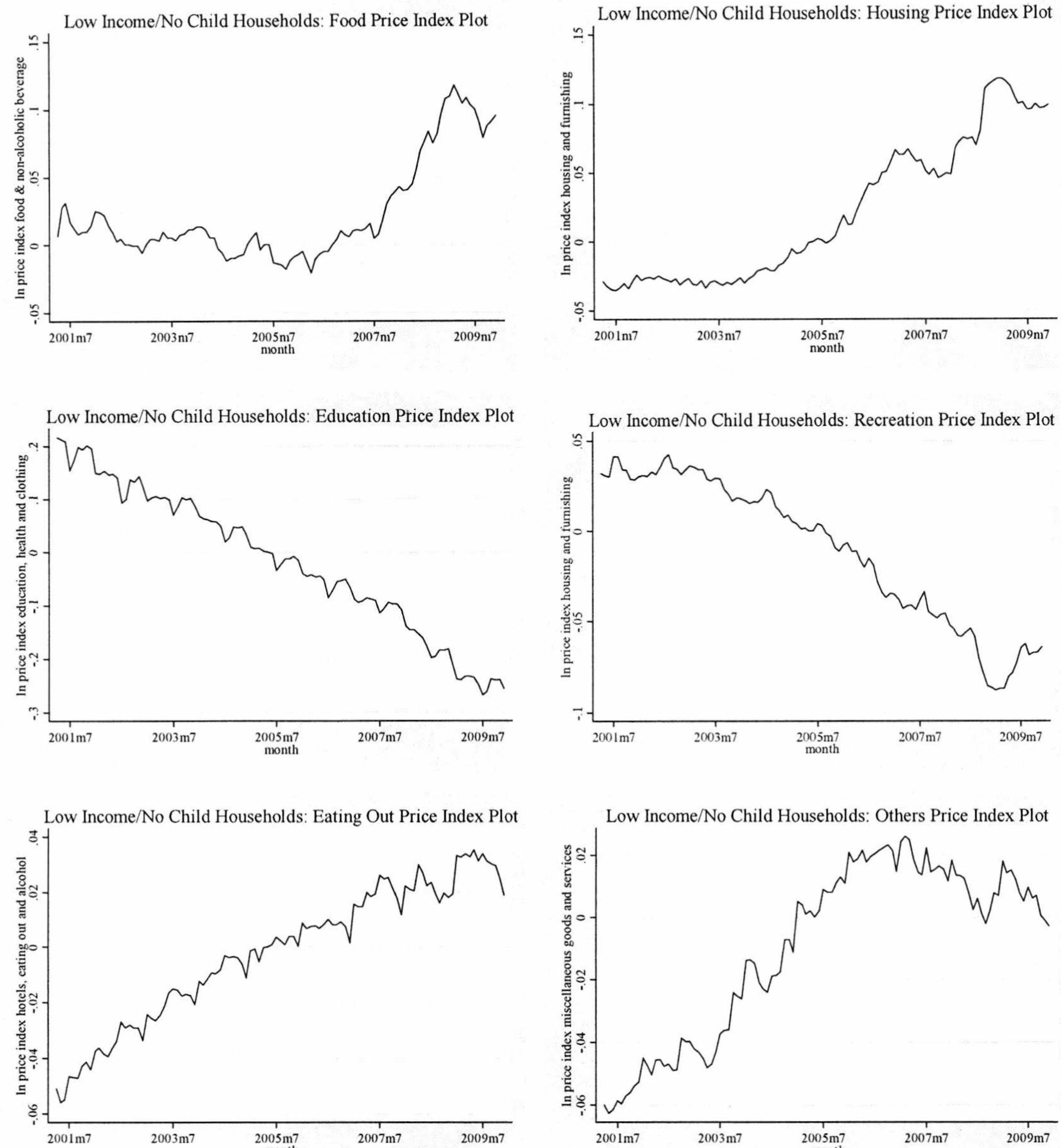

Figure 7.2 Case 1: General Expenditure Price Index Plots

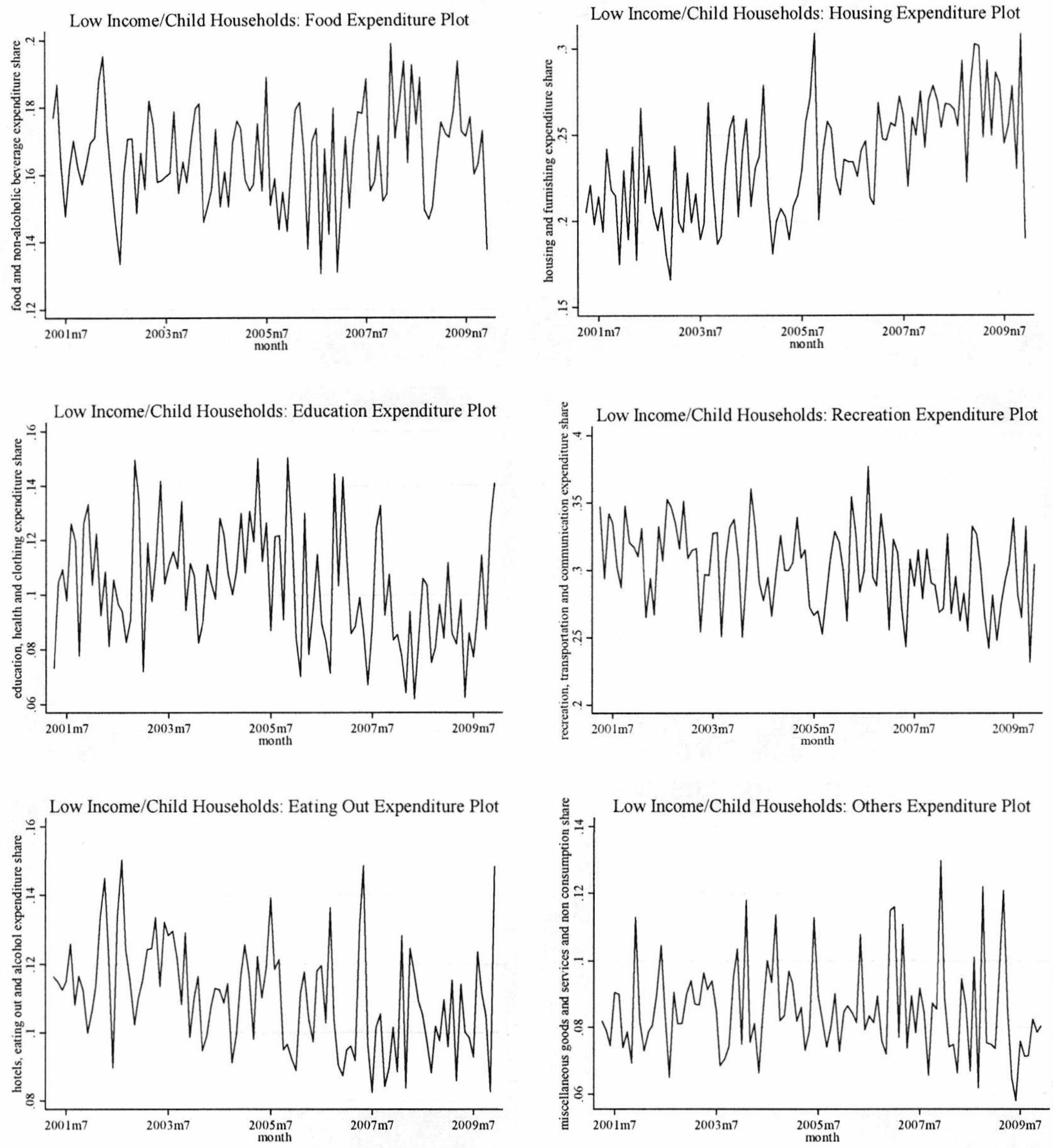

Figure 7.3 Case 2: General Expenditure Budget Shares Plots

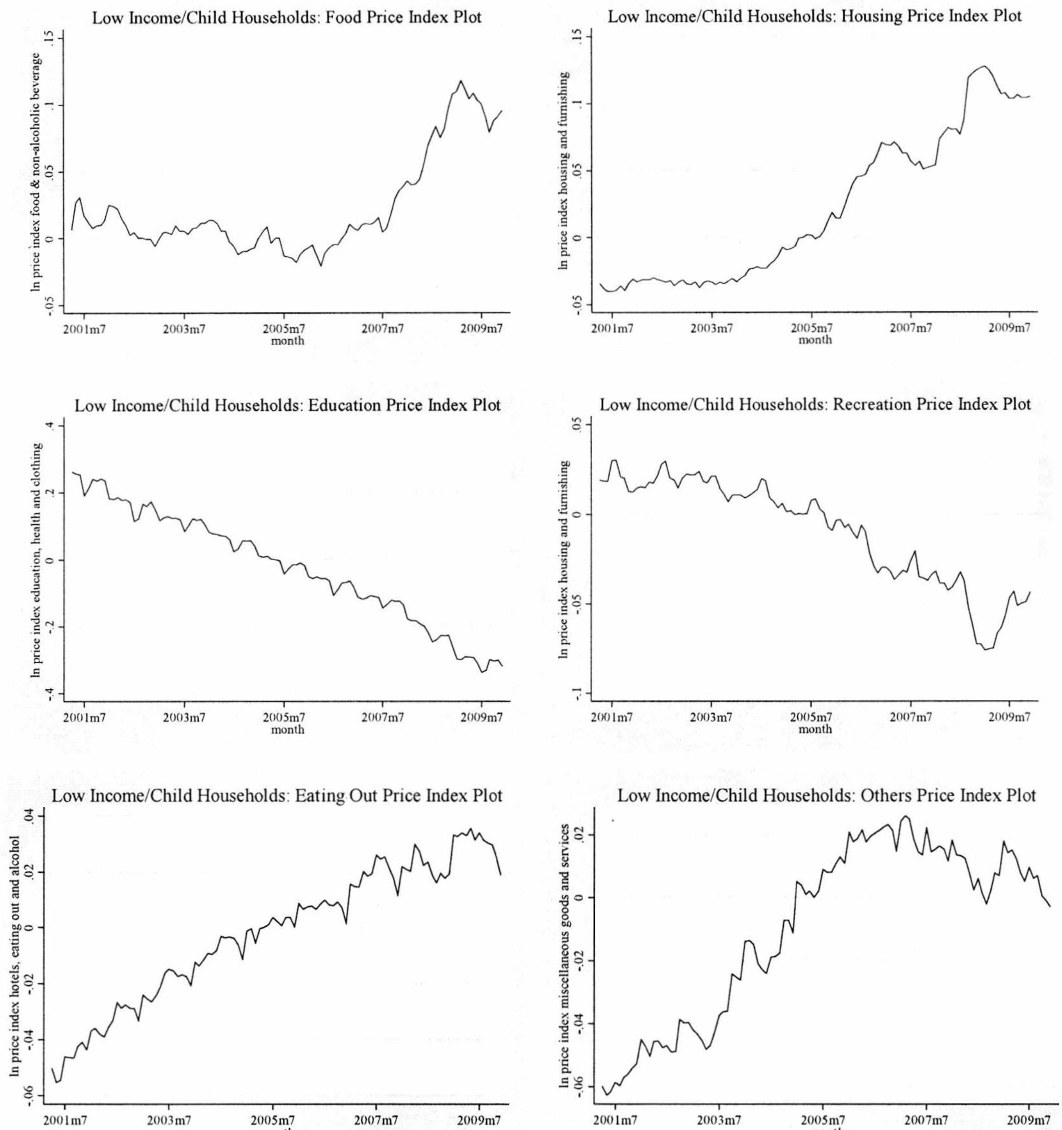

Figure 7.4 Case 2: General Expenditure Price Index Plots

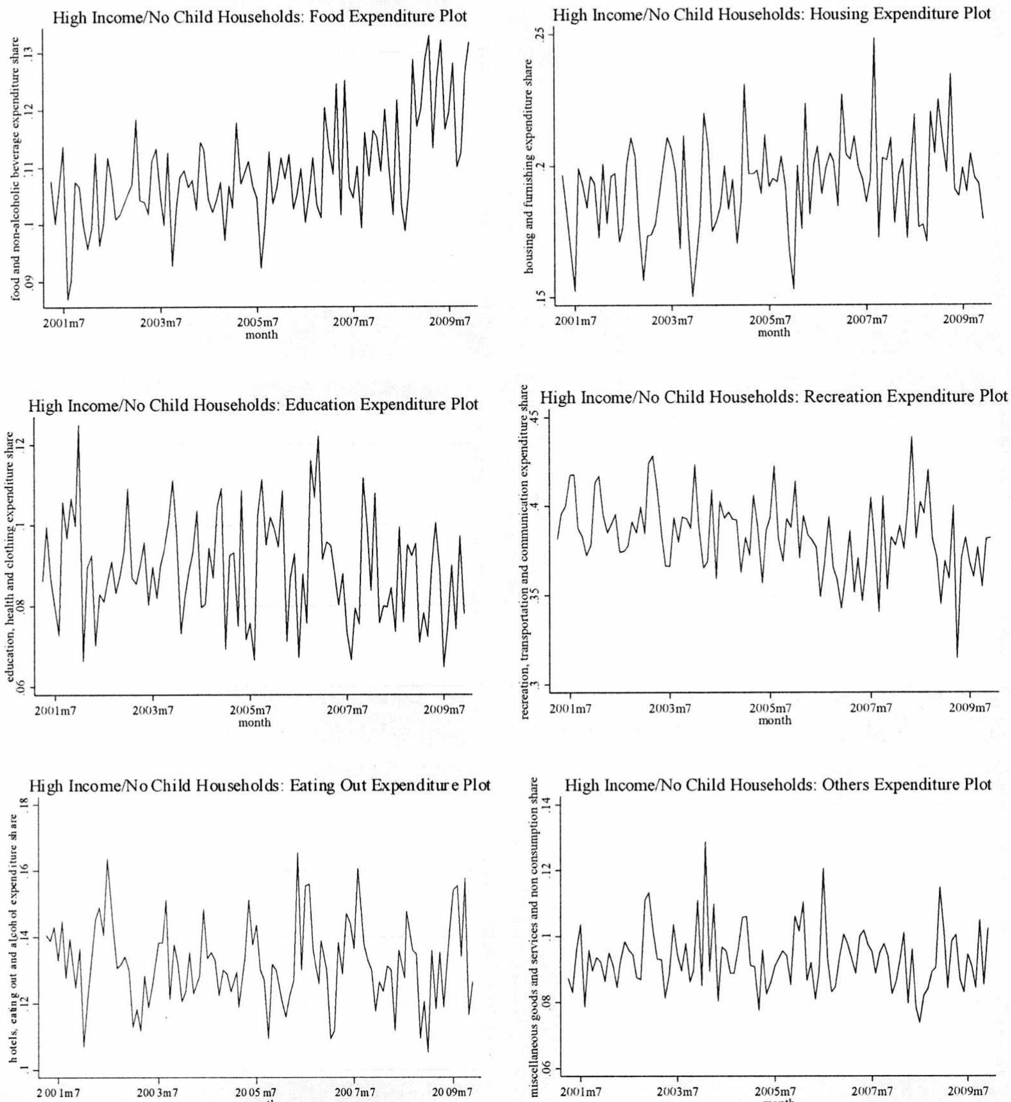

Figure 7.5 Case 3: General Expenditure Budget Shares Plots

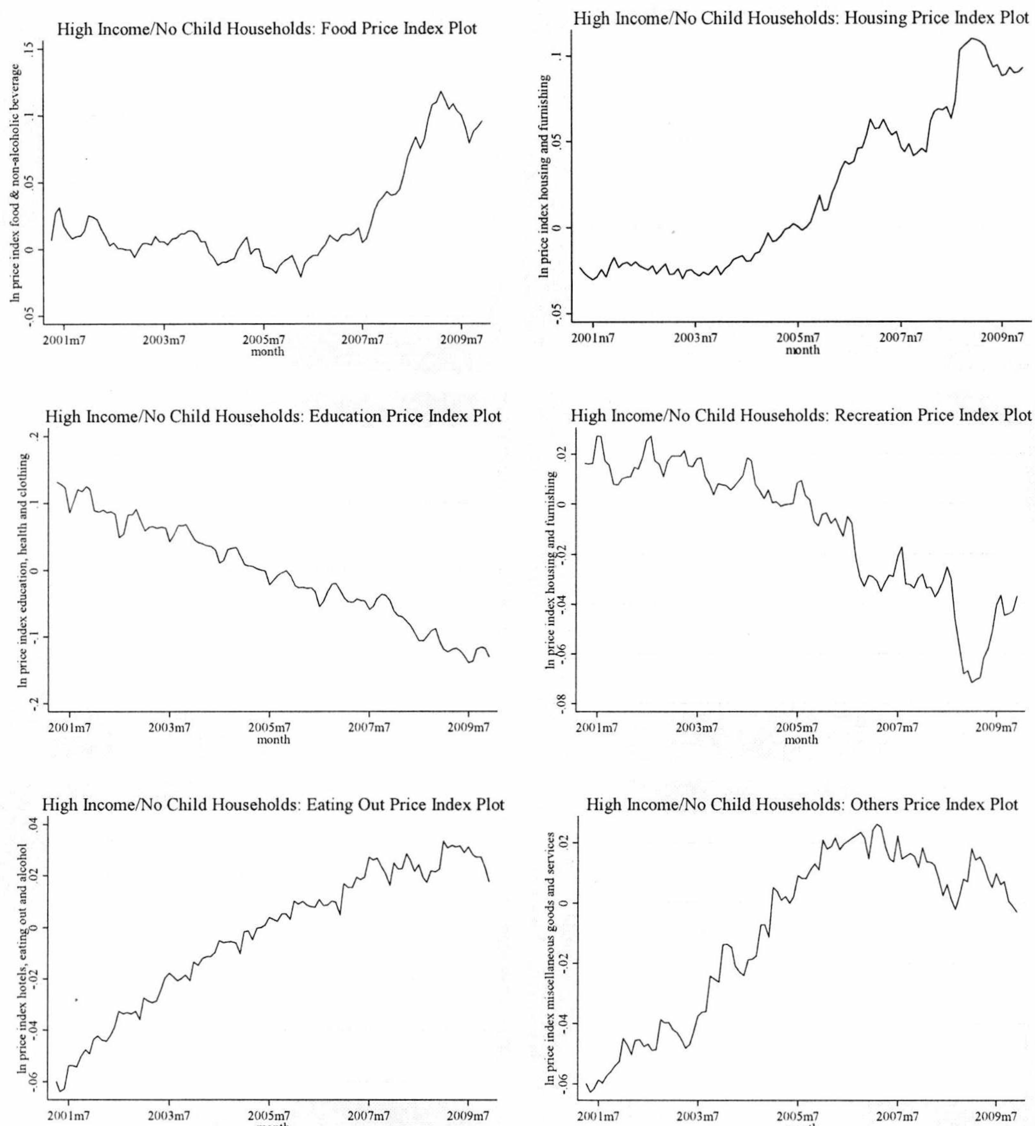

Figure 7.6 Case 3: General Expenditure Price Index Plots

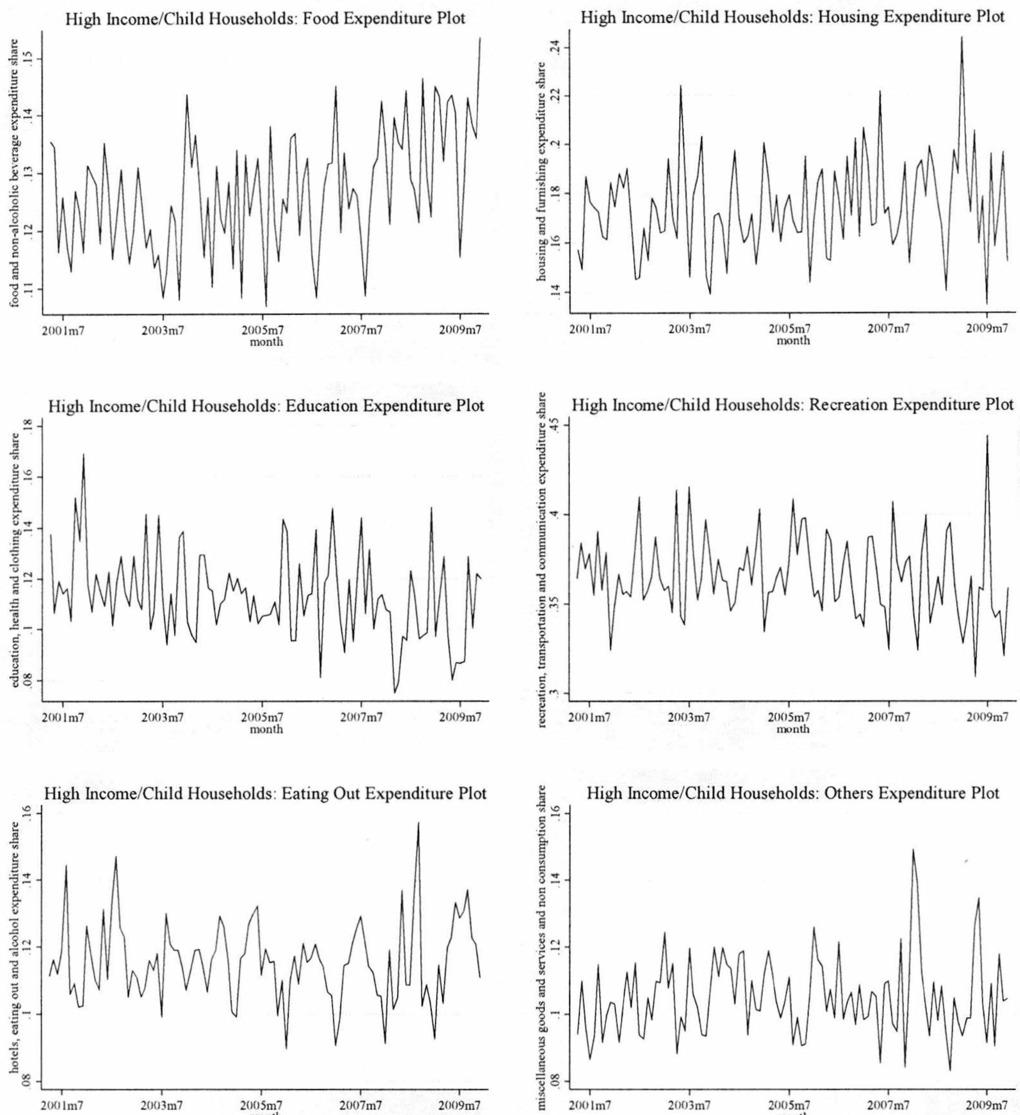

Figure 7.7 Case 4: General Expenditure Budget Shares Plots

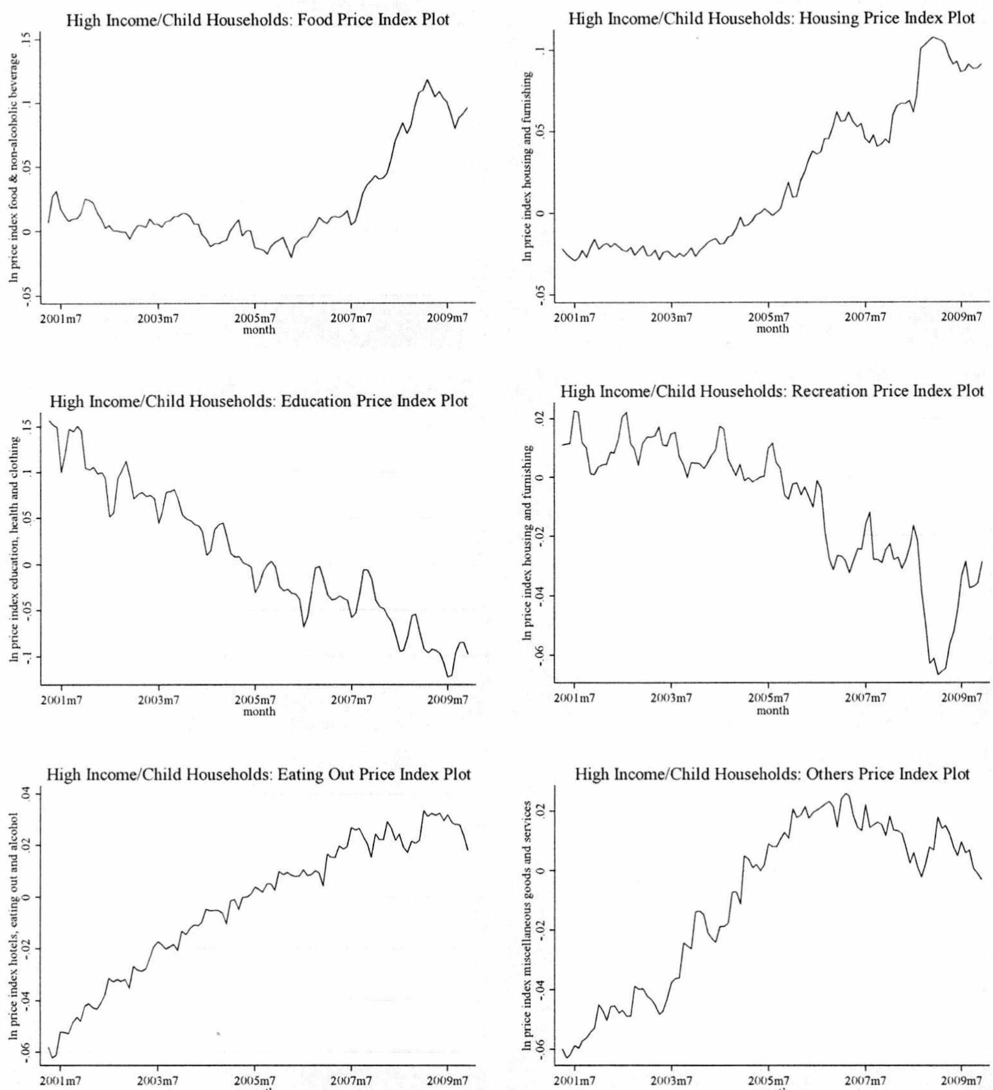

Figure 7.8 Case 4: General Expenditure Price Index Plots

Table 7.1 General Expenditure Concavity Tests

	Low Income/No Child					*Low Income/Child*					*High Income/No Child*					*High Income/Child*				
	Eigenvalue					Eigenvalue					Eigenvalue					Eigenvalue				
Observation	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1	0.09	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.24	-0.61	0.14	-0.02	-0.04	-0.28	-0.62	0.12	0.07	-0.01	-0.29	-0.45
2	0.10	0.02	-0.03	-0.09	-0.48	0.16	0.01	-0.10	-0.23	-0.60	0.14	-0.02	-0.04	-0.28	-0.62	0.13	0.08	-0.01	-0.27	-0.46
3	0.11	0.01	-0.03	-0.11	-0.49	0.17	0.02	-0.10	-0.23	-0.62	0.15	-0.02	-0.03	-0.28	-0.62	0.11	0.08	-0.01	-0.29	-0.45
4	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.02	-0.09	-0.24	-0.61	0.15	-0.02	-0.03	-0.29	-0.61	0.11	0.08	-0.01	-0.28	-0.45
5	0.09	0.02	-0.03	-0.09	-0.48	0.17	0.01	-0.11	-0.22	-0.62	0.15	-0.02	-0.05	-0.27	-0.62	0.12	0.07	-0.01	-0.28	-0.46
6	0.09	0.02	-0.03	-0.10	-0.49	0.16	0.01	-0.10	-0.24	-0.60	0.14	-0.03	-0.04	-0.28	-0.61	0.12	0.08	0.00	-0.28	-0.45
7	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.24	-0.61	0.14	-0.03	-0.04	-0.29	-0.61	0.12	0.07	-0.01	-0.30	-0.44
8	0.10	0.02	-0.03	-0.11	-0.48	0.17	0.02	-0.11	-0.23	-0.61	0.14	-0.03	-0.05	-0.28	-0.61	0.12	0.08	-0.01	-0.29	-0.45
9	0.10	0.02	-0.03	-0.11	-0.48	0.18	0.01	-0.11	-0.22	-0.61	0.14	-0.03	-0.04	-0.28	-0.61	0.11	0.07	0.00	-0.31	-0.43
10	0.10	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.09	-0.24	-0.60	0.13	-0.03	-0.04	-0.28	-0.59	0.12	0.07	-0.01	-0.28	-0.45
11	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.10	-0.23	-0.62	0.15	-0.02	-0.05	-0.27	-0.60	0.11	0.08	-0.01	-0.28	-0.45
12	0.09	0.02	-0.03	-0.11	-0.49	0.15	0.00	-0.10	-0.23	-0.60	0.14	-0.02	-0.04	-0.29	-0.61	0.11	0.08	-0.01	-0.29	-0.44
13	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.22	-0.62	0.14	-0.02	-0.04	-0.28	-0.62	0.11	0.08	-0.01	-0.29	-0.44
14	0.11	0.02	-0.03	-0.10	-0.49	0.16	0.01	-0.09	-0.24	-0.59	0.15	-0.02	-0.04	-0.28	-0.62	0.12	0.07	-0.01	-0.28	-0.45
15	0.10	0.02	-0.03	-0.09	-0.48	0.17	0.01	-0.09	-0.23	-0.60	0.15	-0.02	-0.04	-0.29	-0.62	0.13	0.08	-0.01	-0.28	-0.45
16	0.09	0.02	-0.03	-0.09	-0.48	0.17	0.02	-0.09	-0.24	-0.61	0.15	-0.02	-0.03	-0.29	-0.63	0.13	0.07	-0.01	-0.27	-0.47
17	0.08	0.02	-0.03	-0.09	-0.48	0.17	0.02	-0.09	-0.23	-0.63	0.14	-0.02	-0.04	-0.28	-0.62	0.12	0.07	-0.01	-0.28	-0.46
18	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.23	-0.61	0.14	-0.02	-0.05	-0.28	-0.61	0.12	0.07	-0.01	-0.28	-0.45
19	0.09	0.03	-0.03	-0.12	-0.49	0.17	0.01	-0.09	-0.24	-0.61	0.14	-0.02	-0.05	-0.28	-0.61	0.11	0.07	-0.01	-0.28	-0.45
20	0.09	0.02	-0.03	-0.10	-0.49	0.17	0.01	-0.11	-0.22	-0.62	0.15	-0.03	-0.04	-0.28	-0.61	0.12	0.08	-0.01	-0.28	-0.45
21	0.10	0.02	-0.03	-0.12	-0.49	0.18	0.02	-0.11	-0.22	-0.62	0.15	-0.03	-0.03	-0.28	-0.61	0.12	0.07	-0.01	-0.29	-0.45
22	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.08	-0.24	-0.60	0.14	-0.03	-0.04	-0.29	-0.60	0.12	0.08	-0.01	-0.28	-0.45
23	0.11	0.02	-0.03	-0.10	-0.48	0.17	0.02	-0.10	-0.23	-0.62	0.14	-0.02	-0.04	-0.28	-0.60	0.11	0.08	-0.01	-0.29	-0.44
24	0.10	0.02	-0.03	-0.10	-0.49	0.17	0.01	-0.09	-0.23	-0.61	0.14	-0.02	-0.04	-0.28	-0.60	0.12	0.07	-0.01	-0.29	-0.44
25	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.11	-0.22	-0.60	0.14	-0.02	-0.04	-0.28	-0.61	0.12	0.08	-0.01	-0.27	-0.46
26	0.11	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.11	-0.22	-0.61	0.14	-0.02	-0.05	-0.28	-0.60	0.10	0.08	0.00	-0.30	-0.44
27	0.10	0.02	-0.03	-0.11	-0.48	0.16	0.01	-0.10	-0.23	-0.61	0.14	-0.02	-0.05	-0.28	-0.61	0.11	0.07	0.00	-0.30	-0.44
28	0.09	0.02	-0.03	-0.10	-0.49	0.17	0.02	-0.10	-0.22	-0.62	0.14	-0.02	-0.05	-0.28	-0.61	0.13	0.08	0.00	-0.27	-0.45
29	0.08	0.02	-0.03	-0.08	-0.48	0.17	0.02	-0.10	-0.23	-0.62	0.14	-0.02	-0.04	-0.28	-0.61	0.12	0.08	0.00	-0.27	-0.46
30	0.10	0.02	-0.03	-0.09	-0.48	0.15	0.01	-0.10	-0.23	-0.60	0.15	-0.03	-0.03	-0.29	-0.62	0.11	0.08	-0.01	-0.29	-0.45
31	0.09	0.02	-0.03	-0.10	-0.48	0.17	0.02	-0.11	-0.23	-0.61	0.14	-0.02	-0.05	-0.28	-0.60	0.11	0.08	-0.01	-0.28	-0.45
32	0.11	0.03	-0.02	-0.10	-0.49	0.17	0.01	-0.09	-0.23	-0.62	0.14	-0.03	-0.04	-0.28	-0.61	0.13	0.07	0.00	-0.28	-0.46
33	0.09	0.03	-0.03	-0.11	-0.49	0.18	0.01	-0.09	-0.23	-0.61	0.14	-0.03	-0.03	-0.29	-0.61	0.13	0.07	-0.01	-0.28	-0.45
34	0.11	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.24	-0.60	0.14	-0.02	-0.04	-0.28	-0.60	0.12	0.08	-0.02	-0.28	-0.45
35	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.00	-0.09	-0.23	-0.59	0.15	-0.03	-0.04	-0.28	-0.60	0.12	0.08	-0.01	-0.27	-0.45
36	0.11	0.02	-0.03	-0.09	-0.48	0.16	0.00	-0.09	-0.25	-0.59	0.14	-0.02	-0.05	-0.28	-0.61	0.12	0.08	-0.01	-0.27	-0.45
37	0.10	0.02	-0.03	-0.09	-0.48	0.18	0.02	-0.09	-0.23	-0.61	0.14	-0.03	-0.05	-0.28	-0.60	0.13	0.07	-0.01	-0.28	-0.45
38	0.10	0.02	-0.03	-0.09	-0.48	0.17	0.02	-0.09	-0.25	-0.61	0.14	-0.02	-0.04	-0.29	-0.61	0.12	0.07	-0.01	-0.29	-0.44
39	0.11	0.01	-0.03	-0.09	-0.47	0.16	0.01	-0.09	-0.24	-0.60	0.14	-0.03	-0.04	-0.29	-0.62	0.11	0.08	-0.01	-0.29	-0.44
40	0.10	0.02	-0.03	-0.10	-0.49	0.16	0.01	-0.11	-0.22	-0.60	0.15	-0.02	-0.04	-0.28	-0.61	0.12	0.08	0.00	-0.28	-0.45
41	0.09	0.02	-0.03	-0.09	-0.48	0.17	0.01	-0.10	-0.23	-0.60	0.14	-0.02	-0.05	-0.28	-0.61	0.12	0.08	-0.01	-0.27	-0.45
42	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.23	-0.60	0.14	-0.02	-0.04	-0.28	-0.61	0.12	0.07	-0.01	-0.28	-0.46
43	0.10	0.02	-0.03	-0.11	-0.48	0.16	0.01	-0.09	-0.25	-0.59	0.14	-0.02	-0.05	-0.28	-0.60	0.12	0.07	-0.01	-0.28	-0.45
44	0.11	0.02	-0.03	-0.13	-0.49	0.17	0.01	-0.10	-0.23	-0.60	0.14	-0.03	-0.04	-0.28	-0.61	0.12	0.07	-0.01	-0.28	-0.45
45	0.11	0.03	-0.03	-0.10	-0.49	0.17	0.01	-0.11	-0.22	-0.61	0.14	-0.03	-0.04	-0.29	-0.61	0.12	0.08	0.00	-0.28	-0.45
46	0.11	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.22	-0.61	0.15	-0.02	-0.06	-0.28	-0.61	0.11	0.08	-0.01	-0.29	-0.43
47	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.11	-0.23	-0.61	0.14	-0.02	-0.05	-0.29	-0.61	0.12	0.08	0.00	-0.28	-0.44
48	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.02	-0.10	-0.23	-0.61	0.14	-0.02	-0.05	-0.28	-0.60	0.12	0.08	-0.01	-0.28	-0.45
49	0.10	0.02	-0.03	-0.09	-0.48	0.17	0.02	-0.12	-0.22	-0.62	0.15	-0.02	-0.04	-0.28	-0.61	0.12	0.08	-0.01	-0.28	-0.45
50	0.09	0.02	-0.03	-0.09	-0.48	0.16	0.01	-0.10	-0.23	-0.61	0.14	-0.03	-0.04	-0.29	-0.62	0.12	0.07	-0.01	-0.28	-0.46
51	0.11	0.01	-0.03	-0.09	-0.47	0.16	0.01	-0.11	-0.22	-0.60	0.15	-0.02	-0.05	-0.28	-0.61	0.12	0.07	-0.01	-0.28	-0.45
52	0.09	0.02	-0.03	-0.10	-0.49	0.15	0.00	-0.09	-0.23	-0.60	0.15	-0.02	-0.04	-0.28	-0.62	0.12	0.08	-0.01	-0.28	-0.45
53	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.23	-0.60	0.15	-0.02	-0.05	-0.27	-0.61	0.12	0.08	0.00	-0.28	-0.46

	Low Income/No Child					*Low Income/Child*					*High Income/No Child*					*High Income/Child*				
	Eigenvalue					Eigenvalue					Eigenvalue					Eigenvalue				
Observation	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
54	0.09	0.02	-0.03	-0.10	-0.48	0.15	0.01	-0.11	-0.23	-0.60	0.14	-0.03	-0.04	-0.28	-0.61	0.12	0.08	-0.01	-0.28	-0.45
55	0.10	0.02	-0.03	-0.09	-0.48	0.16	0.01	-0.08	-0.26	-0.58	0.13	-0.03	-0.05	-0.28	-0.60	0.12	0.08	-0.01	-0.28	-0.45
56	0.10	0.02	-0.03	-0.11	-0.49	0.17	0.02	-0.11	-0.22	-0.61	0.14	-0.02	-0.04	-0.28	-0.61	0.11	0.09	-0.01	-0.28	-0.44
57	0.11	0.02	-0.03	-0.11	-0.48	0.17	0.02	-0.10	-0.24	-0.61	0.14	-0.03	-0.04	-0.28	-0.61	0.13	0.07	-0.01	-0.29	-0.45
58	0.09	0.02	-0.03	-0.09	-0.48	0.17	0.01	-0.08	-0.25	-0.59	0.14	-0.03	-0.03	-0.28	-0.60	0.12	0.08	-0.01	-0.29	-0.44
59	0.11	0.02	-0.03	-0.11	-0.48	0.16	0.00	-0.08	-0.25	-0.59	0.14	-0.03	-0.04	-0.28	-0.60	0.11	0.08	-0.01	-0.28	-0.45
60	0.10	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.11	-0.22	-0.60	0.14	-0.03	-0.04	-0.29	-0.60	0.11	0.08	-0.01	-0.28	-0.45
61	0.11	0.02	-0.03	-0.11	-0.48	0.17	0.01	-0.08	-0.24	-0.60	0.15	-0.02	-0.05	-0.28	-0.61	0.12	0.08	-0.01	-0.28	-0.45
62	0.11	0.01	-0.03	-0.10	-0.48	0.17	0.02	-0.09	-0.24	-0.60	0.15	-0.02	-0.04	-0.29	-0.63	0.12	0.08	-0.01	-0.27	-0.46
63	0.09	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.23	-0.60	0.14	-0.02	-0.05	-0.28	-0.61	0.11	0.08	-0.01	-0.29	-0.44
64	0.09	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.09	-0.24	-0.60	0.16	-0.02	-0.04	-0.28	-0.62	0.12	0.08	-0.01	-0.28	-0.45
65	0.10	0.01	-0.03	-0.10	-0.47	0.18	0.02	-0.08	-0.25	-0.61	0.15	-0.02	-0.04	-0.29	-0.62	0.12	0.07	0.00	-0.29	-0.45
66	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.08	-0.24	-0.60	0.15	-0.02	-0.05	-0.28	-0.61	0.11	0.08	-0.01	-0.27	-0.45
67	0.11	0.02	-0.03	-0.10	-0.48	0.16	0.02	-0.11	-0.23	-0.61	0.13	-0.03	-0.05	-0.28	-0.61	0.12	0.08	-0.01	-0.28	-0.45
68	0.11	0.02	-0.03	-0.11	-0.48	0.17	0.01	-0.09	-0.24	-0.60	0.14	-0.03	-0.04	-0.28	-0.61	0.10	0.08	-0.01	-0.30	-0.44
69	0.10	0.03	-0.03	-0.11	-0.49	0.18	0.02	-0.11	-0.22	-0.61	0.14	-0.03	-0.04	-0.29	-0.61	0.12	0.07	-0.01	-0.29	-0.44
70	0.12	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.23	-0.59	0.14	-0.02	-0.05	-0.28	-0.60	0.10	0.08	-0.01	-0.30	-0.43
71	0.11	0.01	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.25	-0.59	0.14	-0.03	-0.05	-0.28	-0.60	0.11	0.09	-0.01	-0.28	-0.44
72	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.24	-0.59	0.14	-0.03	-0.05	-0.29	-0.61	0.12	0.08	-0.01	-0.27	-0.45
73	0.09	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.10	-0.24	-0.60	0.14	-0.02	-0.05	-0.28	-0.61	0.12	0.08	-0.01	-0.28	-0.45
74	0.09	0.02	-0.03	-0.11	-0.48	0.15	0.00	-0.09	-0.23	-0.60	0.15	-0.02	-0.04	-0.29	-0.62	0.10	0.08	-0.01	-0.29	-0.44
75	0.11	0.02	-0.03	-0.10	-0.48	0.16	0.00	-0.08	-0.25	-0.58	0.14	-0.02	-0.04	-0.29	-0.62	0.12	0.07	-0.01	-0.28	-0.45
76	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.00	-0.09	-0.24	-0.58	0.15	-0.02	-0.04	-0.28	-0.61	0.12	0.07	-0.01	-0.30	-0.44
77	0.10	0.02	-0.03	-0.09	-0.48	0.17	0.01	-0.10	-0.23	-0.61	0.16	-0.02	-0.04	-0.29	-0.63	0.12	0.08	0.00	-0.27	-0.46
78	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.11	-0.24	-0.60	0.14	-0.02	-0.05	-0.28	-0.61	0.12	0.07	-0.01	-0.29	-0.45
79	0.10	0.01	-0.03	-0.10	-0.48	0.17	0.01	-0.09	-0.25	-0.59	0.15	-0.02	-0.04	-0.29	-0.61	0.12	0.08	-0.01	-0.27	-0.45
80	0.11	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.09	-0.25	-0.59	0.13	-0.03	-0.05	-0.29	-0.61	0.11	0.08	-0.01	-0.29	-0.44
81	0.11	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.23	-0.59	0.13	-0.02	-0.05	-0.29	-0.60	0.12	0.08	-0.02	-0.27	-0.45
82	0.11	0.01	-0.03	-0.09	-0.48	0.16	0.00	-0.09	-0.24	-0.58	0.14	-0.02	-0.05	-0.29	-0.61	0.12	0.09	-0.01	-0.28	-0.44
83	0.10	0.02	-0.03	-0.09	-0.48	0.16	0.01	-0.09	-0.25	-0.60	0.14	-0.03	-0.04	-0.28	-0.60	0.12	0.08	-0.01	-0.28	-0.44
84	0.10	0.02	-0.03	-0.11	-0.48	0.17	0.00	-0.07	-0.26	-0.58	0.15	-0.02	-0.04	-0.29	-0.61	0.11	0.09	-0.02	-0.27	-0.45
85	0.12	0.01	-0.03	-0.09	-0.47	0.15	0.00	-0.10	-0.24	-0.60	0.14	-0.02	-0.05	-0.28	-0.61	0.12	0.09	-0.01	-0.27	-0.45
86	0.10	0.02	-0.03	-0.11	-0.48	0.16	0.01	-0.07	-0.25	-0.59	0.15	-0.02	-0.04	-0.28	-0.60	0.11	0.07	-0.01	-0.28	-0.45
87	0.11	0.02	-0.03	-0.10	-0.48	0.15	0.00	-0.09	-0.24	-0.59	0.14	-0.02	-0.05	-0.29	-0.61	0.11	0.08	-0.02	-0.28	-0.44
88	0.10	0.01	-0.03	-0.09	-0.47	0.16	0.01	-0.10	-0.24	-0.59	0.14	-0.02	-0.06	-0.28	-0.61	0.11	0.08	-0.01	-0.29	-0.45
89	0.10	0.02	-0.03	-0.09	-0.48	0.16	0.00	-0.10	-0.23	-0.58	0.14	-0.02	-0.04	-0.28	-0.62	0.12	0.07	-0.01	-0.28	-0.45
90	0.10	0.02	-0.03	-0.10	-0.49	0.17	0.01	-0.08	-0.27	-0.59	0.15	-0.02	-0.04	-0.28	-0.61	0.13	0.07	-0.01	-0.26	-0.47
91	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.24	-0.60	0.14	-0.03	-0.04	-0.29	-0.61	0.11	0.09	-0.02	-0.28	-0.45
92	0.11	0.02	-0.03	-0.10	-0.49	0.16	0.01	-0.09	-0.25	-0.59	0.14	-0.02	-0.05	-0.28	-0.60	0.11	0.08	-0.01	-0.28	-0.44
93	0.11	0.02	-0.03	-0.11	-0.48	0.16	0.01	-0.09	-0.25	-0.59	0.14	-0.03	-0.04	-0.29	-0.60	0.11	0.07	-0.01	-0.30	-0.44
94	0.10	0.01	-0.03	-0.09	-0.47	0.15	0.00	-0.10	-0.24	-0.58	0.15	-0.02	-0.06	-0.29	-0.59	0.09	0.09	-0.01	-0.30	-0.43
95	0.10	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.09	-0.24	-0.59	0.15	-0.02	-0.05	-0.30	-0.61	0.11	0.08	-0.02	-0.29	-0.44
96	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.00	-0.08	-0.24	-0.57	0.15	-0.02	-0.05	-0.28	-0.60	0.11	0.08	-0.01	-0.29	-0.44
97	0.10	0.02	-0.03	-0.11	-0.48	0.16	0.01	-0.10	-0.24	-0.60	0.14	-0.03	-0.05	-0.29	-0.61	0.11	0.08	-0.02	-0.28	-0.44
98	0.10	0.02	-0.03	-0.11	-0.48	0.16	0.00	-0.08	-0.26	-0.58	0.14	-0.03	-0.05	-0.29	-0.60	0.13	0.08	-0.02	-0.26	-0.45
99	0.10	0.02	-0.03	-0.10	-0.48	0.16	0.01	-0.09	-0.26	-0.59	0.14	-0.02	-0.04	-0.29	-0.62	0.12	0.08	-0.02	-0.27	-0.46
100	0.10	0.02	-0.03	-0.10	-0.48	0.17	0.01	-0.08	-0.25	-0.59	0.16	-0.02	-0.04	-0.29	-0.62	0.14	0.08	-0.01	-0.25	-0.47
101	0.10	0.01	-0.03	-0.10	-0.48	0.16	0.01	-0.09	-0.24	-0.60	0.15	-0.02	-0.04	-0.30	-0.62	0.11	0.08	-0.01	-0.28	-0.45
102	0.10	0.02	-0.03	-0.10	-0.47	0.16	0.01	-0.10	-0.24	-0.60	0.14	-0.02	-0.05	-0.29	-0.61	0.12	0.07	-0.02	-0.28	-0.45
103	0.10	0.02	-0.03	-0.11	-0.48	0.17	0.01	-0.09	-0.24	-0.60	0.15	-0.02	-0.04	-0.29	-0.63	0.12	0.08	-0.01	-0.28	-0.45
104	0.10	0.02	-0.03	-0.10	-0.48	0.15	0.00	-0.10	-0.24	-0.58	0.14	-0.03	-0.05	-0.29	-0.60	0.11	0.07	-0.01	-0.29	-0.44
105	0.11	0.02	-0.03	-0.13	-0.49	0.17	0.02	-0.12	-0.21	-0.63	0.15	-0.02	-0.04	-0.29	-0.61	0.12	0.08	-0.02	-0.28	-0.45

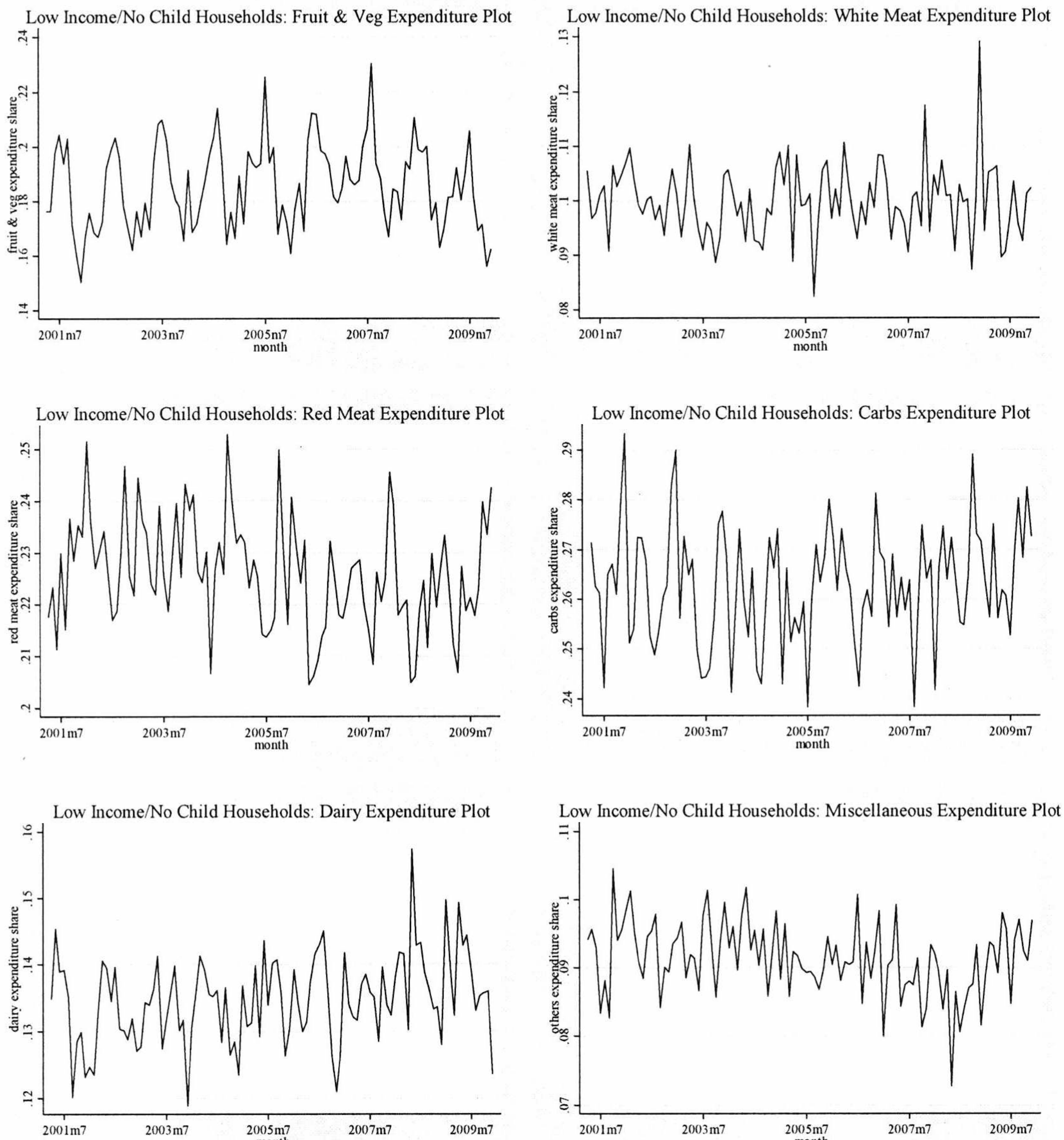

Figure 7.9 Case 1: Food Expenditure Budget Shares Plots

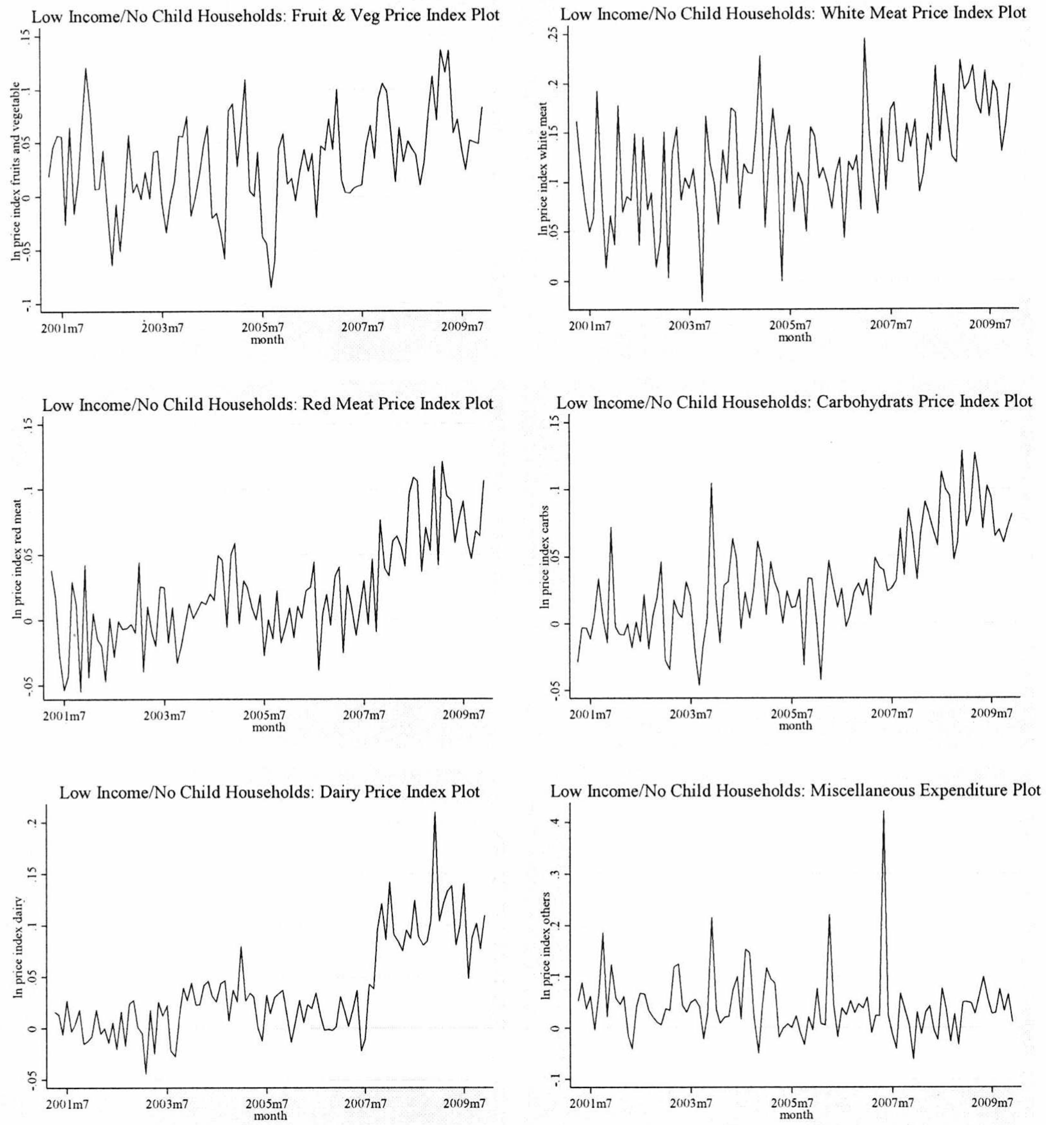

Figure 7.10 Case 1: Food Expenditure Price Index Plots

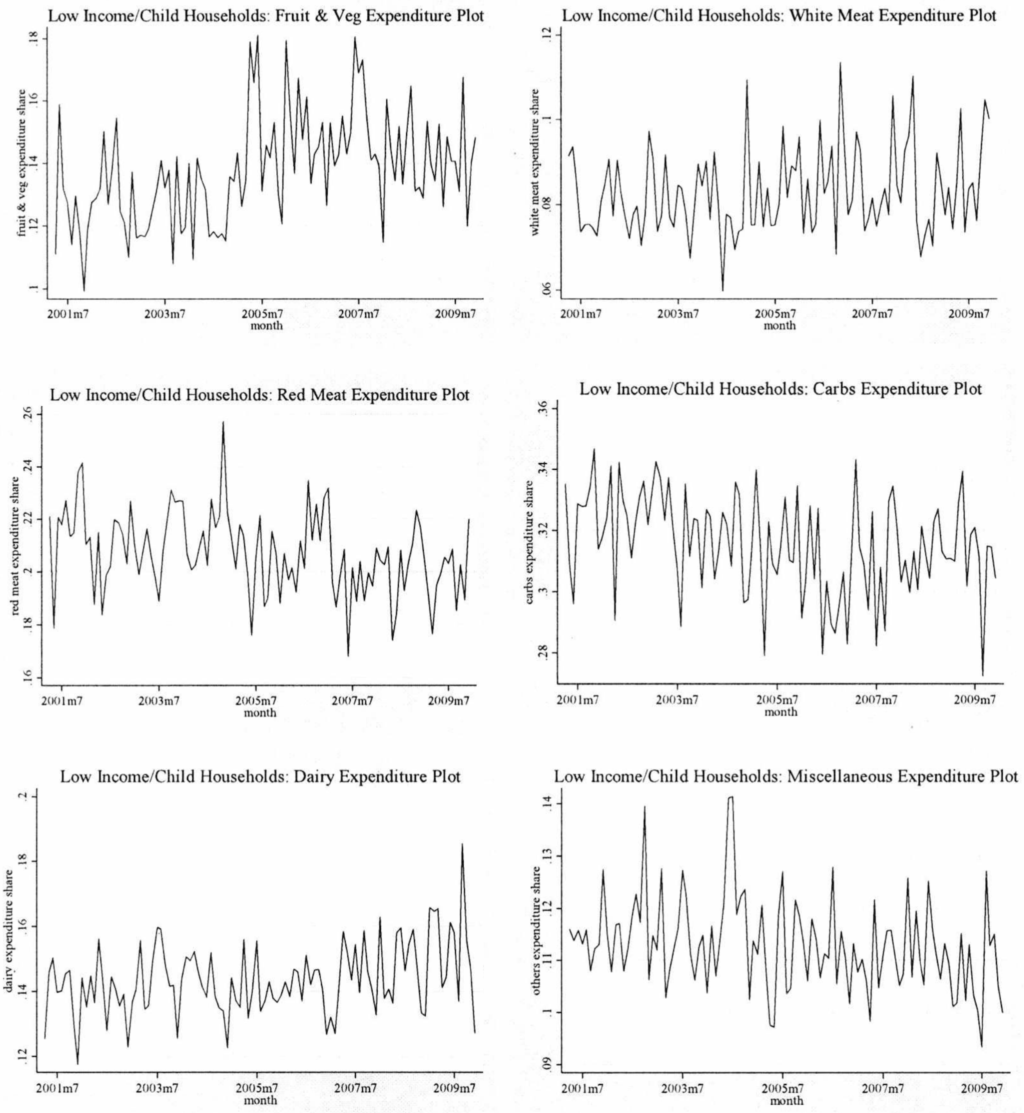

Figure 7.11 Case 2: Food Expenditure Budget Shares Plots

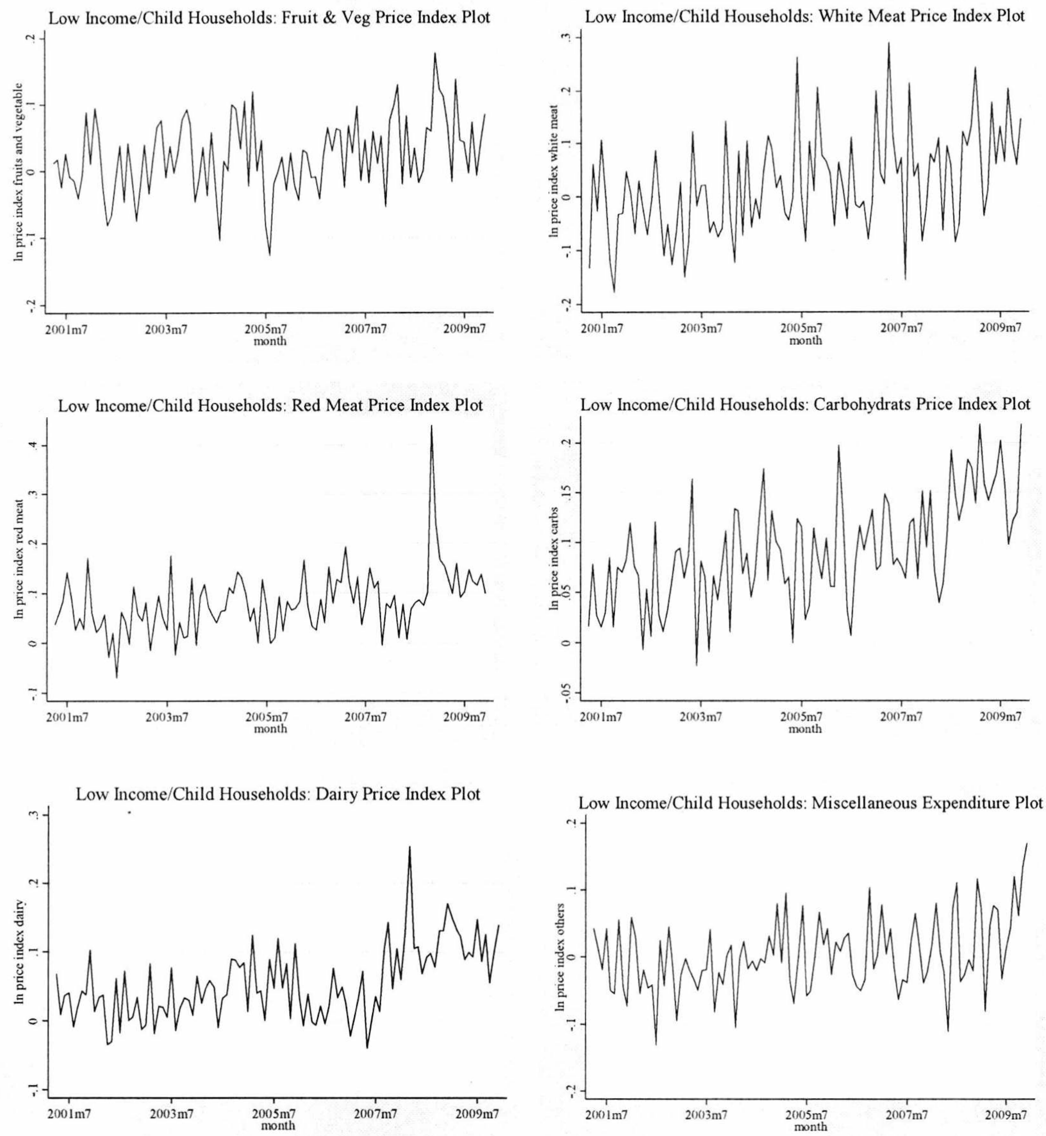

Figure 7.12 Case 2: Food Expenditure Price Index Plots

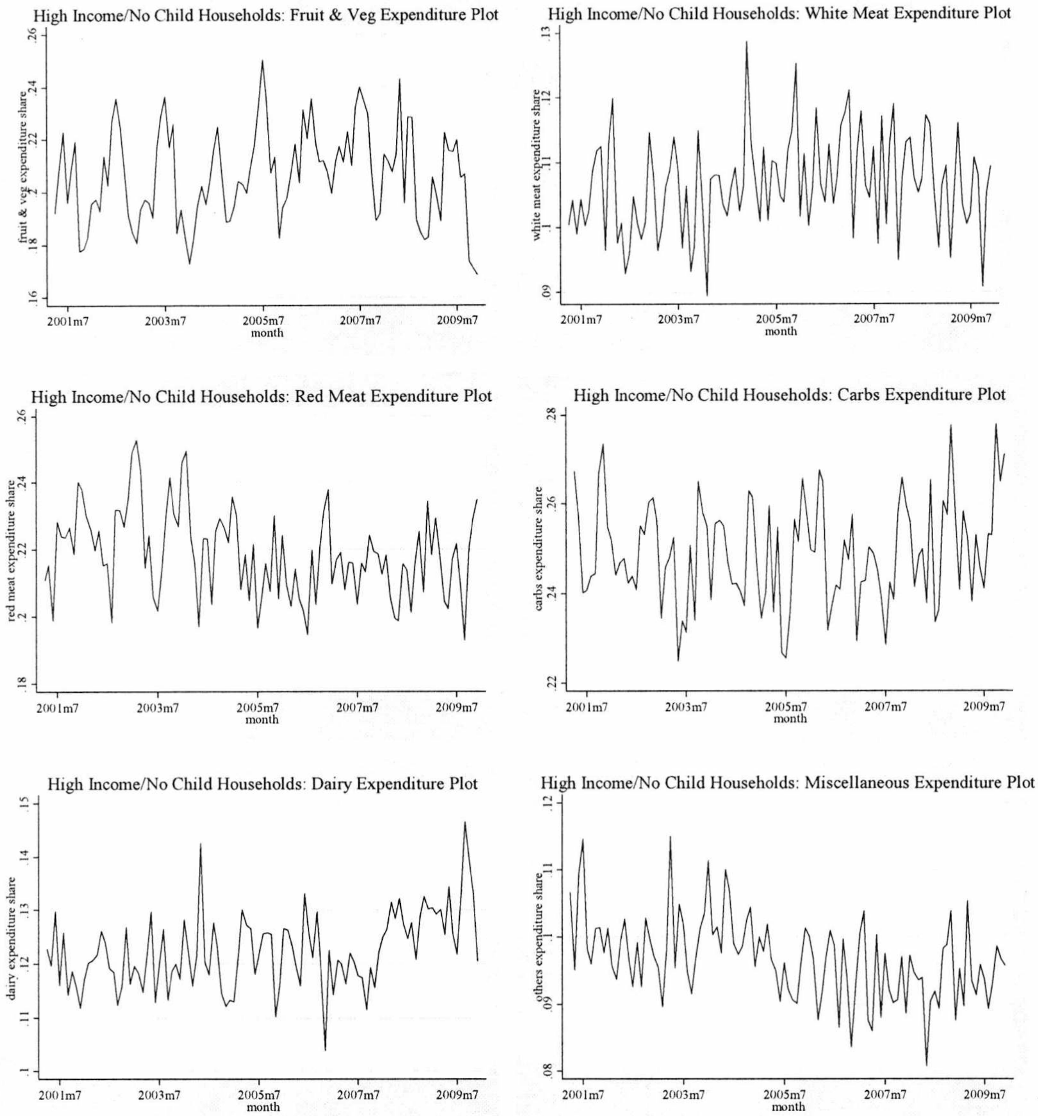

Figure 7.13 Case 3: Food Expenditure Budget Shares Plots

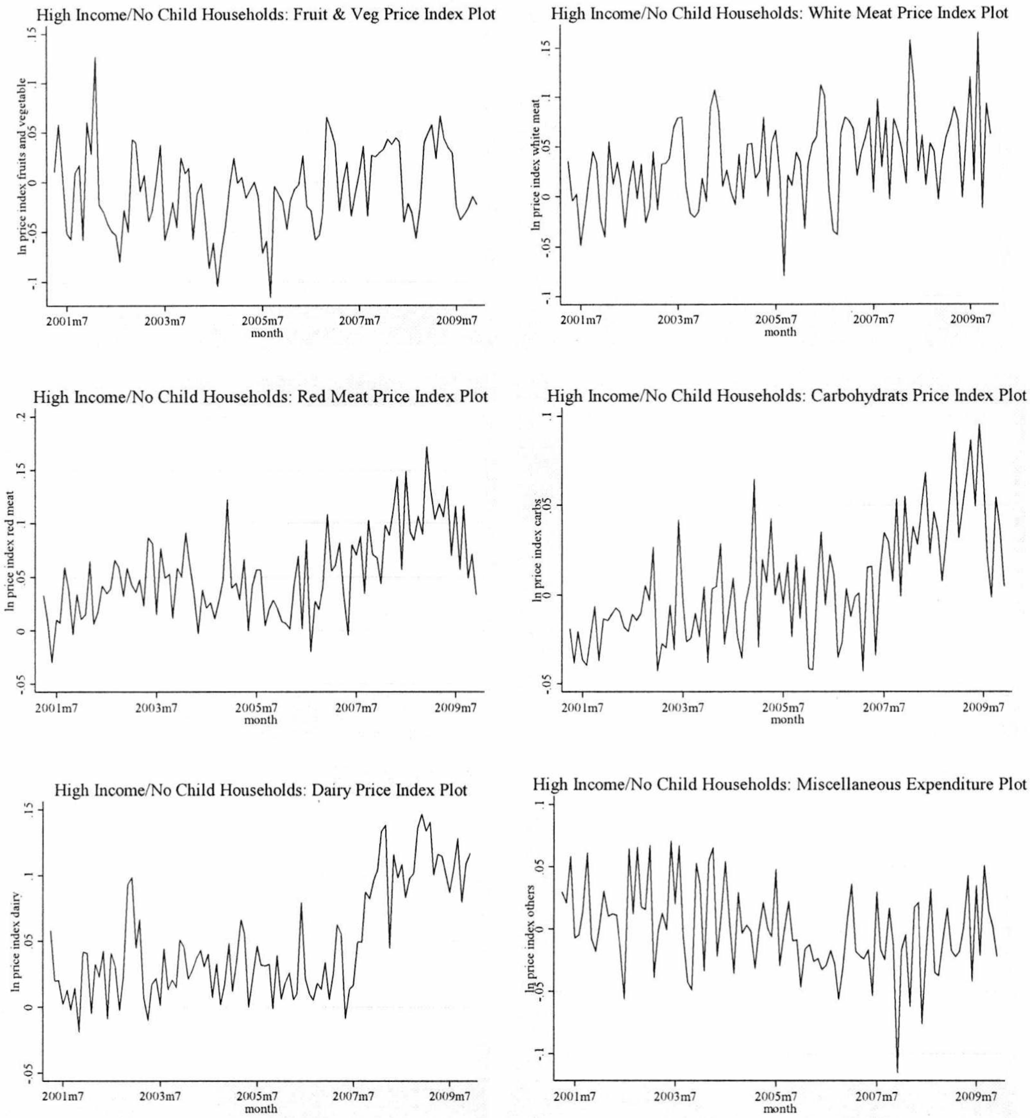

Figure 7.14 Case 3: Food Expenditure Price Index Plots

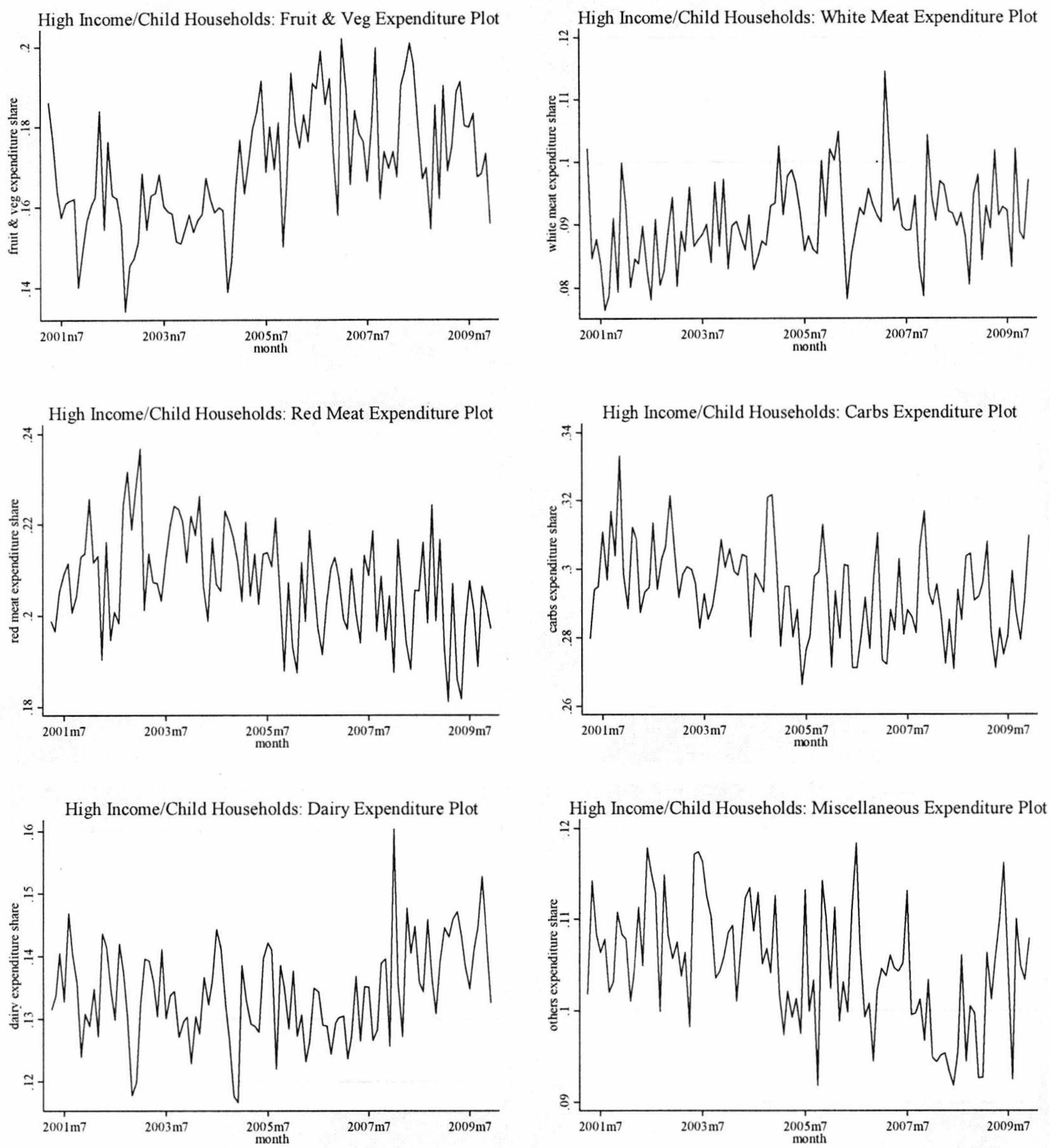

Figure 7.15 Case 4: Food Expenditure Budget Shares Plots

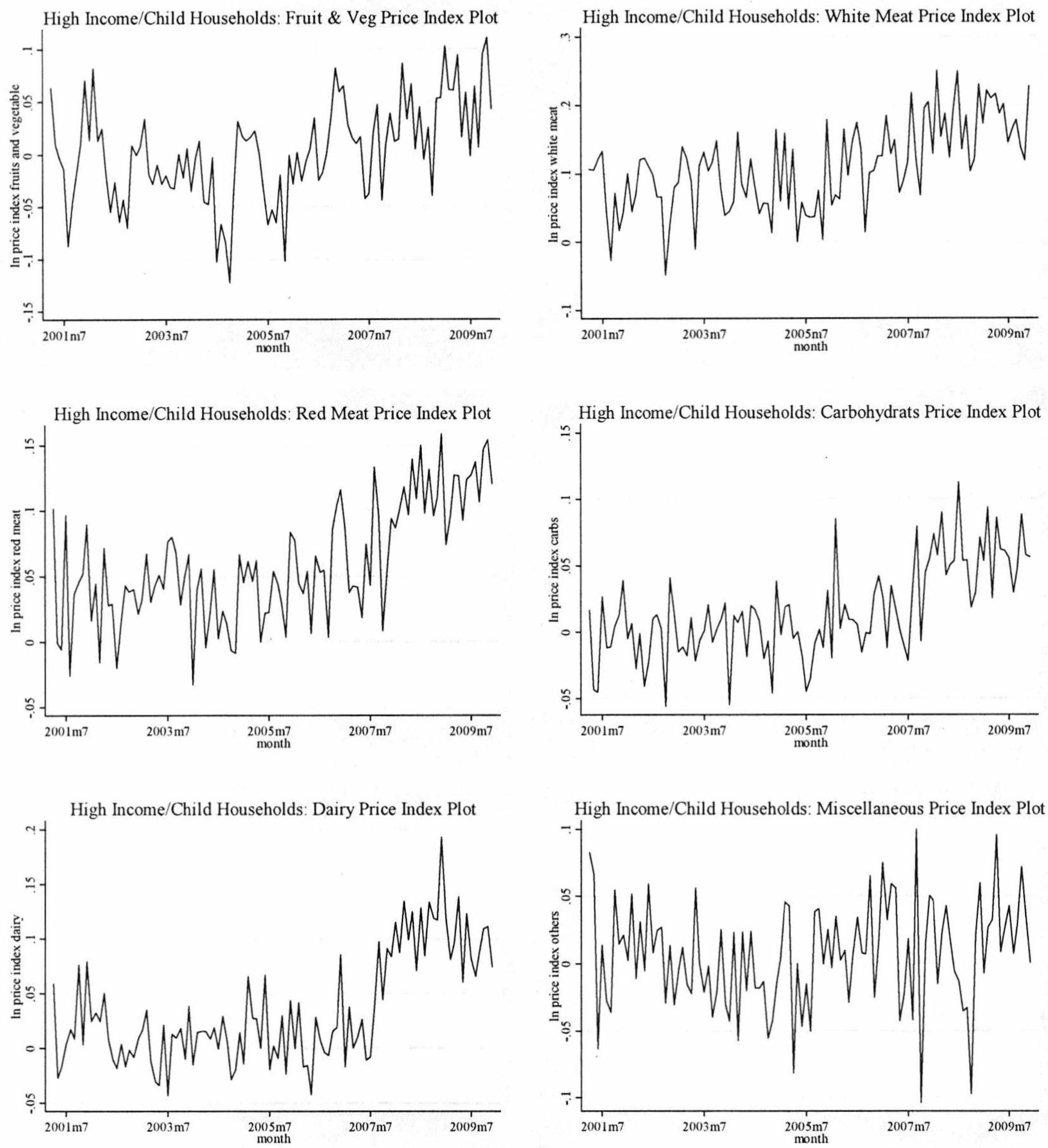

Figure 7.16 Case 4: Food Expenditure Price Index Plots

Table 7.2 Food Expenditure Concavity Tests

	Low Income/No Child Eigenvalue					*Low Income/Child* Eigenvalue					*High Income/No Child* Eigenvalue					*High Income/Child* Eigenvalue				
Observation	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1	-0.01	-0.02	-0.08	-0.12	-0.17	-0.02	-0.05	-0.10	-0.15	-0.21	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.0021	-0.02	-0.08	-0.17
2	-0.01	-0.02	-0.09	-0.12	-0.17	-0.02	-0.04	-0.10	-0.15	-0.21	0.01	-0.02	-0.04	-0.06	-0.18	0.03	-0.0011	-0.02	-0.09	-0.18
3	-0.003	-0.01	-0.09	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.17	0.04	-0.0004	-0.03	-0.08	-0.18
4	-0.01	-0.02	-0.09	-0.12	-0.17	-0.02	-0.04	-0.09	-0.15	-0.22	0.01	-0.02	-0.05	-0.07	-0.18	0.03	-0.0013	-0.02	-0.08	-0.18
5	0.003	-0.01	-0.09	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.0001	-0.03	-0.08	-0.18
6	-0.001	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.09	-0.15	-0.22	0.01	-0.01	-0.06	-0.07	-0.16	0.03	-0.0002	-0.02	-0.09	-0.18
7	-0.005	-0.02	-0.08	-0.12	-0.18	-0.02	-0.03	-0.08	-0.14	-0.23	0.01	-0.01	-0.05	-0.08	-0.16	0.05	-0.0002	-0.04	-0.08	-0.17
8	-0.003	-0.02	-0.07	-0.12	-0.18	-0.02	-0.04	-0.09	-0.14	-0.22	0.01	-0.01	-0.05	-0.08	-0.17	0.04	-0.0005	-0.02	-0.09	-0.18
9	0.004	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.10	-0.15	-0.21	0.01	-0.01	-0.05	-0.07	-0.17	0.04	-0.0005	-0.02	-0.09	-0.18
10	0.004	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.10	-0.15	-0.21	0.01	-0.01	-0.05	-0.08	-0.17	0.03	0.0002	-0.03	-0.08	-0.18
11	-0.01	-0.02	-0.08	-0.12	-0.18	-0.02	-0.05	-0.09	-0.14	-0.22	0.01	-0.01	-0.05	-0.08	-0.17	0.04	0.0000	-0.03	-0.08	-0.18
12	-0.01	-0.02	-0.08	-0.12	-0.18	-0.02	-0.05	-0.10	-0.15	-0.21	0.01	-0.02	-0.05	-0.06	-0.18	0.02	-0.0021	-0.02	-0.08	-0.18
13	-0.01	-0.02	-0.08	-0.12	-0.18	-0.02	-0.04	-0.10	-0.14	-0.22	0.01	-0.02	-0.05	-0.07	-0.18	0.04	-0.0007	-0.02	-0.09	-0.18
14	-0.003	-0.02	-0.09	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.21	0.01	-0.02	-0.04	-0.06	-0.19	0.03	-0.0025	-0.02	-0.08	-0.17
15	-0.004	-0.02	-0.09	-0.12	-0.17	-0.02	-0.05	-0.08	-0.15	-0.21	0.01	-0.01	-0.04	-0.06	-0.19	0.04	-0.0016	-0.03	-0.08	-0.17
16	-0.001	-0.02	-0.09	-0.12	-0.18	-0.02	-0.04	-0.09	-0.15	-0.21	0.01	-0.01	-0.04	-0.07	-0.19	0.03	-0.0018	-0.02	-0.09	-0.18
17	-0.002	-0.01	-0.09	-0.12	-0.18	-0.02	-0.04	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.18	0.04	0.0003	-0.03	-0.08	-0.18
18	-0.001	-0.02	-0.08	-0.12	-0.18	-0.02	-0.03	-0.08	-0.14	-0.22	0.01	-0.01	-0.06	-0.07	-0.17	0.05	-0.0011	-0.03	-0.08	-0.18
19	-0.01	-0.02	-0.08	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.22	0.00	-0.02	-0.05	-0.07	-0.17	0.05	0.0004	-0.03	-0.08	-0.18
20	-0.005	-0.02	-0.08	-0.12	-0.18	-0.02	-0.04	-0.10	-0.14	-0.21	0.01	-0.01	-0.05	-0.08	-0.17	0.05	0.0005	-0.03	-0.09	-0.18
21	0.001	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.10	-0.14	-0.22	0.01	-0.01	-0.05	-0.08	-0.17	0.04	-0.0005	-0.03	-0.08	-0.19
22	-0.01	-0.02	-0.08	-0.12	-0.18	-0.02	-0.04	-0.09	-0.14	-0.22	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.0005	-0.02	-0.09	-0.18
23	-0.004	-0.02	-0.09	-0.12	-0.18	-0.01	-0.04	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.17	0.04	-0.0007	-0.02	-0.09	-0.18
24	-0.01	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.10	-0.15	-0.21	0.01	-0.01	-0.05	-0.07	-0.17	0.03	0.0005	-0.02	-0.09	-0.18
25	-0.01	-0.02	-0.09	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.22	0.01	-0.02	-0.04	-0.07	-0.18	0.03	-0.0018	-0.02	-0.08	-0.18
26	0.003	-0.01	-0.09	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.21	0.01	-0.01	-0.04	-0.07	-0.19	0.03	-0.0024	-0.01	-0.09	-0.18
27	0.001	-0.02	-0.09	-0.12	-0.18	-0.02	-0.04	-0.10	-0.14	-0.21	0.01	-0.02	-0.04	-0.07	-0.19	0.04	-0.0017	-0.02	-0.09	-0.18
28	-0.002	-0.02	-0.09	-0.12	-0.17	-0.02	-0.05	-0.10	-0.15	-0.21	0.01	-0.02	-0.05	-0.06	-0.18	0.03	-0.0013	-0.02	-0.09	-0.18
29	-0.01	-0.02	-0.09	-0.12	-0.18	-0.02	-0.03	-0.09	-0.15	-0.22	0.01	-0.01	-0.04	-0.07	-0.19	0.03	-0.0010	-0.02	-0.08	-0.18
30	-0.004	-0.02	-0.09	-0.12	-0.18	-0.02	-0.05	-0.08	-0.16	-0.22	0.01	-0.01	-0.06	-0.06	-0.17	0.04	0.0003	-0.02	-0.09	-0.18
31	-0.01	-0.02	-0.09	-0.12	-0.18	-0.02	-0.04	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.17	0.04	0.0002	-0.03	-0.08	-0.18
32	0.004	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.10	-0.14	-0.21	0.01	-0.01	-0.05	-0.08	-0.17	0.04	-0.0002	-0.02	-0.09	-0.18
33	0.002	-0.02	-0.09	-0.13	-0.18	-0.02	-0.05	-0.10	-0.15	-0.21	0.01	-0.02	-0.05	-0.07	-0.16	0.04	-0.0003	-0.03	-0.08	-0.18
34	-0.004	-0.02	-0.08	-0.13	-0.18	-0.02	-0.03	-0.10	-0.14	-0.22	0.01	-0.01	-0.06	-0.06	-0.17	0.04	-0.0007	-0.02	-0.09	-0.18
35	-0.01	-0.02	-0.08	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.17	0.04	0.0005	-0.03	-0.09	-0.18
36	-0.01	-0.02	-0.09	-0.12	-0.17	-0.02	-0.05	-0.10	-0.15	-0.21	0.01	-0.01	-0.05	-0.07	-0.18	0.04	-0.0007	-0.02	-0.09	-0.18
37	-0.003	-0.02	-0.09	-0.12	-0.18	-0.02	-0.05	-0.09	-0.15	-0.21	0.01	-0.03	-0.04	-0.07	-0.17	0.03	-0.0014	-0.02	-0.08	-0.17
38	-0.01	-0.02	-0.10	-0.12	-0.17	-0.02	-0.04	-0.07	-0.14	-0.22	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.0016	-0.01	-0.09	-0.18
39	-0.002	-0.02	-0.09	-0.12	-0.18	-0.02	-0.04	-0.09	-0.14	-0.21	0.01	-0.01	-0.04	-0.07	-0.18	0.03	-0.0013	-0.02	-0.08	-0.18
40	0.003	-0.01	-0.09	-0.12	-0.18	-0.02	-0.04	-0.09	-0.15	-0.22	0.01	-0.02	-0.04	-0.07	-0.19	0.03	-0.0018	-0.02	-0.08	-0.18
41	-0.005	-0.02	-0.09	-0.12	-0.18	-0.02	-0.04	-0.08	-0.14	-0.22	0.01	-0.02	-0.04	-0.07	-0.18	0.03	-0.0003	-0.02	-0.09	-0.18
42	-0.002	-0.02	-0.08	-0.12	-0.19	-0.02	-0.04	-0.09	-0.14	-0.22	0.01	-0.01	-0.06	-0.07	-0.17	0.05	0.0001	-0.03	-0.08	-0.18
43	-0.002	-0.02	-0.08	-0.12	-0.18	-0.01	-0.05	-0.09	-0.15	-0.22	0.01	-0.01	-0.05	-0.07	-0.17	0.05	0.0009	-0.03	-0.09	-0.18
44	-0.0003	-0.02	-0.08	-0.13	-0.18	-0.02	-0.04	-0.11	-0.15	-0.21	0.01	-0.01	-0.05	-0.09	-0.17	0.04	-0.0008	-0.02	-0.09	-0.17
45	-0.001	-0.02	-0.09	-0.13	-0.18	-0.02	-0.05	-0.09	-0.15	-0.21	0.01	-0.01	-0.04	-0.08	-0.18	0.03	-0.0005	-0.01	-0.10	-0.18
46	-0.003	-0.02	-0.08	-0.12	-0.18	-0.02	-0.04	-0.09	-0.14	-0.22	0.01	-0.01	-0.05	-0.07	-0.18	0.03	0.0008	-0.02	-0.09	-0.18
47	-0.001	-0.01	-0.09	-0.13	-0.18	-0.02	-0.05	-0.10	-0.15	-0.21	0.01	-0.02	-0.05	-0.07	-0.17	0.03	-0.0001	-0.02	-0.09	-0.18
48	-0.01	-0.02	-0.09	-0.12	-0.18	-0.01	-0.06	-0.09	-0.16	-0.21	0.01	-0.02	-0.04	-0.07	-0.18	0.03	0.0001	-0.02	-0.09	-0.18
49	0.0003	-0.02	-0.09	-0.13	-0.18	-0.01	-0.06	-0.10	-0.15	-0.21	0.01	-0.02	-0.04	-0.07	-0.18	0.03	-0.0003	-0.02	-0.09	-0.18
50	-0.01	-0.02	-0.09	-0.12	-0.17	-0.02	-0.06	-0.09	-0.16	-0.20	0.01	-0.01	-0.04	-0.07	-0.19	0.02	-0.0001	-0.01	-0.09	-0.18
51	0.001	-0.01	-0.10	-0.12	-0.18	-0.02	-0.04	-0.09	-0.15	-0.21	0.01	-0.02	-0.03	-0.07	-0.20	0.03	-0.0020	-0.01	-0.09	-0.18
52	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.05	-0.09	-0.15	-0.21	0.01	-0.02	-0.04	-0.07	-0.19	0.02	-0.0002	-0.02	-0.09	-0.18

	Low Income/No Child					*Low Income/Child*					*High Income/No Child*					*High Income/Child*				
	Eigenvalue					Eigenvalue					Eigenvalue					Eigenvalue				
Observation	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
53	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.05	-0.07	-0.18	0.03	0.0001	-0.03	-0.08	-0.18
54	-0.005	-0.02	-0.08	-0.12	-0.18	-0.005	-0.02	-0.08	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.18	0.02	0.001	-0.02	-0.09	-0.18
55	-0.001	-0.02	-0.09	-0.13	-0.18	-0.001	-0.02	-0.09	-0.13	-0.18	0.01	-0.01	-0.06	-0.08	-0.17	0.04	-0.001	-0.02	-0.09	-0.18
56	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.01	-0.04	-0.08	-0.17	0.03	-0.001	-0.02	-0.09	-0.18
57	-0.01	-0.02	-0.08	-0.12	-0.18	-0.01	-0.02	-0.08	-0.12	-0.18	0.01	-0.02	-0.05	-0.07	-0.17	0.02	-0.001	-0.01	-0.10	-0.18
58	-0.004	-0.02	-0.09	-0.12	-0.18	-0.004	-0.02	-0.09	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.18	0.03	-0.002	-0.02	-0.09	-0.17
59	-0.004	-0.02	-0.09	-0.12	-0.18	-0.004	-0.02	-0.09	-0.12	-0.18	0.01	-0.02	-0.05	-0.07	-0.18	0.03	0.0002	-0.02	-0.10	-0.18
60	-0.003	-0.02	-0.08	-0.13	-0.18	-0.003	-0.02	-0.08	-0.13	-0.18	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.0004	-0.03	-0.09	-0.17
61	-0.01	-0.02	-0.10	-0.12	-0.17	-0.01	-0.02	-0.10	-0.12	-0.17	0.01	-0.01	-0.04	-0.07	-0.19	0.03	0.0004	-0.03	-0.08	-0.18
62	-0.01	-0.02	-0.10	-0.12	-0.17	-0.01	-0.02	-0.10	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.02	-0.002	-0.01	-0.09	-0.18
63	-0.005	-0.02	-0.09	-0.12	-0.17	-0.005	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.19	0.02	-0.003	-0.01	-0.09	-0.18
64	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.19	0.02	-0.002	-0.02	-0.09	-0.17
65	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.02	0.0000	-0.02	-0.09	-0.18
66	0.001	-0.01	-0.09	-0.12	-0.18	0.001	-0.01	-0.09	-0.12	-0.18	0.01	-0.01	-0.05	-0.07	-0.18	0.02	-0.0005	-0.02	-0.09	-0.18
67	0.0001	-0.02	-0.09	-0.12	-0.18	0.0001	-0.02	-0.09	-0.12	-0.18	0.01	-0.01	-0.05	-0.08	-0.18	0.03	0.001	-0.02	-0.09	-0.18
68	-0.001	-0.02	-0.09	-0.12	-0.17	-0.001	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.08	-0.18	0.04	0.0002	-0.03	-0.09	-0.18
69	-0.01	-0.02	-0.09	-0.12	-0.18	-0.01	-0.02	-0.09	-0.12	-0.18	0.01	-0.01	-0.04	-0.08	-0.18	0.02	-0.0013	-0.02	-0.09	-0.18
70	-0.003	-0.02	-0.09	-0.12	-0.18	-0.003	-0.02	-0.09	-0.12	-0.18	0.01	-0.01	-0.04	-0.06	-0.18	0.03	-0.0009	-0.01	-0.10	-0.18
71	-0.004	-0.02	-0.09	-0.12	-0.18	-0.004	-0.02	-0.09	-0.12	-0.18	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.0004	-0.02	-0.10	-0.18
72	-0.002	-0.02	-0.09	-0.12	-0.18	-0.002	-0.02	-0.09	-0.12	-0.18	0.01	-0.01	-0.04	-0.08	-0.19	0.02	-0.001	-0.02	-0.09	-0.18
73	-0.01	-0.02	-0.09	-0.12	-0.18	-0.01	-0.02	-0.09	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.18	0.03	-0.001	-0.02	-0.09	-0.17
74	-0.01	-0.02	-0.09	-0.12	-0.18	-0.01	-0.02	-0.09	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.19	0.03	-0.001	-0.02	-0.09	-0.18
75	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.01	-0.03	-0.07	-0.20	0.03	-0.002	-0.02	-0.09	-0.18
76	0.0004	-0.01	-0.10	-0.12	-0.18	0.0004	-0.01	-0.10	-0.12	-0.18	0.01	-0.01	-0.04	-0.06	-0.19	0.03	0.0002	-0.02	-0.09	-0.18
77	-0.001	-0.02	-0.09	-0.12	-0.18	-0.001	-0.02	-0.09	-0.12	-0.18	0.01	-0.01	-0.04	-0.08	-0.19	0.02	-0.0005	-0.02	-0.09	-0.18
78	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.01	-0.05	-0.07	-0.18	0.03	-0.00003	-0.03	-0.08	-0.18
79	-0.004	-0.02	-0.09	-0.13	-0.18	-0.004	-0.02	-0.09	-0.13	-0.18	0.01	-0.01	-0.05	-0.08	-0.17	0.03	0.0005	-0.03	-0.08	-0.18
80	-0.004	-0.02	-0.08	-0.12	-0.18	-0.004	-0.02	-0.08	-0.12	-0.18	0.01	-0.01	-0.05	-0.08	-0.17	0.03	-0.0001	-0.02	-0.10	-0.18
81	-0.002	-0.02	-0.09	-0.13	-0.18	-0.002	-0.02	-0.09	-0.13	-0.18	0.01	-0.02	-0.05	-0.06	-0.18	0.02	-0.0001	-0.01	-0.09	-0.18
82	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.03	0.0010	-0.02	-0.09	-0.18
83	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.02	0.0005	-0.02	-0.09	-0.18
84	-0.003	-0.02	-0.09	-0.12	-0.18	-0.003	-0.02	-0.09	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.18	0.02	0.0001	-0.01	-0.10	-0.18
85	-0.01	-0.03	-0.10	-0.12	-0.17	-0.01	-0.03	-0.10	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.20	0.02	0.0005	-0.02	-0.09	-0.18
86	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.05	-0.07	-0.17	0.02	0.001	-0.01	-0.09	-0.18
87	-0.01	-0.02	-0.10	-0.12	-0.18	-0.01	-0.02	-0.10	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.19	0.02	0.001	-0.02	-0.09	-0.18
88	0.00	-0.02	-0.09	-0.12	-0.18	-0.005	-0.02	-0.09	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.19	0.03	-0.001	-0.02	-0.09	-0.18
89	-0.01	-0.02	-0.10	-0.12	-0.17	-0.01	-0.02	-0.10	-0.12	-0.17	0.01	-0.01	-0.05	-0.08	-0.17	0.03	0.001	-0.02	-0.09	-0.18
90	-0.01	-0.02	-0.09	-0.11	-0.18	-0.01	-0.02	-0.09	-0.11	-0.18	0.01	-0.02	-0.05	-0.07	-0.17	0.04	0.0003	-0.03	-0.08	-0.18
91	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.05	-0.07	-0.16	0.02	-0.0001	-0.02	-0.09	-0.18
92	0.00	-0.02	-0.08	-0.14	-0.18	-0.002	-0.02	-0.08	-0.14	-0.18	0.00	-0.02	-0.06	-0.07	-0.17	0.03	0.001	-0.02	-0.09	-0.18
93	-0.01	-0.02	-0.08	-0.12	-0.18	-0.01	-0.02	-0.08	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.18	0.02	0.001	-0.02	-0.09	-0.18
94	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.00	-0.02	-0.05	-0.07	-0.17	0.03	-0.001	-0.02	-0.09	-0.17
95	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.05	-0.07	-0.17	0.02	0.000	-0.02	-0.09	-0.18
96	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.19	0.02	-0.002	-0.01	-0.10	-0.18
97	-0.01	-0.02	-0.08	-0.12	-0.17	-0.01	-0.02	-0.08	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.02	-0.002	-0.01	-0.09	-0.17
98	-0.01	-0.02	-0.09	-0.12	-0.17	-0.01	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.02	-0.003	-0.01	-0.09	-0.18
99	-0.005	-0.02	-0.10	-0.12	-0.18	-0.005	-0.02	-0.10	-0.12	-0.18	0.01	-0.02	-0.04	-0.07	-0.18	0.02	-0.001	-0.02	-0.09	-0.18
100	-0.005	-0.02	-0.09	-0.12	-0.17	-0.005	-0.02	-0.09	-0.12	-0.17	0.01	-0.02	-0.04	-0.07	-0.18	0.02	0.001	-0.02	-0.08	-0.18
101	-0.01	-0.02	-0.08	-0.12	-0.17	-0.01	-0.02	-0.08	-0.12	-0.17	0.01	-0.03	-0.04	-0.07	-0.18	0.03	-0.002	-0.01	-0.10	-0.18
102	-0.01	-0.02	-0.08	-0.12	-0.18	-0.01	-0.02	-0.08	-0.12	-0.18	0.004	-0.02	-0.05	-0.07	-0.16	0.02	-0.001	-0.01	-0.09	-0.18
103	-0.01	-0.02	-0.08	-0.12	-0.18	-0.01	-0.02	-0.08	-0.12	-0.18	0.01	-0.02	-0.06	-0.07	-0.16	0.02	-0.001	-0.02	-0.09	-0.18
104	-0.00004	-0.02	-0.08	-0.12	-0.18	-0.00004	-0.02	-0.08	-0.12	-0.18	0.01	-0.01	-0.06	-0.08	-0.16	0.04	-0.001	-0.02	-0.09	-0.18

Table 7.3 Conditional Food Expenditure Elasticities

	Low Income/No Child						
	f&v	w-meat	r-meat	carb	dairy	others	exp
fruit & veg	-0.84	0.14	-0.05	-0.30	-0.11	-0.14	1.20
white meat	0.26	-1.17	-0.21	0.04	-0.08	0.02	1.10
red meat	0.01	-0.06	-0.68	-0.03	0.04	0.13	0.76
carbohydrate	-0.18	0.01	-0.08	-0.56	-0.23	-0.04	1.03
dairy	-0.14	-0.06	0.01	-0.50	-0.38	-0.13	1.15
others	-0.21	0.06	0.32	-0.06	-0.14	-0.75	0.78

	Low Income/Child						
	f&v	w-meat	r-meat	carb	dairy	others	exp
fruit & veg	-0.70	-0.05	0.19	-0.46	-0.06	-0.01	1.03
white meat	-0.10	-1.02	0.02	-0.18	0.12	-0.17	1.16
red meat	0.12	0.01	-0.83	-0.22	-0.16	-0.15	1.12
carbohydrate	-0.18	-0.03	-0.11	-0.70	0.09	0.05	0.92
dairy	-0.04	0.09	-0.18	0.23	-0.90	0.02	0.89
others	-0.01	-0.14	-0.29	0.14	0.02	-0.72	0.99

	High Income/No Child						
	f&v	w-meat	r-meat	carb	dairy	others	exp
fruit & veg	-0.79	0.18	0.06	-0.16	-0.24	-0.19	1.12
white meat	0.29	-0.77	-0.21	-0.34	-0.09	-0.09	1.09
red meat	0.04	-0.10	-0.44	-0.34	-0.07	-0.18	1.03
carbohydrate	-0.11	-0.13	-0.29	-0.47	-0.06	0.15	0.96
dairy	-0.33	-0.06	-0.08	-0.10	-0.27	0.11	0.83
others	-0.39	-0.08	-0.37	0.41	0.14	-0.61	0.90

	High Income/Child						
	f&v	w-meat	r-meat	carb	dairy	others	exp
fruit & veg	-0.10	-0.01	-0.07	-0.13	-0.31	0.07	0.77
white meat	-0.08	-1.20	0.10	-0.08	-0.15	0.08	1.21
red meat	-0.16	0.03	-0.90	-0.65	0.25	-0.28	1.43
carbohydrate	-0.11	-0.02	-0.33	-0.40	-0.05	-0.12	0.97
dairy	-0.37	-0.05	0.46	0.003	-0.43	0.11	0.65
others	0.11	0.10	-0.46	-0.33	0.10	-0.42	0.89