School of
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Environmental Regulation and Sustainability in the Food Sector: Exploring the Impact of Carbon Taxation on Diets, Health and Trade in UK

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Abstract

This thesis is structured around the elaboration of two studies that seek to advance our knowledge on the environmental and nutritional effects of environmental policies targeting food markets. Food consumption causes negative externalities that regulation aims to influence. Carbon taxes are an important tool, because they can be designed to reduce greenhouse gas (GHG) emissions associated with food products. However, environmental impact and nutritional quality are not equivalent measures of foods. Fresh fruits and vegetables are low in fats and GHG, and meat is high in both, but both may be low in specific micronutrients; conversely, soft drinks are widely considered unhealthy, but are low in GHG. Manipulation of environmental regulations which impacts on food markets may have an influence on the nutritional status and health of the population. This thesis seeks to extend our current understanding of food policies by exploring the link between environmental regulation of food markets and the nutritional quality of population diets. This is achieved using a modelling approach based on micro-simulation of the effects of imposing hypothetical carbon taxes on foods and drinks prices on consumption, health, and trade.

To analyse how food consumption changes in the presence of a carbon tax, an Almost Ideal Demand System was applied using data from the UK Living Cost and Food Survey. Two price interventions were tested: a simple carbon tax, scenario (A), where prices were increased proportionally to the carbon content of foods; and a *Bonus-Malus* tax, scenario (B), where carbon tax revenues were recycled into the economy in the form of a flat carbon subsidy. The resulting structural parameters were then used to estimate after-tax food consumption behaviours. Health data from the UK National Diet and Nutrition Survey were used to simulate changes in body mass index (BMI), glycated haemoglobin (HbA1c), glucose and blood cholesterol concentrations in each scenario. Results show that the dietary changes induced by the tax reduce the GHG emissions of diets, with some beneficial health effects.

To analyse the effects of carbon taxes on the trade of food products, a structural gravity model was applied to Eurostat commodities import data. The model regresses trade flows on country size, distance, import prices and a multilateral resistance term, which captures the level of integration of a country into the world economy. This study shows that the imposition of carbon tariffs would reduce UK emissions derived from the European import of dairy and meat products by more than 30.4 $MtCO_2$-eq. This reduction comes at the cost of lower trade flows, especially those for meat products.

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Declaration

I declare that this thesis is a presentation of original work under the guidance and supervision of Dr. Luca Panzone and Professors John Wildman and Chris Seal. They have provided comments and suggestions on drafts of all chapters in this thesis. A substantial part of this research has been enriched with comments received in conferences and discussions with other colleagues in the profession.

An early version of Chapter 3 has been discussed at the Newcastle University SNES School Conference in May 2019 and at the 25th Virtual Annual European Environmental Economics Conference (EAERE 2020). It has also received helpful comments and suggestions from academics during the CRE symposium in February 2019. In addition, it has been presented and discussed at the Toulouse School of Economics in March 2020, within the food and environmental research groups. It was selected for presentation at the N8 Agri-food Conference in York (2019), at the UK Network for Environmental Economists Conference (ENVECON 2020) and at the 9th and 10th Annual Conference of the American Society of Health Economists (ASHEcon 2020).

An early version of Chapter 4 has been discussed at the Summer School in Gravity Model and Panel Econometrics organised virtually by the World Trade Organization in September 2020. In addition, it has benefited from feedback during the CRE symposium in February 2021.

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Chapter 1. Introduction

1.1 Background

The development of unsustainable consumption and production patterns, usually accompanied by socio-economic progress and population growth, represent major contributions to the high level of greenhouse gas (GHG) emissions in the atmosphere. Higher GHG emissions are inexorably linked with global warming and the recent catastrophic climate change events (Intergovernmental panel of climate change IPCC, 2014). Given the importance of environmental protection in international policy agendas, these issues need to be urgently addressed through the design of global solutions, based on prevention or mitigation strategies, appropriate to change the entire system in a more environmental-friendly way (Gemechu *et al.*, 2012).

Whilst research has been typically focused on the energy and transport sectors, more attention should be given to the environmental damage caused by the food sector. Agricultural systems are having increasingly strong global impacts on both environmental and human health, often driven by population dietary changes (Drewnowski and Popkin, 1997; Tilman and Clark, 2014). Global agriculture and food production releases a third of global GHG emissions (Crippa *et al.*, 2021), pollutes fresh and marine waters with agrochemicals, and uses about half of the ice-free land area of the Earth as cropland or pastureland. In the UK, agriculture and food accounts for around 10% of total GHG emissions (not including land use change) (Briggs *et al.*, 2016). The global dietary transition towards more sustainable pathways is one of the greatest challenge facing humanity, given it directly links and negatively affects human and environmental health (Tilman and Clark, 2014).

Solutions to this challenge will need to analyse the linkages between diets, health and environment, and will require the efforts of nutritionists, agriculturists, educators, economists, policy makers and the food industry, and a range of different tools or interventions. Policy instruments can be efficient tools to reduce GHG emissions of food production systems. Demand side instruments include carbon taxation and cap-and-trade mechanisms, while supply-side policies require the adoption of targets and regulations (Zhang and Wang, 2017). Evidence has shown that the design of effective and rational "carbon policies" could address environmental problems, reduce externalities and stimulate sustainable consumption (Panzone *et al.*, 2011).

Emission taxes are market-based instruments, that depending on the tax base (i.e. what is being taxed) and the tax rate, can potentially lead to a major increase in the market price of emission-intensive goods (Baranzini;Goldemberg and Speck, 2000). Many studies have shown how taxing agricultural emissions ensures that the prices paid by individuals are not distorted (Metcalf and Weisbach, 2009a), represent the true social costs of food production (Kehlbacher *et al.*, 2016), and can lead to valuable results in terms of environmental sustainability (Kehlbacher *et al.*, 2016). In addition, given the current global transition towards diets high in processed foods, refined sugars, refined fats, oils and meats has contributed to 2.1 billion people becoming overweight or obese globally (Tilman and Clark, 2014), the expectation is that the implementation of carbon policies will also change food consumption patterns resulting in public health benefits.

Decreasing the consumption of food products which have a higher carbon footprint, mainly foods derived from livestock, has been cited as a good way to reduce food related GHG emissions while simultaneously improving health (Singh;Sabaté and Fraser, 2003). Indeed, the production of animal products, particularly red meat from ruminants, uses more energy and generates more GHG emissions than does that of plant based products. Moreover, red meat is suspected to have a causal inference on colorectal cancer (Santarelli;Pierre and Corpet, 2008) and other forms of cancers (Sinha *et al.*, 2009) and may be associated with cardiovascular diseases because of its high cholesterol (Friel *et al.*, 2009). It is now widely recognised that a global shift towards plant-based diets would have favourable effects on both environmental and human health (Duchin, 2005). However, while some studies have found that diets lower in GHG emissions are also healthier (e.g. Edwards *et al.*, 2011; Clonan and Holdsworth, 2012; Macdiarmid *et al.*, 2012; Sabaté and Soret, 2014), studies of French dietary survey data concluded that foods and diets of high nutritional quality have higher associated GHG emissions than those of low nutritional quality (Vieux *et al.*, 2013). Meat, fish, and dairy products are unique sources of specific and essential nutrients and a reduction in their intakes raises many nutritional challenges (Vieux *et al.*, 2013). In addition, some scholars have found that certain foods and drinks, such as sugar and sugar-sweetened beverages (SSBs), are both very low in GHG emissions and also bad for health (Briggs *et al.*, 2013). Therefore, the consumption of the least healthy food groups (i.e., sweets and salted snacks) could be correlated with a decrease in energy adjusted GHG emissions. In this context, carbon taxation aiming to reduce GHG emissions from foods, might not always promote healthier and nutritional eating patterns, making the nexus between health and sustainability still uncertain.

Attention should also be given to trade within the food sector. Trade is particularly relevant in the UK food market, especially for fruit and vegetable products that are usually lower in terms of environmental impact yet are primarily imported into the UK. Recent studies have found that 20-25% of CO_2 emissions come from the production of internationally traded products (Davis and Caldeira, 2010; Barrett *et al.*, 2013). Reducing the emissions embodied in trade is complex and requires an understanding of how each policy affects the different determinants of international emissions transfers. However, carbon border taxes could be an appropriate mechanism to reduce the amount of embodied emissions imported to the UK from the EU. As a result, part from consumption, we should also estimate the impact of a carbon border tax on trade, specifically import, as this item is more relevant for food market in the UK economy. These changes in trade flows will inevitably affect the food behaviour of UK consumers, with potentially health consequences on the nutritional profile of the population.

1.2 Study aim, objectives and research questions

The aim of this study is to investigate to what extent the introduction of carbon policies on food prices can encourage more sustainable food patterns among UK consumers and producers, and how these transformations can influence the nutritional and health outcomes of the population.

In order to achieve the aim, four objectives are proposed:

a) To explore and define which carbon policies could be implemented in the UK food market;
b) To identify in what ways environmental regulations could become a political alternative in UK;
c) To evaluate the nutritional, health and environmental implications of new diets after regulation;
d) To investigate the environmental and trade effects of carbon border mechanisms implemented between the UK and the EU.

This doctoral project uses modern econometric methods for policy analysis. In particular, it estimates structural demand and gravity models, whose parameters are then used to micro-simulate relevant policy interventions (Mitton;Sutherland and Weeks, 2000) from existing secondary datasets from governmental sources: Living Cost and Food Survey (Office for National Statistics, 2017b); National Diet and Nutritional Survey (MRC Elsie Widdowson Laboratory, 2019a); Eurostat (Eurostat, 2019b). This approach is increasingly becoming the standard for *ex-ante* policy analysis, and takes into account the uncertainty of the estimates as well as the uncertainty of the outcome. The main research questions to address the aims are:

a) Is environmental regulation of food markets invariant to the nutritional content of diets? Does it improve or damage the quality of diets?
b) Can we measure the impact of an environmental policy on food consumption diets?
c) What are the implications on health, in terms of a decrease in the occurrence of a diet-related disease?
d) What are the effects of carbon border taxes on UK food imports from the EU?

1.3 Methodology

This doctoral project contains two main elements. The first considers the impact of carbon taxation on diet and health in the UK. The second aims to analyse the effects of carbon border taxes on trade, particularly imports, in UK (Figure 1.1).

For phase one, two types of scenario are chosen to illustrate the effects of carbon taxation on consumer diet and health and each of these is estimated with the price for the social cost of CO_2 emissions set at £70/tonne CO_2 (Pearce, 2003) :

- Scenario (A): a carbon tax is imposed in all foods considering their environmental footprints;
- Scenario (B): *Bonus-Malus* taxation (revenue-neutral scenario) is introduced as a compensatory mechanism to make it socially acceptable since environmental taxes tend to be regressive in income and tend to affect poorer households more (West and Williams, 2004; Wier *et al.*, 2005).

Bonus-Malus taxation was applied in France to decrease emissions generated by vehicles (d'Haultfoeuille;Givord and Boutin, 2014).These measures can be effective in reducing CO_2 emissions; however, the investigation of their use on sustainable consumption is limited. Regarding the substantial contribution of food consumption to greenhouse gas emissions and lack of studies testing the economic impact of fiscal measures in this context, it is crucial to conduct studies to explore the impact of fiscal measures on food consumption.

The aim of each scenario is to estimate changes in the amount of each food group consumed (i.e., purchased) at household level, and the nutrient composition of the diets (e.g. energy, total fat, cholesterol, sugars, salt). Furthermore, the evaluation of some health indicators at individual level are estimated before and after regulations to see if the new diet induces some positive health consequences. In this analysis, body mass index (BMI), blood cholesterol, glucose, and glycated haemoglobin (HbA1c) concentrations are used in order to see if particular types of food products increase or decrease the probability that a diet-related disease will occur.

The second phase evaluates the potential effects of European carbon border taxes on UK food imports to see if these types of instruments might reduce the amount of embodied emissions coming from trade. In this study only the imports of meat and dairy products are considered, due to their higher level of environmental footprint.

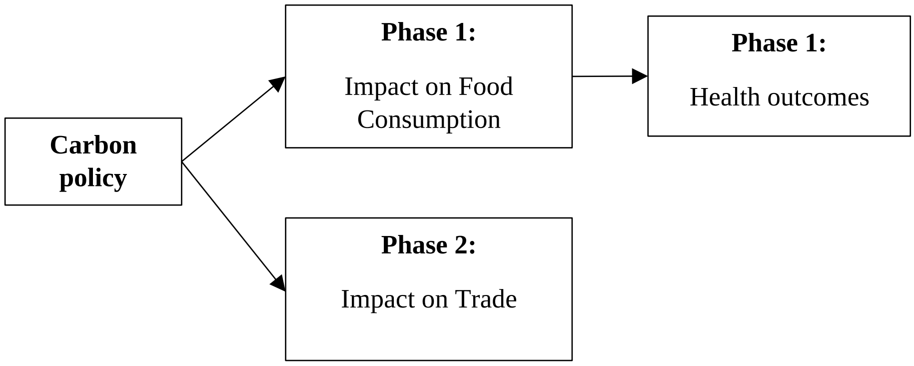

Figure 1.1: Graphical representation of the project

1.3.1 Phase 1: the impact of a carbon tax on food consumption in the UK

In this phase, a demand model is estimated to study the relationship between GHG emissions and demand for different food categories. An Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980; Berry;Levinsohn and Pakes, 1995) of a relatively high level of disaggregation is estimated using the Living Cost and Food Survey data (Office for National Statistics, 2017b). This approach identifies structural demand parameters using individual household data, leading to causal links between price and demand, which are essential to simulate a price change. An Instrumental Variable (IV) strategy is used to examine the effects of food prices and household expenditure on consumer diet. This method, pioneered by Wright (1928) has been widely used in economics to deal with endogeneity issues in the price and expenditure formation. An instrument is a variable that affects the variable of interest but is not directly associated with the variable that is the outcome. In addition, sample selection biases are addressed since many households had no expenditures in some food groups during the measurement period. In this regard, Heckman's two step procedures proposed by Heien and Wesseils (1990) are used in order to keep in the estimation all the households with zero budget shares in at least one category. A micro-simulation approach is then used to evaluate the impact of the tax on the overall nutrition of the population. This simulation determines how diet has changed as a consequence of the tax, and what is the profile of diets before, and after, the intervention.

Once the impact of carbon taxation is predicted, the composition (in quantity of different food products consumed) of the new diet in the population will be known. Using the National Diet and Nutrition Survey (which contains estimates of food intake), diet composition is estimated and linked to a feasible number of diseases through the evaluation of several health measures at an individual level. The parameters obtained from this health model are then used to estimate the risk of specific diseases before and after the intervention at an individual level, which will then be used to determine individual changes in health outcomes.

1.3.2 Phase 2: The impact of a carbon tax on imports in the UK

In the second phase of the project, the impact of a carbon tax on trade is estimated using data from Eurostat on the import to the UK of different food groups. The objective is to be able to link quantities of food traded and their characteristics, to estimate structural trade parameters. To do so, a general gravity model is estimated (Anderson, 2011) to show how the imposition of European carbon tariffs could reduce emissions deriving from trade. This section also uses an IV approach to analyse the effects of import prices on trade flows in the UK. A Poisson pseudo-maximum likelihood estimator controlling for importer and exporter fixed effects is used to control for zero trade flows and heteroskedasticity (Silva and Tenreyro, 2006).

Once the structural parameters are estimated, the impact of carbon border taxation is estimated using a microsimulation approach, to determine the impact of policies on food availability. New trade flows are then estimated, with the respective nutritional and environmental characteristics.

1.4 Plan of the thesis

The thesis is comprised of five chapters, of which this introduction constitutes the first. Chapter 3 and 4 will be part of two main papers that are going to be submitted to journals for publication purposes. For this reason, they are presented in a paper structure.

The aim of the first chapter is to provide an overview of the study and the background. For this, a description of several environmental issues are provided, with particular attention to the food sector. The main objectives and goals are described together with the main research questions of the doctoral project. In addition, an indication of the methodologies and the data used in the analysis is given.

Chapter 2 builds a broad review of the literature by exploring the current knowledge and background information of the research topic. The chapter provides critical examination of what is known about the relationship between carbon footprint and nutrients. In particular, considering the environmental impact of the food sector and the nutritional and healthy characterization of diets. Chapter 2 describes the market-based instruments, with a focus on carbon taxes and *Bonus Malus* taxation and what is acknowledged about their impact on food consumption and trade.

Chapter 3 presents the first phase of the project concerning the implications of carbon policies on UK consumer diet and health. Background information is shared to highlight the main purposes of the study. The estimation of the Almost Ideal Demand System and the health model are described with the respective micro-simulation policy interventions. A comprehensive explanation of the food consumption and health data used in the analyses is given. Information regarding the health biomarkers are provided, with specific considerations around the choice of these types of measures. The key issues around the implementation of the demand model estimation are taken into account and the solutions to how to deal with these are described and explained. The main findings of simulation diets and health are shown with the respective environmental and nutritional consequences. Deep discussion and final considerations following the results are explained in detail.

Chapter 4 presents the second phase of the project concerning the effect of EU carbon tariffs on the UK food trade market and emissions using a micro-simulation approach built upon the estimation of a structural gravity model on trade. It explains the motivations behind the elaboration of the study. The empirical trade model together with the gravity estimation are described and the main issues are explained and addressed. The main findings of the trade analysis are then discussed together with the micro-simulated policy interventions results. Trade flow changes, environmental and nutritional effects after the implementation of carbon border mechanisms are then debated.

Chapter 5 discusses the main policy implications of the findings and the main conclusions of the PhD study. In particular, it describes the contribution of the study with an overview of alternative policy interventions. Suggestions for policy makers and deep consideration of the main limitations of the project are also illustrated.

Chapter 2. Literature review

2.1 Methodology of the Literature Review

This literature review provides an overview of current knowledge, allowing the identification of relevant theories, methods and gaps in the existing research related to the implementation of carbon policies on food and the subsequent effects on consumer diet and health. This review was conducted during the three years of the PhD study, and it is a survey of scholarly sources that were evaluated and analysed in relation to the main aims of this research. In particular, Google Scholar, Research Gate, Science Direct, Philip Robinson Library at Newcastle University, were used to look for the different sources, publications and research papers related to the field. For the purpose of the literature review, these steps were followed:

1. The main objectives of the PhD study were defined:
    a) To explore and define which carbon policies could be implemented in the UK food market;
    b) To identify in what ways environmental regulations could become a political alternative in UK;
    c) To evaluate the nutritional, health and environmental implications of new diets after regulation;
    d) To investigate the environmental and trade effects of carbon border mechanisms implemented between the UK and the EU.
2. The main research questions to address the aims were:
    a) Is environmental regulation of food markets invariant to the nutritional content of diets? Does it improve or damage the quality of diets?
    b) Can we measure the impact of an environmental policy on food consumption diets?
    c) What are the implications on health, in terms of a decrease in the occurrence of a diet-related disease?
    d) What are the effects of carbon border taxes on UK food imports from the EU?
3. Based on these aims and questions, the main key words were identified to look for relevant literature through the different portals:
    - carbon policies applied to the food sector;
    - health and environment;
    - food policies and diet;
    - environmental regulation of food market and trade;

- carbon border taxation;
- nutritional and health effects of carbon taxes on food;
- diet-related diseases.

In particular, a search was conducted in the database Scopus and Web of Science, two popular, comprehensive literature databases (Guz and Rushchitsky, 2009). The search was also refined to peer-reviewed empirical and review articles only, and excluded book chapters, dissertations, etc. Cited reference searches using Google Scholar were conducted on especially relevant articles, in order to identify other empirical and review papers that were not captured by the keyword searches.

4. Some eligibility criteria were used in order to include or exclude the published material in the study:
    - Publication was a UK based study;
    - Publication was applied to the food sector;
    - Publication was considering the nexus between health, nutrition and environment.
    - Publication was dated no more than 10 years' time

Based on these filters and criteria, the literature review provided a good overview of the main theories, framework, research aspects linked to the PhD study. The literature review was then updated constantly during the entire PhD journey, to give updated contextual information of the main research questions explored in this study.

2.2 Introduction

Global climate change is the most urgent environmental problem faced today. According to global annual temperature records, which date back to 1880, 12 of the hottest years have occurred in the 21st century (Intergovernmental panel of climate change IPCC, 2014). Most immediately, climate change is experiencing an increasing temporal and spatial variability in temperature, precipitation, and winds, particularly in the magnitude of extreme events. These include the frequency and intensity of heat waves, heavy precipitations, tropical cyclone events and storm surges (Vermeulen;Campbell and Ingram, 2012). Correspondingly, the incidence of daily tidal flooding due to global sea level rise is accelerating in more than 25 Atlantic and Gulf Coast cities (Rose *et al.*, 2019).

The Intergovernmental Panel of Climate Change (IPCC) details the relationship between climate change and GHG emissions: anthropogenic greenhouse gas emissions[1] have increased since the pre-industrial area, driven largely by economic and population growth. This has led to atmospheric concentration of carbon dioxide, methane and nitrous oxide that are unprecedented in at least the last 800,000 years. The use of fossil fuels has more than tripled since 1960. Their effects have been detected throughout the climate system and are extremely likely to have been the dominant cause of the observed warming since the mid-20th century (Intergovernmental panel of climate change IPCC, 2014).

The food people eat impacts their health and the health of the environment. A third of global GHG emissions come from the food system (Crippa *et al.*, 2021), most of which are related to livestock (Vermeulen;Campbell and Ingram, 2012; Tubiello *et al.*, 2014; Springmann *et al.*, 2017). Agriculture occupies 40% of the Earth's surface (Ramankutty *et al.*, 2008), and uses 70% of all freshwater resources (Shiklomanov and Rodda, 2004) and the over application of fertilizers in some regions has led to pollution of surface waters and ground waters and created dead zones in oceans (Diaz and Rosenberg, 2008). In the absence of mitigation strategies or changes in demand due to the population growth and dietary changes towards emission-intensive animal based foods, GHG emissions from food and agriculture are expected to rise by up to 80% by mid-century (Popp;Lotze-Campen and Bodirsky, 2010; Hedenus;Wirsenius and Johansson, 2014).

In the UK, the Climate Change Committee (CCC) estimates that 11% of territorial UK GHG emissions are attributable to agriculture and land use and predict that the sector will be a more significant emitter by 2050 (Climate Change Committee, 2018). The emissions associated with British food consumption represent approximatively 20 to 30% of the UK's total emissions (Department for Environment Food and Rural Affairs, 2012). With the legislations of a net zero 2050 target in the UK, underwritten by the Paris Agreement's commitment to 1.50 C (UNFCCC, 2015), food system change is being recognized as an increasingly important mitigation option.

The diets of the 'western world' are not only a challenge for the environment but are also a challenge for population health. There is universal agreement that some aspects of the "western world" diets are a major determinants of cancer and cardiovascular disease (CVD); for instance there is some evidence that risk is increased by high intakes of more environmentally impacting

[1] Emissions of greenhouse gases (GHGs), precursors of GHGs and aerosols caused by human activities. These activities include the burning of fossil fuels, deforestation, land use and land-use changes (LULUC), livestock production, fertilisation, waste management and industrial processes.

products as meat and fat, and that risk is decreased by high intakes of fruit and vegetables, dietary fibre, folate and calcium (McAfee *et al.*, 2010; Springmann *et al.*, 2016). The consumption of red and processed meat has been associated with increased mortality from chronic diseases and red and processed meat have been declared by the World Health Organization (WHO) to be carcinogenic (processed meat) and probably carcinogenic to humans (World Health Organization, 2003; Chen *et al.*, 2013; Bouvard *et al.*, 2015). There is an extensive body of literature of how dietary changes may serve health and environmental objectives by reducing diet-related mortality and addressing both dietary composition and energy balance (Revoredo-Giha;Chalmers and Akaichi, 2018; Springmann *et al.*, 2018b; Latka *et al.*, 2021).The concept of sustainable diets itself combines the challenges of creating a food system that supplies healthy diets for a growing population while reducing its environmental impacts and staying within planetary boundaries (Burlingame and Dernini, 2012). However, consistent health analysis of commonly proposed diets are scarce and approaches that are based primarily on health rather than environmental objectives are rarely considered, despite a few exceptions (Tilman and Clark, 2014; Springmann *et al.*, 2018b). In this sense, more research should be addressed in this direction in order to look at the interlinkage between health and environment and propose valuable solutions.

The role that the economic system (businesses, consumers, local and international institutions) plays in the generation of emissions suggests that a strategic design towards a low-carbon world would require in the order of a 40% and 70% reduction in GHG emissions by 2050 (Change, 2014). The interconnections within the system tell us that both consumers and producers are responsible for pollutant emissions. From the production side, industrial processes, particularly those burning fossil fuels, are the main determinants of GHG emissions (Duarte;Pinilla and Serrano, 2018). The advent of free international trade has enabled consumption to be met through increasingly globalized supply chains, so the effects of consumer behaviour on the environment have also been increasingly spread around the globe (Duarte;Pinilla and Serrano, 2018). The impact of trade on the environment has been assessed for CO_2 emissions (Munksgaard;Pedersen and Weir, 2001; Chen;Chen and Chen, 2010) finding evidence of the carbon leakage and pollution haven hypothesis (López;Arce and Zafrilla, 2013). This is a widely recognised hypothesis that posits that the tightening of environmental regulations hurts the productivity of firms and in response firms shift production to locations with relatively lax regulations, thus creating “pollution havens”(Tang, 2015). Since a decrease in emissions in one part of the world leads to an increase in emissions in the rest of the world, this phenomenon is referred to as carbon leakage (Branger and Quirion, 2014). Whilst most of the literature has focused on the identification of the main driving factors underlying the generation of emissions through global supply chains (Duarte;Pinilla and Serrano, 2018), it is still unclear which types of instruments or policies could reduce carbon embodied emissions on trade.

Market based approaches to regulation have gained popularity in public health research and public debate. Demand side policies could be a viable option for addressing the environmental costs associated with food production and consumption. Consumption taxes related to the carbon emissions of products (i.e. carbon taxes) are a potential instrument to partially mitigate carbon emission by changing consumer demand (McAusland and Najjar, 2015). These are so called Pigouvian taxes whose purpose it is to correct for the unintended and previously unaccounted consequences to society of an economic activity by incorporating the cost of those consequences into the price of the activity or good (Pigou, 1929; Baumol, 1972). Measures to change diets away from emission-intensive food commodities, such as meat and dairy, towards more plant based diets are seen to offer great potential for reducing GHG emissions (Stehfest *et al.*, 2009; Smith *et al.*, 2013) and could be associated with additional co-benefits in terms of improvements in human health (Popp;Lotze-Campen and Bodirsky, 2010; Hedenus;Wirsenius and Johansson, 2014; Tilman and Clark, 2014; Springmann *et al.*, 2016; Wollenberg *et al.*, 2016; Springmann *et al.*, 2018a).

In addition, carbon taxes might also play an important role in the trade sector. Carbon border mechanisms have recently been invoked as potential instruments to move towards net zero carbon emissions by 2050 and discourage carbon leakage effects, namely a shift of the more intensive production sites to countries with less stringent environmental policies (Condon and Ignaciuk, 2013). The implementation of these type of policies could discourage the UK from importing less sustainable products from Europe and subsequently reduce the amount of emissions imported from abroad. Furthermore, demand side actions have an additional public health rationale, whereby through improving the emission-intensity of UK diets, there is also scope to improve public health (Garvey *et al.*, 2021). Analysis has revealed that demand side action should constitute a core part of the UK's mitigation strategy for the food sector, with a reduction of over half in the UK's annual GHG emissions between 2017 and 2050, regardless of prospective technological changes to production efficiencies (Garvey *et al.*, 2021).

In this context, the main objectives of this research rely on the possibility of using carbon policies in addressing more sustainable and healthy food consumption and production patterns with a consequent reduction in the emissions deriving from the entire food sector. Firstly, to estimate the effects that carbon consumption taxes would have on the development of more sustainable and nutritional food behaviours among UK consumers, considering also the impact of these regulations on some health biomarkers at individual level. Secondly, on the potential impact that these policies would have on trade flows between the UK and European countries in order to reduce the amount of imported foods' GHG emissions. Making food production more environmental friendly (with taxation) may make diets healthier (more fruit and vegetables) or less healthy (more highly processed foods). These factors are often looked at in isolation but they need to be joined up – and that is what this PhD thesis is going to do.

Section 2.2 describes the relation between carbon footprint and nutrients. In particular, considering the environmental impact of the food sector and the environmental impact of diets. Section 2.3 gives an overview of the market-base instruments in an environmental setting with a deep focus on carbon taxation and *Bonus Malus* interventions, which are the objects of the present research study. Section 2.4 illustrates the relationship between food policy and the environmental and nutritional quality of diets with a deep focus on carbon taxation and its use in sustainable food consumption and trade.

2.3 Relation between carbon footprint and nutrients

2.3.1 The environmental impact of the food sector

Food chain activities are the manufacturing and distribution of inputs (seed, animal feed, fertilizers, pest control); agricultural production (crop, livestock, fisheries, wild foods); primary and secondary processing, packaging storage, transport and distribution, marketing and retail, catering, domestic food management and food waste. Food systems consist not only of food chain activities, but also on the outcomes of these activities and their governance (Ericksen, 2008; Ingram, 2011). Food systems move due to changes in demand side drivers, like population growth, shifting patterns of consumption, urbanization and income distribution. In addition, they depend on trends in food supply, which are related to climate change, to competition and the interaction of food production and ecosystem services. Additional factors are trade liberalization, market penetration by transnational food companies, food marketing and consumer behaviour.

The food sector gives rise to the production of greenhouse gases and other climate change forces, such as aerosols and changes in albedo (Garnett, 2011). The exceptions are that some agricultural practices, such as certain agroforestry systems, can have sequestration effects that restore degraded land. The contribution of food systems to total anthropogenic GHG emissions was 35% for the year 2015 (Garnett, 2011; Vermeulen;Campbell and Ingram, 2012). Globally, GHG emissions from the food system were 18 $GtCO_2$-eq in 2015, with 27% emitted by industrialized countries and the remaining 73% emitted by developing countries (Crippa *et al.*, 2021). In 2015, 71% of global GHG emissions from the food system was associated with the land-based sector, as agriculture and associated land use and land use change activities.

In industrialized countries, the contribution of the downstream energy related sectors (53%) which includes industry and waste, was larger than the land based sector (Crippa *et al.*, 2021). In UK, territorial emissions are estimated to account only a fraction of the total consumption-based impact of food at the global scale (Audsley *et al.*, 2010). Territorial emissions accounting approaches considers the GHG emissions occurring under a particular national jurisdictions, discounting those emissions occurring from international aviation and shipping (Barrett *et al.*, 2013). By contrast, in a consumption based accounting approach emissions are allocated according to the country of the consumer, usually based on final consumption (Barrett *et al.*, 2013). That is, the consumption based footprint of the UK's food intake would be the UK emissions from producing food, subtracting those emissions from exported goods and adding the emissions from imported foods (Garvey *et al.*, 2021). The UK food system is at a structural turning point, facing new demands and challenges stemming from demographics, economic and political change. With likely future population growth in the UK, of at least 4.5% between 2018 and 2028 and the noted trend for overconsumption, there is need to re-evaluate the structure of the UK food system (Department for Environment, 2019a). It is possible that the UK could become increasingly reliant on food imports if current trends in declining self-sufficiency continue, and as part of a highly globalized food chain (Department for Environment, 2019a).

2.3.2 The environmental impact of food diets

Many studies have analysed the impact of food consumption on environmental indicators such as carbon footprint, water footprint, land use and ecological footprint (Leach *et al.*, 2016; Arrieta and González, 2019; Danish and Wang, 2019). These measures offer an integrated impact view of the various phenomena, allowing for to definition of the ecological footprint of man and consequently to reduce GHG emissions (Karwacka *et al.*, 2020). From an analysis of the Life Cycle Assessment (LCA) studies, it is possible to conclude that food products of animal origin have a higher impact related to climate and land use than plant products, accounting for 80% of total emissions from the food system (Springmann *et al.*, 2016). The greatest impact was found for ruminant meat compared to pork or poultry, which have a similar carbon footprint. The type of production system used for livestock could also affect the environmental impact (Nguyen;Hermansen and Mogensen, 2010). Indeed, even if livestock grazing helps carbon sequestration, extensive production systems may generate more GHG emissions than intensive production system per unit of output (Bonnet *et al.*, 2020). The processes contributing to major GHG emissions during meat production are: production of feed, enteric fermentation from feed digestion by animals (mainly ruminants), manure handling and energy use in animal houses (Röös *et al.*, 2013). Per unit of expenditure (GBP £), meat products consumed in the UK are 21 times more emissions intensive than the average for fruit, vegetables and cereals and dairy is three times more emissions intensive (Garvey *et al.*, 2021). Green Alliance estimated that livestock agriculture is responsible for around 70% of emissions from the agriculture sector in the UK (Caterina Brandmayr, 2019) and the CCC estimated that 58% of UK agricultural emissions were attributable to cattle and sheep farming in 2016 (Climate Change Committee, 2018). Across all environmental indicators examined , some scholars found that ruminant meat had 20-100 times more impact than plant based foods, and that dairy, pork, poultry and seafood had impacts 2-25 times higher than plants per kcal of food produced (Clark and Tilman, 2017). The literary pool that demonstrates the environmental benefits deriving from a reduction in the consumption of red meat is vast (Karwacka *et al.*, 2020). Although a diet based mainly on plant-based foods is associated with fewer emissions, this does not mean that these products are immune to the environmental footprint. Another issue to consider when thinking about a plant-based diet is the seasonality of crops. Many countries rely on imports once their growth period is over. This trading pattern causes greenhouse gas emissions through air, land and sea transport (Gurtu;Searcy and Jaber, 2017). Furthermore, transport emissions are not the only negative to consider. Popular foods such as avocados, mangoes and nuts require a huge supply of water and are often grown in areas where water stress is greatest. To address these issues, some researchers suggest that people should eat seasonal and locally produced foods, regardless of whether they are plant-based (Magkos *et al.*, 2019).

Carbon emissions of food choices are estimated to account for around 30% of total household greenhouse gas emissions in developed economies, with supermarkets capturing a large share of food expenditures (Panzone;Wossink and Southerton, 2013). In this sense, different consumer choices in store can lead to significant reductions in the carbon footprint of food baskets (Panzone *et al.*, 2016). The literature presents limited research on the distribution of carbon footprint in the UK and on what households and personal characteristics are associated with high or low carbon footprint baskets. Government surveys such as the Living Cost and Food Survey (LCFS) in UK collect accurate consumption data over a two-week period, using expensive personal interviews, but do not collect the environmental preferences of respondents. Further studies can be conducted to analyse the carbon footprint associated with household profiles and their relationship with the healthy and nutritional quality of food diets. This may help policy makers to efficiently implement strategies and actions aiming to reduce the environmental impact of the food sector and address the global challenge associated with dietary changes.

2.3.3 The nutritional and healthy characterization of diets

In the developed world, obesity is a major health problem associated mainly with diseases such as diabetes, cardiovascular disease and some cancers (World Health Organization, 2003). The sustainable diet concept implies assessing the environmental concerns together with healthiness and nutritional adequacy (Perignon *et al.*, 2016).

A positive correlation exists between low-carbon food choices and the health population profile. High red and processed meat consumption, whilst among the most impactful products in terms of environmental sustainability, is also associated with an increased risk of cardiovascular disease (CVD) and cancer mortality (Micha;Wallace and Mozaffarian, 2010; Pan *et al.*, 2012). Conversely, consumption of fruit and vegetables, characterised by a low-carbon profile, is inversely associated with coronary heart disease (CHD) risk in western populations. Similarly, a high increase in dietary fibre and whole grains is linked to a reduced risk of colorectal cancer, CVD and diabetes (Seal, 2006; Aune *et al.*, 2011; Gan *et al.*, 2015). The most recent US Dietary Guidelines Advisory Committee claimed that shifts toward more plant-based foods could promote health as well as long-term environmental sustainability of the nation's food supply. This was also confirmed by the study of the Barilla Center for Food and Nutrition (BCFN) through the double food and environmental pyramid, which shows how the foods with greater environmental impact, such as fats and red meat, are those that, despite having important nutrients, must be consumed in moderation, to avoid negative impacts on health and the environment; while fruit, vegetables and carbohydrates, with a healthier profile, are also the most sustainable ones (Ruini *et al.*, 2015; BCFN, 2016).

However, how consumers substitute meat is crucial with some foods possibly leading to an increase in GHG emissions when energy loss is balanced. In addition, avoiding animal products does not necessarily means health benefits (Key;Appleby and Rosell, 2006); as eating meat can provide a high concentration of protein for children and undernourished people in developing countries (Friel *et al.*, 2009). An American study (Rose *et al.*, 2019) compared low-and high-CO_2 diets and showed significant differences in nutrient composition. Low-GHG diets contained more fibre and vitamin E, less sodium and saturated fat. However, the nutritional profiles of these diets contained significantly less iron, calcium, vitamin D, vitamin A, and potassium than the high-GHG diets, probably due to the lower consumption of foods of animal origin and dairy products. This was also found in the Health Eating Index (HEI) scores, an indicator developed by the United States Department of Agriculture to assess how well a particular diet is aligned with dietary recommendations in America (Rose *et al.*, 2019).

The higher mortality and chronic diseases associated with Western diet is due not only to a high content of red and processed meat but also to an excessive consumption of refined cereals, fried foods, soft drinks, sweets and energy dense, nutrient poor food products, mainly low in environmental impact (World Cancer Research Fund and American Institute for Cancer Research, 2007; McEvoy;Temple and Woodside, 2012). The same findings were confirmed by some French researchers who showed that, in their sample, the least impacting diets were associated with a lower nutritional quality (Vieux *et al.*, 2013).

In this sense, more investigation in these topics is needed in order to achieve the best trade-off between health, environment and nutrition. Further research should address these points simultaneously and influence political recommendations with the aim to improve public health and, at the same time, sustainability in the food sector.

2.4 Market based instruments

2.4.1 What are market-based policy instruments?

Market-based instruments are regulations that encourage behaviour through market signals rather than through explicit directives regarding pollution control levels or methods (Stavins, 2003). These are incentive-based instruments that generate incentives for firms or individuals in order to voluntarily alter their behaviour (Perman *et al.*, 2003). OECD economies have increased the use of these instruments in order to achieve environmental goals since 1970 (OECD, 2017). In 2000, revenues gathered from environmentally motivated taxes constituted 7% of the total OECD tax revenue (Perman *et al.*, 2003). These are used in different fields, such as water quantity management, forestry, fisheries and oil preservation.

2.4.2 Carbon taxes

Price changes can affect consumers' decisions from a standard economic approach. A "standard economic model of decision-making" would consider an individual who has a set of choices with their prices and a budget to take into account. Among these options, a choice set would contain the options that the individual can afford. Individuals would have preferences against these options and they would choose the options, which maximise their utility (Leicester;Levell and Rasul, 2012). Therefore, a change in prices can influence consumer behaviour.

Market-based instruments are one of the instruments used in environmental policy agendas to address the main environmental challenges such as climate change or water pollution (OECD, 2017). The aim of these instruments is to address market failure generated from environmental externalities by integrating consumption or production activities' external costs via charges or taxes on products or processes. In other words, the damage generated by pollution is manifested on market prices, an approach related to the internalization of the external cost (OECD, 2017).

Environmental taxes are a sub-group of market-based instruments (OECD, 2017). Climate change, pollution, biodiversity and consumption of natural resources are four big environmental problems to which environmental taxes can be applied. These taxes are implemented to reach environmental goals and are important tools to change consumer behaviour in a more sustainable way. Carbon taxes are an example of environmental taxes. As Metcalf and Weisbach (2009a) stated, carbon tax could be considered as a tax on greenhouse gases whose aim is to internalize externalities related to climate change caused by human activities (Khemani, 1993). A carbon tax obligates agents to consider the consequences of the activities they conducted, which generated carbon emissions, following the idea developed by Pigou (1929).

Carbon pricing is considered an effective tool to reduce greenhouse gases. It may diminish these emissions through the increase of the prices of the products with high emissions, which in turn may reduces the demand for them. In addition, products with lower emissions would be cheaper compared to the ones with higher emissions; therefore the demand for the former may increase (Flues and Dender, 2020).

Carbon taxes have been used in different countries. A carbon tax was introduced in Australia in 2012 after Government's commitment to decrease carbon emissions by 80% (Meng;Siriwardana and McNeill, 2013). The tax reduced carbon emission after its introduction; however, as a result of the reaction coming from voters and industry, the programme was repealed. Similarly, in 2008, a carbon tax was used in British Columbia, which covered around three quarters of the whole emissions in the province (Murray and Rivers, 2015). In 1990, it was introduced in Finland to apply to gasoline, light and heavy fuel oil, diesel, natural gas, coal, jet fuel and aviation gasoline; in 1991, in Norway and in 1992 in Denmark to apply on natural gas, petroleum and mineral fuel and in Sweden in 1991 on all fuel oil (Lin and Li, 2011). Finally, in France, a carbon tax has been applied to the consumption of fossil fuel since 2014 (Dussaux, 2020).

2.4.3 Bonus-Malus (i.e. Feebate)

Another type of environmental taxation is the *Bonus-Malus* system. *Bonus-Malus* is a policy tool to internalize externalities of certain commodities such as cars, through implementing a fee on consumers who choose vehicles with higher emissions and a rebate for those who buy cars with lower emissions (d'Haultfoeuille;Givord and Boutin, 2014). In other words, while non-polluting or energy efficient goods receive a subsidy, goods that are greatly polluting or consuming energy are taxed according to their level of harmfulness. Moreover, this system can be revenue-neutral if the revenues collected from the malus (tax) finance the bonus (subsidy). Hence, this scheme can, on average, be budget-neutral for consumers. A feebate system (e.g. bonus-malus) was applied in France in 2008 on the sales of new cars. Through this policy, individuals purchasing cars with emission lower than 130g of CO_2 per km profited from a reduction on their invoice which could reach €1000 contingent on the type of car (d'Haultfoeuille;Givord and Boutin, 2014).

2.5 Food policy and the environmental and nutritional quality of diets

2.5.1 Carbon taxation of consumption and its relationship with nutrition

The use of carbon consumption taxes are not the only instruments available for implementing sustainable behaviour and changing the demand side of food consumption. Different types of carbon abatement policies could be applied by varying between high income countries usually associated with demand-side instruments (e.g. tax, cap-and-trade...) and low-income countries dependent on supply-side policies, such as targets and regulations (Zhang and Wang, 2017). In general, a combination of stronger regulations and softer measures (e.g. awareness campaigns) could be an optimal solution in industrialized countries (Schanes;Giljum and Hertwich, 2016), even though information campaigns may not be seen as the most effective instruments in UK (Mazzocchi *et al.*, 2014). Other instruments are command and control with regards of banning high carbon footprint food products, or labelling (Panzone *et al.*, 2011).

The use of taxation for discouraging overconsumption of certain products is not a new concept given the use of consumption taxes and duties with regard to tobacco and alcohol consumption (Mytton;Clarke and Rayner, 2012). A review of trials and modelling studies suggests that any tax would need to be 20% or higher to have a significant impact on purchasing patterns and population health (Mytton;Clarke and Rayner, 2012). While more recently countries such as Hungary and Denmark have applied taxes on food products based on fat content, no country has yet applied a carbon consumption tax. Taxing food-related emissions would ensure that the price paid by the individuals are not distorted (Metcalf and Weisbach, 2009a). In other words, taxing agricultural emissions is one way of including climate change related costs in the market price of GHG based agricultural products thereby reducing their consumption to socially optimal levels (Kehlbacher *et al.*, 2016). However, carbon consumption taxes are unlikely to result in an optimum outcome in terms of carbon emission reduction, since finding a price on carbon emissions that reflects the true cost to society is difficult (Revoredo-Giha;Chalmers and Akaichi, 2018). Nevertheless, it is possible to have a tax that "controls" and "lowers" externalities (Baumol, 1972).

A carbon consumption tax being applied to all the major food products has been modelled for Denmark (Edjabou and Smed, 2013), Spain (García-Muros *et al.*, 2017a) and the UK (Briggs *et al.*, 2013). Caillavet;Fadhuile and Nichèle (2016) studied the effects of applying a 20 percent tax to food products with the highest carbon footprint such as meat and cheese (while other food products with lower carbon footprint were exempt from the tax). The paper showed that when all animal based food products are taxed, the net reduction in carbon emission is 7.5 %. Kehlbacher *et al.* (2016) found that a tax of £2.841/tCO2 on all foods would reduce emissions by 6.3% and a tax on food with above average levels of emissions would decrease environmental impact by 4.3%. On the other hand, Wirsenius;Hedenus and Mohlin (2011) focused only on consumption taxes on animal products and showed that a tax of €60 per ton CO_2-eq is estimated to reduce emissions by 32 million tons CO_2-eq, of which 80% is related to ruminant meat consumption. Edjabou and Smed (2013) found that GHG emission could be reduced by between 4 to 19.4 % for Danish households in the uncompensated tax scenarios. García-Muros *et al.* (2017a) used three scenarios of a high tax rate, high tax rate with exemption on certain products, and a low tax rate and found a reduction in emissions for Spanish households of 7.6 and 3.8 %.

Bonus-Malus taxation system can also be used to alter food purchase behaviour. Dogbe and Gil (2018) highlighted the importance of a revenue-neutral scenario to decrease the environmental impact of food consumption. They pointed out that taxing all products according to their CO_2 emissions would not be realistic since food prices can be increased to 55% higher than their existing price. Some scholars suggested that bonus-malus system can be efficient to increase fruit and vegetables consumption and decrease that of less healthy food such as fatty products by subsidising the former and taxing the latter (Bontems and Réquillart, 2009). For instance, Darmon *et al.* (2014) tested different price manipulations one of which was implementing a 30% discount on fruit and vegetables and the other was implementing a discount of 30% on vegetables and increasing prices of unhealthy food products by 30%. Results showed that the purchase of vegetables and fruits increased in both price treatments, for both low and middle-income groups. Nonetheless, the amount of less healthy food diminished only in the second price manipulation condition. Authors concluded that a simultaneous application of a subsidy on healthier food products and a tax on less healthy ones might be an effective policy tool to increase healthier food consumption.

Others scholars also considered also the nutritional dimension and the effects on death averted rates of carbon consumption taxes. Briggs *et al.* (2013) found that GHG emissions could be reduced by 7.5% for the UK population and could save 7770 lives in the UK each year. In addition, carbon taxation of food products would change energy intake by 1.4% and lead to a reduction in consumption of cholesterol, saturated fatty acid, total fat, vitamin A and vitamin B12 by more than 2%. However, they also showed how health and sustainability are not always aligned when they implemented subsidies together with carbon taxation (revenue-neutral scenario). Indeed, they predicted shifts in the number of people consuming below the recommended daily amounts of dietary micro-nutrients and an increase in the sugar level consumed by 2.2%. In this sense, a tax to make food carbon neutral may not always lead to the same distribution of prices that makes consumption decisions healthy. Further research is needed in this regard, with the aim to improve nutrition and environmental characteristics of food diets.

What seems to be lacking, however, is a study that not only analyses the impact of carbon taxation on diets, averted deaths and nutrients, but also on particular health indicators at individual level. The aim of this research is to fill this gap and in a wider sense provide a method for such simulation. In particular, this research will show how diets change with environmental regulations by considering two scenarios. The first, unfunded reform, Carbon Taxation only and the second, tax revenue neutral, with a *Bonus-Malus* taxation.

Interestingly, new diets will affect individual health. In doing so, this PhD research will provide evidence of how resulting diets affect some individual health biomarkers, which are Body Mass Index, Blood Cholesterol, Glucose and Glycated Hemoglobin (HbA1c). Thereby, information regarding particular diseases, like diabetes and obesity will be given.

2.5.2 Carbon taxation of trade and its impact on food imports

The economic development of a specific country is characterised by the opening of economies to the exterior with the consequences that the trade relations of a country with others are determinants of its economic evolution. It is relevant to consider which effects international relations would have on the environmental situation of a country and the respective pollution generated by its own needs and exterior requirements.

Consumption based and production based accounts show that CO_2 emissions associated with UK imports from abroad are greater than CO_2 associated with UK exports. From a production point of view, emissions in 2009 amounted to 558 $MtCO_2$ whilst consumer emissions were 669 $MtCO_2$. Production based emissions are falling in the UK, in line with Kyoto targets. Yet despite enormous time and effort devoted to international and national climate policies, global emissions associated with UK consumption of goods are increasing. Most CO_2 emissions associated with UK imports originated in industries that are more energy intensive and typically more polluting. On average, 64% of emissions embodied in UK imports originate in energy intensive industries associated with manufacturing. Emissions from non-manufacturing energy intensive industries accounted for another 8% making the total amount of 72% . The agriculture sector is of particular interest as it is both a significant source of non-CO_2 emissions, causing about 10-12% of global GHG emissions and significantly trade exposed (Kulionis, 2014). Furthermore, this sector provides a largely unusual potential to reduce GHG emissions.

Although the Paris Agreement brings almost all nations into the common cause to undertake ambitious efforts to combat climate change, it is up to each participating country to decide on its mitigation strategy, which mitigation policy and which sectors they include. Concerns about emission leakage and competitiveness have led to a special treatment or complete exemption of emission-intensive trade-exposed sectors from carbon pricing (Nordin *et al.*, 2019). In the European Union (EU), for example, certain sectors like agriculture and transport are not included in the emission trading system (EU-ETS) and some sectors that are covered by the EU-ETS but considered to be exposed to a high risk of leakage received emissions allowances for free.

In this context, should trade rules be altered to ensure international trade has a benign environmental impact? Several studies point out that achieving the goal of the Paris Agreement to limit the temperature increase to below 2 degrees Celsius by the end of the century requires the contribution of agriculture to the GHG emissions reduction efforts. A cost effective solution for the inclusion of agriculture in global GHG emissions mitigation has to be found. Such a strategy should counteract emissions leakage and alleviate competitiveness losses. One policy option to face emissions leakages is import tariffs based on the carbon footprint of imports, so called carbon border adjustments (BCA). BCA are intended to level the playing field between producers in carbon taxing countries and in non-carbon taxing countries and in times of uneven climate action BCA are a policy option that is gaining political interest (Condon and Ignaciuk, 2013). The three most cited arguments for the use of border carbon measures are: to address domestic constituencies' concerns about the loss of competitiveness, to reduce carbon leakage and to leverage other countries' participation in climate agreements (Condon and Ignaciuk, 2013). However, some argue that unilateral carbon border adjustments could impede future cooperation on multinational climate agreements and spark protectionist trade wars (Dröge *et al.*, 2009).

Several widely ranging alternatives to border carbon adjustments have been proposed by both governments and academics. Some researchers discuss the possibility of imposing an import ban or punitive tariffs on imports from countries that do not have sufficient carbon regulations. Some researchers claim that government ought to impose anti-dumping or countervailing duties on imports from countries without GHG regulations (Bhagwati and Mavroidis, 2007). Carbon footprint labels and government procurement guidelines for green goods might be put in place together with biofuel standards (Moïsé and Steenblik, 2011). In general, more integration with emerging economies in reducing their own emissions to contribute to the international funds implemented by the developed countries could be essential to strengthen the co-operation of countries to combat climate change.

Britain has pledged to cut emissions by 78% by 2035 on the way to achieving so-called net zero by the middle of the century (Committee on Climate Change, 2019). In this regard, the UK is considering a carbon border tax to protect domestic industries and manufacturers from becoming uncompetitive due to the higher costs triggered by policies to tackle climate change. The theory behind a carbon border tax is that it could be applied to imported goods produced in countries with weaker climate laws. The aim is to protect industries in countries that have higher carbon pricing, while encourage other regions to move ahead with similar climate actions. To meet World Trade Organization (WTO) rules, the tax would have to cover the same industries as the UK's Emission Trading Scheme (ETS) – which the Government is considering extending to cover agriculture and land use. However, it could allow for the removal of free emissions allowances, the current approach to addressing carbon leakage. The introduction of such a charge is one of the policies set up by the European Commission Green Deal and could be in force by the end of 2022.

In this regard, this study will also simulate the impact of pricing GHG emissions of foods imported from EU to the UK to assess the efficiency of BCA in addressing more sustainable import strategies among UK producers. The research will add to the existing literature on BCA assessing their performance in the agricultural sector and provide insights on the impact of unilateral climate policies for the UK agricultural sector.

2.6 Post-Note Chapter 2

2.6.1 Contextual Information

Food consumption is a major issue in the politics of sustainable consumption and production because of its impact on the environment, individual and public health, social cohesion and the economy. In particular food consumption is associated with the bulk of global water used and is responsible for the generation of approximately one-third of greenhouse gas emissions (GHGs)(Crippa *et al.*, 2021). At the same time, population growth and rising economic prosperity are expected to increase demand for energy, food and water, which will compromise the sustainable use of natural resources and could aggravate social and geopolitical tensions. Considering the demographic changes and the growing global population, these problems are only expected to worsen in the future (Reisch;Eberle and Lorek, 2013).

Achieving behaviour change in favour of more sustainable food consumption is a long term goal that involves several stages and requires the constant effort of all actors. Many barriers at institutional, informational and personal level are involved. Research and policy agree on the main drivers of no sustainability in the current food domain. These include, distance between food consumers and producers, the significant loss of biomass and the high consumption of animal products in the form of meat and dairy products.

Overall, policy makers trying to enhance food system sustainability have three major types of instruments available: information-based, market-based and regulatory (Lebel and Lorek, 2008; Reisch;Eberle and Lorek, 2013). The latest literature related to consumer behaviour has been extended with “nudging” instruments, such as choice architecture, in which the person or organization “designing” the choice can harmonize the default outcome with the desired outcome (Leonard, 2008). These behaviourally informed social regulations have been included in political legislations, specifically for consumer policy. In the food sector, these types of strategies have been quite successful to promote healthier and sustainable choices (Wansink;Just and Payne, 2009).

Among the policy tools listed above, tax policies, information intervention programs and subsidies can be used to change consumption patterns. Informational measures have been analysed in the literature mainly as social marketing campaigns, labelling regulation and educational measures. These tools seem to modify attitudes and behaviours towards healthy diet, but they do not cause significant impact on household consumption, at least in the short or medium term (Bonnet;Bouamra-Mechemache and Corre, 2018). Environmental subsidies could be an option if they provide incentives to invest in environmental innovations.

However, they are expensive as all taxpayers will have to pay for the subsidies whatever their consumption. In addition, these subsidies are not able to drastically change household consumption behaviour because households will not have to pay a higher price for high polluting animal products.

Following these considerations, taxes might be the most efficient tools as they directly address the negative externalities linked with environmental damage. The resulting prices can integrate environmental cost impacts such that both households and firms will adapt their behaviours to reduce their environmental footprint. Indeed this policy instruments is that which is recommended by most economists (Bonnet;Bouamra-Mechemache and Corre, 2018).

A tax can be implemented either directly on emissions, on the product input at the origin of the environmental impact or at the final products purchased by household. From the economic theory it would be more efficient to use a tax that directly targets the source of the market failure. Nevertheless, as suggested by Edjabou and Smed (2013) and Wirsenius;Hedenus and Mohlin (2011), in the case of agricultural products, the monitoring costs are high, the technical potential for emissions reduction is low and the possible output substitution exists such that emissions or input taxes are less efficient than output-based taxes. Henderson *et al.* (2018) stated how carbon policies that target livestock producers are unlikely to reduce substantial share of global GHG emissions and recommend more research like the present study, to reduce environmental impact of foods, especially in high income countries. Taking these aspects into account, this PhD project aims to estimate whether consumption taxes can mitigate environmental indicators. Taxes can be efficient tools to guide household decision-making; nevertheless, the implementation of such taxes have not been fully explored. Moreover, a carbon tax on food could provide an incentive for consumers to modify their diets to be more climate friendly, which would provide health benefits by reducing calorie consumption from proteins and/or increase the importance of plant proteins compared to animal proteins (Caillavet;Fadhuile and Nichèle, 2019).

Therefore, environmental taxation on food consumption has been considered in recent literature; however, it raises several specific issues. Considering the substitution among all food groups and addressing compatibility between the environment and nutritional outcomes are important issues. The possibility that households could respond to the internalization of environmental costs in food prices through virtuous substitution implying all foods and changes in consumption patterns that would reduce GHGs is not guaranteed (Wirsenius;Hedenus and Mohlin, 2011; Briggs *et al.*, 2013; Edjabou and Smed, 2013; Caillavet;Fadhuile and Nichèle, 2016; Bonnet *et al.*, 2020). Another issue concerns the distributional aspect of carbon taxation. On methodological basis, carbon pricing is key for the establishment of emission-based taxes and is among the policy tools for meeting distributional challenges (Change, 2018). However, a major disadvantage to food taxation policies is their regressivity because lower-income households spend higher proportions of their budget on foods (García-Muros *et al.*, 2017b).

The regressivity nature of environmental taxes have been a very discussed topic of concern during recent decades following the introduction of energy taxes in several countries or in simulation scenarios targeting reduced GHG emissions (Caillavet;Fadhuile and Nichèle, 2019). Addressing regressivity, revenue-neutral approaches are key strategy to target distribution neutrality. In Metcalf (2020) the regressivity of the carbon tax in the US case was offset by using the revenue to fund a reduction in the income tax. These literatures suggest how any policy increasing the cost of energy will impact low-income household, making equity a major concern when taxes are discussed. Considering these issues, food can be compared to energy, even though very few studies have been addressing the distributional issues of a carbon tax on food and have neglected social issues, welfare and acceptability. The key issue of introducing compensating mechanisms with a combination of taxes and subsidies has been used in certain carbon scenarios designed for food consumption (Briggs *et al.*, 2013; Edjabou and Smed, 2013; Markandya *et al.*, 2016) and this is also what this PhD study is going to do.

From the production side, the EU is at the forefront of international efforts to fight climate change. The European Green Deal sets out a clear path towards realising the EU’s ambition target of a 55% reduction in carbon emissions compared to 1990 levels by 2030 and to become a climate-neutral continent by 2050. As part of these efforts, the Carbon Boarder Adjustment method is a climate measure that should prevent the risk of carbon leakage and support the EU’s increased ambition on climate mitigation while ensuring WTO compatibility. Climate change is a global problem that needs global solutions. As we raise our own climate ambition and less stringent environmental and climate policies, there is risk of carbon leakage – i.e. companies based in EU could move carbon-intensive production abroad to take advantage of lax standards, or EU products could be replaced by more carbon-intensive imports. Such carbon leakage can shift emissions outside of Europe and therefore seriously undermine EU and global climate efforts. The CBAM will equalise the price of carbon between domestic products and imports and ensure that the EU’s climate objectives are not undermined by production relocating to countries with less ambitious policies. Based on these considerations, this mechanism will be used in the second paper to address sustainability goals at European level.

This PhD projects contributes to the literature by analysing the effects of implementing different scenarios of carbon taxation aiming to address the environmental damage of the food sector at production and consumption level. At the same time, distributional effects are taken into consideration to face tax regressivity and to support lower-income household in the changing of consumption patterns. Compared to the literature, the health consequences of changing diets are also evaluated at individual level, to assess the link between health and sustainability using a unique database that contains information on disaggregate household purchases, including price paid for each product and the respective health and nutritional characteristics at individual level. The second part of the project considers the implementation of a carbon border adjustment to reduce emission embodied on trade. This mechanism will help reduce the risk of carbon leakage by encouraging UK producers to green their production processes.

2.6.2 Detailed description of the thesis

The first paper does and *ex ante* simulation to explore the environmental, health and food consumption implications of carbon consumption taxes. A unique database of GHG emissions will be used, providing a consistent methodology for evaluating the emissions for all products. This considers the implementation of two different scenarios: (A) carbon taxation only and (B) Bonus-Malus interventions which constitutes a revenue neutral fiscal policy for food consumption, where environmental revenues after taxation have been redistributed to all the households in the form of a subsidy. Applied to food consumption, a taxation policy may have important distributional and nutritional disadvantages which can be addressed through specific scenarios design. The reallocation of revenues in the second scenario can modify distributional outcomes and diet quality. Furthermore, the importance of carbon pricing can be questioned to obtain not only substantial emissions mitigation but also health benefits. In this regard, this study provides further implications at nutritional and health level that were barely considered in the literature. The new consumption patterns simulated after the implementation of carbon taxation on food will be linked to specific health biomarkers at individual level to understand if new and more sustainable diets after the application of carbon policies on food are also providing health advantages. More specifically, the following biomarkers at individual level will be considered: Body Mass Index, Blood Cholesterol, Glucose and Glycated Hemoglobin (HbA1c). The revenue neutral scenario and the carbon taxation are compared in terms of environmental, food and health consequences to find the better trade-off among the different indicators. This study retains an Almost Ideal Demand System (AIDS) demand system (Deaton and Muellbauer, 1980) to simulate the effects of these fiscal policies on environmental inequality and nutritional indexes based on UK consumption data retrieved from the Living

Cost and Food Survey (Department for Environment, 2019b). The individual nutritional and health effects will be evaluated because of changes in consumption patterns at the household level based on the National Diet and Nutritional Survey (MRC Elsie Widdowson Laboratory, 2019b).

The second paper investigates the effects of the implementation of carbon taxes at produces level on the trade flows between the UK and the EU, in order to make these collaborations more sustainable. More specifically, a carbon boarder tax will be implemented at EU level by increasing the price of imported dairy and meat products in UK considering their carbon footprint. These policies might adjust the import strategies of UK producers in an eco-friendlier way. This study adopts a micro-simulation approach built upon the estimation of a Gravity Model on Trade, broadly used in the trade literature surrounding trade policies (Anderson and Van Wincoop, 2003; Silva and Tenreyro, 2006). This study contributes to the research surrounding the implementation of carbon border adjustment and the subsequent carbon leakage and pollution heaven effects. The nutritional and environmental implications of these types of taxation will be explored in detail to evaluate the different aspects related to food consumption.

2.6.3 New Developments in the Field

The ways in which we produce food and manage our lands are responsible for almost a third of global greenhouse gas emissions along the entire supply chain (Crippa et al., 2021). Current food production and consumption trends are inconsistent with the Convention on Biological Diversity's 2050 vision of living in harmony with nature (Smart, 2016). Some authors suggested how, and under what conditions, the post 2020 biodiversity framework can support transformative change in food system. Subsidy reform, valuation, food waste reduction, sustainability standards, life cycle assessments, sustainable diets, mainstreaming biodiversity and strengthening governance can support more sustainable food production and consumption (Delabre et al., 2021).

Food is an essential contribution from nature to people, ultimately underpinned by biodiversity. Food systems are responsible for around 60% of global terrestrial biodiversity loss and the overexploitation of 33% of commercial fish population. At the same time, one-third of all food goes to waste between the points of production and consumption, while around 11% of the world population is undernourished and 39% are obese or overweight (Delabre et al., 2021). It is understood that shifting toward more sustainable and varied diets that include fewer animal products could support people in reducing their higher environmental footprint (Willett et al., 2019). However, there are numerous political and economic barriers to do so (Lang, 2012). These include the powerful meat and dairy industries, subsidies supporting unsustainable production and consumption, and a lack of uptake of the issues by environmental groups. There are complexities in measuring sustainable diets and there are uncertainties related to the rebound effects in market and consumer behaviours. On the other hand, alternative protein sources may be deemed too radical for mainstream consumption (Delabre et al., 2021).

Shrinking the size of our current food system will not substantially cut emissions. Recent research updates state how fundamental transformation in the very nature of the global food systems are necessary to fix these problems. This includes that people consume what they need in terms of nutritional requirements, curb food waste and eat a more balanced diet. On the other hand, a qualitative transformation means more efficiency, producing food in a less polluting way: smarter dosing of fertilizers or planting higher yield crops. Also, carbon pricing could help steer farmers towards lower-emission agricultural practices. All together, these could drastically reduce greenhouse gas emissions (Bodirsky et al., 2022). In addition, since a sustainable food system transformation that takes into account all costs to the environment would lead to a slight increase in food prices, any such changes must be accompanied by a comprehensive policy mix of smart taxing scheme, social compensation for carbon dioxide pricing and international transfers (Bodirsky et al., 2022).

Traditional research and policy methods have proven insufficient for widespread change in diets, food practices and food production: a food system transition requires participation of all actors. The new development of citizen science (and similar) is a participatory research method that actively involves citizens in scientific enquiry to generate new knowledge or understanding. This participation involves engaging with communities and seeking the participation in data collection and or co-creation. In this regard, it builds upon traditional research methods by providing a framework for investigation while offering a concurrent platform for intervention, community engagement and teaching. These outcomes could stimulate a faster and smoother transition to sustainable diets and a wider sustainable food system (Oakden et al., 2021).

On the other hand, an increasing amount of research of consumer preferences for alternative proteins has been carried out in recent years. Moreover, how consumers combine different types of proteins in their diets and what kind of processes are currently taking place have been considered (Niva and Vainio, 2021). Currently, the consumption of plant-based protein products is more widespread compared to insect-based protein products, even if animal based-protein still possess an important role in diet, even among those consumers who are transitioning toward less meat and more alternative proteins. The consumption of insect-based, on the other hand, may catch up plant-based innovations in the future. This could take place within the wider development of alternative proteins, which will in the future include food produced by means of cellular agriculture (Niva and Vainio, 2021). The development of new and innovative eating habits might need to be enforced together with a deep understanding of consumers behaviours for developing strategies and educational interventions necessary to transition towards more sustainable diets at the individual and population levels. In this context, social and psychological models can be effective in identifying and understanding the role of cognitive constructs behind the consumer behaviour (Biasini et al., 2021).

Taking these innovation strategies and actions into consideration, more research and government interventions might need to be implemented simultaneously in order to deep in the knowledge surrounding these topics. More information and education tools are necessary to shift population behaviours through a more sustainable pattern together with the development of technological innovations at producer level.

Chapter 3. Implications of carbon policies on the quality of UK consumers' diet and health

3.1 Abstract

There is increasing recognition that food markets should be regulated to reduce the environmental impact of diets. For instance, food prices could be increased by carbon taxes, which incorporate the level of greenhouse gas (GHG) emissions associated with food production. However, environmental impact and nutritional quality are not perfect complements in foods: while fresh fruits and vegetables are low in fats and have lower GHG emissions compared to most food products, they can be low in other essential nutrients (e.g., essential ammino acids). Similarly, soft drinks are generally considered unhealthy, but are low in carbon footprint. Therefore, a diet which has a lower environmental impact may be nutritionally imbalanced. This chapter seeks to extend our present understanding of food policies by exploring the link between environmental regulation of food markets and the health quality of the resulting diets. The aim is to model the effects of hypothetical carbon consumption reforms on the prices of foods and drinks and how these affect household consumption and individual health. Preliminary results show high substitution between food categories. This suggests environmental policies can lead to more sustainable food consumption patterns. Interestingly, this change in diet composition has the potential to have few beneficial health effects, though the analyses requires further investigation to accurately estimate the changes in outcomes.

3.2 Introduction

Rising greenhouse gas emissions (GHG) are an increasing concern for policymakers. The literature currently indicates that over 30% of GHG emissions globally are associated with food products, from agricultural production, processing and transport (Poore and Nemecek, 2018; Springmann *et al.*, 2018b; Crippa *et al.*, 2021). Dietary choices – the types and amounts of foods that individuals consume – are a major determinant of human health and environmental sustainability (Clark *et al.*, 2019). Because world demand for proteins and meat is expected to steadily increase due to population growth and a preference for animal protein, the unsustainability of this demand is threatening global environmental resources (Caillavet;Fadhuile and Nichèle, 2019). If meat and dairy consumption continue to increase at current rates, by 2050, the agricultural sector alone will produce 20 $GtCO_2$-eq of the 23 $GtCO_2$-eq yearly limit, leaving only 3 $GtCO_2$-eq for the remainder of the global economy (Wellesley;Froggatt and Happer, 2015). Therefore, there is increasing support for the introduction of policy instruments that will reduce the GHG emissions of food (Panzone *et al.*, 2011; Mazzocchi *et al.*, 2014; Schanes;Giljum and Hertwich, 2016; Zhang and Wang, 2017). The literature aiming for the regulation of food consumption has mainly focused on two independent streams: most of the literature (Dubois;Griffith and Nevo, 2014) has focused on the nutritional implications of food purchases; while a separate strand on the environmental implications of consumer food choices, measured as their carbon footprints (Panzone *et al.*, 2016; Panzone *et al.*, 2018). However, a specific feature of food consumption is that the GHG emissions associated with food choices are a consequence of the demand for nutrients, making environmental and nutrition policies inevitably interlinked. As an example, reducing the consumption of food products with a high carbon footprint (e.g. meat) has been associated with improvements in health status, e.g. lower risk of cardiovascular disease and cancers, primarily from substituting the origin of food from animals to plants (e.g. Edwards *et al.*, 2011; Clonan and Holdsworth, 2012; Macdiarmid *et al.*, 2012; Sabaté and Soret, 2014; Caillavet;Fadhuile and Nichèle, 2016).

Nevertheless, while a positive correlation between nutrient content and GHG exists (Drewnowski *et al.*, 2015), it is not always the case that low-carbon options are healthy: for instance, foods rich in sugar and starch are low in GHG emissions even though are detrimental to health, like soft drinks in Briggs *et al.* (2016). As a result, classical policy instruments such as carbon taxes targeting GHG reduction associated with diets might not be fully successful in promoting healthy eating, and it is uncertain what the impact of a carbon tax would be once it is introduced. First, the possibility that households could respond to the internalization of environmental costs in food prices through virtuous substitutions that reduce GHG emissions is not guaranteed (Wirsenius;Hedenus and Mohlin, 2011; Briggs *et al.*, 2013; Caillavet;Fadhuile and Nichèle, 2019). Second, nutritional outcomes are not clear. Some changes in food consumption behaviours might worsen the health profile of the population. Third, distributional issues are critical: a major disadvantage of food taxation policies is their regressivity because lower-income households spend a higher proportion of their budgets on food and might be the most affected by these types of regulations (García-Muros *et al.*, 2017a).

In this context, this study explores the impact of a carbon tax on both health outcomes and GHG emissions by considering two types of scenario: taxes-only, scenario (A), and a revenue neutral fiscal scenario, scenario (B), through subsidies for food consumption. Because carbon taxation has not yet been introduced in any food market, this research project does an *ex-ante* policy evaluation, using a micro-simulation approach, built around an Almost Ideal Demand System estimation (Deaton and Muellbauer, 1980; Dhar;Chavas and Gould, 2003). The environmental and nutritional effects are then computed after regulation. Health implications of carbon policies are evaluated at individual level considering specific health biomarkers: body mass index (BMI), blood cholesterol, glucose and glycated haemoglobin (HbA1c).

This chapter is organized as follow. Section 3.3 describes the food consumption and health data. Section 3.4 studies the empirical demand model and health model, section 3.5 the micro-simulated policy interventions. Section 3.6 the demand system and health results and section 3.7 the simulation findings. Section 3.8 the environmental and nutritional effects, section 3.9 the discussion and section 3.10 the concluding remarks.

3.3 Data

3.3.1 Food Consumption Data

The data used for this analysis came from the Living Cost and Food Survey 2015-2016 (LCFS) (Office for National Statistics, 2017b), that collects detailed information on food purchases in a two-week window by 6232 UK households. For the analysis, only data related to the year 2015 were considered and households with no income information were excluded. In total, the sample ready for the analysis includes data from 4947 nationally-representative UK households, representative by household size, number of children, social class, geographical region and age group. The dataset includes both household (demographic and income) information and a food diary, where each individual aged 16 or more was asked to keep records of all food expenditure over a two-week period. This diary has 266 code categories for food and drinks, including quantity purchased and expenditure. While the LCFS includes all food and drink consumed out-of-home, this is not included in the analysis, which focuses on purchases for in-home consumption. The data also include the nutritional information (e.g. energy, sugar, fats, sodium) of each food purchased, for each quarter of the year. The list of nutrients is available in Table A.1 in Appendix A. The carbon footprint of all the products listed in the LCFS was obtained and collated into a new database (Appendix A Table A.2) from data published in the literature (Flysjö;Thrane and Hermansen, 2014; Scarborough *et al.*, 2014; Drewnowski *et al.*, 2015; Clune;Crossin and Verghese, 2017).

To make the estimation feasible, all food and drinks were combined into macro-categories, following two types of aggregations:

- the first one grouped products into the 7 categories of the Eatwell Guide (in grey in Figure 3.1), a framework used by the UK Government to help consumers identify a healthy and nutritionally balanced diet (England, 2016);
- the second one grouped products into 11 categories, defined by similarity as sub-categories of the first grouping as for instance in Fang;Kasteridis and Yen (2011) (in blue in Figure 3.1 and in Table 3.1).

These aggregations were then used to obtain two different datasets at the household level. The first will be called in this study "Eatwell aggregation" and the other "second type of aggregation". The household individual item purchases were aggregated to fortnightly expenditures and quantities in each group from which unit prices were calculated as a ratio of the expenditures and quantity purchased (pence/grams). Missing prices in a particular category due to non-consumption were replaced by the average of all the prices paid for that category within the same geographical region. The Eatwell dataset was implemented as a starting point for the present study, helping to develop the methodology and the demand model estimation. The main results related to the simulation of diet and health consider the second type of aggregation, more in line with the research questions of this project.

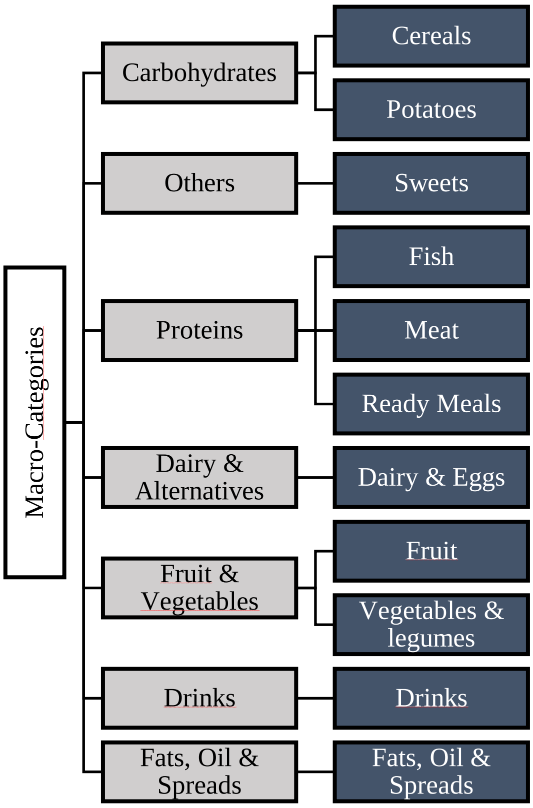

Figure 3.1: Food macro-categories

Macro-Categories	CO_2 impact	Health Profile
Cereals	Medium	Positive, especially whole grain
Dairy & Eggs	Medium	Positive
Drinks	Low	Negative (sugar sweetened beverages)
Fats, Oils & Spreads	Medium	Positive
Fish	Medium	Positive, especially oily fish
Fruit	Low	Positive
Meat	High	Negative red meat, positive white meat
Potatoes	Low	Positive
Ready meals	High	Negative
Sweets	Low	Negative
Vegetables & Legumes	Low	Positive

Table 3.1: Macro-categories in the second type of aggregation, classified by CO_2 impact and health profile

Note: high, medium and low CO_2 impact were defined by considering the average of the carbon footprint data in each category. A positive health profile reduce the risk of non-communicable diseases and a negative profile increase the risk.

3.3.2 Health Data

Data used for the health analysis came from the UK's National Diet and Nutrition Survey. The analysis covers data from 2008/2009 to 2016/2017 (MRC Elsie Widdowson Laboratory, 2019a). This review contains nutrition, food consumption and general health information at an individual level for the UK population aged 1.5 years and above, living in private households. The survey aimed to collect data from a UK representative sample of 1000 people per year, 500 adults and 500 children. There are two main parts to the survey: an interviewer stage and a nurse visit. During the interviewer part, data were collected including a four-day food dairy, height and weight, smoking and drinking habits, sport activities and a spot urine sample. During the nurse visit, a fasting blood sample and urine collection, physical measurement, blood pressure and information about prescribed medicines and dietary supplements were collected (Department of Health, 2016).

The different files (nutrient, food and health data at individual and daily level) were merged in a unique dataset. Food and drink categories, in terms of quantities consumed, were then created following the same aggregations used for the LCFS (Figure 3.1) in order to facilitate the implementation of the simulation during the next stage. The weighted prices were obtained from the LCFS and the individual expenditures were calculated at food and drink category levels. In order to obtain food expenditures at household level, different weights were used for children and adults, assuming that children eat half amount compared to adults (Wheeler, 1991). The yearly food categories expenditures at household level for each food category were then calculated.

3.4 Methodology

The introduction of a carbon tax, intended to tackle GHG emissions, may affect households by increasing the price of different products based on their carbon footprint. Household responses depend on the size of this price effect. Given their own budget, households may substitute high taxed products for less taxed ones or they can reduce their budget share for untaxed in favour of the more expensive ones. To analyse how consumers change their food consumption behaviour after the introduction of a climate tax on food and their implication on health, a two-step approach was followed. Firstly, a demand model in expenditure share forms was estimated to provide a set of estimates of the compensated cross and own-price, expenditure elasticities of the food categories analysed. The specification of the health model is then presented to determine the effects of particular foods purchased at household level on some types of health biomarkers at individual level. Secondly, these structural model estimates were used to predict changes in household food budget shares generated by the tax rates and their implications on individual health.

The methodology is described as follow. In section 3.4.1 the empirical demand model and in section 3.4.2 the specification of the health model are presented. Section 3.4.3 describes the model estimation. The microsimulation policy intervention of diet and health is explained in detail in section 3.5.

3.4.1 Empirical demand model

For the first step, we estimated demand using an Almost Ideal Demand System (AIDS), which gives an arbitrary first order approximation to any demand system and it is easy to estimate in its linear approximate form. It has a functional form which is consistent with known household budget data (Deaton and Muellbauer, 1980) and it is derived from an expenditure minimization framework rather than an utility maximisation (Deaton and Muellbauer, 1980). In addition, the model satisfies the economic consumption theory axioms of choice exactly and does not impose constraints on the utility function (García-Muros *et al.*, 2017a). It aggregates perfectly over consumers without invoking parallel linear Engel curves and it can be used to test the restrictions of homogeneity and symmetry through linear restrictions on fixed parameters (Deaton and Muellbauer, 1980).

The AIDS model proposed by Deaton and Muellbauer (1980) defines demand as:

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left(\frac{x}{P*}\right) + e_i \tag{3.1}$$

where w_i is the food or beverage expenditure share for food or beverage group i, x represents total food and drink expenditure, $x = \sum_{i=1}^{n} p_i q_i$,. p_j are the prices of commodity j. α_i , β_i , γ_{ij} are the parameters to be estimated. $P*$ is the corrected Stone price index (or expenditure deflator) as in Moschini (1995), that in logarithmic form (Deaton and Muellbauer, 1980), is defined as:

$$\ln P^* = \sum_{i=1}^{n} w_i \ln p_i \tag{3.2}$$

The term ($\frac{x}{P*}$) characterises "real expenditure". Finally, e_i is the idiosyncratic error term. In this form, with $P*$ as a price index, the coefficients are easily interpreted. The w_i budget share is expressed in terms of prices and real income or expenditure ($\frac{x}{P*}$) . The α_i is the intercept and represents the average budget share when all logarithmic prices and real expenditure are equal to 1. The γ_{ij} is equivalent to the change in the budget share with respect to a change in the price p_j, with real expenditure or income held constant, that is $\gamma_{ij} = \partial w_i / \partial p_j$.

The demand properties, commonly known as adding up, homogeneity, and Slustky symmetry can be shown to be satisfied for the AIDS. First, for adding up, the budget shares sum up to 1 if:

$$\sum_{i=1}^{n} \alpha_i = 1, \quad \sum_{i=1}^{n} \gamma_{ij} = 0, \quad \sum_{i=1}^{n} \beta_i = 0 \tag{3.3}$$

Second, the homogeneity condition holds if:

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \tag{3.4}$$

And finally, the symmetry restriction holds when:

$$\gamma_{ij} = \gamma_{ji} \tag{3.5}$$

Provided these constraints, the demand system equations add up to total expenditure $\sum w_i = 1$, are homogeneous of degree zero in prices and total expenditure and satisfy Slutsky symmetry. This means that in the absence of changes in relative prices and "real expenditure" ($\frac{x}{P^*}$) the budget shares are constant and this is the natural starting point for predictions using the model. Changes in relative prices work through the γ_{ij} and changes in real expenditure with the β_i coefficients (Deaton and Muellbauer, 1980).

Endogeneity issues can arise when there are some unobservable variables influencing consumer behaviour that are correlated with expenditure and price formation (Dhar;Chavas and Gould, 2003). Unobserved product characteristics could include attributes that are not measured, or marketing efforts such as advertising, sales, promotions and shelf positions that are observed by the retailer, but not the econometrician. The resulting endogeneity means that all parameters estimates will be biased and inconsistent (Bonnet and Richards, 2016). Endogeneity is typically addressed through the control function approach (Petrin and Train, 2010).The control function approach is a two-step approach in which the endogenous variable is regressed on the exogeneous product attributes and instrumental variables in the first stage. The estimated error term from the first stage is then included in the second stage. The estimated error term includes some omitted variables that are correlated with the endogenous variable and not captured by the other exogeneous variables of the demand equation or by the instrumental variables. Introducing this term in the indirect utility function captures unobserved product characteristics that vary across time and essentially purge the equation of bias as the endogenous variable is now uncorrelated with the new error term (Bonnet and Richards, 2016).

The choice of instrumental variable is crucial. Good instruments must be independent of the error term, make economic sense, be sufficiently correlated with the endogenous regressor, but must not be correlated between themselves (Bonnet and Richards, 2016).

To reduce possible endogeneity between expenditure share and total expenditure, household expenditure was instrumented with gross normal weekly household income (Blundell;Pashardes and Weber, 1989). Income was scaled using the OECD equivalence scale provided in the LCFS. Equivalisation is a standard way of adjusting household income to take into account the different financial needs of different types of household. Households with the same equivalised income can be said to have a comparable standard of living.

In the first stage, household per capita food and drink expenditure (endogenous variables) was regressed on all the exogenous variables in the model: income (I_h), family size, sex of the oldest adult in the household, age of the household reference person, log of instruments of prices. The predicted residuals were then used as instruments for total expenditure (Blundell;Pashardes and Weber, 1989).

$$ln\, x_h = \alpha_i + \eta_h\, ln\, I_h + \sum_{j=1}^{n} \lambda_{ij}\, ln\, z_j + \sum_{k=1}^{s} \rho_{ik} d_{kh} + \xi_h \quad (3.6)$$

Where x_h represents (endogenous) household expenditure, I_h the exogeneous instrument represented by the household income, z_j representing the instruments for the endogenous prices (that are explained below) and d_{kh}, representing the covariates at household level that affect consumer behaviour, which are family size, sex of the oldest adult in the household, age of the household reference person. The predicted values of the residual in the first stage ($\widehat{\xi_h}$) were then estimated and used as instruments in the second stage.

Regarding the endogeneity in the price formation, different approaches have been tested. The first one considered the average of the price paid by all the other households that bought the same item in the same region, as an instrumental variable for each household price. Another, by using Living Cost and Food Survey prices of the previous year, 2014, derived from the family food dataset (Office for National Statistics, 2017b). However, assuming no spatial and temporal correlation between markets, prices in other markets can also be valid proxies for the cost of production (Hausman;Leonard and Zona, 1994). In this regard, the average of the price paid by households in all the other regions and months that bought the same category was used as an instrumental variable for each household price in this study. These instruments are expressed as (z_j) in equation (3.6) and (3.7)

In the case of price endogeneity $\ln p_{jh}$ was the endogeneous dependent variable and the same set of exogeneous variables used for household expenditure, were used in the first stage:

$$ln\, p_{jh} = \alpha_i + \eta_h\, ln\, I_h + \sum_{j=1}^{n} \lambda_{ij}\, ln\, z_j + \sum_{k=1}^{s} \rho_{ik} d_{kh} + \varepsilon_{ij,h} \quad (3.7)$$

The predicted values of the residuals in the first stage were then estimated $\widehat{\varepsilon_{ij,h}}$ and used as instruments in the second stage.

Another important issue that can arise in the estimation of the model is that many households have no expenditures in at least one of the food commodity groups, i.e. their dependent variable is zero. This is very common in family budget surveys since they are surveys of spending, not use. Survey information is usually insufficient to determine whether a zero value represents a household that never consumes an item, a household that does not consume the item at given prices relative to its income, or a household that consumes an item infrequently (Maddala, 1983). If these households were dropped from the estimation, there would be a risk of biased estimation because of the much smaller sample size. Furthermore, this can lead to sample selection bias since non-censored households are probably non-randomly selected among the population. In general, estimation techniques that fail to take into account that the dependent variable is truncated and that the sample is censored will produce biased parameter estimates. This issue was addressed by using a variant of the Heckman's two step procedures proposed by Heien and Wesseils (1990) in order to keep in the estimation all the households with zero budget shares in at least one category. The first step was similar to Heckman (1979): it uses a probit regression to find the purchasing probability of a certain item according to a set of explanatory variables.

In the first stage, the decision to consume is modelled as a dichotomous choice problem. More specifically, using probit analysis we estimate for each food equation (Lazaridis, 2004):

$$Z_i = \Phi\big(h(\boldsymbol{x_i}, \boldsymbol{a})\big) + u_i \tag{3.8}$$

This equation is estimated using all available observations. Z_i takes the value of one if spending is reported by the household (i.e. if $w_i > 0$) and zero if it is not.

The specific form of *h* is:

$$h(\boldsymbol{x_i}, \boldsymbol{a}) = a_0 + \textstyle\sum_{j=1}^{n} a_1 \ln p_j + a_2 \ln\left(\frac{x_h}{P^*}\right) + \sum_{k=1}^{s} a_3 d_{kh} \tag{3.9}$$

The vector $\boldsymbol{x_i}$ represents the explanatory variables that include log of prices (p_j), real expenditure ($\frac{x_h}{P^*}$) and all the set of households characteristics d_{kh} (size, sex of the oldest adult in the household, age of the household reference person). The vector $\boldsymbol{a}$ represents the corresponding coefficients**.** Φ is the cumulative probability function of the standard normal distribution and u_i is the error term.

Little, if any, theoretical work has been done regarding the specification of (3.8); however, prices and demographics effects should play similar roles to those expected in traditional demand analysis. In addition, food expenditure is included in the specification, since Jackson (1984) showed that variety is an increasing function of income, here proxied by expenditure. It can be argued that if the interview period were longer, more items would be observed entering the consumers' market basket. This is especially true for those food categories that include storable items. The model given by (3.8) was estimated using the probit technique for each food group.

From this estimation, we then computed the Inverse Mills Ratio (IMR) for each household that was then used as an instrument in the second stage. To keep the censored observations in the estimation of the demand system, Heien and Wesseils (1990) suggest computing the IMR as follows. For uncensored households, thus if $Z_i = 1$, it is equal to:

$$R_{ih} = \frac{\varphi(\widehat{h_\iota})}{\Phi(\widehat{h_\iota})} \tag{3.10}$$

While for censored households, thus if $Z_i = 0$, it is equal to:

$$R_{ih} = \frac{\varphi(\widehat{h_\iota})}{1 - \Phi(\widehat{h_\iota})} \tag{3.11}$$

Where $\widehat{h_\iota}$ is the function of the set of explanatory variables related to the consumption decision defined before (prices, demographics for households, real expenditure), φ and Φ are the density and cumulative-probability functions. The Inverse Mills Ratio was then used as an instrumental variable linking the purchasing decision with the demand system. If its coefficient in the second stage was significant, then it means that sample selection bias occurred and hence it is worth accounting for the zero consumption problem (Serse;Hindriks and Hungerbühler, 2015).

As a result, the final model to be estimated is the following:

$$w_{ih} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jh} + \beta_i \ln(\frac{x_h}{P^*}) + \sum_{k=1}^{s} \rho_{ik} d_{kh} + \delta_i R_{ih} + \lambda_i \widehat{\xi_h} + \sum_{j=1}^{n} \theta_i \widehat{\varepsilon_{\iota J,h}} + e_{ih} \tag{3.12}$$

where w_{ih} is the food or beverage expenditure share for food or beverage group *i* and household *h* ; α_i , β_i , γ_{ij} , ρ_{ik} , δ_i, λ_i, θ_i are the parameters to be estimated, p_{jh} the prices. P* represents the Stone price index in logarithmic form (Deaton and Muellbauer, 1980), defined in equation (3.2). $\frac{x_h}{P^*}$ represents "real expenditure", d_{kh} the covariates at household level that affect consumer behaviour. R_{ih} the Inverse Mills Ratio, $\widehat{\xi_h}$ and $\widehat{\varepsilon_{\iota J h}}$ the predicted values from the first stage that are used respectively as instruments for household expenditure and prices and e_{ih} the error term.

3.4.2 Health Model

The aim of the health model was to compute linear regressions to model the effects of particular food and drinks purchased at household level on different types of health biomarkers at an individual level. In other words, to understand how the consumption of particular types of foods affects individual health. The parameters obtained from these regressions were then used to implement the simulation during the next stage and to understand if new food consumption patterns at household level after the carbon regulation on foods would improve the health profile of the population at individual level.

Simple linear regression uses an Gaussian identity link and models the relationship between a dependent variable Y_i and independent variables and residuals for the household $h = 1,\dots n$. The model can be denoted as:

$$Y_i = \beta_i + \sum_{k=1}^{s} \nu_{ik} d_{kh} + \sum_{i=1}^{n} \tau_i S_{ih} + \varepsilon_i \tag{3.13}$$

Where Y_i is the type of biomarker considered at individual level. In this analysis, body mass index (BMI), blood cholesterol, glucose, and glycated haemoglobin (HbA1c) concentrations were used in order to see if particular types of food purchases increase or decrease the probability that a particular disease will occur. β_i, ν_{ik}, τ_i in the model are the parameters to be estimated and S_{ih} represent the yearly expenditures of different food and drink categories purchased at household level, which were defined following the same aggregation of the food consumption data (Figure 3.1). d_{kh} are the same socio demographic household covariates that were used before for the demand model, which are family size, income, age and sex of household representative, ε_i the error term. The food consumption, nutrition and health data were available in the National Diet and Nutritional Survey (NDNS) dataset presented before in the data section. Since the data coming from the NDNS were at individual level, the yearly food expenditures were calculated at household level by assuming that adults eat double the amount of the children in a particular household.

3.4.3 Model estimation

The demand model was estimated using the purchase data described in section 2 aggregated at household and food group level. The Eatwell demand model uses a set of 7 food groups (Figure 3.1): carbohydrates, dairy & alternatives, drinks, fruit & vegetables, proteins, fats and "other products" (mainly sweets). The second aggregation demand model uses 11 categories, defined by similarity: cereals, dairy and eggs, drinks, fats and spreads, fish, meat, potatoes, ready meals, sweets, fruit, vegetables (Figure 3.1).

The model in equation (3.12) was estimated implementing the maximum likelihood (ML) routines on the whole sample by means of non-linear Seemingly Unrelated Regression (SUR) using Stata (Moon and Perron, 2006), after having imposed homogeneity, adding up and symmetry restrictions, in order to account for the possibility of simultaneous correlation between random errors and the demand system. In this context, this is very likely to be the case since there could be a number of unobserved factors explaining budget allocation across commodities. Importantly, if random errors are correlated, SUR estimation will lead to more efficient estimates compared with OLS and the results will be more robust. Since the sum of budget shares is 1, one equation was omitted in order to avoid singularity in the variance-covariance matrix of the disturbance terms. The "other" food products in the Eatwell aggregation was arbitrarily deleted to overcome singularity problems. In the second type of aggregation, the "cereal" category was deleted.

The coefficient for the deleted food categories could be recovered by means of the summation restrictions. The other restrictions of homogeneity and symmetry were instead imposed as constraints in the estimation of the system of equations. The cross and own price elasticities were then calculated in order to understand how consumers change their food purchasing behaviour, after an increase in prices, within the same category or across different ones (Panzone, 2013).

Uncompensated own-price elasticity:

$$\epsilon_{ii} = -1 + \frac{\gamma_{ii}}{w_i} - \beta_i \tag{3.14}$$

Uncompensated cross-price elasticity:

$$\epsilon_{ij} = \frac{\gamma_{ij}}{w_i} - \beta_i \frac{w_j}{w_i} \tag{3.15}$$

Compensated own-price elasticity:

$$\sigma_{ii} = 1 + \frac{\gamma_{ii}}{w_i^2} - \frac{1}{w_i} \tag{3.16}$$

Compensated cross-price elasticity:

$$\sigma_{ij} = 1 + \frac{\gamma_{ij}}{w_j w_i} \tag{3.17}$$

Expenditure Elasticity:

$$\eta_i = 1 + \frac{\beta_i}{w_i} \tag{3.18}$$

The Health Model was estimated through an OLS linear regression model in Stata. The list of codes that were used for the estimation of the demand system and health estimation and simulation are available in Appendix A.

3.5 Micro-simulated policy intervention

The empirical model from the previous section was used to illustrate responses of households to changes in food and drink prices due to carbon taxation. Carbon taxes that have sizeable impacts on prices are likely to affect households' incomes. The demand model used here considered the income effect. In addition, the demand system takes into account the substitution effect, which might be relevant because of the changes in taxation. The model builds upon the assumption that food consumption, as well as other consumption, is a result of rational choices (Deaton and Muellbauer, 1980).

3.5.1 Policy Reforms

Carbon taxes can cause greater welfare losses since they tend to be slightly regressive. An important obstacle to introducing carbon prices are distributional concerns. Pricing emissions in developed countries is often believed to harm the poorest part of the population due to the higher share of their income these households spend on carbon-intensive goods (Klenert and Mattauch, 2016). The tax burden falls disproportionally on households in the lowest socio-economic class also because they buy cheaper products and therefore experience relatively larger price increases (Kehlbacher *et al.*, 2016). Specific attention must be given to make interventions and policies appropriate for all income groups (Reynolds *et al.*, 2019). In this regard, the idea is to implement a *Bonus-Malus* tax to obtain a revenue neutral scenario and reduce the negative impact of the regulation on the economy (d'Haultfoeuille;Givord and Boutin, 2014). In this study, carbon tax revenues will be redistributed to all the households in the form of a subsidy.

Two different types of scenarios were chosen to illustrate the effect of a tax on GHG emissions and each of these was estimated with the price for the social cost of CO_2 emissions set at £70/tonne CO_2 (Pearce, 2003). Both scenarios are based on the idea that the climate-related costs of food consumption for society should be internalised and hence the price of specific food products should be increased based on their climate impact (Edjabou and Smed, 2013).

- **Scenario (A) (Carbon Taxation)**: a carbon tax is imposed on all foods, which is equivalent to the climate impact of the food. New budget shares (w_{ih}), expenditures and quantities are estimated. This unfunded reform is the natural starting point for the analysis, essential for the implementation of the second scenario.

- **Scenario (B) (*Bonus-Malus* Taxation)**: total tax revenues derived from taxation are unaltered (compensated). This is achieved by reducing the current level food prices (*bonus*) in parallel with the introduction of climate taxes on food (*malus*), so that the resulting tax is revenue neutral.
  More specifically, the variation in household expenditure (predicted from the first scenario) is used as the price reduction for the *bonus* part. In other words, if household expenditure increases by a certain level due to the tax, the prices will be reduced by the same amount. This reduction represents the discount to apply to all the prices in the second scenario. In this way, the compensated reform requires that the price will rise by the carbon tax and at the same time decrease by the discount. This enables the estimation of new budget shares when the *malus* and the *bonus* part are applied simultaneously to the system and mitigate the negative impact of carbon taxes on social welfare.

The objective of these simulations was to study the effects on the intake of different nutrients from combined reforms aiming to reduce the environmental impact of diets and the efficiency of the different funding methods.

3.5.2 Simulation model on diets

The simulation method can be described as follow. The carbon tax rate, t_i for each item is defined as:

$$t_i = E_i \times p_e \tag{3.19}$$

where E_i is the level of emissions of the i-good and p_e is the carbon price per tonne (Edjabou and Smed, 2013). As a result, t_i is a cost of carbon emissions charged on each item or product. These emission values are based on life cycle analysis (LCA) estimates, i.e. emissions from farming, food processing, packaging, transportation and distribution to the point of final consumption are accounted for. These data are available in the Appendix A in Table A.2.

The price level on good *i* after the first scenario was calculated according to the following formula:

$$p_{ih}^1 = p_{ih}^0 + (t_i + \tau_i \times t_i) \tag{3.20}$$

Where the superscript denotes tax regime (0 is baseline tax), t_i is the carbon tax based on the carbon footprint, τ_i is the VAT rate (20%) for t_i which is paid only for certain types of food categories, such as sweets, ready meals and drinks. Note that p_{ih}^0 already includes the VAT. In the simulation we do not allow for possible general equilibrium effects, i.e. we assume that taxes are shifted completely on consumer prices.

The after-tax change Stone Price Index for household *h* equals:

$$ln\, P_{ih}^{1} = \sum w_{ih}\, ln\, p_{ih}^{1} \tag{3.21}$$

where, as previously, w_{ih} is household *h*'s initial expenditure share on commodity *i*. Substituting the post-reform Stone price indexes into the demand system gives the new allocation across the different commodities group for household *h.* The new consumption vector is given by:

$$w_{ih}^{1} = \hat{\alpha}_i + \sum_{j=1}^{n} \hat{\gamma}_{ij} \ln p_{jh}^{1} + \hat{\beta}_i \ln(\frac{x_h^0}{P_{ih}^{1*}}) + \sum_{k=1}^{s} \hat{\rho}_{ik} d_{kh} + \hat{\delta}_i R_{ih} + \widehat{\lambda_\iota} \widehat{\xi_h} + \widehat{\theta_\iota} \widehat{\varepsilon_{\iota J,h}} \tag{3.22}$$

Where the superscript ^ denotes the estimates obtained from the Almost Ideal Demand System (AIDS). The superscript ^{0} indicates the point of reference (baseline). In the simulation of the new budget shares, the theoretical assumption is that household expenditure remains unchanged after the policy on food (x_h^0), spending just differently, as in Nordström and Thunström (2009).

The new budget shares w_{ih}^1 were estimated by using the new prices after tax and the demand parameters of the AIDS. The previous theoretical assumption was then empirically removed and new household expenditure was predicted after the policy intervention.

Household expenditure in scenario (A) was estimated by:

$$ln\, x_h^1 = \hat{\alpha}_i + \widehat{\eta_h}\, ln\, I_h + \sum_{j=1}^{n} \hat{\lambda}_{ij}\, ln\, z_j + \sum_{k=1}^{k} \hat{\rho}_{ik} d_{kh} \tag{3.23}$$

Where, as before, a ^ denotes the parameters obtained from the household expenditure reduced form used for the expenditure endogeneity in equation (3.6). The superscript^1 indicates the after-tax reference for new prices and new expenditure.

From the last equation, it is possible to define post-reform expenditures s_{ih}^1 on commodity *i* for the two-week period of the survey*:*

$$s_{ih}^1 = w_{ih}^1 * x_h^1 \tag{3.24}$$

and the quantity V_{hi}^1 of good *i*, as:

$$V_{hi}^1 = \frac{s_{ih}^1}{p_{ih}^1} \tag{3.25}$$

The yearly expenditure for each food group is then estimated for the following health analysis.

The survey is related to a two-weeks period, the yearly expenditure is given by:

$$S_{ih}^{1} = \left(\frac{s_{ih}^{1}}{14}\right) * 365 \tag{3.26}$$

Given the new household expenditure (x_h^1), according to equation (3.23), change in household expenditure (σ) will be:

$$\sigma = (\ x_h^1 - \ x_h^0)/x_h^0 \tag{3.27}$$

This value, σ, is then used as the price reduction *(bonus)* for scenario (B). To this extent, the new price after scenario (B) is:

$$p_{ih}^2 * = p_{ih}^1 - \sigma \tag{3.28}$$

Household expenditure was predicted to increase by a certain amount due to the carbon tax. For this reason, we decided to reduce prices by the same level as household expenditure increased in scenario (A), in order to maintain social welfare and obtain a carbon neutral scenario, scenario (B). In this way, carbon policy revenues were redistributed to all the households in the form of a price subsidy (*bonus*).

The after *Bonus-Malus* tax Stone Price Index for household *h* equals:

$$ln\, P_{ih}^2 \ = \ \sum w_{ih}\, ln\, p_{ih}^2 \tag{3.29}$$

Given the new prices, the new budget shares in scenario (B) were estimated by:

$$w_{ih}^2 = \ \hat{\alpha}_i + \sum_{j=1}^{n} \hat{\gamma}_{ij} \ln p_{jh}^2 \ + \hat{\beta}_i \ln(\frac{x_h^0}{P_{ih}^{2*}}) + \sum_{k=1}^{s} \hat{\rho}_{ik} d_{kh} + \hat{\delta}_i R_{ih} + \widehat{\lambda_\iota} \widehat{\xi_h} + \widehat{\theta_\iota} \widehat{\varepsilon_{\iota J,h}} \tag{3.30}$$

And household expenditure:

$$ln\, x_h^2 = \widehat{\alpha_i} \ + \widehat{\eta_h} \ ln\, I_h + \sum_{j=1}^{h} \widehat{\lambda_{ij}}\, ln\, z_j + \sum_{k=1}^{k} \widehat{\rho_{ik}} d_{kh} \tag{3.31}$$

Expenditure for each food group for the two weeks:

$$s_{ih}^2 = \ w_{ih}^2 * \ x_h^2 \tag{3.32}$$

And yearly:

$$S_{ih}^{2} = \left(\frac{s_{ih}^{2}}{14}\right) * 365 \tag{3.33}$$

The quantity V_{hi}^2 of good *i*, as:

$$V_{hi}^2 \ = \ \frac{s_{ih}^2}{p_{ih}^2} \tag{3.34}$$

3.5.3 Simulation model on health

Carbon taxes have an impact on food consumption at household level. This change in food behaviour has

some consequences for the health of the population. To understand how carbon regulation affects individual health, a micro-simulation approach was applied to the health production function described before. The health parameters obtained from the regression model were used to predict new health indicators at individual level by considering the diets before and after the application of scenario (A) and scenario (B).

Firstly, the health measures were estimated at individual level considering the predicted baseline diets coming from the empirical demand model estimation.

$$Y_i = \widehat{\beta_i} + \sum_{k=1}^{s} \widehat{v_{ik}} d_{kh} + \sum_{i=1}^{n} \widehat{\tau_i} S_{ih} \tag{3.35}$$

Where S_{ih} is the yearly food expenditure for each commodity predicted for the baseline at household level. d_{kh} are the socio-demographics variables at household level, $\widehat{\beta_i}\ \widehat{v_{ik}}, \widehat{\tau_i}$ are the parameters estimated from the health regressions in equation 3.13.

Secondly, these health indicators were estimated following the same techniques considering the predicted diets after the implementation of scenario (A) and (B).

$$Y_i^1 = \widehat{\beta_i} + \sum_{k=1}^{s} \widehat{v_{ik}} d_{kh} + \sum_{i=1}^{n} \widehat{\tau_i}\, S_{ih}^1 \tag{3.36}$$

$$Y_i^2 = \widehat{\beta_i} + \sum_{k=1}^{s} \widehat{v_{ik}} d_{kh} + \sum_{i=1}^{n} \widehat{\tau_i}\, S_{ih}^2 \tag{3.37}$$

Where S_{ih}^1 and S_{ih}^2 are the yearly food expenditure for each food commodity predicted from scenario (A) and (B) respectively.

3.6 Results

In this study, LCFS data were used to estimate UK food carbon footprints at household level for a two weeks period (Figure 3.2) by considering GHG emissions of carbon footprint data published in the literature (Appendix A Table A.2) (Flysjö;Thrane and Hermansen, 2014; Scarborough *et al.*, 2014; Drewnowski *et al.*, 2015; Clune;Crossin and Verghese, 2017).

The same data were used to estimate the relationship between emissions values and energy kcals for each food category considered in the analysis. A positive correlation was found for all the food groups, as shown in the graphs below (Figures 3.3 - 3.13). Higher emissions values products were characterized by higher energy kcals.

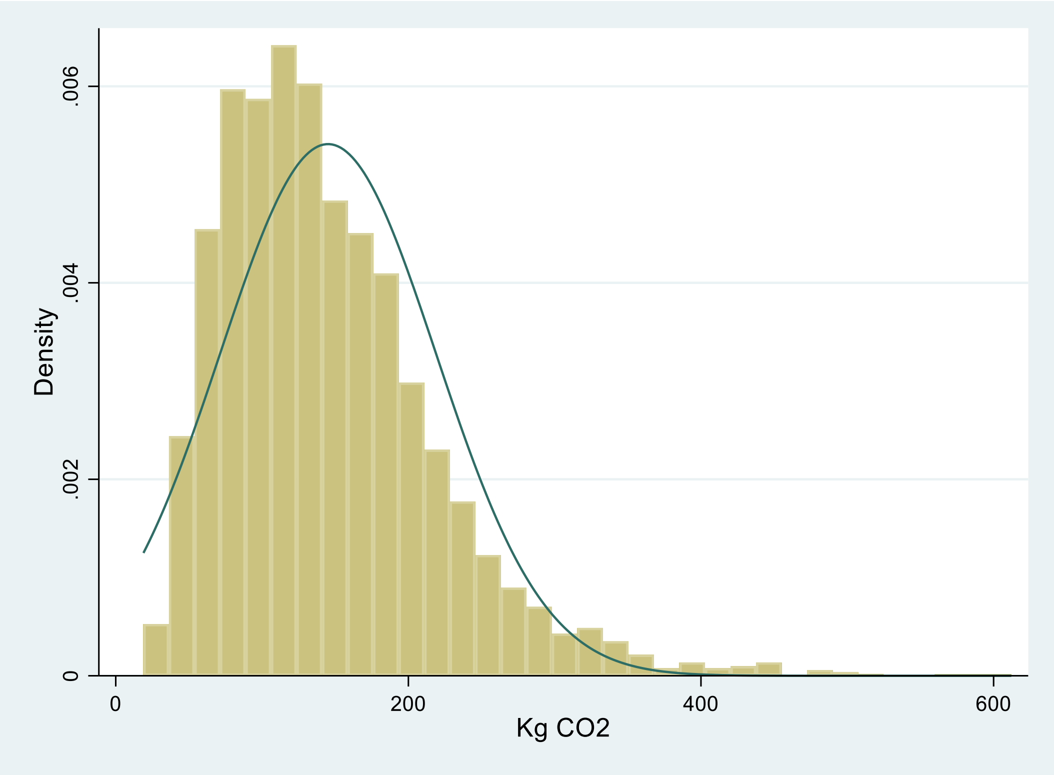

Figure 3.2: Food-related carbon footprint in the UK from LCFS data

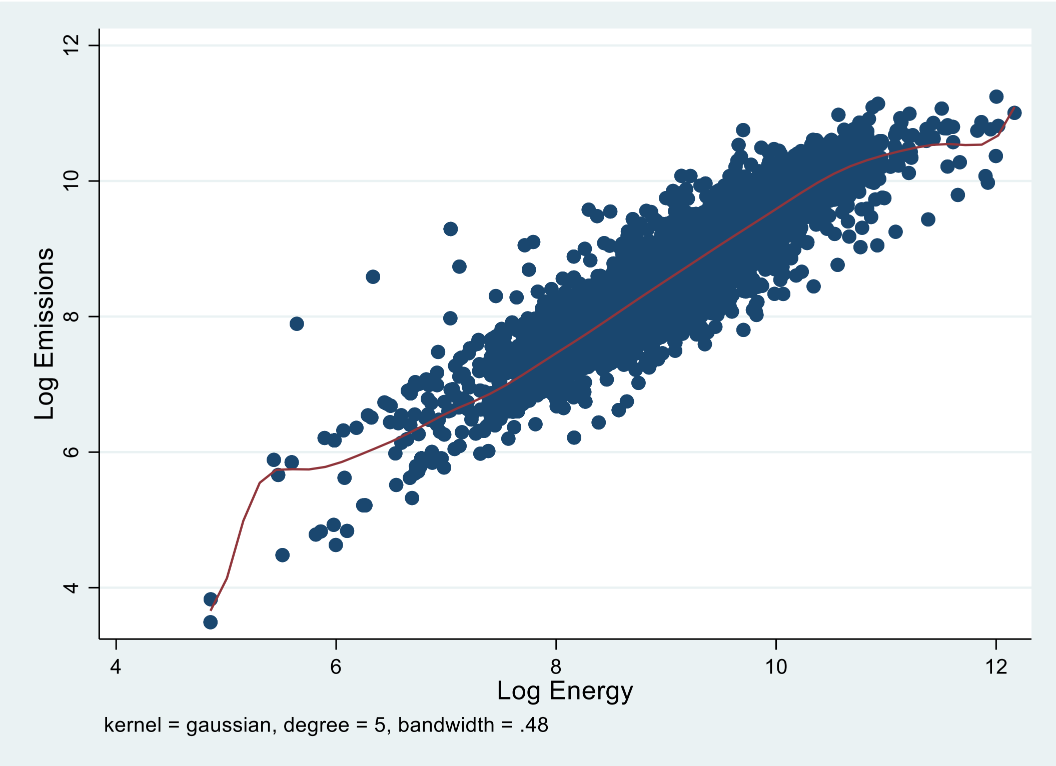

Figure 3.3: Relationship emissions/energy - cereals

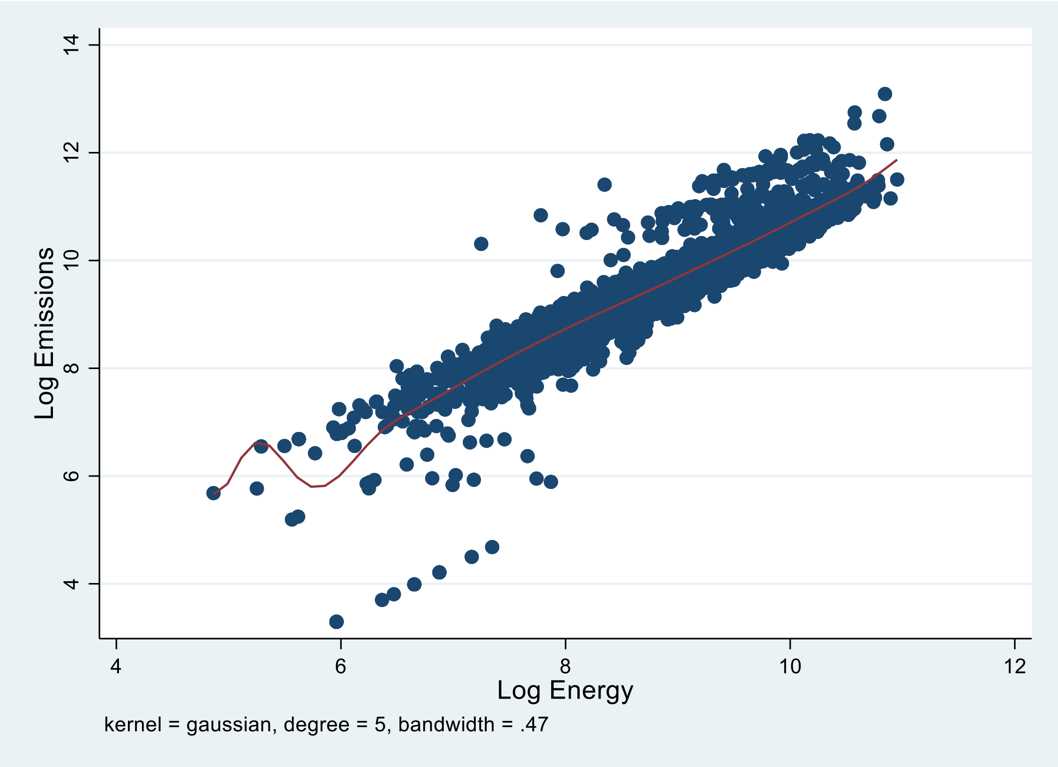

Figure 3.4: Relationship emissions/energy - dairy and eggs

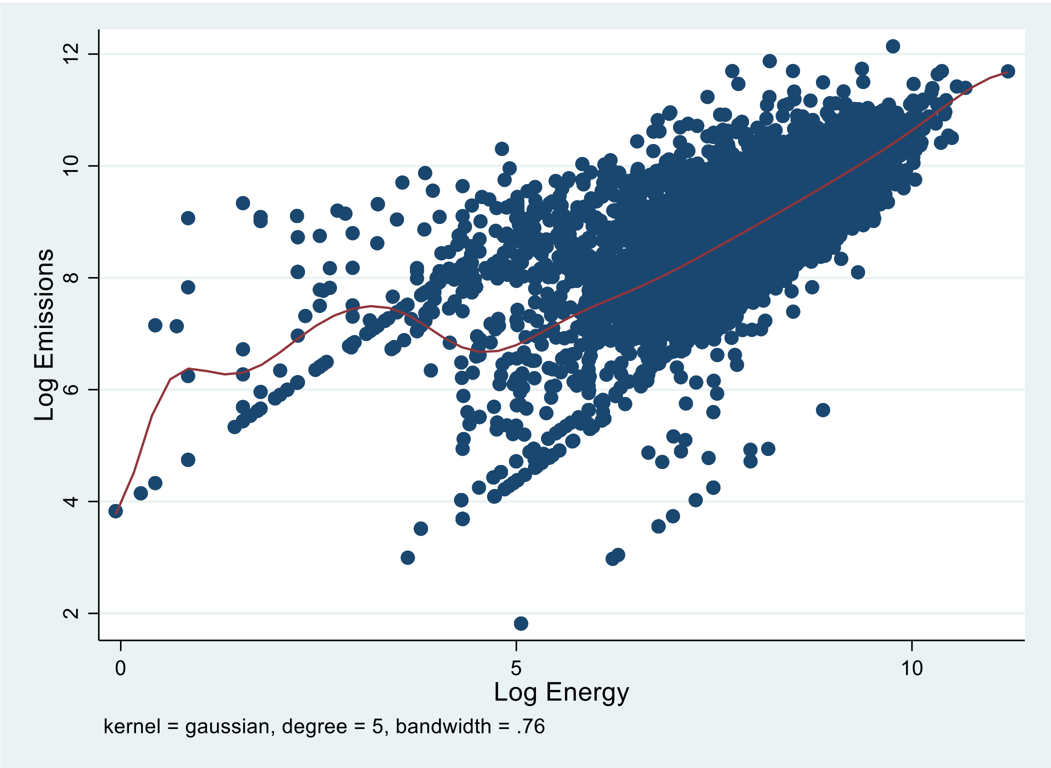

Figure 3.5: Relationship emissions/energy - drinks

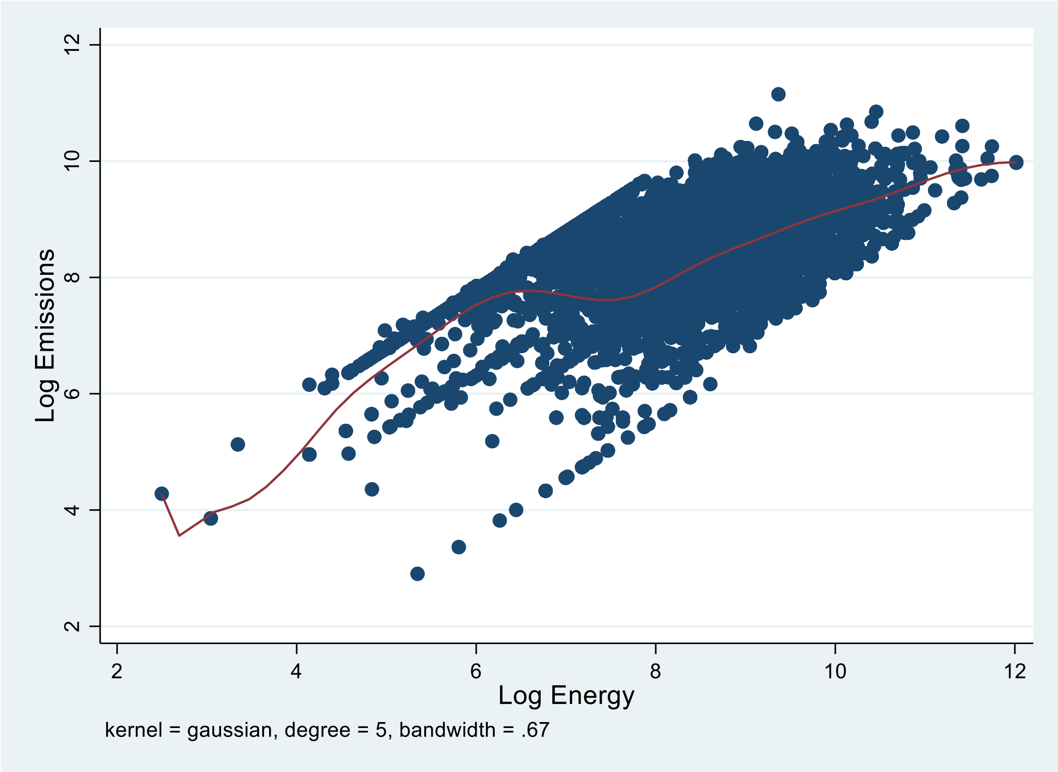

Figure 3.6: Relationship emissions/energy - fats, oils and spreads

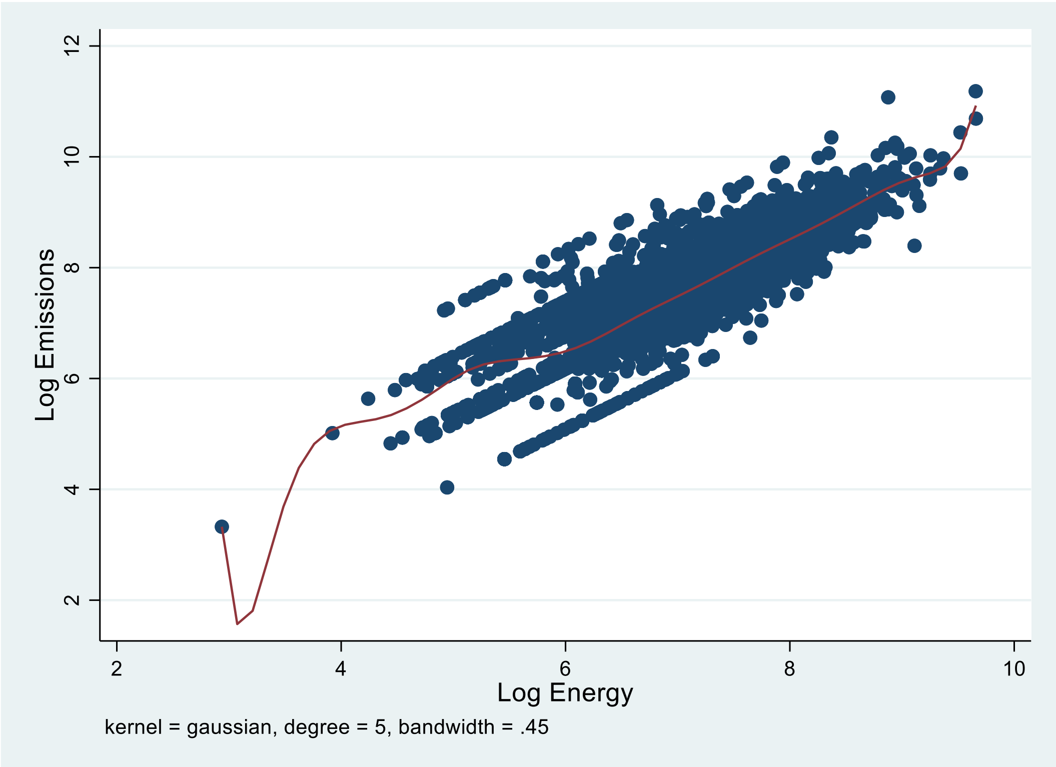

Figure 3.7: Relationship emissions/energy - fish

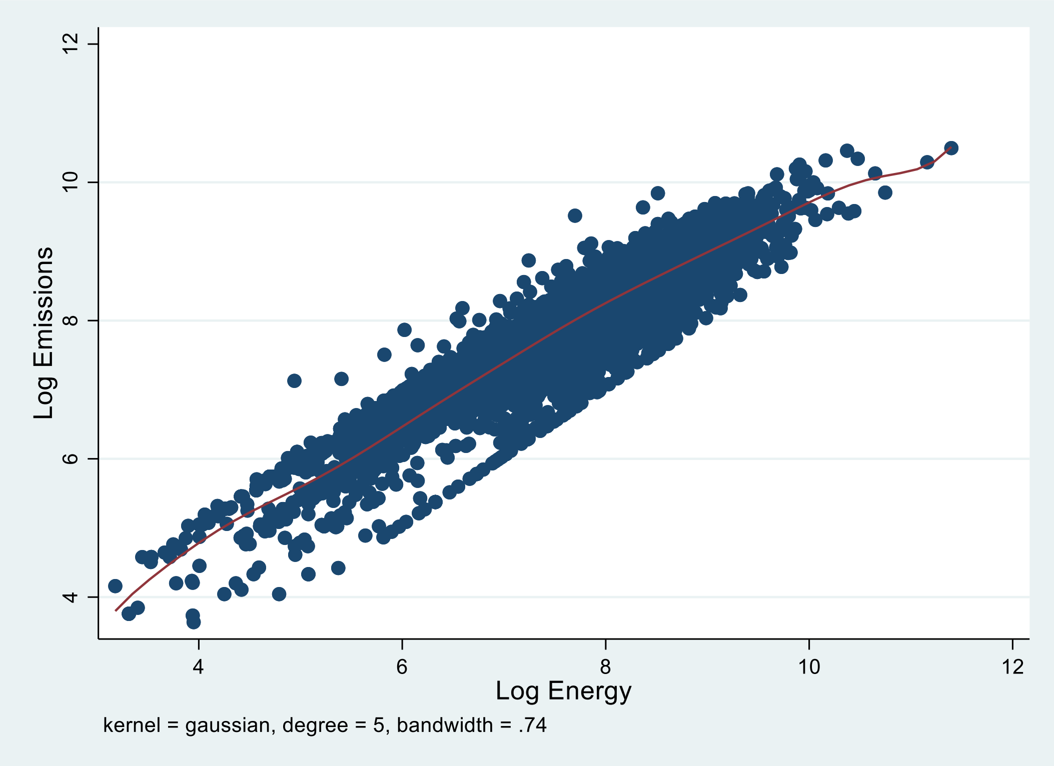

Figure 3.8: Relationship emissions/energy - fruit

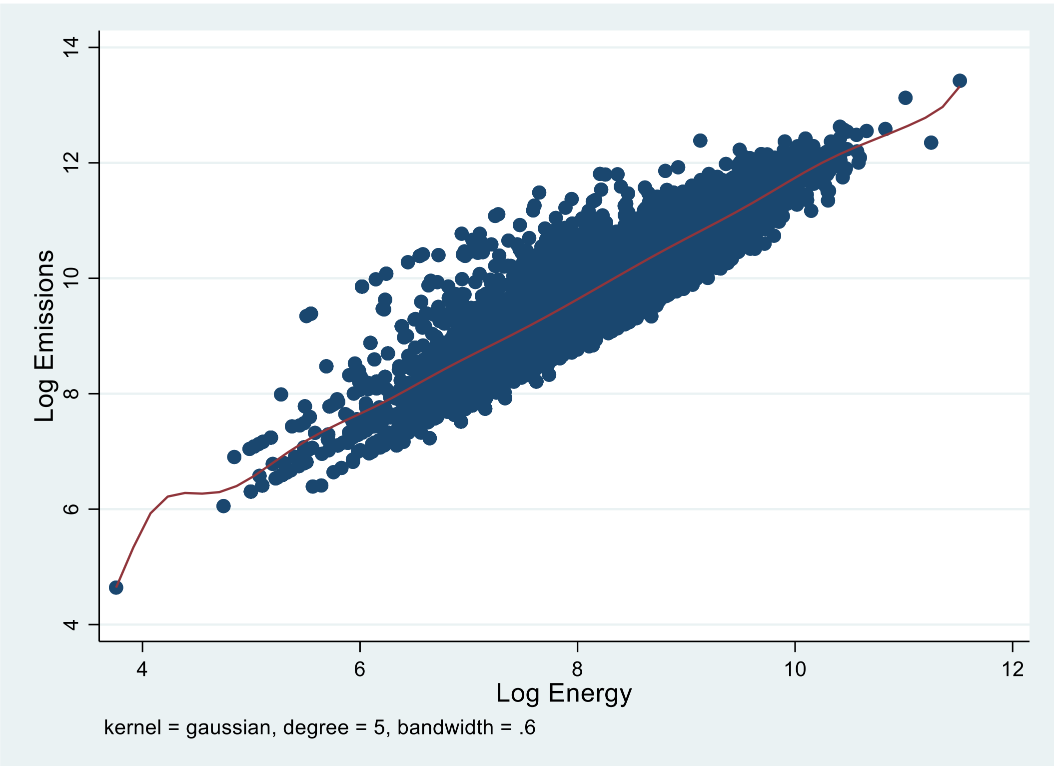

Figure 3.9: Relationship emissions/energy - meat

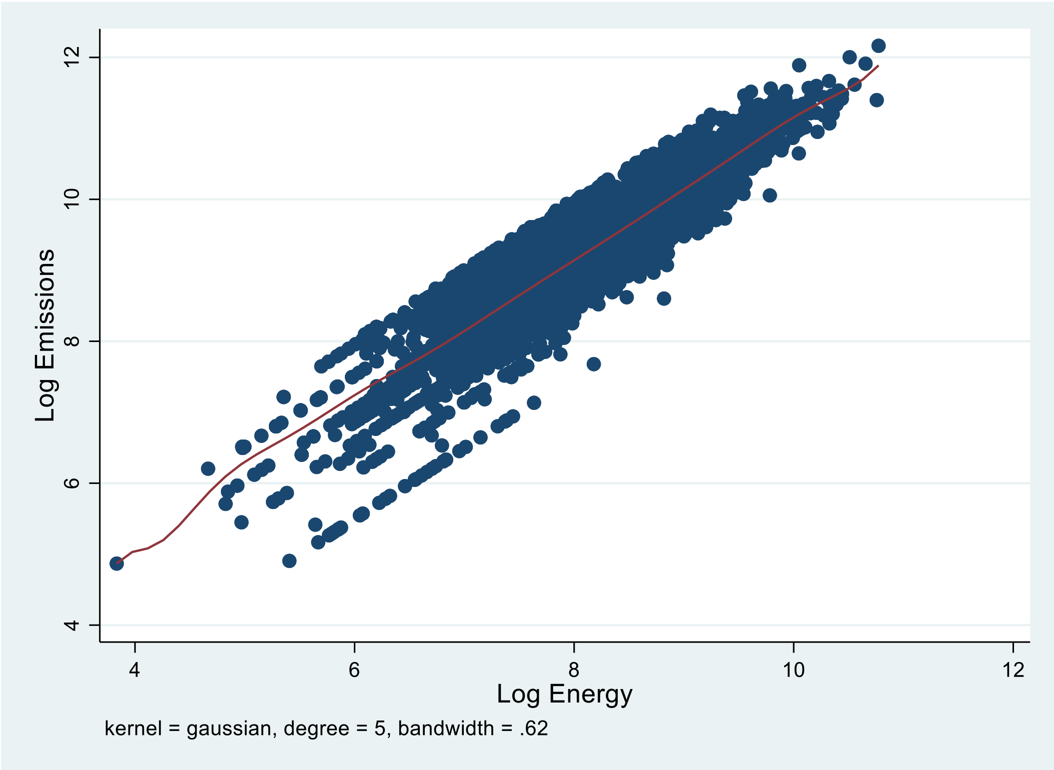

Figure 3.10: Relationship emissions/energy - ready meals

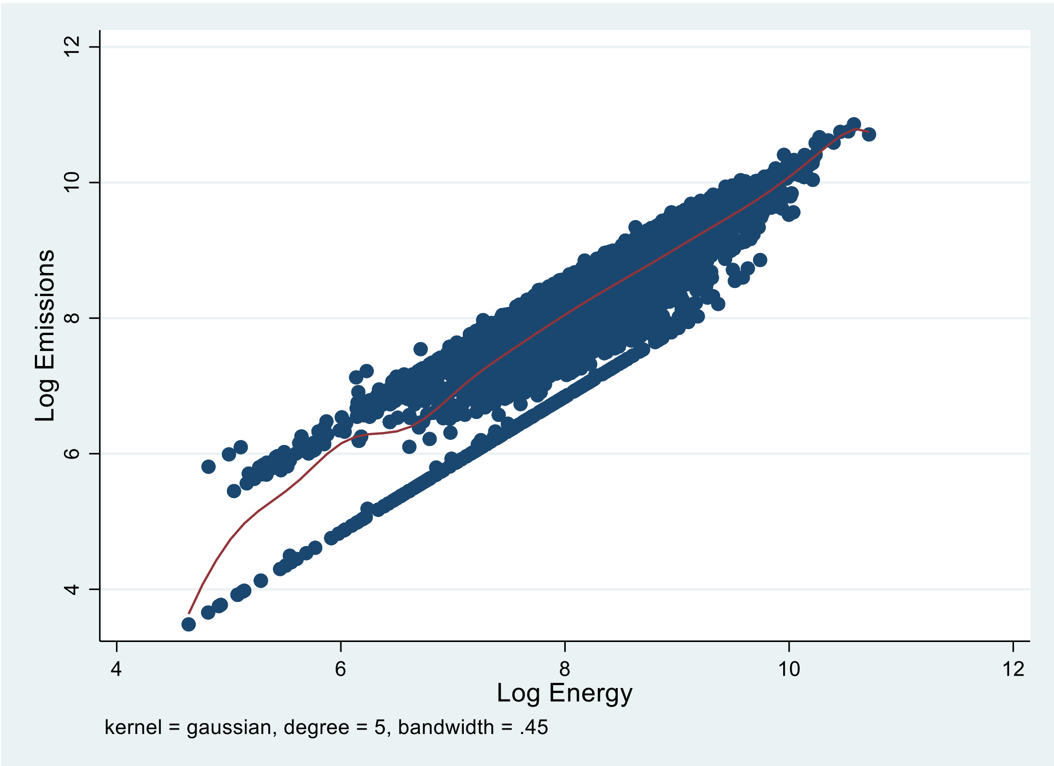

Figure 3.11: Relationship emissions/energy - potatoes

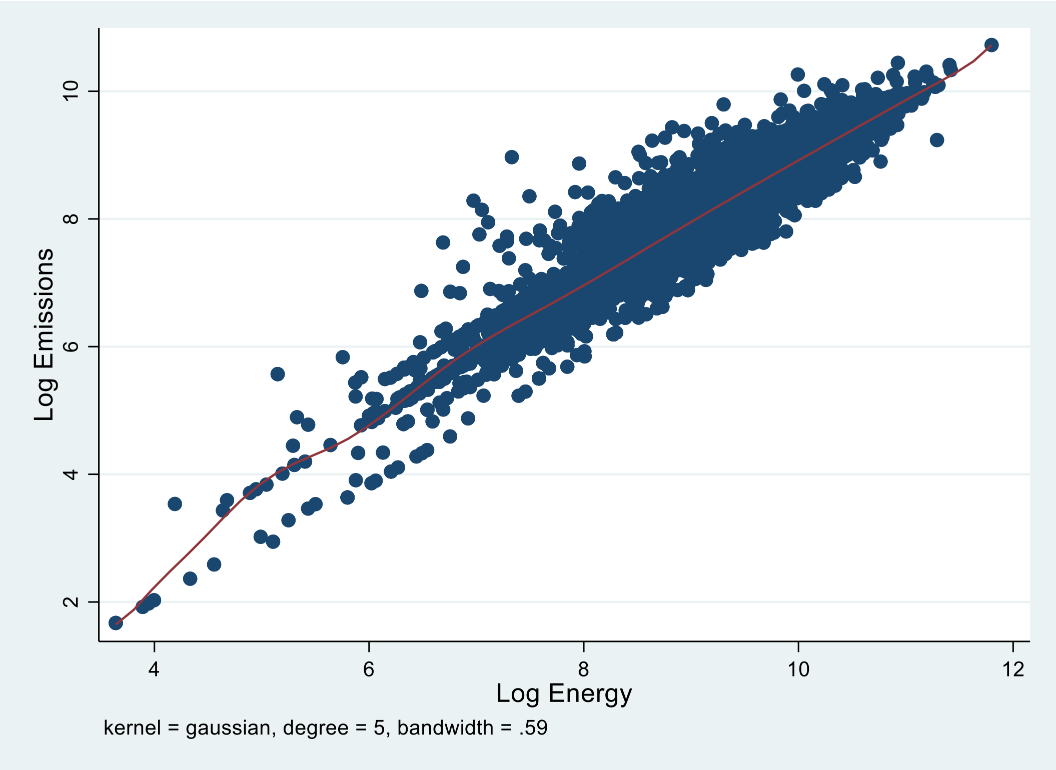

Figure 3.12: Relationship emissions/energy - sweets

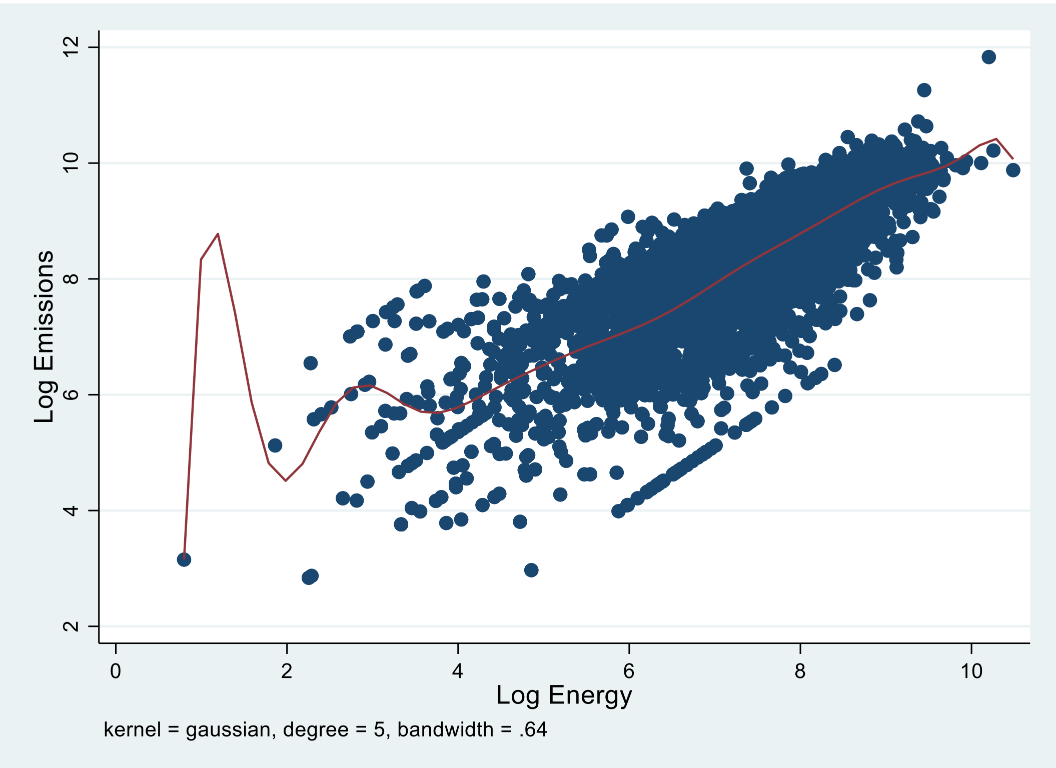

Figure 3.13: Relationship emissions/energy - vegetables

Table 3.2 presents the socio-demographic profile of the sample. Table 3.3 and Table 3.4 present average observed total expenditure and expenditure shares relative to both types of aggregations across all households and split into low and high-income groups. Low-income families are defined where their OECD weekly equivalised income was equal or below £742.6. High-income families had higher weekly income than this threshold. Expenditure on proteins represented 27% of total expenditure, of which 14% were covered by meat and only 4% by fish. Carbohydrates (including cereals, potatoes and some ready meals), and drinks (both alcoholic and not) represented 16% of total expenditure. Fruit and vegetables made up 14% of total expenditure. A big share was represented by sweet products (12%). Higher income families consumed fewer cereals, dairy and sweets compared with lower income families while they spent more money on drinks, fruit and vegetables. This distinction between low and high income families is not essential for the present study. However, it is needed to have a general understanding of the differences in the consumption patterns of different types of households.

Number of households	4947
Household size	2.38
St. Dev	1.27
Age of Main Shopper	53.69
St. Dev	16.0
Number of children (if have children)	0.54
St. Dev	0.95
Share of households that have children (%)	30
Highest Qualification (%)	
Degree level (or equivalent)	28.7%
College	15%
Secondary Education	22.7%
Other qualifications	13.6%
No formal qualifications	2.4%

Table 3.2: Demographic characteristics of the study sample

	All	St Dev	Low Income	St Dev	High Income	St Dev
Expenditure Shares (%)						
Carbs	16.09	0.09	16.96	0.09	15.22	0.08
D&A	10.09	0.07	10.71	0.07	9.48	0.06
Drinks	16.32	0.14	14.90	0.13	17.74	0.14
F&V	14.38	0.10	13.14	0.09	15.62	0.09
F,O & S	3.96	0.04	4.05	0.04	3.87	0.03
Proteins	26.65	0.12	26.96	0.12	26.35	0.12
Others	12.50	0.09	13.28	0.08	11.72	0.08
Total Expenditure (£)	**143.27**	**91.6**	**106.87**	**67.6**	**179.64**	**97.8**

Table 3.3: Mean expenditure shares and total expenditure - Eatwell

	All	St Dev	Low Income	St Dev	High Income	St Dev
Expenditure shares (%)						
Cereals	8.8	0.06	9.1	0.07	8.5	0.05
D&E	11.2	0.07	11.9	0.07	10.4	0.06
Drinks	16.3	0.14	14.9	0.14	17.6	0.13
F,O&S	3.9	0.03	4.0	0.04	3.9	0.03
Fish	4.3	0.05	4.3	0.05	4.4	0.05
Fruit	7.1	0.06	6.8	0.07	7.4	0.06
Meat	14.2	0.09	14.3	0.10	14.2	0.08
Potatoes	4.4	.035	4.7	0.04	4.1	0.03
RM	9.6	.09	9.6	0.09	9.5	0.08
Sweets	11.7	.08	12.3	0.08	11.1	0.07
Veg.	8.3	.05	7.7	0.06	8.7	0.05
Total Expenditure (£)	**143.27**	**91.6**	**106.87**	**67.6**	**179.64**	**97.8**

Table 3.4: Mean expenditure shares and total expenditure – second aggregation

3.6.1 Demand System Estimation Results – Eatwell

The estimation results are summarized by elasticities. Compensated own, cross-price and expenditure elasticities of the Eatwell aggregation are shown in Table 3.5. It is important to emphasise that the Eatwell results were obtained from the demand model estimation correcting only for the endogeneity of total expenditure. All compensated own-price elasticities were significant (P<0.01) and negative, indicating that the negativity condition was satisfied for all the macro-categories. They ranged from -0.9 for drinks to -2.5 for dairy and alternatives (in diagonal in the table). Carbohydrates showed the second lowest price sensitivity while fats, oil and spreads showed high responsiveness to price variations. In the following section, the results of the second type of aggregation are presented taking into account the complete model specification with the correction of sample selection biases and prices endogeneity.

	Carbs	**D&A**	**Drinks**	**F&V**	**F,O&S**	**Proteins**	**Others**	**Exp.**
Carbs	-0.937***	.346***	.725***	.217***	.564***	.960***	.834***	**1.05*** **
	(.012)	(.008)	(.003)	(.008)	(.0065)	(.001)	(.002)	**(.004)**
D&A		-2.47***	1.16***	.744***	1.064***	1.741***	.960***	**1.53*** **
		(.033)	(.002)	(.003)	(.001)	(.007)	(.001)	**(.005)**
Drinks			-.876***	.937***	.901***	.587***	.702***	**1.062*** **
			(.010)	(.001)	(.001)	(.004)	(.004)	**(.007)**
F&V				-1.63***	1.001***	1.206***	.729***	**1.328*** **
				(.014)	(.001)	(.002)	(.003)	**(.003)**
F,O&S					-2.387***	1.109***	.885***	**1.104*** **
					(.054)	(.001)	(.001)	**(.001)**
Proteins						-1.47***	.808***	**.484*** **
						(.012)	(.002)	**(.003)**
Others							-1.75***	**.913*** **
							(.016)	**(.001)**

Table 3.5: Mean compensated own, cross price elasticities of demand and expenditure – Eatwell

Note: *, **, *** denotes statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

3.6.2 Demand System Estimation Results – Second Aggregation

Table 3.8 reports parameters estimated of the Almost Ideal Demand System for the second type of aggregation (from equation 3.12). The results of the first stage of the control function approach for the endogeneity of prices and expenditures are reported in Table 3.6. The Probit estimates of the Heckman's two step procedures to correct for sample selection biases in Table

3.7. In Table A.3 and A.4 (Appendix A) are listed the variables used respectively in Table 3.6 and in Table 3.7.

In Table 3.9 the cross and own price elasticities of the second type of aggregation correcting also for the endogeneity of prices and the sample selection bias are shown. As before, all the own price elasticities are significant and negative. Potatoes and fats showed the highest price sensitivity while drinks the lowest. However, in contrast the cross price elasticities were not all positive: some food categories were complements to each other. In particular, the results for drinks were negatively correlated with dairy, fats, fruit, potatoes and vegetables, suggesting that an increase in the price of drinks results in a decrease in the consumption of those food categories and vice versa. Fats were complements to potatoes and vegetables, suggesting that those groups could be purchased together. Fish, fruit and meat were negatively linked to ready meals, and potatoes were negatively correlated with vegetables. Table A.5 in Appendix A are reports the own, cross-price and expenditure elasticities considering only the endogeneity of expenditure in the second type of aggregation.

	Cereals	D&E	Drinks	F,O&S	Fish	Fruit	Meat	Potatoes	RM	Sweets	Veg.	Exp.
z_1	-88.27***	10.86	-25.12	-17.89	-10.14	0.07	6.45	4.79	12.95	9.22	13.87	-29.55**
	(10.38)	(15.51)	(21.94)	(14.23)	(11.22)	(12.20)	(9.61)	(16.81)	(12.00)	(12.91)	(11.32)	(14.45)
z_2	19.26**	-115.49***	19.99	4.31	-0.77	11.77	20.24**	25.47	5.29	20.59*	11.64	-22.99*
	(9.61)	(14.36)	(20.30)	(13.17)	(10.38)	(11.29)	(8.90)	(15.56)	(11.11)	(11.95)	(10.48)	(13.37)
z_3	-0.78	8.89	-56.38***	-9.96	4.28	-3.75	-0.35	8.31	-3.79	5.85	4.09	-21.14***
	(4.98)	(7.45)	(10.54)	(6.83)	(5.39)	(5.86)	(4.62)	(8.08)	(5.77)	(6.20)	(5.44)	(6.94)
z_4	-4.29	7.98	-4.10	-27.80***	-7.67	-13.85**	-1.85	0.85	-5.30	-4.92	-6.85	-17.21**
	(5.56)	(8.31)	(11.75)	(7.62)	(6.01)	(6.54)	(5.15)	(9.01)	(6.43)	(6.92)	(6.06)	(7.74)
z_5	6.28	-4.84	11.97	6.23	-53.19***	-7.38	7.82	-3.31	-9.82	2.27	-1.65	5.25
	(6.32)	(9.44)	(13.35)	(8.66)	(6.83)	(7.43)	(5.85)	(10.23)	(7.31)	(7.86)	(6.89)	(8.80)
z_6	-6.90	16.67	-50.91***	-2.31	-3.24	-76.03***	-2.53	-10.72	-8.46	-4.86	-2.06	5.10
	(9.31)	(13.91)	(19.68)	(12.76)	(10.06)	(10.94)	(8.62)	(15.08)	(10.77)	(11.58)	(10.15)	(12.96)
z_7	-7.32	0.43	14.58	-21.04	-5.97	17.17	-93.20***	10.15	-0.78	-15.21	-2.02	13.07
	(11.19)	(16.73)	(23.65)	(15.34)	(12.10)	(13.15)	(10.36)	(18.13)	(12.94)	(13.92)	(12.20)	(15.58)
z_8	-8.86	-1.98	15.97	2.30	2.93	1.48	-2.15	-88.77***	-6.43	-11.10	-6.36	7.33
	(6.23)	(9.31)	(13.16)	(8.53)	(6.73)	(7.32)	(5.77)	(10.09)	(7.20)	(7.75)	(6.79)	(8.67)
z_9	-4.50	11.35	-8.37	-27.93***	-16.12*	-2.38	-1.19	-14.87	-64.01***	11.41	-1.32	-7.61
	(7.78)	(11.64)	(16.46)	(10.67)	(8.42)	(9.15)	(7.21)	(12.61)	(9.01)	(9.69)	(8.49)	(10.84)
z_{10}	4.07	-4.76	2.13	4.71	-3.95	9.64	-3.21	-5.72	7.92	-85.35***	-0.12	4.15
	(5.83)	(8.71)	(12.32)	(7.99)	(6.30)	(6.85)	(5.40)	(9.44)	(6.74)	(7.25)	(6.35)	(8.11)

	Cereals	**D&E**	**Drinks**	**F,O&S**	**Fish**	**Fruit**	**Meat**	**Potatoes**	**RM**	**Sweets**	**Veg.**	**Exp.**
z_{11}	5.66	-6.63	29.97	18.70	7.58	-4.18	-6.79	-9.33	-1.36	-20.51^{*}	-78.49^{***}	-2.55
	(9.61)	(14.37)	(20.32)	(13.17)	(10.39)	(11.30)	(8.90)	(15.57)	(11.12)	(11.96)	(10.48)	(13.38)
I_h	0.14^{***}	0.15^{***}	0.20^{***}	0.16^{***}	0.14^{***}	0.12^{***}	0.11^{***}	0.06^{***}	0.11^{***}	0.15^{***}	0.14^{***}	0.30^{***}
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.05^{***}	-0.08^{***}	-0.17^{***}	-0.06^{***}	-0.04^{***}	-0.04^{***}	-0.05^{***}	-0.04^{***}	-0.01	-0.05^{***}	-0.07^{***}	0.23^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.00^{***}	-0.00	0.01^{***}	0.00^{**}	0.00^{***}	-0.00	0.00^{***}	-0.01^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex	0.03^{***}	0.06^{***}	-0.01	0.03^{**}	0.03^{***}	0.03^{***}	0.01	0.01	0.00	0.04^{***}	0.03^{***}	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Const.	-116.87^{***}	-171.08^{***}	-94.65^{**}	-53.45^{**}	-25.23	-95.93^{***}	-18.87	-119.32^{***}	-35.56^{*}	-76.22^{***}	-94.93^{***}	-110.84^{***}
	(18.37)	(27.46)	(38.82)	(25.18)	(19.86)	(21.59)	(17.01)	(29.76)	(21.25)	(22.85)	(20.03)	(25.57)
N	4947	4947	4947	4947	4947	4947	4947	4947	4947	4947	4947	4947
R^2	0.09	0.06	0.11	0.05	0.09	0.06	0.08	0.04	0.08	0.09	0.09	0.35
R^2 Adj.	0.08	0.06	0.11	0.05	0.09	0.05	0.08	0.04	0.08	0.09	0.09	0.35
F	30.90	22.61	40.42	18.07	33.94	19.78	27.74	15.15	29.73	33.35	31.76	174.79
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F test	72.35	64.68	28.63	13.31	60.66	48.28	80.87	77.44	50.52	138.59	56.07	652.16
IV p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3.6: Parameters estimates of the 1st stage (price and expenditure) – IV Control Function

Note: In the rows are listed the exogeneous variables (instruments for each price and income and covariates at household level) in logarithmic form. The column represents the endogenous prices for each food category and the household expenditure

	D&E	Drinks	F,O&S	Fish	Fruit	Meat	Potatoes	RM	Sweets	Veg.
p_1	-0.05	0.07	-0.07	0.20***	-0.02	0.19***	0.11*	0.42***	-0.02	0.08
	(0.11)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)
p_2	-0.23***	0.14***	0.06*	0.08**	0.21***	0.00	0.03	-0.01	0.02	0.25***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
p_3	0.09	-0.08**	0.05*	0.08***	0.05*	0.00	0.00	0.04	-0.04	0.06*
	(0.06)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
p_4	-0.06	0.07	-0.11**	0.01	0.07	0.06	0.04	-0.10**	-0.12	0.05
	(0.10)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.07)	(0.07)
p_5	0.29*	0.08	0.03	0.71***	0.15**	0.09	0.16**	-0.01	-0.10	0.11
	(0.15)	(0.08)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.10)	(0.09)
p_6	0.13	0.04	0.02	-0.04	-0.13**	-0.08	-0.08	-0.03	-0.01	0.02
	(0.12)	(0.07)	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.08)	(0.07)
p_7	0.17	0.16*	0.13**	-0.01	0.21***	0.13*	0.01	0.03	-0.02	0.24***
	(0.15)	(0.08)	(0.06)	(0.05)	(0.07)	(0.08)	(0.07)	(0.06)	(0.10)	(0.09)
p_8	0.06	0.23***	0.06*	0.02	-0.05	-0.04	-0.06	0.15***	0.03	-0.24***
	(0.08)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)
p_9	-0.20*	0.10	0.00	-0.08**	0.08	0.00	-0.06	-0.11**	0.10	-0.05
	(0.12)	(0.07)	(0.05)	(0.04)	(0.06)	(0.06)	(0.06)	(0.05)	(0.08)	(0.07)

	D&E	**Drinks**	**F,O&S**	**Fish**	**Fruit**	**Meat**	**Potatoes**	**RM**	**Sweets**	**Veg.**
p_{10}	-0.14	0.02	-0.06	-0.03	0.17***	-0.10*	-0.04	0.00	-0.01	0.00
	(0.10)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.07)
p_{11}	-0.086	0.052	-0.107	-0.026	0.008	-0.133**	-0.179**	0.051	-0.11	-0.024
	(0.12)	(0.07)	(0.05)	(0.04)	(0.05)	(0.06)	(0.58)	(0.56)	(0.86)	(0.08)
$\frac{x_h}{P^*}$	0.67***	1.08***	0.96***	0.65***	.86***	.68***	0.84***	0.86***	0.68***	0.93***
	(0.08)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)
Size	0.20**	-0.07*	0.03	-0.00	0.01	0.00	0.04	-0.02	0.17***	0.05
	(0.08)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Age	0.01*	-0.01***	-0.00	0.01***	0.01***	0.00	0.00	-0.00**	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex	0.11	-0.03	0.01	0.02	0.07	-0.03	0.07	-0.09**	0.11	0.08
	(0.11)	(0.06)	(0.04)	(0.03)	(0.05)	(0.05)	(0.05)	(0.04)	(0.07)	(0.07)
Const.	-5.47***	-7.75***	-8.57***	-6.12***	-7.77***	-5.46***	-7.45***	-2.81***	-7.79***	-7.35***
N	4947	4947	4947	4947	4947	4947	4947	4947	4947	4947
Pseudo R^2	0.27	0.29	0.22	0.143	0.21	.015	0.20	0.08	0.27	0.29
F										

Table 3.7: Parameters estimates of the 1st stage - Probit

Note: the dependent variables represent the probability that a particular food category is purchased. Cereals food category is omitted because there are no missing values in the purchase decision.

	Cereals	**D&E**	**Drinks**	**F,O&S**	**Fish**	**Fruit**	**Meat**	**Potatoes**	**RM**	**Sweets**	**Veg.**
γ_{i1}	0.03										
	(0.03)										
γ_{i2}	0.00	-0.04***									
	(0.01)	(0.01)									
γ_{i3}	0.01	-0.08***	0.12***								
	(0.01)	(0.01)	(0.02)								
γ_{i4}	-0.01	-0.01	-0.03***	0.00							
	(0.01)	(0.01)	(0.01)	(0.02)							
γ_{i5}	-0.00	0.02***	0.00	0.02*	0.03***						
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)						
γ_{i6}	-0.05***	0.03***	-0.06***	0.01	-0.03***	0.09***					
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)					
γ_{i7}	0.01	0.04***	0.04***	0.02**	-0.02**	-0.00	0.01				
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)				
γ_{i8}	0.01	-0.00	-0.01**	-0.02***	-0.01	0.02***	0.00	0.02***			
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)			
γ_{i9}	0.01	0.04***	0.05***	0.03**	-0.03***	-0.03***	-0.05***	0.02**	-0.03		
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)		
γ_{i10}	0.01	0.01	-0.01	0.01	-0.01	-0.01	-0.05***	0.00	-0.01	0.09***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	
γ_{i11}	-0.01	-0.01	-0.03***	-0.03***	0.03***	0.03**	0.00	-0.03***	0.01	-0.02**	0.05***

	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
β_i	0.05***	0.09***	0.07***	-0.00	-0.03***	0.05***	-0.11***	-0.01***	-0.12***	-0.04***	0.05***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Size	0.01***	-0.04***	-0.02***	-0.01***	0.01***	-0.02***	0.05***	-0.00	0.04***	0.02***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.00	0.00***	-0.00***	0.00	0.00*	0.00***	0.00	0.00**	-0.00***	0.00***	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex	0.00	0.00**	0.00	-0.00	-0.00**	0.00	-0.00	-0.00	-0.01***	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\boldsymbol{R_{ih}}$		-0.08***	-0.06***	-0.04***	-0.05***	-0.06***	-0.07***	-0.05***	-0.06***	-0.07***	-0.06***
		(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\boldsymbol{\lambda_i}$	0.00	-0.12***	-0.01	-0.01***	0.03***	-0.06***	0.12***	-0.00	0.09***	0.01***	-0.06***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$\boldsymbol{\theta_{i1}}$	0.02	-0.00	-0.02	0.00	-0.00	0.05***	-0.03*	-0.02*	-0.00	-0.01	0.02
	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$\boldsymbol{\theta_{i2}}$	-0.01	0.05***	0.09***	0.01	-0.02***	-0.03***	-0.05***	0.00	-0.06***	-0.01*	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
$\boldsymbol{\theta_{i3}}$	-0.02	0.09***	-0.07***	0.03***	-0.01	0.06***	-0.06***	0.01*	-0.07***	0.00	0.03***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\boldsymbol{\theta_{i4}}$	0.00	0.01**	0.02***	0.00	-0.02*	-0.01	-0.02**	0.02***	-0.03***	-0.01**	0.03***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

$\boldsymbol{\theta_{i5}}$	0.01	-0.01*	-0.01	-0.02*	-0.01	0.03***	0.01	0.01	0.01	0.00	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\boldsymbol{\theta_{i6}}$	0.05***	-0.03***	0.06***	-0.01	0.02**	-0.06***	-0.01	-0.02***	0.03**	0.01	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\boldsymbol{\theta_{i7}}$	-0.01	-0.03**	-0.04***	-0.02**	0.02	0.02	-0.01	0.00	0.03**	0.04***	-0.00
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$\boldsymbol{\theta_{i8}}$	-0.01	0.00	0.03***	0.02***	0.01	-0.02***	-0.02***	-0.01**	-0.01	0.00	0.02***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
$\boldsymbol{\theta_{i9}}$	-0.01	-0.04***	-0.04***	-0.03***	0.02*	0.04***	0.03**	-0.02**	0.06***	-0.00	-0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$\boldsymbol{\theta_{i10}}$	-0.01	0.00	0.02*	-0.01	0.01	0.01*	0.03***	-0.00	-0.00	-0.06***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
$\boldsymbol{\theta_{i11}}$	0.01	0.02***	0.03***	0.02***	-0.03***	-0.02**	-0.03**	0.02***	-0.01	0.00	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
α_i	-0.70***	-0.82***	-0.47***	0.00	0.41***	-0.36***	1.35***	0.14***	1.41***	0.44***	-0.40***
	(0.07)	(0.04)	(0.08)	(0.03)	(0.03)	(0.04)	(0.06)	(0.02)	(0.05)	(0.05)	(0.04)
Adj.R^2		0.2312	0.2410	0.1993	0.3442	0.2378	0.2411	0.2397	0.3389	0.1691	0.2125
N	4947	4947	4947	4947	4947	4947	4947	4947	4947	4947	4947

Table 3.8: Parameter estimates of the Almost Ideal Demand System

Note: *, **, *** denotes statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

Food Group	Cereals	D&E	Drinks	F,O&S	Fish	Fruit	Meat	Potatoes	RM	Sweets	Veg.	Exp.
Cereals	-.968***	1.118***	1.555***	.308***	.879***	-2.734***	1.314***	2.434***	1.22***	1.274***	.205***	**1.39*** **
	(.024)	(.002)	(0.006)	(.012)	(.0 02)	(.061)	(.003)	(.02)	(.004)	(.004)	(.011)	**(.003)**
D&E		-2.91***	-2.15***	.297***	2.35***	2.45***	2.478***	.687***	2.971***	1.25***	.434***	**1.55*** **
		(.043)	(.036)	(.011)	(.025)	(.025)	(.017)	(.004)	(.03)	(.003)	(.008)	**(.004)**
Drinks			-.446***	-.989***	1.012***	-1.439***	2.01***	-.021***	2.318***	.590***	-.214***	**1.255*** **
			(.008)	(.03)	(.001)	(.037)	(0.13)	(0.14)	(.02)	(.005)	(.016)	**(.002)**
F,O&S				-2.40***	3.26***	2.353***	2.412***	-2.05***	3.548***	1.50***	-1.62***	**.989*** **
				(.055)	(.05)	(.027)	(.022)	(.058)	(.047)	(.008)	(.047)	**(.001)**
Fish					-2.05***	-.836***	-.160***	.112***	-.896***	.255***	2.95***	**.691*** **
					(.027)	(.04)	(.021)	(.02)	(.04)	(.014)	(0.41)	**(.004)**
Fruit						-1.08***	.879***	3.55***	-1.27***	.686***	2.272***	**1.39*** **
						(0.298)	(.001)	(.046)	(.042)	(.005)	(.025)	**(.004)**
Meat							-2.02***	1.030***	-.724***	-.652***	1.182***	**.449*** **
							(.02)	(.001)	(.025)	(.02)	(.002)	**(.004)**
Potatoes								-4.70***	2.23***	1.026***	-2.66***	**.877*** **
								(.042)	(.023)	(.001)	(.05)	**(.001)**
RM									-2.04***	.523***	1.87***	**.368*** **
									(.031)	(.007)	(0.13)	**(.007)**
Sweets										-1.03***	-.108***	**.790*** **
										(0.13	(.014)	**(.002)**
Veg.											-2.08***	**1.42*** **
											(.018)	**(.004)**

Table 3.9: Mean compensated own, cross price elasticities of demand and expenditure - second aggregation

Note: *, **, *** denotes statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

With respect to the endogeneity in the price formation, different assessments were tested as instrumental variables for each household price. As stated before, the price paid by households in all the other regions and months was chosen as instrument in this study, for each food category. Household income was chosen as instrument for household expenditure. Some tests were executed to check the strength of the chosen instruments, as can be seen from the F-tests of the IV in Table 3.6. Moreover, the coefficients for the error terms were positive and significant which suggests that the unobserved part explaining prices was positively correlated with the choice of the product, thus justifying the need to control for the endogeneity problem. In addition, since the coefficients of the Inverse Mills Ratio (R_{ih}) in Table 3.8 were significant in the demand system estimation, sample selection bias occurred and therefore it was necessary to account for the zero consumption problem.

3.6.3 Health Results

Each health biomarker at an individual level was regressed with the household yearly expenditure of each food and drink category purchased and some covariates at household level, namely family size, age of the household representative person and sex of the oldest in the family. This was done in order to understand if the food quantities purchased by each household over a year had an effect on individual health. The results of the health regressions can be seen below (Table 3.10). The dependent variables represents the chosen health measures: blood glycated haemoglobin (HbA1c), glucose, blood cholesterol and body mass index (BMI).

The effects after modelling were minimal. Higher expenditure on cereal and potatoes was associated with a decrease in concentrations of blood cholesterol, while drinks were associated with an increase in this biomarker probably due to the sugar content of these products. Fats were associated with an increase in blood glucose concentration, while fruit was associated with a decrease in this biomarker and in the BMI index. Surprisingly, higher expenditure on sweets were linked to a decrease in glucose and BMI level; however, these effects were minimal. Age was a significant determinant of outcome: older people that did the food shopping in the house were associated with an increase in blood glucose and cholesterol and the BMI at an individual level.

Dependent Variable	**HbA1c**	**Glucose**	**Cholesterol**	**BMI**
Cereals	-0.01	-0.01	-0.06***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
D&E	0.01	-0.00	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Drinks	0.00	-0.00	0.04***	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
F,O&S	0.00	0.01**	0.01	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
Fish	0.01	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Fruit	-0.00	-0.01**	-0.01	-0.01*
	(0.01)	(0.00)	(0.01)	(0.01)
Meat	-0.00	-0.00	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Potatoes	-0.00	0.00	-0.03***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Sweets	0.01	-0.01**	-0.01	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
RM	-0.00	-0.00	-0.01	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
Veg.	-0.02	-0.00	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Income	-0.01	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.01	0.00	0.02**	-0.00
	(0.01)	(0.00)	(0.01)	(0.01)
Sex	-0.03	-0.03**	-0.00	0.02
	(0.02)	(0.01)	(0.02)	(0.01)
Age	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	3.56***	1.73***	2.09***	3.12***
	(0.20)	(0.12)	(0.17)	(0.16)
N	375	1072	1246	1356
R^2	0.18	0.11	0.13	0.04
R^2 Adj.	0.15	0.10	0.12	0.03
F	5.20	7.97	12.26	4.05
P	0.00	0.00	0.00	0.00

Table 3.10: OLS regressions for the different health indicators

Note: *, **, *** denotes statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis. The dependent variables represent health biomarkers at individual level in logarithmic form.

3.7 Simulation Results

This section analyses the results obtained from simulating the hypothetical reforms described above. The carbon tax rate was set at £70/tonne CO_2 (Pearce, 2003). Firstly, the results from the Eatwell aggregation are shown and then considering the second aggregation. It is relevant to see how the policy reforms would affect prices of individual food products and how these would affect household consumption and individual health. Simulation results were driven by the combination of own-price, cross-price and income effects, as well as by the nutritional content of the products.

3.7.1 Effects of simulation reforms – Eatwell

Table 3.11 shows the impact on food prices of implementing the unfunded and funded reforms. Price Scenario (A) show the predicted price changes due to scenario (A) and Price Scenario (B) the predicted price changes from scenario (B) in the Eatwell dataset. All the reformed prices resulted significantly different from the initial prices for each food category except for drinks and fats, where the bonus price was the same as the initial one.

Food Group	Price (pence/gram)	Price Scenario (A) (pence/gram)	Price Scenario (B) (pence/gram)	Δ Scenario (A) (%)	Δ Scenario (B) (%)
Carbs	.275	.288	.279	5	1
D&A	.170	.185	.180	9	6
Drinks	.321	.331	.321	3	0
F&V	.255	.261	.253	2	-1
F,O& S	.516	.535	.518	4	0
Proteins	.792	.847	.819	7	3
Others	.476	.487	.472	2	-1

Table 3.11: Price changes in scenario (A) and (B)

Table 3.12 reports predicted changes in the budget shares of the different macro-categories following the different scenarios. Surprisingly, by considering only the effect of the carbon tax, budget shares of fruit and vegetables would decrease as well as dairy products, while the other categories would remain almost the same and protein increase. The same changes occur in scenario (B), but with different rates, probably due to the lowest increase in prices compared to scenario (A).

Food Group	Budget Share (%)	Budget Share Scenario (A) (%)*	Δ scenario (A) (%)	p-values Δ scenario (A)	Budget Share Scenario (B) (%)*	Δ scenario (B) (%)	p-values Δ scenario (B)
Carbs	16.1	16.0	-0.5	0.0905	16.1	-0.2	0.3831
D&A	10.1	8.0	-20.4	0.0000	8.3	-18.2	0.0000
Drinks	16.3	16.1	-1.2	0.0000	16.2	-0.8	0.0004
F&V	14.4	11.7	-18.4	0.0000	11.9	-17.1	0.0000
F,O& S	4.0	3.9	-0.8	0.0000	4.0	-0.2	0.1852
Proteins	26.7	27.8	4.2	0.0000	27.2	2.2	0.0001
Others	12.5	12.5	0.0	0.2151	12.4	-0.4	0.0000

Table 3.12: Budget share changes in scenario (A) and (B)

Note: Scenario (A) represents Carbon Taxation only, while Scenario (B) the *Bonus Malus* intervention.

3.7.2 Effects of simulation results – Second aggregation

The table below (Table 3.13) reports predicted changes in prices in the second type of aggregation. All the reformed prices resulted significantly different from the initial prices for each food category except for drinks, fats and potatoes and vegetables, where the price in scenario (B) were the same as the initial ones.

Food Group	Price (pence/grams)	Price Scenario (A) (pence/grams)	Price Scenario (B) (pence/grams)	Δ Scenario (A) (%)	Δ Scenario (B) (%)
Cereals	0.256	0.269	0.260	5	2
D&E	0.239	0.254	0.247	7	4
Drinks	0.320	0.330	0.320	3	0
F,O&S	0.511	0.531	0.514	4	0
Fish	0.907	0.920	0.890	1	-2
Fruit	0.267	0.273	0.264	2	-1
Meat	0.720	0.793	0.768	10	7
Potatoes	0.277	0.287	0.277	4	0
RM	0.643	0.691	0.669	7	4
Sweets	0.500	0.510	0.494	2	-1
Veg.	0.244	0.252	0.244	3	0

Table 3.13: Prices changes in scenario (A) and (B)

Food Group	Budget Share (%)	Budget Share scenario (A) (%)	Budget Share scenario (B) (%)	Δ scenario (A) (%)	p-values Δ scenario A	Δ scenario (B) (%)	p-values Δ scenario B
Cereals	8.8	8.8	8.9	-0.7	0.0000	1.2	0.0000
D&E	11.2	10.8	11.1	-3.4	0.0000	-0.8	0.0000
Drinks	16.3	16.0	16.2	-1.8	0.0000	-0.3	0.0000
F,O&S	4.0	4.1	4.1	3.3	0.0000	3.2	0.0000
Fish	4.4	4.4	4.3	0.4	0.0000	-2.3	0.0000
Fruit	7.1	6.7	6.8	-6.4	0.0000	-3.9	0.0000
Meat	14.2	15.1	14.7	6.2	0.0000	3.5	0.0000
Potatoes	4.4	4.5	4.5	2.9	0.0000	2.2	0.0000
RM	9.6	10.3	9.9	7.2	0.0000	3.1	0.0000
Sweets	11.7	11.5	11.4	-1.6	0.0000	-2.7	0.0000
Veg.	8.3	7.8	8.0	-5.6	0.0000	-3.4	0.0000

Table 3.14: Budget shares changes in scenario (A) and (B)

Table 3.14, Table 3.15 and Table 3.16 display simulation results obtained correcting for zeros, endogeneity of prices and expenditure, respectively. The following analysis is based on these results. In Table A.6 in Appendix A are reported the results of the simulation in the second type of aggregation considering only the endogeneity of expenditure.

Looking at budget share and expenditure, people would spend more on fats, meat and ready meals, as expected from the high increase in prices, while they would spend less in fruit and vegetables. Focusing on the variation in consumption (Table 3.15 and Figure 3.14), quantities in all the food categories would decrease in scenario (A), except for fish and ready meals. The highest reduction was predicted for dairy products, vegetables and fruit. In scenario (B), people would consume less meat and ready meals, but more dairy compared with scenario (A). Vegetables and fruit consumption would decrease, but much less than in scenario (A). All the other food categories remain almost constant.

Food group	Quantity (kg)	Quantity scenario (A) (kg)	Quantity scenario (B) (kg)	Δ scenario (A) (%)	p-values Δ scenario (A)	Δ scenario (B) (%)	p-values Δ scenario (B)
Cereals	4.84	4.69	4.84	-3.1	0.0000	0.2	0.0002
D&E	9.81	8.73	9.11	-11.2	0.0000	-7.1	0.0000
Drinks	12.39	12.09	12.49	-2.1	0.0000	0.8	0.0000
F,O&S	1.38	1.38	1.40	0.1	0.8076	1.2	0.0000
Fish	0.61	0.62	0.61	1.8	0.0000	-0.1	0.5392
Fruit	3.89	3.66	3.82	-5.7	0.0000	-1.7	0.0000
Meat	2.92	2.85	2.81	-2.2	0.0000	-3.5	0.0000
Potatoes	3.24	3.22	3.24	-0.8	0.0000	-0.2	0.0931
RM	2.01	2.04	1.97	1.1	0.0000	-2.1	0.0000
Sweets	3.67	3.64	3.64	-0.9	0.0000	-0.7	0.0000
Veg.	5.03	4.70	4.87	-6.5	0.0000	-3.0	0.0000

Table 3.15: Consumption changes in scenario (A) and (B)

Food group	Expenditure (£)	Expenditure scenario (A) (£)	Expenditure scenario (B) (£)	Δ scenario (A) (%)	p-values Δ scenario (A)	Δ scenario (B) (%)	p-values Δ scenario (B)
Cereals	11.30	11.58	11.56	2	0.0000	2	0.0000
D&E	14.29	14.26	14.34	0	0.0037	0	0.0000
Drinks	21.06	21.36	21.24	1	0.0000	1	0.0000
F,O&S	5.09	5.42	5.30	6	0.0000	4	0.0000
Fish	5.67	5.88	5.62	4	0.0000	-1	0.0000
Fruit	9.29	9.01	9.06	-3	0.0000	-3	0.0000
Meat	18.21	19.95	19.05	10	0.0000	5	0.0000
Potatoes	5.65	5.99	5.83	6	0.0000	3	0.0000
RM	12.09	13.36	12.60	11	0.0000	4	0.0000
Sweets	15.11	15.34	14.87	2	0.0000	-2	0.0000
Veg.	10.78	10.53	10.54	-2	0.0000	-2	0.0000

Table 3.16: Expenditure changes in scenario (A) and (B)

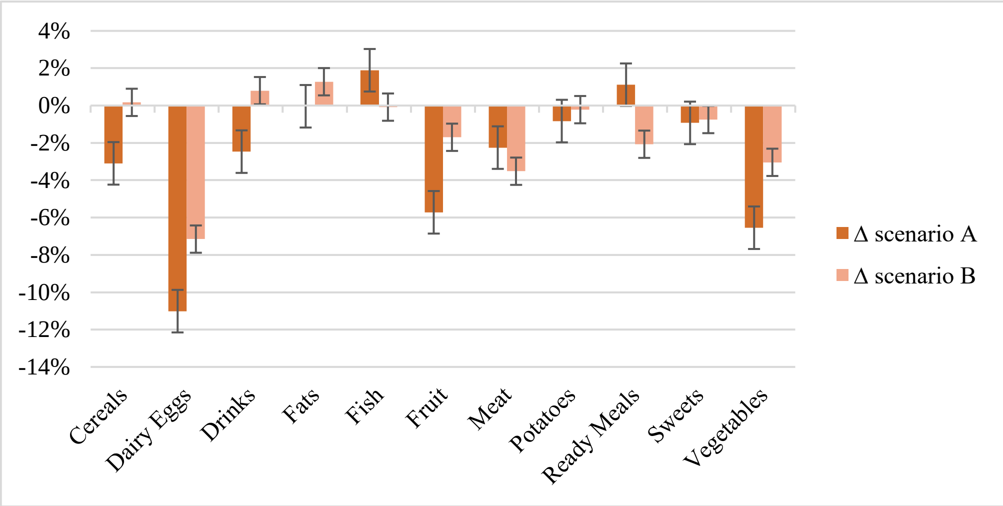

Figure 3.14: Consumption changes in scenario (A) and (B)

3.7.3 Health simulation results

This section contains information regarding the simulation health outcomes due to changes in diets followed by the implementation of scenarios (A) and (B). To remind, scenario (A) represents carbon taxation only and scenario (B) the *Bonus-Malus* taxation. Results are shown in Table 3.17 at individual level considering the average of all the population and classified in quintiles.

On average, the Body Mass Index of adult population (without considering children) would increase slightly in scenario (A) and (B), compared with baseline. This was evaluated considering the median of the UK population, since BMI data are usually positively skewed (Beyerlein *et al.*, 2008). Blood glucose concentrations would remain constant in both scenarios. Total cholesterol (including LDL-and HDL:-cholesterol) would decrease slightly in both scenarios, showing a positive impact in terms of health. On average, HbA1C ratios were predicted to be slightly higher in both scenarios.

In Table 3.18 the health indicators are predicted considering different types of households; i.e. low and high income, large or small, young or old families. Socio-demographic characteristics play a key role in the health characteristics of a particular household (Table 3.18).

Measure	Baseline	Scenario (A)	p-values Scenario (A)	Scenario (B)	p-values Scenario (B)
Valid Body Mass Index*	26.97	27.06	0.0000	27.04	0.0000
1st	25.79	25.86	0.0000	25.85	0.0000
2nd	26.44	26.51	0.0000	26.50	0.0000
3rd	26.97	27.06	0.0000	27.06	0.0000
4th	27.56	27.65	0.0000	27.63	0.0000
5th	28.26	28.36	0.0000	28.35	0.0000
Glucose (mmol/L)	5.17	5.18	0.0000	5.18	0.0000
1st	4.75	4.76	0.0000	4.76	0.0000
2nd	4.98	4.99	0.0000	4.99	0.0000
3rd	5.16	5.17	0.0000	5.17	0.0000
4th	5.36	5.37	0.0000	5.37	0.0000
5th	5.61	5.62	0.0000	5.62	0.0000
Cholesterol (mmol/L)	4.00	3.98	0.0000	3.99	0.0000
1st	3.63	3.61	0.0000	3.62	0.0000
2nd	3.83	3.81	0.0000	3.82	0.0000
3rd	3.97	3.95	0.0000	3.96	0.0000
4th	4.12	4.11	0.0000	4.11	0.0000
5th	4.45	4.43	0.0000	4.42	0.0000
HbA1c (mmol/mol)	37.20	37.24	0.0000	37.22	0.0000
1st	33.22	33.26	0.0000	33.24	0.0000
2nd	35.20	35.24	0.0000	35.22	0.0179
3rd	37.06	37.09	0.0000	37.07	0.0443
4th	39.10	39.12	0.0000	39.10	0.5842
5th	41.38	41.43	0.0000	41.39	0.3883

Table 3.17: Health measures in scenario (A) and (B), total and in quintiles

		Baseline	**Scenario (A)**	**p-values Scenario (A)**	**Scenario (B)**	**p-values Scenario (B)**
Valid Body Mass Index	Low income	27.33	27.40	0.0000	27.39	0.0000
	High income	26.76	26.82	0.0000	26.81	0.0000
	Large	26.47	26.52	0.0000	26.50	0.0000
	Small	27.39	27.48	0.0000	27.47	0.0000
	Young	26.31	26.36	0.0000	26.35	0.0000
	Old	27.68	27.74	0.0000	27.73	0.0000
Glucose (mmol/L)	Low income	5.26	5.27	0.0000	5.27	0.0000
	High income	5.09	5.09	0.0000	5.09	0.0000
	Large	4.98	4.98	0.0000	4.99	0.0000
	Small	5.28	5.29	0.0000	5.29	0.0000
	Young	4.92	4.93	0.0000	4.93	0.0000
	Old	5.41	5.42	0.0000	5.42	0.0000
Cholesterol (mmol/L)	Low Income	4.07	4.05	0.0000	4.05	0.0000
	High Income	3.93	3.92	0.0000	3.92	0.0000
	Large	3.83	3.81	0.0000	3.82	0.0000
	Small	4.10	4.08	0.0000	4.08	0.0000
	Young	3.87	3.85	0.0000	3.86	0.0000
	Old	4.13	4.11	0.0000	4.11	0.0000
Haemoglobin A1c (mmol/mol)	Low Income	38.15	38.20	0.0000	38.19	0.0002
	High Income	36.22	36.25	0.0000	36.23	0.0328
	Large	35.00	35.04	0.0000	35.03	0.0000
	Small	38.45	38.48	0.0000	38.46	0.3384
	Young	34.73	34.77	0.0000	34.76	0.0000
	Old	39.54	39.57	0.0000	39.55	0.3552

Table 3.18: Health measures in scenario (A) and (B) for different types of households

3.8 Effects on calculated CO_2 emissions and nutrition

When assessing the effectiveness of the different scenarios, the focus is primarily on whether they would result in a significant reduction in the climate footprint of foods. However, a reduction in the consumption of particular types of foods can also be translated in a decrease in the intake of specific nutrients with potential negative health consequences.

In Table 3.19 and Figure 3.15, the projected changes in carbon footprint are shown for scenario (A) and (B), by considering the different food groups. On average, there would be a reduction of 4% of the total emissions coming from the different food groups consumed at a household level in a two-weeks period. In particular, 5.2 kgCO_2-eq would be saved with scenario (A) and 4.15 kgCO_2-eq with scenario (B), at a household level. Translating those values for all the households in the analysis, on average 25 tCO_2-eq could be saved with scenario (A) and 20.5 tCO_2-eq with scenario (B). The major reductions on CO_2 emissions were associated with dairy, meat and ready meals products in scenario (B) and with dairy, meat and vegetables in scenario (A). In terms of cost efficiency, scenario (B) would be the most effective with a lower price increase of the different food products compared with scenario (A).

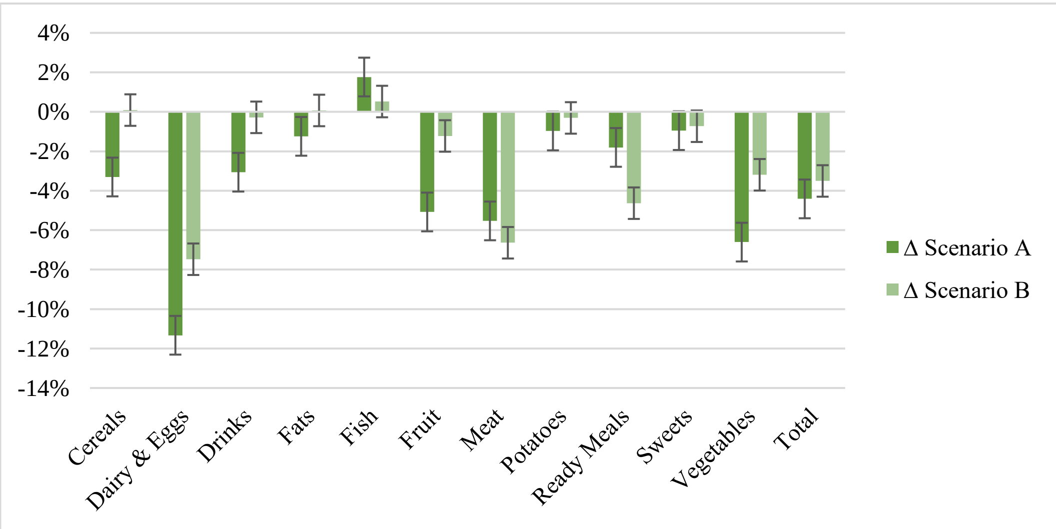

Figure 3.15: Calculated changes in CO_2 equivalents (%)

Food Group	**Carbon Footprint (kg CO_2-eq)**	**Carbon Footprint (A) (kg CO_2-eq)**	**Carbon Footprint (B) (kg CO_2-eq)**	**Δ scenario (A) (%)**	**p-values Δ scenario (A)**	**Δ scenario (B) (%)**	**p-values Δ scenario (B)**
Cereals	8.63	8.35	8.64	-3	0.0000	0	0.1184
D&E	20.07	17.79	18.57	-11	0.0000	-7	0.0000
Drinks	10.44	10.12	10.41	-3	0.0000	0	0.0211
F,O&S	4.86	4.80	4.87	-1	0.0000	0	0.6524
Fish	2.26	2.29	2.27	2	0.0000	1	0.0001
Fruit	3.39	3.22	3.35	-5	0.0000	-1	0.0000
Meat	33.02	31.19	30.83	-6	0.0000	-7	0.0000
Potatoes	5.10	5.05	5.08	-1	0.0000	0	0.0108
RM	14.37	14.11	13.70	-2	0.0000	-5	0.0000
Sweets	4.45	4.41	4.42	-1	0.0000	-1	0.0000
Veg.	5.67	5.29	5.49	-7%	0.0000	-3%	0.0000
Total	**118.40**	**113.17**	**114.25**	**-4%**	**0.0000**	**-4%**	**0.0000**

Table 3.19: Change in CO_2-eq emissions from scenario (A) and (B) (kg CO_2-eq per household)

Table 3.20 shows the average nutrients intake in a UK household based on their food consumption for a two-weeks period, classified by food categories. On average, the UK household comprises two people. As expected, consumption of cereals products contain more energy, carbohydrates, fibre and vegetable proteins compared with the other categories, but also more sodium. Dairy and meat are high in saturated fats and animal protein. Sweets, although high in energy, carbohydrates and total sugars, also contain elevated levels of total fats and saturated fats. Vegetables and fruit are the second and the third highest categories contributing to fibre intake.

Nutrient consumption following scenario (B) was predicted not to change considerably for calorie, sugar and fibre consumption (-1%) compared with the baseline values. Furthermore, vegetable protein consumption would remain almost the same. On the other hand, the model predicted a large decrease in consumption of animal protein (-4%), saturated fat (-3%) and total fat. The low-GHG diets obtained from scenario (A) predicted significantly higher reductions in all the nutrient intakes, especially for animal protein and saturated fat, but also for total energy, sugar and fibre (Table 3.21 and Figure 3.16). This is likely to be due to the lower consumption of animal-based foods, meat and dairy as well as vegetables and fruit.

Food Group	Total Energy (Kcal)	Total Sugar (g)	Carbs (g)	Vegetable Protein (g)	Animal protein (g)	Total Fat (g)	Saturates (g)	Sodium (g)	Fibre Southgate (g)
Cereals	13668.6	259.8	2811.1	416.4	3.8	161.3	46.9	16.7	248.8
D& E	9780.3	565.6	579.9	0.5	500.4	622.6	379.3	9.5	2.8
Drinks	4109.3	541.2	548.9	40.4	0.4	7.7	2.3	1.1	1.1
F, O & S	6491.8	135.4	167.2	23.7	12.6	634.8	118.5	14.1	9.6
Fish	1478.9	4.7	64.1	9.7	137.4	72.1	16.3	3.2	2.4
Fruit	2953.2	462.7	488.0	59.9	0.0	98.4	22.5	2.9	92.1
Meat	6495.4	13.3	57.6	11.1	583.2	433.5	160.7	13.5	4.5
Potatoes	4865.7	32.6	848.1	83.3	0.6	149.7	23.8	3.3	23.5
RM	4964.60	63.78	433.39	85.54	176.83	252.9	94.2	10.5	34.9
Sweets	13085.9	1516.5	2145.7	85.0	69.4	490.7	235.7	7.3	47.4
Veg.	2510.6	205.6	382.6	115.7	0.7	69.3	12.9	4.3	139.2

Table 3.20: UK households' nutrients intake classified by food category

Nutrient	Δ scenario (A) (%)	Δ scenario (B) (%)
Total Energy (kcal)	-3%	-1%
Total Sugar (g)	-3%	-1%
Carbohydrates (g)	-3%	0%
Vegetable Protein (g)	-3%	0%
Animal Protein (g)	-4%	-4%
Total Fat (g)	-3%	-2%
Saturates (g)	-4%	-3%
Sodium (g)	-2%	-1%
Fibre: Southgate (g)	-4%	-1%

Table 3.21: Calculated changes in nutrient intakes from scenario (A) and (B)

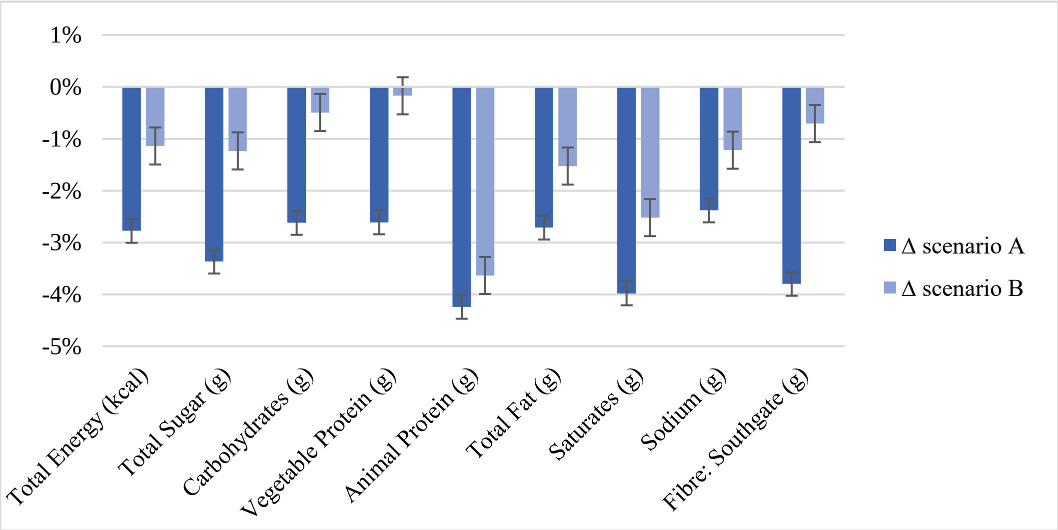

Figure 3.16: Calculated changes in nutrient intakes from scenario (A) and (B) (%)

3.9 Discussion

The overall results of Chapter 3 are that some changes in dietary patterns across UK population could be achieved through the use of combined regulations of food prices. When comparing the predicted reductions in GHG emissions using both scenarios (A) and (B), two parameters are taken into account: the total reduction in carbon footprint and the dietary health effects. Due to the uncertainties in the elasticities, the quantitative results in this study should be interpreted with care. This methodological approach does not allow for any consideration of the potential dynamic effects of taxation, such as providing consumers with information and influencing social trends. The effectiveness of GHG weighted taxation on food could therefore be enhanced if it were completed by information efforts.

Starting from the Eatwell dataset, in scenario (B) people are predicted to spend less money on dairy and alternatives, oils and fats, protein and other products. The consumption of fruit and vegetables would decrease as well, but at a lower level compared with scenario (A). Thanks to the second type of aggregation it is possible to see the effects at more detailed level of food categories, where the consumption of dairy, eggs and meat (most impactful in terms of GHG emissions), but also vegetables would decrease the most. These changes in dietary patterns have the potential to provide some positive environmental effects. Both scenarios would reduce households' food-related emissions by 4% during a two week period with a social cost of £70/tonne CO_2. Over one full year a single household could save up to 135.5 kg CO_2-eq with scenario (A) and 108.2 kg CO_2-eq with scenario (B). Considering the UK population of 66 million people, this value would on average sum up to 8.91 MtCO_2 saved with scenario (A) and 7.14 Mt CO_2 saved with scenario (B). This is in line with another study that found that an emission based food tax in the UK on all foods reduces GHG emissions from food consumed at home by on average 6.3% (-8.023 MtCO_2e) (Kehlbacher *et al.*, 2016). However, higher levels of taxation or interventions more targeted to specific food groups might have to be put in force in order to achieve greater magnitude in the decrease of GHG emissions.

This study shows that policy interventions to reduce GHG emissions from the food sector may also have health benefits, mainly in a predicted significant reduction of individual blood cholesterol concentrations. Haemoglobin A1c is a measure of average blood glucose concentrations over a two to three month period. A high haemoglobin A1c ratio is associated with a higher risk of developing Type 2 diabetes. On average, A1c ratios were predicted to be slightly higher in both scenarios, but acceptable. The other health indicators examined were either stable or slightly worse after the fiscal changes. In this sense, health and sustainability are not always aligned. This was demonstrated also by Briggs *et al.* (2013). However, it is quite hard to compare these results with the literature in the field. The idea to consider biomarkers as a measure for individual health is new and present innovative aspects in the context of environmental regulations. The majority of research has focused on epidemiological methods, aiming to model the effects on mortality and deaths averted with comparative risks assessment models (Briggs *et al.*, 2013). Despite the different methodologies, ambiguity remains around the consumption of particular unhealthy but sustainable foods (Briggs *et al.*, 2016) making the nexus among health and sustainability still uncertain.

The data reveal that, due to the change in the quantity of food and drinks consumed at household level, the new diets would result in a decrease in the consumption of some essential micro-nutrients. This happens mainly in scenario (A), with reductions in energy (calories), total sugars and fibre in parallel with a reduction in animal protein and saturated fats. Scenario (B) would maintain the same broad micronutrient composition as the baseline with major reductions in saturated fat and animal protein, showing overall better nutritional outcomes. However, despite small absolute percentage changes in micro-nutrient composition, at a population level there may be significant changes to the number of people consuming below the recommended daily intake, especially in the case of fibre intake. Care needs to be taken that changes in targeted food groups are balanced in their nutritional implications. Despite the negative impacts of overconsumption of certain foods which represent health risks, moderate intake amounts can be a source of valuable nutrients like protein and iron in the case of red meat.

One of the constraints of this study is that in both scenarios, carbon regulations were applied to all of the food groups. This means that both healthy and not healthy products were affected by changes in prices. Households were not incentivized to substitute animal protein for vegetable protein directly. In addition, it was not possible to observe substitution within categories. In this regard, different levels of taxation for products within the same group could be a good incentive. Bonnet;Bouamra-Mechemache and Corre (2018) consider scenarios with taxation only and show that, by taxing beef products rather than all meat products, one gets most of the impact of the taxation policy at a much lower cost for consumers. The idea of the *Bonus-Malus* tax had good consequences in terms of household welfare effects, not penalizing low-income households. However, it would be sensible to consider other scenarios and implement the subsidy only for some products, like fruit and vegetables, in order to observe an increase in selected vitamin intakes and improve the nutritional profile of the population. This was suggested by Springmann *et al.* (2016) in their revenue neutral scenario, where they conclude that `the greater the tax coverage, the greater the tax revenue, the more revenue could be used to subsidize F&V consumption and the greater the associated health benefits'. On the other hand, even though the changes needed to achieve more sustainable and healthy diets are required across all the income groups, more attention should be given to low-income households, as suggested by Reynolds *et al.* (2019). Subsidies could be applied only to specific types of social classes, requiring carbon taxation only from high-income families, for example. However, implementation costs would be high.

In general, it is challenging to compare directly these findings with other studies because of differences in the structure of the tax across countries and because of different scenarios. Stehfest *et al.* (2009) supported the idea that a change in dietary patterns can be an effective tool to decrease GHG emissions when considering the climate benefits of a low-meat diet. On the other hand, Vieux *et al.* (2012) found that an increase in fruit and vegetables to substitute for meat in order to keep calories constant would lead to a rise in GHG emissions. Latka *et al.* (2021) found that food group taxes contribute effectively to nutritional and environmental sustainability objectives. They stated, however, that increased awareness due to the implementation of the fiscal diet interventions may increase consumer responses more than high levels of taxation alone. Some studies implemented a budget neutral tax design in which products with GHG above a given threshold are taxed and products with GHG below are subsidised (Briggs *et al.*, 2013). Others implemented a redistribution of tax revenues via income-dependent or lump sum transfers to reduce social equity concerns (Klenert and Mattauch, 2016; Carattini;Carvalho and Fankhauser, 2018). Edjabou and Smed (2013) use a similar rule to this study: all products were taxed proportionally to their GHG content and all products benefited from the same abatement in VAT. Their scenarios lead to a predicted decrease in the consumption of saturated fat, as in this study, and they show a low cost potential for using consumption taxes to promote climate-friendly diets. Additional assessments using micro level data would be needed in this study to address distributional issues, while also taking differences in diets, and thus exposure to diet-related health risks, into account.

In order to assess the full welfare economic benefits of imposing climate taxes, the long term consequences in terms of changes in land use as a result of changed demand for ruminant meat and dairy products should be considered (Edjabou and Smed, 2013). This could result in land being freed up to produce feeds for non-ruminant, i.e. pigs and poultry. Carbon emissions from land use change, especially deforestation in relation to meat production, are believed to be a significant contributor to climate change, accounting for 20-25% of total anthropogenic emissions during 1990s (Watson *et al.*, 2000) In addition, more pollutants other than GHG emissions, like nitrogen and phosphorus, should be studied (Säll and Gren, 2015).

Environmental effects other than CO_2 emissions may be important for people's wellbeing. Acidification, eutrophication, and effects on local air quality are examples of environmental effects that are not considered, but which are important. At present, however, these types of analyses cannot be undertaken due to data limitations, but it is of course ranked high in the next future steps.

Whether a climate-related tax on foods is politically feasible is uncertain. Despite the advantages of introducing differentiated climate taxes on food products, there is also an associated disadvantage in that tax levels are static in the sense that they are not automatically adjusted if technological improvements are implemented. In this sense, an increased incentive to develop eco-efficient technologies could be created if a political decision was made to use tax revenues to subsidise technological improvements.

3.9.1 Strength and Limitations

This study attempted to model the impact of internalising the societal cost of food-related GHG emissions through price changes on consumer diet and health. A strength is that two scenarios were implemented, in order to face the negative impact of carbon taxation and improve social welfare. This showed how different types of regulation could lead to different outcomes in promoting sustainable dietary patterns. Another strong point is that endogeneity of prices and sample selection biases were corrected in order to get more accurate estimations in the demand system analysis. Limitations of this work include that the estimates of GHG emissions of some products are assumed to be identical to related products due to lack of carbon footprint information relative to specific types of foods. Moreover, carbon footprint data were derived from different sources and this may result in a non-consistent analysis where non-UK data were used sometimes (Table A.2 in Appendix A). In this study, estimates of pre-tax and post-taxation were based on the mean population diet. Population diets vary between individuals and they may respond differently to price changes both in terms of purchasing and consumption. Furthermore, data were aggregated in 7 and 11 categories, respectively and whilst some constituents will vary, the percentage change in consumption for any group was assumed to be identical to all foods within that group which many not be the case. Other limitations are that health data are reported at individual level whereas consumption and expenditure data are at household level. The assumption was that individual health outcomes changed based on expenditure made at household level. Another issue regards the very low spatial variation of the food price indexes included in model. Surely, the data on prices that are used have the advantages of varying enough in time to give significant estimates of price elasticities.

Nevertheless, the measure of prices faced by consumers is rather rough since it is an aggregate of the consumer price index for each food category taken at the UK national level. This means it does not account for any difference in prices across states, cities and stores. As a result, the estimate of the elasticities can be unprecise to some extent.

3.10 Conclusion

This chapter investigates whether carbon taxes can be used to support better nutritional and sustainable choices among UK national households. The main findings is that, in the context of climate change, internalising the cost of food-related emissions through a *Bonus-Malus* tax on food offers a potential cost-efficient solution to reduce GHG emissions and move diets towards more sustainable patterns. However, the health analysis reveals that only modest changes can be achieved at population level with the levels of taxation applied. Even though these results showed a decrease in the consumption of saturated fat and animal protein, there was also consistent reduction in the intake of other essential nutrients.

Care needs to be taken when designing carbon taxation that does not damage the nutritional quality of the population's diet. More disaggregation within each food category and different revenue neutral scenarios aiming to subsidise only healthy products need to be implemented in order to observe valuable substitutions at household level. On the other hand, additional health indicators could be integrated together with the implementation of a risks assessment model in order to study the mortality consequences of eco-compatible dietary patterns.

Overall, this study points out that there are possibilities to design and provide consumers with the incentives to adopt healthier and more climate-friendly diets. However, since food consumption changes slowly, there is the necessity to improve the performance of the production system in a way that limits GHG. In this regard, supply side measures targeted at producers and the entire value chain are required in addition to further push food production towards environmental sustainability goals.

3.11 Post-Note Chapter 3

3.11.1 Tax rate variability and aggregation of data sources methods

Current UK food consumption patterns are taken from the Living Cost and Food Survey 2015/2016 (LCF), to provide the baseline level of food purchasing prior to the application of the tax. The LCF is a survey of purchasing data for 256 food categories compiled for 2-week long food expenditure diaries of 6232 household across the UK (Office for National Statistics, 2017a). However, only private households are surveyed, so excluding people living in hostels, boarding nurses and institutions, care and nursing homes – large part of the population (Department for Environment, 2019b). The survey measures purchasing habits and we assumed that all food purchased is consumed. For the analysis, only data related to the year 2015 were considered and households with no income information were excluded, because income was used as an instrument to deal with expenditure endogeneity. While the LCFS includes all food and drink consumed out-of-home and takeaways brought home, these are not included in the analysis, which focuses on purchases for in-home consumption. This had some implications and limitations because, since 2012, eating out expenditure on food and drinks rose by 2.4% (Department for the Environment Food and Rural Affairs, 2017), representing a large increase of people eating outside of their home. Many people that usually eat outside, for work or personal reasons, were consequently excluded from the study. However, this was done to get more consistent and comparable findings with the literature surrounding this field (Briggs *et al.*, 2013; Briggs *et al.*, 2016) that consider only food consumed at home. Also, there is a high heterogeneity of foods and ready meals that people eat outside that cannot be observable in detail. Food consumed away from home is not properly described in the survey, in terms of quantities and ingredients with a consequent non-correct evaluation of the carbon footprint and the nutritional content of the food consumed away from home. These are the reasons behind the decision to consider only food purchased and brought at home. This could be seen as a current limitation, but, at the same time, a potential expansion of the current research study, where also food purchased in restaurants and/or taken as takeaways could change in price as a result of the tax.

Another issue linked with the use of the Living Cost and Food Survey is the fact that this survey considers only a 2-week period in which household recorded what they purchased. For this reason, there are many zeros - missing values - in the dataset. Of course, this is not completely accurate in the sense that these households might have also eaten food that was in stock, for example, or they might not purchase a particular item because they want to purchase in the following weeks. It is difficult to say, because this information is not expressed clearly in the survey. However, an advantage of this survey is that it is undertaken continuously throughout the year to account for seasonal effects (Hayes and Finney, 2014), even if the period is quite short. On the other side, there are no information about where the food was purchased exactly. This might be a limitation in the sense that the carbon footprint might be lower if the food was purchased in local shops or directly at the farm. This might be another suggestion for a further development of the study. Another limitation of the LCF is that the survey does not include any specific information or question about the interest on sustainability issues that might have been linked with the simulation of carbon taxation. However, it includes many socio-demographic and income information that help us to understand the result of the analysis from a contextual perspective.

In terms of aggregation of consumption data, broad macro-categories were chosen in order to reduce the number of zeros in the dataset. A more detailed and accurate level of disaggregation would need to separate legumes and vegetables because of the different nutrient composition. In this study, they were aggregated because they both can be seen as a side for the main deal, so people might consume them in similar circumstances. In other words, they can be seen as substitute products. However, the aggregation of these products did not enable the opportunity to observe proteins substitution effect between meat and legumes – that could have been achieved in terms of nutritional and environmental content after the application of the tax.

Furthermore, a more levelled disaggregation should be implemented within the category of ready meals, that contain different types of ingredients in the same package. The category of ready meal is the more heterogeneous and for that reason is one of the least accurate, in terms of nutrient end environmental information. For some instance, this category should be deleted from the study, but, on the other hand, a large share of UK population buys this type of products and excluding them from the analysis might cause inaccurate results. A more detailed disaggregation within the category of meat could be necessary, distinguishing between white and red meat because of the different level of carbon footprint that they have, or even at the level of the type of meat – pork, beef, lamb for example. This would enable more substitution effects within the same categories. As mentioned before, these choices were made mainly to have less zeros in the dataset. Maintaining the broad categories enables more people to purchase that category in that timeframe, even though it causes the current limitations.

Carbon taxes have been used in different countries. Tax rate varies between different contexts and different sectors. In order to give some examples, a carbon tax of A$23 (£13) per tonne of CO2-e was introduced in Australia in 2012 after Government's commitment to decrease carbon emissions by 80% (Meng;Siriwardana and McNeill, 2013). The tax reduced carbon emission after its introduction; however, as a result of the reaction coming from voters and industry, the programme was repealed. Similarly, in 2008, a carbon tax was used in British Columbia, which covered around three quarters of the whole emissions in the province (Murray and Rivers, 2015). The tax started at C$10 per ton of carbon dioxide and then it reached C$30 per ton in 1012, where it remains today. In 1990, it was introduced in Finland to apply to gasoline, light and heavy fuel oil, diesel, natural gas, coal, jet fuel and aviation gasoline; in 1991, in Norway and in 1992 in Denmark to apply on natural gas, petroleum and mineral fuel and in Sweden in 1991 on all fuel oil at $44.37 (£35.20) per metric ton CO2 (Lin and Li, 2011). Finally, in France, a carbon tax £38.24 has been applied to the consumption of fossil fuel since 2014 (Dussaux, 2020).

A tax can be implemented directly on emissions, on the product input at the origin of the environmental impact or on the final products purchased by households. From economic theory we know that it is more efficient to use a tax that directly targets the source of the market failure. However, as highlighted by Edjabou and Smed (2013) and Wirsenius;Hedenus and Mohlin (2011), emissions or input taxes are less efficient than output based taxes. On the other hand, carbon policies that target livestock producers are unlikely to reduce substantial share of global GHG emissions. Moreover, Herrero *et al.* (2016) show that dramatically higher emission reduction can be achieved by designing policies that reduces share of red meat in human diets. Taking these aspects into consideration, in this thesis the idea is to estimate whether food consumption taxes on food might mitigate environmental indicators.

Few studies have explored the impact of an environmental tax on food consumption. Edjabou and Smed (2013) analyse the impact of a tax in Denmark based on CO_2 emissions of more than 20 food products, differentiated with respect to average GHG emissions. Their first scenario leads to a decrease in GHG emissions for an average household by 2.3%-8.8% (at a cost of 0.15-1.73 DKK per kg CO_2-eq) and their most efficient scenario in reducing the carbon footprint leads to a larger decrease in the GHG emissions by 10.4%-19.4% but at a higher cost (3.53-6.90 DKK per kg CO_2 equivalent). Wirsenius;Hedenus and Mohlin (2011) focus on GHG weighted consumption taxes on animal food products in EU. They show that agricultural emissions in the EU27 can be reduced by approximately 32 million tonnes of CO_2-eq with a tax of €60 per tonne of CO_2-eq, and that most of the effect of a GHG-based tax on animal food can be captured by taxing the consumption of ruminant meat alone. Bonnet;Bouamra-Mechemache and Corre (2018) consider taxes of €56 and €200 per tonne CO2-eq applied to the consumption of all animal products, only ruminant meats or only beef and they show that a high level of tax does not allow meeting the 20% objective threshold of GHG emissions reduction for 2020 since it would lead to a 6% decrease in GHG emissions only. In the case of the UK, the DEFRA guidance on the social cost of carbon, come close to the suggestion that the £70/tonne of CO_2 figure is a convenient justification for the UK's climate-change policy to achieve its Kyoto target. This is the value estimated by Pearce (2003) and that appears also in Stern (2006). In addition, the figure is likely to be at least roughly consistent with the level of effort that will be needed to meet international commitments on climate change (Pearce, 2003).

For this reason, in this study, the first scenario considered only the carbon tax, measured as the CO_2e content of each products multiplied by a £70/tonne of CO_2, in line with estimates from DECC (2016), that was added to the price baseline (Panzone *et al.*, 2021).

3.11.2 More reflection on the methodology trade-off (Bonus Malus)

This study also considers the implementation of a second scenario, the Bonus-Malus intervention. This was done in order to address the regressive nature of these regulations. Feng *et al.* (2010) evaluated the incidence of a CO_2 tax on UK households as a tax burden relative to an income of 6% in the lower decile compared to only 2.4% in the highest decile. Addressing regressivity, revenue-neutral approaches are key strategies to target distributional neutrality. In Metcalf and Weisbach (2009b) the regressivity of the carbon tax in the US case was offset by using the revenue to fund a reduction in the income tax.

The key issue of introducing compensating mechanisms has been used in certain carbon scenarios designed for food consumption (Briggs *et al.*, 2013; Edjabou and Smed, 2013; Caillavet;Fadhuile and Nichèle, 2019). Briggs *et al.* (2013) modelled 2 scenarios: (A) a tax of £2.72/tonne carbon dioxide equivalents (tCO2e)/100g product applied to all food and drink groups with above average GHG emissions. (B) As with scenario (A) but food groups with emissions below average are subsidised to create a tax neutral scenario. Also Edjabou and Smed (2013) implemented two scenarios. The A scenarios are based on Tol's estimate of 0.26 DKK per kg, whereas the B scenarios are based on Stern's estimate of 0.76 DKK per kg. In scenarios 1A and 1B, a tax is imposed on all foods (uncompensated), whereas scenarios 2A and 2B are designed so that the total tax revenue derived from food taxation is unaltered (compensated). This is achieved by reducing the current level of VAT of 25% on all food in parallel with the introduction of the differentiated climate taxes on food so that the resulting tax is revenue neutral. Caillavet;Fadhuile and Nichèle (2019) implemented three scenarios. The first (TAX_ALL) concerns all food; the second (TAX_ANI) taxes only the four-highest-emitting food groups and the third (TAX_SUB) is the revenue neutral scenario. This last scenario uses the revenues to subsidize two food groups rich in plant proteins, fresh fruit and vegetables and starchy food, including beans. This PhD study takes as reference the paper from Edjabou and Smed (2013) in the sense that, the *bonus-malus* interventions is a revenue neutral scenario where the total tax revenues are unaltered (compensated). This is achieved by reducing the current level food prices (bonus) in parallel with the introduction of climate taxes on food (malus), so that the resulting tax is revenue neutral.

More specifically, the variation in household expenditure (that increased due to the tax from the first scenario) is used as the price reduction for the bonus part. In other words, if household expenditure increases by a certain level due to the tax, the prices will be reduced by the same amount. This reduction represents the discount to apply to all the prices in the second scenario. In this way, the compensated reform requires that the price will rise by the carbon tax and at the same time decrease by the discount. This enables the estimation of new budget shares when the malus and the bonus part are applied simultaneously to the system and mitigate the negative impact of carbon taxes on social welfare.

It was chosen to redistribute the carbon tax revenues to all the household by subsidising all the food products, rather than only healthy products, because of the high heterogeneity of the macro-categories of foods in this study. Fruit and vegetable category are quite broad in the sense that the carbon footprint within the category might vary substantially. It would have not been accurate to subsidise the entire category for environmental purposes, because some products might have worse environmental impact than others, depending if they are raw or processed foods, for example. Moreover, this was done to be equal among all the households, no matter what they bought. Subsidising healthier foods will provide greater benefits for those consumers who currently consume more of these foods, i.e. higher income households, as suggested by Caillavet;Fadhuile and Nichèle (2019). In this sense, the application of subsidy would have been useless, in terms of welfare effects towards low-income households.

In terms of wider effects, this revenue-neutral scenario showed good results in terms of changing diets through a more sustainable pattern and, on the other hand, showed positive nutritional outcomes. The health implications, on the other hand, were not as significant as expected. The new diets predicted after taxation did not show health benefits directly, considering the health biomarkers used in this study. The implementation of the subsidy only to healthy products could be implemented, for healthy purposes rather than for environmental reasons.

On the other hand, this scenario resulted the most efficient because of the lower price increase compared to the scenario with carbon taxation only. The Bonus-Malus intervention had good consequences in terms of household welfare effects, not penalizing low-income households. Further research could consider a policy of targeted subsidy on fresh fruit and vegetables via stamps issued to lower-income households, in order to enrich the nutritional quality of diets (Metcalf and Weisbach, 2009b).

Other reflections around the implementation of a Bonus-Malus intervention might consider the implementation of a combined carbon and health tax that maximise the effects in terms of both environmental and health outcomes. Recent research suggested that such a combined policy could contribute to around one third of the reductions in residual emissions required to achieve the United Kingdom 2050 net-zero commitments, while discouraging the purchase of especially unhealthy snacks and increasing the purchase of fruit and vegetables (Faccioli *et al.*, 2022).

Bonus-malus interventions could be extended in a way that maximise the nutritional and sustainable outcomes of the entire food categories, and at the same time provide welfare effects. More actions and strategies behind the application of compensated mechanisms could be supported at governmental level to address environmental and nutritional issues simultaneously.

Chapter 4. The effect of EU carbon tariffs on the UK food trade market and emissions

4.1 Abstract

The world's economy has changed radically in recent years, becoming much more integrated. This integration is particularly relevant in the generation and management of global public goods, and global environmental threats like greenhouse gases (GHG). In fact, despite the contribution of trade in reducing poverty levels around the world, concerns remain regarding the impact of trade on the environment. To this extent, carbon tariffs can be a very important tool to reduce global carbon emissions. In this chapter, the ex-ante effects of a (hypothetical) carbon tax on the prices of imported food products on trade flows and carbon emissions are modelled. To analyse the effects of carbon taxes on the UK trade market, a structural gravity model was developed, which models trade flows by country size, distance, import prices and a multilateral resistance term that captures the level of integration of a country into the world economy. This study shows that the imposition of EU carbon tariffs would reduce UK emissions derived from the European import of dairy and meat products by more than 30.4 MtCO_2-eq. This reduction comes at the cost of lower trade flows, especially related to meat products. The analysis requires further investigation in order to accurately estimate the environmental outcomes related to the entire food sector.

4.2 Introduction

Climate change is a global problem that requires global actions. The concentrations of greenhouse gases (GHG) in the atmosphere is the product of different sources of emissions from all over the world. The global nature of the problem makes the fight against climate change a global public good: the costs of abatement are national, while the benefits are global and independent of where the emissions reductions come from. In this context, countries have the motivation to disregard environmental regulations aimed at reducing domestic emissions and to rely on the reductions achieved by other countries. This is known as the free-rider problem (Rocchi *et al.*, 2018). National solutions cannot be successful when these goods are global. Government have the legal right to determine laws and institutions within their territories but there is no formal mechanism to force reluctant free-riding countries into international negotiations or agreements that would ensure the provision of global public goods (Rocco *et al.*, 2020).

In countries that impose strong environmental policies, pollution-intense industries either experience a loss of competitiveness or try to avoid the rise in production costs by migrating to areas where the policies are more loose or non-existent, a phenomenon known as the "pollution haven hypothesis". Furthermore, as domestic importers will substitute foreign products for domestic ones, imports are expected to rise (Van Beers and Van Den Bergh, 1997). On the other hand, by applying more lenient environmental policies, countries tend to reduce production costs of their manufactures and thus improve their ability to export, despite the possibility of becoming countries that specialize in polluting industries, namely pollution havens (Ederington;Levinson and Minier, 2004; Jug and Mirza, 2005). The pollution haven hypothesis indicates that profit-maximising manufacturers will locate their operations in countries with low resources and labour costs; however, countries with these characteristics generally have looser environmental regulations and often lack strict environmental standards, which keep costs down, therefore crowding in carbon-intensive investments but producing global and local environmental externalities (Taylor, 2005).

GHG emissions move via international trade. As a result, some of these emissions are produced within the boundary of a state, but some may be produced in areas with lower GHG costs (Oates and Portney, 2003). A phenomenon called "carbon leakage" (Felder and Rutherford, 1993). This phenomenon may occur in two ways: *strong carbon leakage* occurs when an industry in an environmental controlled country shuts down and opens in a non-participating region with lax ecological regulation; *weak carbon leakage* occurs when demand for goods is not covered anymore by internal production, but by imports from economies relying on a less efficient technological structure (Peters, 2010). For example, starting in 1997, the UK has shifted its economy from manufacturing to the services sector, with more goods produced overseas. One of the consequences is the growing rate of emissions imported from China, EU or the Rest of the World. Early estimates indicate that emissions associated with trade, namely embodied emissions, increased by 49% from 1997 to 2007 when they reached a peak. In 2017 they were 358 $MtCO_2$-eq (Department for Environment Food and Rural Affairs, 2012).

The first best solution to reduce global greenhouse gas (GHG) emissions in an efficient way would require the participation of all countries. However, previous United Nations climate conferences have shown the difficulties associated with agreeing on an effective and binding global pact. Instead, national and regional initiatives have prevailed (Larch and Wanner, 2017). The lack of global coordination has raised questions concerning the relationship of national climate policies and international trade (Larch and Wanner, 2017). In general, the following regulatory tools are taken into consideration as optimal solutions to reduce carbon emissions: 1) a classical command and control administrative legislation which sets limits and conditions for the polluting activity, allowing emissions up to a certain threshold; 2) a levy or a tax, whose tax base and or rate is linked to the amount of carbon emissions from the polluting activity; 3) a tax or a charge, imposed on specific products, whose production is considered to be the cause of significant carbon emission on the environment; 4) a tradable permit scheme, which allows polluters to emit CO_2 as much as they like, as long as they are in possessions of permits, which are exchangeable among private entities (Rocco *et al.*, 2020). Tax-based instruments seem to be easier to put in place and implement compared to non-tax compulsory regulatory schemes (Haites, 2018) even though they could lead to carbon leakages that might increase global emissions (Garella and Trentinaglia, 2019). However, if revenues from a tax are used to reduce other distortionary taxes, like a tax on income, the final effect on welfare is increased (Goulder, 1995; Garella and Trentinaglia, 2019). Considering the growing pre-eminence of tax related instruments as CO_2 embodied emissions reduction schemes among OECD countries, this study will analyse the effects of environmental regulations on trade and global emissions by way of a tax measure, classified as carbon tariffs.

Carbon tariffs are very prominently discussed in the environmental policy debate. The European Union have repeatedly called for carbon tariffs by the European Union. Named the European Green Deal, the proposed measures aim to reduce greenhouse gas emissions by 50% over the next decade and make Europe the world's first climate neutral continent. The EU recently adopted a resolution "Towards a WTO-compatible EU carbon border adjustment mechanism (CBAM)", more commonly referred to a carbon border tax (European Commission, 2021). The tax would reflect the amount of carbon emissions attributed to goods imported into the 27-nation region. This mechanism is related to the Consumption Based Accounting (CBA) approach rather than Production Based Accounting (PBA) scheme (Rocco *et al.*, 2020). In this sense, each country is responsible for the overall emissions caused by the production of goods and services invoked as its own final demand, even if these emissions occur beyond the borders of the country. Although the exact mechanism and timing of a carbon border tax must still be determined and approved, placing a carbon tax on imports could go long way toward meeting this goal. Trade policies may be a good tool in the case of non-economic objectives such as carbon emissions that do not respect national borders. The main purposes of the CBAM would be to discourage EU businesses from moving their production to countries with less ambitious climate change policies (carbon leakage), and to encourage a global move towards net zero carbon emissions by 2050 in line with the Paris Agreement (UNFCCC, 2015). This policy measure is the object of investigation of this work.

In this context, as carbon tariffs have a strong international perspective, the idea is to analyse the effects in a trade model typically used to evaluate these policies. In particular, the aim of this chapter is to investigate the implications of European carbon tariffs on trade and embodied emissions in the UK. The carbon tax is imposed at EU level and only applied to the food sector. This was done in order to evaluate potential consequences of Brexit on the trade market, when all the countries in the EU would potentially impose a tariff on the UK, in this case represented by a carbon tax. In the absence of real-life carbon tariffs, a micro-simulation approach was adopted to estimate the impact of the tax on import flows built upon the estimation of a gravity model on trade (Eaton and Kortum, 2002; Anderson and Van Wincoop, 2003; Head and Mayer, 2014). This (structural) trade model explains trade flows by country size, distances and multilateral resistance terms, the barriers to trade that each country faces with all its trading partners (Adam and Cobham, 2007). Compared to its alternatives, such as Computational General Equilibrium (CGE) models, structural gravity models have stronger micro-foundations, and provide a close link between theory and data by estimating the parameters from the same model and data used for the counterfactual analysis (Copeland and Taylor, 2009; Costinot and Rodríguez-Clare, 2014). In this study, a carbon border tax was adopted in the form of an *ad valorem* tax that sets a rate per unit of CO_2, which increases the price of imported food and drinks proportionally to their carbon emissions. With this governmental intervention, producers and retailers would need to adjust their market strategies by importing different, more sustainable products.

The chapter is organized as follows. Section 4.3 describes the gravity model implementation and estimation and section 4.4 the counterfactual trade policy scenario. Section 4.5 the data. Section 4.6 the gravity model results and 4.7 the simulation findings. Section 4.8 the environmental and nutritional outcomes. Section 4.9 the general discussion and section 4.10 the concluding remarks.

4.3 Methodology

The introduction of a carbon border tax, intended to tackle GHG emissions, may affect UK trade flows by increasing the price of imported food products based on their carbon footprint. To analyse how UK producers would change their imports strategies after the introduction of a climate tax on food and their effects on global emissions, a two-step approach was followed. Firstly, a structural gravity model was estimated to provide a set of estimates of the trade parameters. Secondly, these structural model estimates were used to predict changes in trade flows generated by the tax rates charged on each import price.

4.3.1 Gravity Model on Trade

This section presents the structure of the gravity model, following Anderson and Van Wincoop (2003). First introduced by Tinbergen (1962), the gravity equation has dominated the international trade literature in studying the determinants of trade flows. With its theoretical foundation developed in Anderson (1979), the gravity model relates the trade value between countries to their size and the economic distance between them.

The theory-consistent gravity model of Anderson and Van Wincoop (2003) can be written as:

$$X_{ij} = \frac{Y_i Y_j}{Y} \left(\frac{\tau_{ij}}{\Pi_i P_j}\right)^{1-\sigma} e_{ij} \tag{4.1}$$

where X_{ij} is export from country *i* to country *j*; Y_i and Y_j are the GDPs of the trading countries; Y is world GDP; and σ is intra-sectoral elasticity of substitution (between varieties). The term τ_{ij} are trade costs, which can be specified as a vector of observable variables that are believed to significantly influence bilateral trade. In the gravity model literature they usually represent distance between countries, contiguity and common language (Yotov *et al.*, 2016).

The first notable feature of the Anderson and Van Wincoop (2003) model is its additional inclusion of two variables, the multilateral resistance terms. The term:

$$\Pi_i = \sum_{j=1}^{C} \left\{\frac{\tau_{ij}}{P_j}\right\}^{1-\sigma} \frac{Y_j}{Y} \tag{4.2}$$

is the "*outward multilateral resistance*", which captures the dependence of exports from country *i* to country *j* on trade costs across all possible export markets.

The term:

$$P_j = \sum_{i=1}^{C} \left\{\frac{\tau_{ij}}{\Pi_i}\right\}^{1-\sigma} \frac{Y_i}{Y} \tag{4.3}$$

is the "*inward multilateral resistance*", representing importer *j*'s ease of market access, which captures the dependence of imports into country *j* from country *i* on trade costs across all possible suppliers. Together, these terms are crucial to the model to avoid the omitted variable bias in the gravity model (Cheong;Kwak and Tang, 2014). They allow for changes in trade costs on one bilateral route to affect trade flows on all other routes because of relative price effects (Shepherd, 2013; Yotov *et al.*, 2016). For estimation purposes the gravity equation is usually log-linearized. The multilateral resistance terms are unobservable because they do not correspond to any price indices collected by national statistic agencies. A possible estimation approach is the fixed effect estimation by exporter and importer, which can be entered as dummy variables in the model.

4.3.2 Gravity estimation

We can rewrite Equation (4.1) to derive the following estimable log-linearized equation of our OLS estimation model with an appropriate set of importer and exporter fixed effects to account for the multilateral resistance terms:

$$log\, X_{ij,t} = \pi_i + \chi_j + \beta_1 \ln p_{ij,t} + \beta_2 \ln \tau_{ij} + \beta_3 \ln F_{jt} + \beta_4 year + e_{ij,t} \tag{4.4}$$

where $X_{ij,t}$ is import in quantities of a particular food category over countries *i* and *j* at time t. The term π_i denotes the vector of exporter fixed effects, which will account for the outward multilateral resistance. The vector χ_j denotes the set of importer fixed effects to capture the inward multilateral resistance. $p_{ij,t}$ represents import prices from country *i* to *j* at time *t* (calculated as value on volume). τ_{ij} represents a vector of bilateral trade costs variables that includes geographical distance between countries *i* and *j* (the distance from the capital cities); a contiguity dummy variable equal to unit for countries that share a common land border; a common language dummy variable (equal to one if two countries share a common language). The model takes into account a vector of country specific variables F_{jt} that might affect trade flows in the food sector at time *t*. These are the number of farms in the importer country, the utilised agriculture area in the importer country and the livestock units in the importer country. The yearly time trend enters linearly in the model.

It is well known that trade data are plagued by heteroskedasticity (Silva and Tenreyro, 2006). If e_{ij} is heteroskedastic, then the expected value of the error term depends on one or more explanatory variables because it includes the variance term that is a function of the covariates in the model. The problem is important because, as pointed out by variance Silva and Tenreyro (2006), in the presence of heteroscedasticity (and owing to Jensen's inequality) (Mnasri and Nechi, 2021), the estimates of the effects of trade costs and trade policy are not only biased but also inconsistent when the gravity model is estimated in log-linear form with the OLS estimator.

Silva and Tenreyro (2006) show that under a mild assumption –that the gravity model contains the correct set of explanatory variables – the Poisson pseudo-maximum likelihood estimator provides consistent estimates of the original model. In essence, this is equivalent to running a non-linear least squares of the original equation. Since it is a pseudo-maximum likelihood estimator, it is not necessary that the data be in fact distributed as Poisson. So, although Poisson is more commonly used as an estimator for count data model, it is appropriate to apply it far more generally to non-linear models such as gravity models. The Poisson estimator is consistent in the presence of fixed effects, which can be entered as dummy variables as in simple OLS. Moreover, the Poisson estimator naturally includes observations for which the observed trade value is zero, which is a relatively common value in the trade matrix, since not all countries trade all products with all partners. Dropping zero observations in the way that OLS does potentially leads to sample selection bias, which has become an empirical issue. Interpretation of the coefficients from the Poisson model is straightforward, and follows exactly the same pattern as under OLS.

The gravity specification, which accounts for the full set of exporter time and importer time fixed effect, is then reformulated in multiplicative form and re-estimated by applying the Poisson PML estimator instead of the OLS estimator:

$$X_{ij,t} = exp\left[\pi_i + \chi_j + \beta_1 \, ln \, p_{ij,t} + \beta_2 \, ln \, \tau_{ij} + \beta_3 \, ln \, F_{jt} + \beta_4 year\right] \times \, e_{ij,t} \tag{4.5}$$

Endogeneity issues can arise when there are some unobservable variables influencing trade flows that are correlated with import price formation (Dhar;Chavas and Gould, 2003). For this reason, supply was modelled as a price function (the first stage) and the control function approach was implemented. The control function approach is a two-step approach in which the endogenous variable is regressed on the exogeneous product attributes and instrumental variables in the first stage. The estimated error term from the first stage is then included in the second stage. The estimated error term includes some omitted variables that are correlated with the endogenous variable and not captured by the other exogeneous variables of the demand equation or by the instrumental variables.

In the 1st stage:

$$ln\, p_{ij,t} = \pi_i + \chi_j + \beta_1\, ln\, Z_{ij,t} + \beta_2\, ln\, \tau_{ij} + \beta_3\, ln\, F_{jt} + \beta_4 year + \xi_{ij,t} \quad (4.6)$$

Where $p_{ij,t}$ represent the endogenous import price, $Z_{ij,t}$ represents the vector of instrumental variables. $\tau_{ij}, F_{jt}, year$ are the same set of exogeneous variable explained before. The predicted values of the residuals in the first stage are then estimated $\widehat{\varepsilon_{ijt}}$ and used as instruments in the second stage. For the OLS specification :

$$log\, X_{ij,t} = \pi_i + \chi_j + \beta_1\, ln\, p_{ij,t} + \beta_2\, ln\, \tau_{ij} + \beta_3\, ln\, F_{jt} + \beta_4 year + \beta_5 \widehat{\varepsilon_{ijt}} + e_{ij,t} \quad (4.7)$$

And Poisson:

$$X_{ij,t} = exp\left[\pi_i + \chi_j + \beta_1\, ln\, p_{ij,t} + \beta_2\, ln\, \tau_{ij} + \beta_3\, ln\, F_{jt} + \beta_4 year + \beta_5 \widehat{\varepsilon_{ijt}}\right] \times e_{ij,t} \quad (4.8)$$

The model is estimated on the whole sample by means of the IVREG and IVPOISSON control function approach with Stata.

4.4 Counterfactual trade policy scenario

The empirical model from the previous section is used to illustrate responses of UK producers to changes of food import prices due to carbon taxation. The gravity parameters estimate import price elasticities; these parameters are used to simulate changes in trade flows after the introduction of a carbon border tax.

4.4.1 Policy Reforms

The following scenario is chosen to illustrate the effect of a tax on GHG emissions with the price for the social cost of CO_2 emissions, €70/tonne CO_2 from Pearce (2003). This reform is based on the idea that the climate-related costs of food consumption for society should be internalised and hence the price of specific food products should be increased based on their climate impact. The carbon border tax is imposed on all imported food products, based on their emission content, which is equivalent to the climate impact of the food. New trade flows are then estimated, with the respective nutritional and environmental characteristics.

The objective of these simulations is to study the effects of carbon taxation on UK trade flows within European countries with the objective to reduce their environmental impact and to evaluate the efficiency of the policy reform.

4.4.2 Simulation model

The simulation method can be described as follows: the carbon tax rate, t_i for each item is defined as:

$$t_i = E_i \times p_e \tag{4.9}$$

where E_i is the level of emissions of the i-category and p_e is the carbon price (€/Kg of CO_2). As a result, t_i is a cost of carbon emissions charged on each foodstuff or product. These values are based on the life cycle analysis estimates, i.e. emissions from farming, food processing, packaging, transportation and distribution to the point of final consumption are accounted for.

The price level on good *i* after the tax scenario is calculated according to the following formula:

$$p_{ij,t}^{1} = p_{ij,t}^{0} + (\, t_i + \tau_i \times \, t_i) \tag{4.10}$$

Where the superscript denotes tax regime (0 is baseline tax), t_i is the carbon tax based on the carbon footprint, τ_i is the VAT rate (20%) for t_i. Note that p_{hi}^{0} already includes VAT. It should be noted that taxes are shifted completely on prices.

The new OLS import vector is given by:

$$log\, X_{ij,t}^{1} = \widehat{\pi_i} + \widehat{\chi_j} + \widehat{\beta_1}\, ln\, p_{ij,t}^{1} + \widehat{\beta_2}\, ln\, \tau_{ij} + \widehat{\beta_3}\, ln\, F_{jt} + \widehat{\beta_4} year + \widehat{\beta_5} \widehat{\varepsilon_{ijt}} \tag{4.11}$$

Where a ^ denotes the estimates obtained from the gravity model. The same was done for the Poisson specification. In Appendix B, the simulation codes are presented.

New import flows were predicted after the introduction of carbon tariffs on trade.

4.5 Data

The analysis covers a cross section of EU-28 countries from 2009 to 2019. Bilateral food trade data were downloaded from Eurostat (Eurostat, 2019b). This research considers only the import stream. The imported food products were aggregated in the main categories: meat, fish, dairy & eggs, fruit, vegetables. In this study we focus only on dairy and meat food groups because of the higher environmental impact compared to the other food categories. Data on real GDP per capita and population come from World's Bank's *World Development Indicators* (The World Bank, 2020). All common distance measures across virtually all country pairs in the world are available online (Mayer and Zignago, 2011). Data on location and dummies indicating continuity, common language are constructed from the CIA's World Factbook (CIA, 2020).The remaining explanatory variables came from Eurostat (Eurostat, 2019a). The carbon footprint of all the products was obtained from data published in the literature (Flysjö;Thrane and

Hermansen, 2014; Scarborough *et al.*, 2014; Drewnowski *et al.*, 2015; Clune;Crossin and Verghese, 2017). The data also include the average nutritional information (e.g. energy, sugar, fats, sodium) of each imported food category. These data were constructed from the Living Cost and Food Survey dataset (Office for National Statistics, 2017b), used in the previous chapter.

Missing data of utilised agricultural areas, number of farms, livestock units and instruments were replaced by linear interpolation in Stata. Import prices (€/kg) were calculated within the model, as value on volume of trade flows. Missing import prices due to lack of trade flows were replaced by European regional prices. Table 4.1 provides summary import statistics for the UK importer country; in particular, bilateral and country specific variables.

Variable	**Obs.**	**Mean**	**St. Dev.**	**Min**	**Max**
Bilateral Variables					
Import dairy products, tonne	297	53335	102013	0	525512
Import meat products, tonne	297	64267	118796	0	460454
Distance	297	1388	665	323	3223
Contiguity	297	.037	.18	0	1
Common Language	297	.074	.26	0	1
Country Specific variables					
Emission dairy products, kt of CO_2	297	206	394	0	2031
Emission meat products, kt of CO_2	297	896	1657	0	6423
Utilised Agriculture Area, thousand hectare	297	16776	387	16019.55	17326
Livestock, thousand units	297	13316	136.35	13106.29	13574
Farm number, thousand	297	185	1.18	183.04	187

Table 4.1: Summary statistics for the UK importer country

Note: The table shows summary statistics of bilateral and country-specific gravity variables.

There are 297 country pairs between UK and the 27 European partners in an 11-year time window, from 2009 to 2019. Average bilateral imported products amount to 53,335 tonnes for dairy products and 64,267 tonnes for meat products. The distance between the UK and the major European economic centres of country pairs averaged about 1388 km. Average UK embodied carbon emissions in imports amount to 200 $ktCO_2$-eq for dairy products and 900 $ktCO_2$-eq for meat foods. The average utilised area for agriculture in the UK is 16,776,000 hectares. The number of farms is 185,000 and the livestock units are 13,316,000.

4.6 Results

Prices before and after taxation are reported with the respective variation for the two categories presented in the analysis (Table 4.2).

Food Group	**Price before tax (€/kg)**	**Price after tax (€/kg)**	**Δ Price variation**
Dairy	2.9	3.2	14%
Meat	3.2	4.1	38%

Table 4.2: Price variation after taxation

4.6.1 Structural gravity parameters estimates

Tables 4.3 and 4.4 provide the estimates of the gravity equation for dairy and meat products respectively, using different approaches as in Silva and Tenreyro (2006). This was done in order to evaluate the efficiency of the different estimators. All regressions control for multilateral resistance by introducing exporter and importer fixed effects. The first column reports OLS estimates using the logarithm of imported products as a dependent variable; this regression omits pairs of countries with zero bilateral trade flows. The second column reports the OLS estimates where one is added to zero prior to taking the logarithm zeros, so that $y=\ln(1+T_{ij})$. The third column presents Tobit estimates based on Eaton and Tamura (1994). The fourth column shows Poisson PML estimator (PPML) results for the whole sample (including zero pairs) and the fifth using only the subsample of positive trade pairs.

The first thing to notice is that PPML coefficients are remarkably similar using the whole sample and using the positive-trade subsample. However, these results differ substantially from OLS estimates. This suggest that heteroskedasticity is relevant in this dataset. The same issues was highlighted in Silva and Tenreyro (2006). Import prices and distance negatively affect the import of dairy and meat products. Both variables are substantially larger under OLS. Sharing a border and common language have positive significant effects on trade with all the estimation techniques adopted. Livestock units' importer are negative correlated with trade flows under OLS estimated using $\ln(1+T_{ij})$ as dependent variable. Under PPML, import of dairy products decreases with a high number of farms in the importer country (Table 4.3). Under OLS, import of meat products decreases with a high number of farms in the importer country (Table 4.4).

Estimator **Dependent Variable:**	**OLS** **ln(T_{ij})**	**OLS** **ln(1+T_{ij})**	**Tobit** **ln(α+ T_{ij})**	**PPML** **T_{ij}**	**PPML** **T_{ij} > 0**
Log import price	-1.47***	-1.80***	-1.47***	-1.09***	-1.08***
	(0.05)	(0.07)	(0.05)	(0.09)	(0.09)
Log distance	-1.37***	-2.31***	-1.37***	-0.93***	-0.92***
	(0.04)	(0.07)	(0.04)	(0.12)	(0.12)
Contiguity dummy	1.19***	0.62***	1.19***	0.81***	0.82***
	(0.07)	(0.12)	(0.07)	(0.17)	(0.18)
Common-language dummy	0.59***	1.06***	0.59***	0.82***	0.82***
	(0.10)	(0.19)	(0.10)	(0.18)	(0.18)
Log utilised agricultural area's importer	-0.79	0.08	-0.79	0.15	0.16
	(0.68)	(1.30)	(0.68)	(0.62)	(0.62)
Log livestock units' importer	-0.23	-1.42*	-0.23	-0.24	-0.23
	(0.38)	(0.74)	(0.38)	(0.39)	(0.40)
Log farm number's importer	-0.03	0.51	-0.03	-0.42***	-0.41***
	(0.20)	(0.40)	(0.20)	(0.16)	(0.16)
Year	0.08***	0.18***	0.08***	0.03***	0.03***
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)
Constant	-144.06***	-322.59***	-135.05***	-39.97***	-44.83***
	(20.43)	(39.46)	(22.91)	(11.56)	(11.61)
Importer and Exporter Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	7235.00	8263.00	7235.00	8263.00	7235.00
r2	0.78	0.70		0.90	0.89
r2_a	0.77	0.69			
F	438.81	289.52	442.60		
P	0.00	0.00	0.00		
RESET test p-values	0.000	0.000	0.000	0.3651	0.5165

Table 4.3: Dairy results without correcting for endogeneity of prices

Note: *, **, *** denotes statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

Estimator **Dependent Variable:**	**OLS** **ln(T_{ij})**	**OLS** **ln(1+T_{ij})**	**Tobit** **ln(α+ T_{ij})**	**PPML** **T_{ij}**	**PPML** **T_{ij} > 0**
Log import price	-0.81***	-0.98***	-0.81***	-0.59***	-0.58***
	(0.05)	(0.07)	(0.05)	(0.13)	(0.13)
Log distance	-1.74***	-2.71***	-1.74***	-0.69***	-0.69***
	(0.04)	(0.07)	(0.04)	(0.10)	(0.10)
Contiguity dummy	1.14***	0.82***	1.14***	0.87***	0.88***
	(0.07)	(0.12)	(0.07)	(0.12)	(0.12)
Common-language dummy	0.46***	0.89***	0.46***	0.56***	0.56***
	(0.11)	(0.20)	(0.11)	(0.18)	(0.18)
Log utilised agricultural area's importer	0.25	4.60***	0.25	0.32	0.27
	(0.71)	(1.37)	(0.71)	(0.46)	(0.46)
Log livestock units' importer	-0.49	-1.33*	-0.49	-0.30	-0.28
	(0.38)	(0.75)	(0.38)	(0.24)	(0.24)
Log farm number's importer	-0.51**	-0.95**	-0.51**	-0.15	-0.14
	(0.20)	(0.40)	(0.20)	(0.11)	(0.11)
Year	0.05***	0.10***	0.05***	0.03***	0.03***
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)
Constant	-66.11***	-193.07***	-62.68***	-34.22***	-36.81***
	(20.49)	(40.09)	(22.94)	(11.12)	(11.07)
Importer and Exporter Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	7160.00	8263.00	7160.00	8263.00	7160.00
r2	0.77	0.70		0.88	0.88
r2_a	0.77	0.70			
F	384.03	285.52	387.39		
P	0.00	0.00	0.00		
RESET test p-values	0.000	0.000	0.000	0.0231	0.0228

Table 4.4: Meat results without correcting for endogeneity of prices

Note: *, **, *** denotes statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

Table 4.7 and Table 4.8 report estimates controlling for endogeneity of import prices with a control function approach. Import dairy prices were instrumented with price of raw milk and prices of eggs; import meat prices were instrumented with deadweight prices of pig. Parameter estimates of the 1st stage for dairy and meat prices are respectively shown in Table 4.5 and Table 4.6. Sharing a border and common language have positive significant effects on trade with all the estimation techniques adopted while imports decrease with higher distance between economic centres both for meat and dairy products. Import dairy prices are negative and significant only when the zeros are dealt with using log(1+T_{ij}) under OLS regression analysis. In the other estimation techniques, dairy prices are negatively correlated with trade flows, but are not significantly different. Higher livestock units of importer countries are negatively related with the import of dairy products under PPML and under OLS with log(1+T_{ij}) correction. Import meat prices are negative and significantly correlated with the import of meat products under all the estimation techniques. A higher number of farms in the importer countries is negatively correlated with the import of meat products under OLS and Tobit models.

Estimator **Dependent Variable:**	**OLS** **ln($p_{ij,t}$)**	**OLS T_{ij} > 0** **ln($p_{ij,t}$)**
Log row milk price	0.43***	0.49***
	(0.05)	(0.06)
Log egg prices	0.05*	0.05
	(0.03)	(0.03)
Log distance	0.30***	0.30***
	(0.01)	(0.01)
Contiguity dummy	-0.28***	-0.24***
	(0.02)	(0.02)
Common-language dummy	-0.05*	-0.11***
	(0.03)	(0.03)
Log utilised agricultural area's importer	-0.04	-0.06
	(0.21)	(0.23)
Log livestock unit's importer	0.47***	0.52***
	(0.12)	(0.14)
Log farm number's importer	-0.03	0.00
	(0.07)	(0.08)
Year	0.00	0.01***
	(0.00)	(0.00)
Constant	-14.27*	-22.88***
	(7.40)	(8.26)
Importer and Exporter Fixed Effects	Yes	Yes
N	8263	7235
R^2	0.38	0.40
R^2 Adj.	0.38	0.40
F	100.63	104.87
P	0.00	0.00
F-statistic (Instrument Strength)	31.85 Prob > F = 0.0000	
Hausman Test	F(1, 7171) = 7.95 Prob > F = 0.0048	

Table 4.5: Parameters estimates 1st stage - dairy

Note: *, **, *** denote statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis

Estimator **Dependent Variable:**	**OLS** **($\ln(p_{ij,t})$)**	**OLS $T_{ij} > 0$** **$\ln(p_{ij,t})$**
Log price dead pig	0.22***	0.24***
	(0.05)	(0.06)
Log distance	0.07***	0.07***
	(0.01)	(0.01)
Contiguity dummy	-0.05***	-0.05***
	(0.02)	(0.02)
Common-language dummy	0.13***	0.11***
	(0.03)	(0.03)
Log utilised agricultural area's importer	0.00	0.04
	(0.18)	(0.21)
Log livestock unit's importer	0.10	0.13
	(0.09)	(0.11)
Log farm number's importer	-0.01	-0.03
	(0.06)	(0.06)
Year	0.01***	0.01***
	(0.00)	(0.00)
Constant	-23.77***	-27.89***
	(6.09)	(6.90)
Importer and Exporter Fixed Effects	Yes	Yes
N	8263.00	7160.00
R^2	0.36	0.37
R^2 Adj.	0.35	0.36
F	98.52	93.79
P	0.00	0.00
F-statistic	19.81 Prob > F = 0.0000	
Hausman Test	F(1, 7096) = 6.43 Prob > F = 0.0112	

Table 4.6: Parameters estimates 1st stage - meat

Note: *, **, *** denote statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

Estimator **Dependent Variable:**	**IVREG** **ln(T_{ij})**	**IVREG** **ln(T_{ij} + 1)**	**IVTOBIT** **ln(α+ T_{ij})**	**IVPOISSON** **T_{ij}**	**IVPOISSON** **T_{ij} >0**
Log Import Price	-0.48	-1.76**	-0.49	-0.09	-0.24
	(0.36)	(0.73)	(0.37)	(0.44)	(0.34)
Log distance	-1.67***	-2.32***	-1.68***	-1.98***	-1.72***
	(0.12)	(0.23)	(0.12)	(0.14)	(0.11)
Contiguity dummy	1.43***	0.63**	1.43***	1.59***	1.55***
	(0.12)	(0.25)	(0.11)	(0.15)	(0.11)
Common-language dummy	0.69***	1.07***	0.70***	0.71***	0.47***
	(0.12)	(0.21)	(0.11)	(0.13)	(0.10)
Log utilised agricultural area's importer	-0.70	0.08	-0.70	-0.55	-0.11
	(0.72)	(1.29)	(0.73)	(0.68)	(0.60)
Log livestock unit's importer	-0.59	-1.44*	-0.58	-0.97**	-0.50
	(0.42)	(0.74)	(0.43)	(0.41)	(0.35)
Log farm number's importer	-0.01	0.51	-0.01	0.10	-0.09
	(0.23)	(0.42)	(0.21)	(0.21)	(0.18)
Year	0.07***	0.18***	0.07***	0.07***	0.05***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Constant	-106.83***	-320.26***	-107.15***	-104.74***	-74.03***
	(26.54)	(45.71)	(26.89)	(26.57)	(23.17)
Importer and Exporter Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	7235.00	8263.00	7235.00	8263.00	7235.00
R^2	0.75	0.70			
R^2 Adj.	0.75	0.69			
F	327.57	289.57			
Underidentification test	LM statistic): 68.146	Chi-sq(1) P-val = 0.0000			
Weak identification test (Cragg-Donald Wald F statistic):	34.093				
Sargan statistic (overidentification test of all instruments):	0.009 Chi-sq(1) P-val = 0.9245				
Endogeneity test of endogenous regressors:	8.539 Chi-sq(1) P-val = 0.0035				
RESET test p-values	0.4506	0.0101	0.1678	0.8362	0.0072

Table 4.7: Dairy results correcting for endogeneity of prices

Note: *, **, *** denote statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

Estimator **Dependent Variable:**	**IVREG** $\ln(T_{ij})$	**IVREG** $\ln(T_{ij}+1)$	**IVTOBIT** $\ln(\alpha + T_{ij})$	**IVPOISSON** T_{ij}	**IVPOISSON** $T_{ij} > 0$
Log Import Price	-2.64***	-3.98**	-2.66***	-1.99**	-1.73**
	(0.85)	(1.66)	(0.85)	(0.90)	(0.72)
Log distance	-1.61***	-2.51***	-1.61***	-1.86***	-1.59***
	(0.08)	(0.14)	(0.08)	(0.08)	(0.07)
Contiguity dummy	1.05***	0.67***	1.04***	0.98***	1.04***
	(0.10)	(0.19)	(0.09)	(0.09)	(0.08)
Common-language dummy	0.66***	1.29***	0.67***	0.58***	0.40***
	(0.15)	(0.31)	(0.15)	(0.16)	(0.12)
Log utilised agricultural area's importer	0.29	4.55***	0.29	-0.78	-0.48
	(0.79)	(1.39)	(0.80)	(0.88)	(0.73)
Log livestock unit's importer	-0.39	-1.23	-0.40	-0.26	-0.12
	(0.44)	(0.76)	(0.42)	(0.47)	(0.38)
Log farm number's importer	-0.59**	-1.01**	-0.59**	-0.05	0.05
	(0.25)	(0.45)	(0.24)	(0.27)	(0.22)
Year	0.07***	0.13***	0.07***	0.06***	0.06***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Constant	-106.83***	-270.85***	-106.93***	-77.30**	-78.79***
	(33.44)	(58.04)	(34.47)	(34.07)	(29.32)
Importer and Exporter Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	7160.00	8263.00	7160.00	8263.00	7160.00
R^2	0.70	0.65			
R^2 Adj.	0.69	0.65			
F	283.49	264.35			
Underidentification test	LM statistic): 19.520	Chi-sq(1) P-val = 0.0000			
Weak identification test (Cragg-Donald Wald F statistic):	19.401				
Sargan statistic (overidentification test of all instruments): (equation exactly identified)	0.000				
Endogeneity test of endogenous regressors:	6.126 Chi-sq(1) P-val = 0.0133				
RESET test p-values	0.3309	0.0429	0.0000	0.0231	0.0228

Table 4.8: Meat results correcting for endogeneity of prices

Note: *, **, *** denote statistical significance at the 10, 5 and 1% level, respectively. Robust Standard Errors are shown in parenthesis.

To check the adequacy of the estimated models, a heteroskedasticity- robust RESET test was performed (Ramsey, 1969). This is essentially a test for the correct specification of the conditional expectation, which is performed by checking the significance of the additional regressor constructed as $(x'b)^2$, where b denotes the vector of estimated parameters. The corresponding p-values are reported at the bottom of each table. Considering the results from Tables 4.3 and 4.4, in the OLS regressions, the test rejects the null hypothesis that the model has no omitted variables. This means that the model estimated using the log specification is inappropriate. A similar result is found for the OLS estimated using ln $(1+T_{ij})$ and Tobit. In contrast, the models estimated using the Poisson regression pass the RESET test, showing that the test provides no evidence of misspecification of the gravity equation estimated using the PPML.

The heteroskedasticity robust RESET after the control function instrumental variable approach (tables 4.7 and 4.8) revealed that controlling for endogeneity improves the specification of the OLS estimations. This test also confirms that the Poisson model is correctly specified.

The strength of the instruments was checked, with a test statistic of $F(1, 8197) = 31.85$ for dairy and $F(1, 8197) = 19.81$ for meat. The Hausman Test was performed to check the endogeneity of import prices. The small p-value found under OLS and PPML techniques indicates that import prices are endogenous (at the bottom of Table 4.5 and 4.6). Ivreg2 (in STATA) automatically reports tests of both under identifications and weak identification tests. The Sargan Test accepts the null hypothesis that the instruments as a group are exogeneous for the dairy products (P-val =0.9245). For the meat category, the equation result perfectly identified[2].

The F version of the Cragg-Donald Wald statistic is higher than the critical values meaning that the equation is not weakly identified for both categories (Andrews, 2005). The endogenous options reveals that import price for meat and dairy is endogenous under OLS setting with a p-value < 0.05.

4.7 Counterfactual trade policy analysis

Table 4.9 shows some preliminary results of the simulation analysis. It is important to remember that carbon taxation was applied at the European level, without considering the UK, exempt of taxation. It is estimated that a single European country would decrease the import of dairy products from a respective European partner at a high rate due to carbon taxation under OLS and PPML estimation, when not controlling for endogeneity of prices. On the other hand, when

[2] In order for the model to be exactly identified, the number of excluded instruments for meat (deadweight prices of pig) is equal to the number of endogenous explanatory variables (import meat prices).

taking into account the price endogeneity, under Poisson and OLS, the average reduction is much smaller. This is easily explained by the non-significant price effect that import dairy prices have on trade flows when good instruments to correct for endogeneity were found. Conversely, in the meat category, larger effects were found when correcting for the price endogeneity under OLS and Poisson estimates. This is explained by the fact that import prices resulted a statistical significant variables of trade flows when correcting for price endogeneity.

	OLS **ln(T_{ij})**	**PPML** T_{ij}	**IVREG** **ln(T_{ij})**	**IVPOISSON** T_{ij}
Δ ***Import Dairy***	-14.8%	-11.4%	-5.3%	-1.03%
Δ ***Import Meat***	-18.9%	-14.4%	-45.6%	-38.1%

Table 4.9: Trade effects - dairy and meat

There is strong evidence that the estimation methods based on the log-linearization of the gravity equation suffer from severe misspecification, which hinders the interpretation of the results, whether or not fixed effects are used. As explained before, the basic problem is that log-linearization of the empirical model in the presence of heteroskedasticity leads to inconsistent results. An additional problem of OLS log-linearization is that it is incompatible with the existence of zeros in trade data. Poisson estimates are robust to different patterns of heteroskedasticity and provide a natural way to deal with zeros (Silva and Tenreyro, 2006). Dealing with these issues, this analysis considers the results obtained with the Poisson PML findings to estimate the environmental and nutritional consequences, controlling for fixed effects and endogeneity of import prices for both categories.

4.7.1 Trade flows changes

Figures, 4.1 to 4.4 show the most important results of the counterfactual introduction of carbon tariffs. As a carbon tariff is a climate policy related trade policy instrument, a plausible starting point for the evaluation of its effects is to look at the changes in dairy and meat trade flows. The changes in the amount of imported products are shown for dairy (Figure 4.1) and for meat (Figure 4.3). It is evident that trade flows decrease in all countries, but there are considerable differences among them.

On average, each reporter country would reduce the amount of imported dairy products from a single European country by about -1% (Figure 4.1). Germany and Italy report the greatest reductions (> -1.3%) while Ireland, Finland, Estonia and Latvia only slight changes (< - 0.8%). Particular attention is given to the effects reported in the UK, the country object of the analysis and exempt of taxation (Figure 4.2). Interestingly, the UK reports a major reduction in imported dairy products from Germany, Spain, Romania, Latvia and Slovenia (-1.1% or more), while the trade collaboration does not change particularly with Italy, Croatia and Slovakia (<-0.04%).

On the other hand, countries that decide to reduce the highest amount of imported meat products due to carbon taxation are in East-Europe (-45% or more), including Poland, Hungary, Romania, Bulgaria, and the Netherlands. On the other hand, countries that reduce imports by less than 23% are Finland and Luxemburg (Figure 4.3). The UK reduced by more than half the meat imported from Finland, Estonia, Czech Republic and Cyprus while by roughly 30% from Italy and Austria (Figure 4.4).

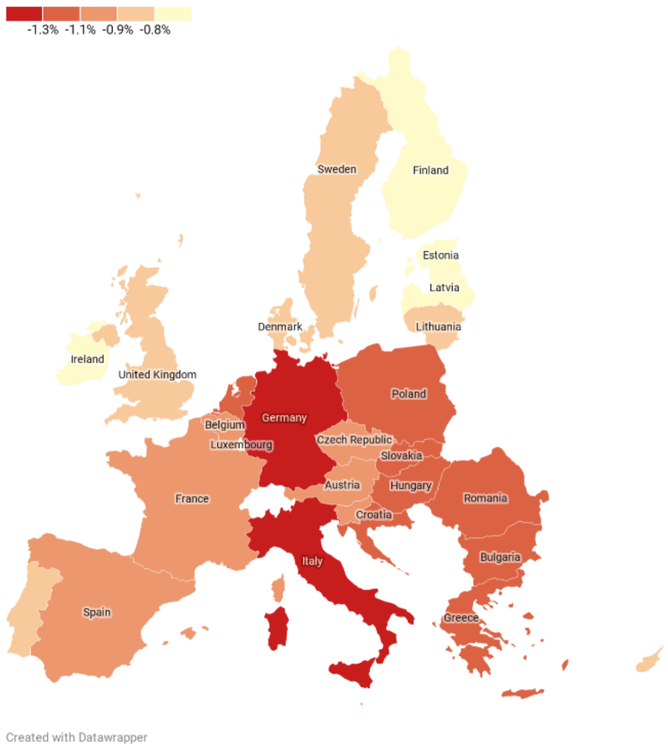

Figure 4.1: Import reduction (%) in each reporter country - dairy

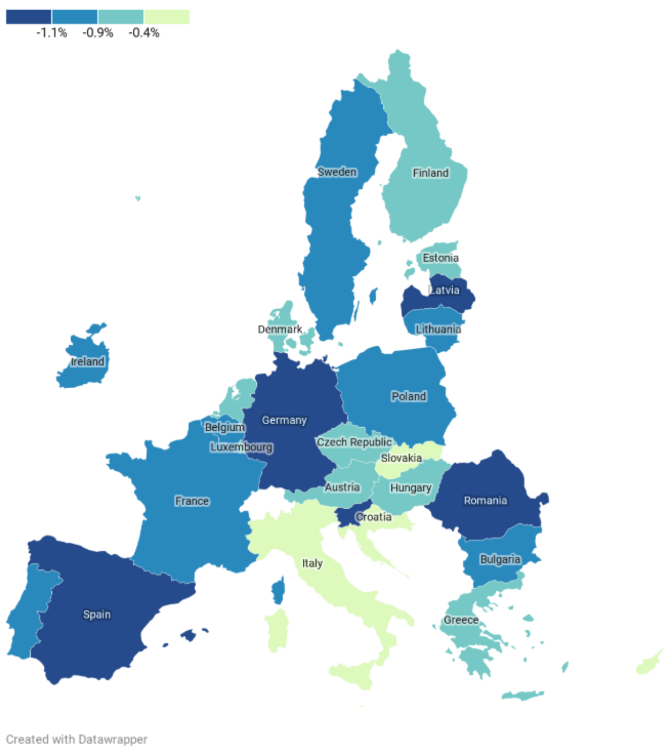

Figure 4.2: Import reduction (%) in UK from European partners - dairy

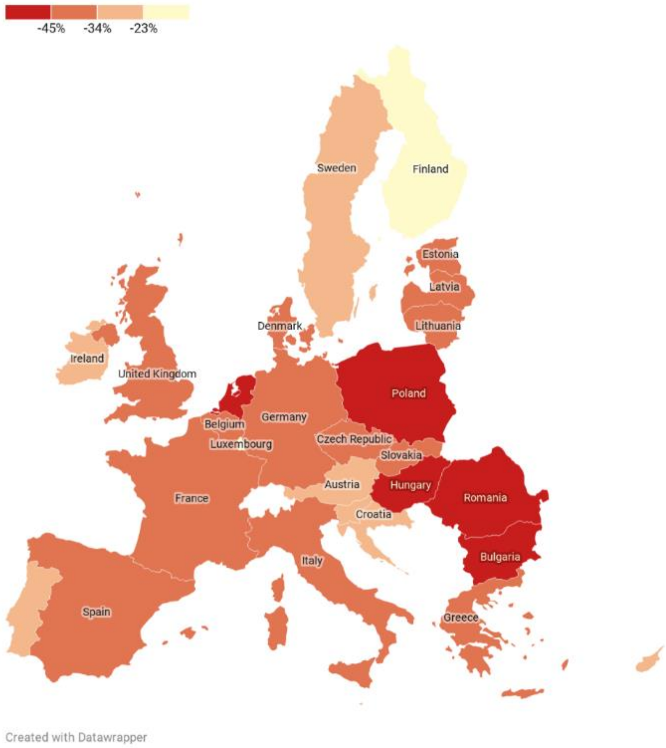

Figure 4.3: Import reduction (%) in each reporter country - meat

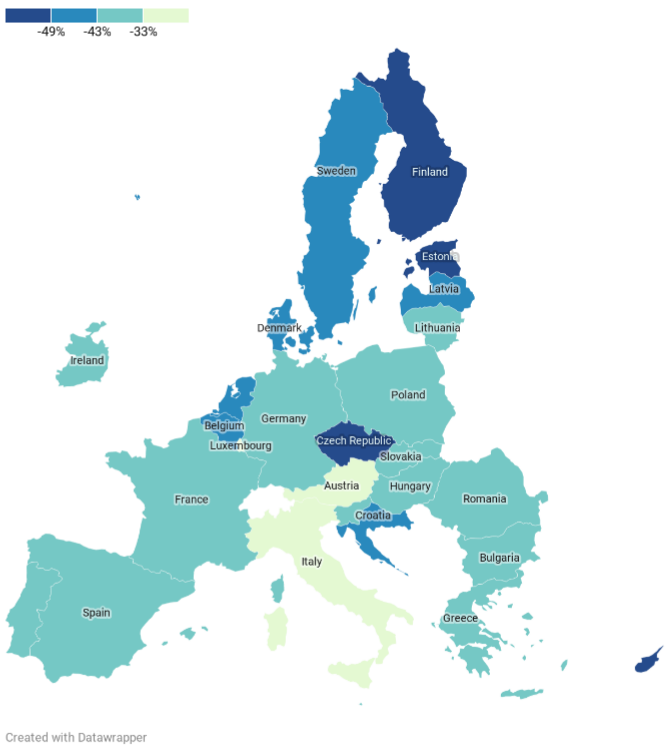

Figure 4.4: Import reduction (%) in UK from European partners - meat

4.8 Emission and nutritional effects

The introduction of carbon tariffs would lead to significant changes in UK national carbon emissions. More than 90 $MtCO_2$-eq in the UK came from imports (goods and services) from the EU (Department for Environment Food and Rural Affairs, 2012). The data estimate an initial carbon footprint deriving from the import of dairy products to the UK from a single European country of 0.77 $MtCO_2$-eq, by considering the initial quantity of dairy products imported in UK estimated within the model and the carbon footprint data. This value would add up to 20.9 $MtCO_2$-eq by considering the total carbon footprint related to the UK import of dairy products from all the EU. For the meat category, the initial carbon footprint of meat imported into the UK from the EU would be about 70 $MtCO_2$-eq, and 2.6 $MtCO_2$-eq from a single European country.

Carbon taxation would improve the sustainability of trade by reducing the emission values embedded in the UK dairy market of 8.14 $ktCO_2$-eq from a single country and of 220 $ktCO_2$-eq from all Europe. The highest reductions of CO_2 are estimated to be from Ireland, Germany and Belgium, while the lowest from Malta, Croatia and Slovakia.

In addition, the model predicted a reduction of 30.4 $MtCO_2$-eq deriving from the high decrease of the meat imported to the UK from the EU. The highest reduction in emissions is estimated to be from the Netherlands, Belgium and Ireland.

The reduction of imported dairy and meat products would lead to a different micro-nutrient profile associated with food traded in the UK: high reductions of total and saturated fat, total sugars and sodium, vegetable protein (-42%) and fibre intakes (-37%). In parallel, carbohydrates intakes would be reduced by 22% and energy kcals by 15%.

4.9 Discussion

The results show how carbon taxation could lead to more sustainable trade flows between the UK and EU. Using a structural Gravity Model (Anderson and Van Wincoop, 2003), carbon taxation was introduced counterfactually to investigate the trade and emission effects. Price elasticity of dairy products does not operate as a high determinant of import streams. This finding is consistent with another study, where the demand for processed food imports from both developed and developing countries was price inelastic (Suanin, 2020). On the other hand, import prices of meat have a significant influence on the UK trade market. This means that higher prices due to carbon taxation would reduce the amount of imported meat products at a high rate. In this study, it is predicted that EU carbon tariffs would lead to a high reduction of meat imported in UK from Europe, by more than a half from Finland, Estonia, Czech Republic and Cyprus. These changes in trade flows would have some desirable environmental effects: a decrease in UK embodied carbon emissions of 30.6 $MtCO_2$-eq. In addition, the model predicted some positive nutritional effects due to the changes in foods traded.

These environmental outcomes have to be integrated with further analyses to see if a decrease in trade flows would be compensated by an increase in local production of meat and dairy products, or, if this might lead to a rise in other foods imported from abroad. This could be seen as a consequence of pollution haven effects, where the UK, without the imposition of carbon regulations towards the EU, would increase its ability to produce and export more intensive carbon products. The analysis would then explore the carbon leakage effect with particular attentions to the emissions shifted via international trade (Monjon and Quirion, 2010; Atkinson *et al.*, 2011; Antimiani *et al.*, 2013).

There are some issues in this framework which require particular attention. Firstly, the estimates of GHG embodied emissions of meat and dairy are expressed as averages of those categories. It was not possible to distinguish among diverse types of meat and dairy products imported from each country; for this reason, the associated carbon footprint reflected the average of different foods within the same group. Moreover, the values derived from different sources and this may result in a non-consistent analysis with non-UK data used sometimes. Other limitations are that only two food categories were considered. The aim is to expand the present research to investigate the total environmental revenues deriving from a reduction of the emissions within the entire food sector, even fruit and vegetables. This may also lead to an increase in the consumption of selected micro nutrients that improve the nutritional quality of imported foods in the UK. In addition, prices of agriculture and food products should increase with a carbon tax that considers not only the embodied emissions but also international freight transport, even if data availability could be an issue (López *et al.*, 2015). Finally, lower trade flows benefits the environment, but this might reduce welfare across countries, the impact of which requires attention in future studies (Larch and Wanner, 2017). Despite this research has mainly focused on the implications that carbon border taxes would have on trade flows at producer level, other investigations should explore the evaluation of consumer perceptions around the food miles concept (López *et al.*, 2015). In other words, to understand if consumers would be concerned about where their food has come from and if this might be reflected in their actual purchasing behaviour.

Policy efforts should be directed through a global climate deal. Climate policy should target all the embodied emissions in consumption, even if considerable information is required about a good's emission intensity and production chain. Equivalently, a domestic CO_2 tax could be integrated with carbon related border tax adjustments for import and export streams (Bhagwati and Mavroidis, 2007; Ismer and Neuhoff, 2007). In addition, environmental regulations and standards should consider options not only to eliminate incentives for firms to relocate their plans abroad, but to create parallel incentives to deliver a win -win solution by investing in replacement technologies leading to greener production, in accordance with the Porther Hypothesis (Ranocchia and Lambertini, 2021). Promoting the use of environmental technologies is expected to bring economic and environmental benefits worldwide. The acceleration of trade in environmental goods (EGs) is at the heart of the sustainable development strategy of the EU. Higher emission taxes could make the use of EGs or clean technologies more attractive to polluting firms (Gaigné and Tamini, 2021).

4.10 Conclusion

This chapter investigates the effectiveness of EU climate policies as a way to support sustainable trade flows with a structural gravity model. This approach enables the estimation of import streams in the UK food market and the consequent quantification of the amount of embodied emissions associated, before and after the implementation of carbon tariffs. The findings show that, in the context of climate change, the imposition of EU carbon tariffs would reduce the level of embodied emissions imported into the UK, though this is associated with lower rates of trade flows of meat and dairy products. The evaluation of the remaining food categories is necessary to investigate the dynamics within the entire food sector and to assess welfare, nutritional and pollution haven effects. This study contributes to the literature by providing a framework in which counterfactual analysis with carbon tariffs can be conducted for policy interventions and constitutes a starting point for future research.

4.11 Post-Note Chapter 4

4.11.1 Additional reflection on the methodology trade-offs

This chapter showed how the implementation of carbon border tariffs could improve the sustainability of trade flows between the UK and the EU. In particular, the gravity model estimated a reduction in the quantity of meat and dairy imported in the UK. High reductions of meat imported from Finland, Estonia, Czech Republic and Cyprus. These translate in good environmental outcomes - a decrease in UK embodied emissions of 30.6 $MtCO_2$-eq. However, this methodology has some limitations in the sense that the model doesn't consider the wider system effects consequent to the application of carbon regulations. Firstly, it is not clear what happens within the UK local economy, or in a more specific way, what happens in the UK local production of meat and dairy products. This could bring some negative consequences in the environmental impact of the food sector if the UK local production of meat would increase, for example. From another perspective, this could be seen as a potential consequence of the pollution haven effect in which the UK, without the imposition of the carbon tax, would become a pollution heaven and increase its ability to produce and export more intensive carbon products. The model should consider also what happens with the other food categories – fruit and vegetables for example. These substitution effects are not observed with the current model, and it is something that should be included in the overall system evaluation. The welfare effects of lowering trade flows between the UK and the different European countries should also been included in the model specification, to get an idea of the general equilibrium effects surrounded the implementation of these types of policies.

More reflection should be directed on the consumer side. What is the current view of UK consumers about where their food comes from? How do they value the local production of the food they purchase? Consumer perceptions about this issue should be included in the model to get a general understanding of the topic from the demand side.

Overall, a global climate deal should be proposed in the UK policy agenda where the implementation of a domestic carbon tax applied to food consumption should be accompanied by carbon border regulations for import and export streams. In addition, the model should also consider what happens with the total revenues that come from taxation. These can be re-included in the model to create incentives for firms by investing in replacement technologies leading to greener productions. These ideas and suggestions could be included in the model specification to get a general understanding of the overall system effects and propose final recommendations.

4.11.2 Current trade flows of meat and dairy products

The tables listed below provide information about the import of meat and dairy products in the UK from 2018 to 2021 in millions pound. They are distinguished among EU and non-EU partners (Office for National Statistics, 2022) .

Meat	2018	2019	2020	2021
Total EU (28)	5512	5488	5246	4764
Extra EU 28 (Rest of World)	1235	1168	1073	1006
Whole world	6747	6656	6319	5770
% EU	81.7	82.5	83.0	82.6
% non-Eu	18.3	17.5	17.0	17.4

Table 4.10 Import of meat products in the UK - EU and non-EU

COUNTRY	2018	2019	2020	2021	% 2018
AT Austria	29.92	21.2	20.43	15	0.54
BE Belgium	183.5	194.21	154.88	250.11	3.33
BG Bulgaria	4.67	4.12	4.2	3.99	0.08
CY Cyprus	0.01	0.1	0	2.28	0.00
CZ Czechia	1.63	2.52	2.48	0.76	0.03
DE Germany	702.91	727.03	740.96	580.74	12.75
DK Denmark	513.47	497.75	504.67	394.85	9.32
EE Estonia	0.03	0.01	0	0.03	0.00
ES Spain	190.69	213.93	223.38	195.45	3.46
FI Finland	0.33	0.15	0.02	0	0.01
FR France	216.64	221.9	200.52	205.54	3.93
GR Greece	1.28	6.49	7.45	5.79	0.02
HR Croatia	5.79	4.2	9.01	3.86	0.11
HU Hungary	33.08	38.56	33.16	49.94	0.60
IE Ireland	1656.2	1562.04	1480.12	1318.18	30.05
IT Italy	189.6	185.28	182.7	182.36	3.44
LT Lithuania	5.31	5.08	5.57	4.57	0.10
LU Luxembourg	0	0	0	0	0.00
LV Latvia	1.78	2.12	3.01	2.92	0.03
MT Malta	0	0.01	0.01	0	0.00
NL Netherlands	1060.65	1052.22	898.53	757.61	19.24
PL Poland	628.45	673.61	711.56	738.01	11.40
PT Portugal	11.28	9.03	14.65	12.56	0.20
RO Romania	52.52	51.75	32.13	28.65	0.95
SE Sweden	15.98	10.26	11.32	6.93	0.29
SI Slovenia	4.64	2.68	3.29	2.64	0.08
SK Slovakia	1.65	1.74	1.94	1.24	0.03
Total EU(28)	5512	5488	5246	4764	100.00

Table 4.11 Import of meat products in the UK from different European partners

Dairy	2018	2019	2020	2021
Total EU (28)	3343	3276	3198	2854
Extra EU 28 (Rest of World)	44	44	48	57
Whole world	3387	3320	3246	2911
% EU	98.7	98.7	98.5	98.0
% non-EU	1.3	1.3	1.5	2.0

Table 4.12 Import of dairy products in the UK - EU and non-EU

COUNTRY	2018	2019	2020	2021	% 2018
AT Austria	11.6	13.02	13.49	10.91	0.35
BE Belgium	225.19	203.49	195.14	268.3	6.74
BG Bulgaria	3.71	7.25	9.33	5.39	0.11
CY Cyprus	79.59	95.77	111.44	91.99	2.38
CZ Czechia	5.16	4.49	5.18	4.2	0.15
DE Germany	414.11	417.08	374.94	236.59	12.39
DK Denmark	208.9	174.34	161.88	161.09	6.25
EE Estonia	0.04	0.09	0.11	0.05	0.00
ES Spain	71.24	76.25	67.36	69.65	2.13
FI Finland	2.67	4.65	0.84	0.19	0.08
FR France	562.14	546.64	503.16	463.06	16.82
GR Greece	102.88	118.72	122.43	109.39	3.08
HR Croatia	0.21	0	0	0	0.01
HU Hungary	7.73	8.68	13.48	18.31	0.23
IE Ireland	835.86	821.5	780.5	689.22	25.00
IT Italy	255.44	253.43	277.21	254.22	7.64
LT Lithuania	8.71	9.58	11.18	10	0.26
LULuxembourg	0.07	0.08	0.05	0.03	0.00
LV Latvia	0.6	1.06	1.68	1.21	0.02
MT Malta	0.46	0.17	0	0	0.01
NL Netherlands	417.82	374.43	377.44	262.09	12.50
PL Poland	80.12	87.3	100.81	130.92	2.40
PT Portugal	7.13	6.34	5.73	6.87	0.21
RO Romania	6.3	11.16	8.94	7.69	0.19
SE Sweden	8.3	10.23	15.28	15.24	0.25
SI Slovenia	11.6	12.83	14.03	20.48	0.35
SK Slovakia	15.44	17.41	26.37	16.9	0.46
Total EU(28)	3343	3276	3198	2854	100.00

Table 4.13 Import of dairy products in the UK from different European countries

The EU share represents on average the 82% for the meat products and the 98% for the dairy products (Table 1 and 3). Most meat products come from Ireland (30% in 2018) followed by

Netherland (19%) and Germany (13%) (Table 2). For dairy, the highest proportion from Ireland (25%), followed by France (17%), Netherlands and Germany (both 12%) (Table 4). The highest proportion of meat products from outside EU is from Thailand (7%), followed by New Zealand and Brazil (both 4%). The highest proportion of dairy product from outside EU (1%) comes from US.

COUNTRY	2018	2019	2020	2021	% 2018
AE United Arab Emirates	0	0.17	0.03	0	0.00
AG Antigua and Barbuda	0	0	0	0.11	0.00
AR Argentina	10.94	10.28	7.12	7.73	0.16
AU Australia	68.34	49.48	51.48	57.59	1.01
BR Brazil	240.57	245.06	239.7	261.34	3.57
BW Botswana	13.33	0.15	0	0.09	0.20
CA Canada	1.35	2.63	1.62	2.7	0.02
CH Switzerland	0.15	0.09	0	0.01	0.00
CL Chile	31.69	28.88	10.43	2.11	0.47
CN China	26.5	31.61	27.64	28.67	0.39
CZ Czechia	1.63	2.52	2.48	0.76	0.02
FK Falkland Islands	1.91	1.39	1.7	0.8	0.03
HK Hong Kong	0.1	0.07	0	0	0.00
HU Hungary	33.08	38.56	33.16	49.94	0.49
IL Israel	1.48	1.24	0.34	1.29	0.02
IN India	0	0.12	0.03	0	0.00
IS Iceland	4.59	4.07	3.57	3.17	0.07
JP Japan	3.54	4.68	2.5	4.51	0.05
MK North Macedonia	0	0	0	0.01	0.00
ML Mali	0	0	0	0.01	0.00
MY Malaysia	0	0	0.01	0.18	0.00
NA Namibia	9.01	12.51	1.05	1.01	0.13
NI Nicaragua	0	0	0	0.05	0.00
NO Norway	0.21	0.01	0.01	0.02	0.00
NZ New Zealand	290.59	229.94	232.46	201.43	4.31
PH Philippines	0	0.13	0.05	0.03	0.00
PY Paraguay	3.07	0.12	0.88	0.16	0.05
QA Qatar	0	0	0	0.07	0.00
RS Serbia	0.01	0	0	0	0.00
SA Saudi Arabia	0	0	0.21	0	0.00
SG Singapore	0.04	0.03	0	0.37	0.00
SI Slovenia	4.64	2.68	3.29	2.64	0.07
SK Slovakia	1.65	1.74	1.94	1.24	0.02
TH Thailand	499.37	520.76	476.28	399.53	7.40
TR Turkey	0	0.01	0	0.09	0.00
TW Taiwan	0	0.06	0	0	0.00
UA Ukraine	0.15	0.49	0.48	4.23	0.00
US United States inc Puerto Rico	7.49	6.12	6.22	9.5	0.11

UY Uruguay	20.21	17.66	8.78	17.4	0.30
VG British Virgin Islands	0	0.04	0	0.19	0.00
VN Vietnam	0.02	0.04	0.08	0.17	0.00
YE Yemen	0	0.01	0	0	0.00
ZA South Africa	0.35	0.14	0.3	1.44	0.01
D5 Extra EU 28 (Rest of World)	1235	1168	1073	1006	18.30
W1 Whole world	6747	6656	6319	5770	100.00

Table 4.14 Import of meat products from non-EU partners

COUNTRY	2018	2019	2020	2021	% 2018
AE United Arab Emirates	0.02	0	0	0.01	0.00
AU Australia	1.16	0	0	0.02	0.03
BA Bosnia and Herzegovina	0.03	0.02	0.03	0	0.00
BR Brazil	0.04	0.18	0.2	0.15	0.00
CA Canada	0.22	0.42	0.66	0.29	0.01
CH Switzerland	9.09	9.68	11.89	17.59	0.27
CI Ivory Coast	0	0	0	0.01	0.00
CN China	0.02	0	0.02	0.16	0.00
CZ Czechia	5.16	4.49	5.18	4.2	0.15
GE Georgia	0	0	0	0.12	0.00
GH Ghana	0.11	0.28	0.15	0.12	0.00
HK Hong Kong	0	0	0	0.07	0.00
HU Hungary	7.73	8.68	13.48	18.31	0.23
IL Israel	0.43	0.41	0.33	0.48	0.01
IS Iceland	1.32	0	0	1.41	0.04
KR South Korea	0.01	0.02	0.01	0.01	0.00
KZ Kazakhstan	0	0	0.08	0	0.00
MK North Macedonia	2.13	0.99	3.56	4.06	0.06
MX Mexico	0.03	0	0	0	0.00
NO Norway	3.6	4.14	3.85	2.19	0.11
NZ New Zealand	1.31	3.52	0.21	0.02	0.04
PA Panama	0	0	0	0.01	0.00
PE Peru	0.04	0	0	0	0.00
PH Philippines	0	0.03	0	0	0.00
PY Paraguay	0	0	0	0.02	0.00
RS Serbia	1.86	4.12	2.98	6.46	0.05
SG Singapore	0.04	0	0	0	0.00
SI Slovenia	11.6	12.83	14.03	20.48	0.34
SK Slovakia	15.44	17.41	26.37	16.9	0.46
SR Suriname	0	0	0	0.01	0.00
TH Thailand	0.08	0.11	0.14	0.25	0.00
TR Turkey	0.01	0	0.15	0.6	0.00
TW Taiwan	0.01	0	0.01	0.03	0.00
UA Ukraine	0	0.02	0	0	0.00

US United States inc. Puerto Rico	22.45	20.01	23.71	22.87	0.66
VN Vietnam	0	0.01	0.01	0.02	0.00
ZA South Africa	0	0.03	0	0	0.00
D5 Extra EU 28 (Rest of World)	44	44	48	57	1.30
W1 Whole world	3387	3320	3246	2911	100.00

Table 4.15 Import of dairy products from non-EU partners

Currently, there are no import tariffs implemented between the UK and the EU. The new Trade and Cooperation Agreement agreed in December 2020 because of the UK leaving the Single Market and Custom Unions. To export goods to the EU, the UK businesses now need to comply with new customs procedures, including UK export declarations and import requirements on entry to EU Member States. For importing goods into the UK, border controls are being introduced in stages to give businesses time to adapt, with full customs checks applying from January 2022. It is still allowed to import and export goods tariff and quota free, provided that those goods meet the 'Rules of Origin' requirements set out in the agreement. These rules relate to the amount of UK or EU content in a particular good and the amount of processing which goods undergo in the UK or EU before export. Together these determine whether goods qualify as UK or EU originating and therefore qualify for zero tariffs and quotas. Goods that have not been sufficiently produced or processed in the UK or EU cannot be re-exported tariff free under the agreement's preferential tariff rate. The VAT and excise rules that apply to goods coming into or leaving the UK from or to EU countries and non-EU countries are now the same (Foreign, 2020) .

In terms of international trade, the below tariffs rate the average UK and EU prices to applied dairy and meat products (AHDB, 2020) (Table 7). These rules apply unless:

- the country imports come from has a preferential trade agreement;
- an exception applies, such as a relief or tariff suspension;
- the goods come from developing countries covered by the Generalised Scheme of Preferences

As the UK and EU have agreed a trade deal these tariffs do not apply to trade between the two parties. The dairy prices are higher for butter, cheese and curd, fats. The meat products relate mainly to beef and pork products. Here, they are presented in average to make a comparison with the trade values that are expressed as average for those categories.

The registered decrease of imported dairy products in the UK from non-EU countries compared to EU countries due to the average tariffs (£125.73) is estimated at around 98%; if we were to impose the carbon tax at £70/tonne CO_2, the average decrease would reach 55% (Table 8). For meat products, the average decrease due to the import tax (£170) from outside EU led to a decrease of around 78% of imported products. With the imposition of the £70 carbon tax, the reduction would be estimated at around 32% (Table 9). These reflections let us to understand the scale and ground-truth of impacts proposed. Or in other words, let us to understand how big the effect of the hypothetical carbon border tax would be when imposed.

Product	**Average UK tariff rate GBP/100 kg**
Meat	170
Dairy	125.73

Elaborated from https://ahdb.org.uk/uk-and-eu-import-tariffs-under-no-deal-brexit

Table 4.16 UK tariffs import rates from non-EU Partners

DAIRY PRODUCTS	**2018**	**2019**	**2020**	**2021**
Total EU(28) - dairy	3343	3276	3198	2854
D5 Extra EU 28 (Rest of World)	44	44	48	57
Average decrease due to the tariff from non-EU (125.73 GBP/100KG) %	-98.7	-98.7	-98.5	-98.0
Hypothetical decrease due to the carbon tax (70 GBP/100KG) %	-54.6	-54.9	-54.8	-54.6

Table 4.17 Estimated decrease in import flows due to carbon tariffs - dairy

MEAT PRODUCTS	**2018**	**2019**	**2020**	**2021**
Total EU(28)	5512	5488	5246	4764
D5 Extra EU 28 (Rest of World)	1235	1168	1073	1006
Decrease due to the tariff from non-EU (125.73 GBP/100KG)	-77.6	-78.7	-79.5	-78.9
Hypothetical decrease due to the carbon tax (70 GBP/100KG) %	-32.0	-32.4	-32.8	-32.5

Table 4.18 Estimated decrease in import flows due to carbon tariffs - meat

How this relates to UK diet and consumption of meat products?

These data relates to UK diet and consumption because meat processing companies rely on imports for 26% of their supply, with the rest coming from UK farms (The British Meat Processors Association, 2021).

British consumers tend to eat a limited range of meat cuts. When producers process a carcase, they have excess meat, which cannot be sold in the UK market and needs to be exported. However, popular cuts of meat still need to be imported to meet the UK's needs.

Beef makes up nearly half of all meat imports to the UK with pork accounting for just over a third and lamb around 20 percent. The largest source of imported meat is the Republic of Ireland, which is home to more cattle than people and is among the top four beef exporters worldwide (The British Meat Processors Association, 2021).

Other top sources of meat products are New Zealand, Germany, and the Netherlands but, over the last few years, improvements in meat preservation and transportation methods have seen a rise in products coming from places like Brazil.

Exports account for about 17% of the UK meat processing industry's revenue with most coming from customers in France, Republic of Ireland and the Netherlands. China also grew to be an important export market despite its recent economic slowdown in 2015-6. The US beef market is also growing after the UK gained access to it in 2014 and could potentially be very lucrative.

Beef accounts for the largest share of export revenue at 40%, followed closely by lamb and sheep at around 36%, with pork bringing in around 20%. The remaining revenue comes from the sale of other animal products (the less popular meat products that attract a low price here but a much higher price in other countries).

Income received for the cuts of meat eaten by UK consumers does not come close to covering the cost of buying the animal and processing it, which is why a healthy export market for offals and other animal by-products is crucial for British meat processors and enables them to achieve what's known in the trade as 'carcase balance' and therefore profitability.

At the moment (2017) the plunge in the UK Pound after the EU referendum has made British meat products more competitive and boosted exports.

The challenge will be to maintain the level of imports to meet UK demand whilst preventing the market from being flooded with low quality, cheap produce from abroad. In this scenario the ability of British producers to produce food competitively will be undermined, forcing retailers and food service companies to become overly dependent on cheap imports. The medium to long-term effect of such damage to the UK meat industry would restrict the consumer's choice and ultimately cause the price and supply of meat to become much more volatile.

In terms of dairy products, there is little overseas trade in liquid milk, but considerable trade in processed products. In 2019 the UK recorded a trade surplus in volume terms for dairy for the first time since 1997. This was partially due by a reduction in the import of skim milk and buttermilk and higher exports and lower imports of cream and butter. The surplus reduced in size in 2020. Dairy exports to the EU reduced after the end of the EU Exit transition period in 2021. The Food and Drink Federation, a trade body representing food and drink producers, reported that milk and cream exports from the UK to the EU decreased by 96% in February 2021 (year-on-year). However, their report for the first half of 2021 shows that while milk and cream exports to the EU were lower than in 2019 (by 19.0%), they were up slightly on 2020 (by 5.0%). Comprehensive figures for 2021 are not yet available. In 2020, the UK had a negative trade balance in butter and cheese, but a positive trade balance in milk and cream.

How does this relate to UK consumption of dairy products?

Imports make up a very small proportion of total supply of liquid milk in the UK. 0.8% of milk available to UK dairies was imported in 2020. However, milk imports have risen from 88 million litres in 2010 to 118 million litres (provisional) in 2020. In 1995, doorstep delivery accounted for 45% of household purchases of milk in England and Wales. Nowadays, Dairy UK, the trade body for the UK dairy industry, estimates the proportion to be around 3% across the UK. The Agriculture and Horticulture Development Board reported that the number of customers using milkmen increased substantially during the pandemic. This decline has been accompanied by a growing price differential between milk from retailers and from doorstep delivery. In the UK in 1995, a pint of milk cost an average of 37.9p on the doorstep and 23.9p from retailers. In August 2021, a pint cost 81p on the doorstep and 28.3p from retailers (House of Commons Library, 2021).

Considering these data and the results obtained with this PhD thesis, the implementation of carbon tax at border level would have an actual impact on the trade flows of meat products. Imported meat represents a consistent share of meat consumed in the UK. A reduction in the quantity of meat imported would translate in an actual reduction in the meat consumed in the UK, with shifting in dietary patterns across the population. This doesn't affect the imported dairy products; these not only represent a very insignificant share of the consumed dairy products in the UK, but also were not quite affected by the implementation of carbon policies.

4.11.3 Reflections: Does this proposal work as a non-tariff trade barrier?

In general terms, a nontariff barrier is a way to restrict trade using trade barriers in a form other than a tariff. Countries frequently use nontariff barriers to restrict the amount of trade they conduct with other countries. Countries can use nontariff barriers in place of or in conjunction with conventional trade barriers. Types of nontariff barriers include licenses, quotas, embargoes, sanctions, voluntary export restraints (Genç and Law, 2014).

This proposal would not directly work as a nontariff trade barrier because the main objective of this work is to analyse shifts in trade flows when the import price increases with carbon taxation. Border taxes focus on making carbon emissions more costly by changing relative prices and should not be used for erecting protectionist barriers. In addition, it would be difficult to implement the gravity model since the measurement of non-tariff measures is more problematic than the measurement of tariff measures because they are not published in tariff schedules and are not expressed as percentages or monetary values. The margin change in trade flows that can be observed with the implementation of carbon border taxes on prices is the main outcome of this research. This would not be possible to study if non-tariff measures were imposed. A suggestion would be to combine the implementation of tariff and non-tariff measures as a way to support more sustainable importing strategies between the UK and the EU. In this regard, non-tariffs could enter as barriers in the market that ban the entry of imported food products with a high environmental footprint.

Chapter 5. Policy implications and conclusions

5.1 Introduction

This final chapter of this thesis presents, consolidates and relates the main findings of the study back to the aim and objectives of the research. Overall, it indicates and describes policy actions and strategies that can increase awareness and lead to changes among the UK population towards more eco-friendly food consumption choices and their implications on human health based primarily on the findings described in Chapter 3. At the same time, it reveals issues and other aspects that need to be taken into account when implementing policy reforms on food prices. In addition, it presents the advantages of considering carbon adjustment mechanisms and the possibility of these measures of making trade more sustainable between the UK and the EU considering the insights of Chapter 4. Alternative policy interventions are suggested in order to achieve the best connection between environmental and nutritional goals both at consumer and producer level. The main policy and economic implications are described with the intention to influence further studies and political strategies aiming to achieve sustainable behaviours. It is organized as follows. Section 5.2 describes the contributions of this study, section 5.3 the alternative policy scenarios, section 5.4 the policy implications, section 5.5 the limitations and section 5.6 the conclusions.

5.2 Contribution of the study

This doctoral study aimed to simulate the effects of environmental regulations of food markets on consumer diet, health and trade in the UK. This was done in order to reduce the level of GHGs derived from the entire food sector and promote more sustainable and nutritional choices among UK consumers and producers.

In the first part, a micro-simulation method was implemented under the specification of an Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980) to assess the implications of carbon policies on UK consumers' diets and health. A demand model was estimated to provide a set of estimates of the substitution, own-price and expenditure elasticities of the goods analysed taking into account potential biases caused by sample selection and the endogeneity of prices. These parameters were then used to simulate new consumption patterns when regulations were applied to all the food groups. Like carbon taxes on energy, emission based food taxes may be regressive as several studies find an association between socio-economic status and diet (Tiffin and Arnoult, 2010, Billson et al., 1999). For this reason, two scenarios were chosen to illustrate the environmental and dietary outcomes of food policies: carbon taxation, scenario (A), and *Bonus-Malus* taxation, scenario (B), both with a societal cost of £70/tCO_2-eq. In scenario (A), food prices increased according to their environmental impact based on carbon footprint values. In scenario (B), total tax revenues derived from taxation were unaltered. This was achieved through the implementation of a subsidy that reduced the current level of food prices in parallel with the introduction of climate taxes on food, so that the resulting tax was revenue neutral. In particular, the variation in household expenditure estimated in scenario (A) was used as the price reduction for the bonus part. This was done because the tax burden falls disproportionately on households in the lowest socio-economic classes because they tend to spend a larger proportion of their food expenditure on emission intensive foods and because they buy cheaper products and therefore experience relatively larger price increases (Kehlbacher *et al.*, 2016). The aim of the health analysis was to compute linear regressions to model the effects of particular food and drinks purchased at household level on different types of health biomarkers at an individual level. Body mass index (BMI), blood cholesterol, glucose, and glycated haemoglobin (HbA1c) concentrations were used as health biomarkers in order to see if particular types of food products increase or decrease the probability that a particular disease will occur. The parameters obtained from these functions were then used to simulate new health outcomes after the implementation of environmental taxations.

The data used in this study came from the Living Cost and Food Survey 2015-2016 (Office for National Statistics, 2017b) that contains detailed socio-demographic information and home food consumption purchases of the UK population over a two-week period. These data were aggregated in different macro-categories following the Eatwell Guide and then by similarity in 11 subcategories as explained in Chapter 3. These are cereals, potatoes, sweets, fish, meat, ready meals, dairy and eggs, fruit, vegetables and legumes, drinks, fats oil and spreads (Figure 3.1). Data used for the health analysis came from the UK's National Diet and Nutrition Survey. The analysis covers data from 2008/2009 to 2016/2017. This review contains nutrition, consumption and general health information at an individual level for the UK population aged 1.5 years and above, living in private households.

The findings suggest that environmental regulations on food products might lead to sustainable shifts across UK population consumption patterns. In both scenarios consumption of dairy, eggs, meat and vegetables were predicted to decrease the most after the application of carbon taxation on foods. These changes benefit the environment in terms of substantial reductions in the total GHG emissions deriving from the entire food sector. In particular, this simulation estimated overall ~ 9 $MtCO_2$-eq saved with scenario (A) and ~7 $MtCO_2$-eq with scenario (B). At the same time, these policy reforms, that target new foods consumed at household level, could have the potential to bring some positive health effects, mainly in the predicted slight reduction of individual blood cholesterol level. Reductions of meat and dairy foods consumed were mainly characterized by a decline in saturated fats and animal protein intakes. However, uncertainty still remains around the consumption of unhealthy but sustainable foods and the fact that sustainable diets might result in a decrease of other essential micro-nutrients, like iron, vitamin E and B12 and energy (kcals). Furthermore, new diets after regulation were predicted to negatively affect the other health parameters considered in this study, namely Body mass index (BMI), and glycated haemoglobin (HbA1c). This uncertain relationship between health and sustainability was also demonstrated by other studies that focused on epidemiological methods and considered the effects on mortality rates and deaths averted with comparative risks assessment models (Briggs *et al.*, 2013; Briggs *et al.*, 2016).

In the second part, the main purpose was to evaluate the effects of environmental policies on trade in the UK. The EU recently adopted a resolution "towards a WTO-compatible EU carbon border adjustment mechanism (CBAM)", namely a carbon border tax. In this sense, each country is responsible for the overall emissions caused by the production of goods and services, even if produced abroad. This regulation is designed to discourage EU businesses from moving their production to countries with less ambitious environmental policies and to encourage a global move to zero carbon emissions in line with the Paris Agreement. In this context, this research proceeded with an *ex ante* analysis of the effects of European carbon border taxes on trade and embodied emissions in the UK using a micro-simulation approach structured around a gravity model on trade. The carbon border tax was implemented in the form of an *ad valorem* tax that sets a rate per unit of CO_2 that increases the price of imported foods in UK, specifically meat and dairy products, based on their carbon emissions. This was done in order to reduce the amount of embodied emissions on goods imported to the UK from Europe. The findings demonstrated the ability of this policy reform to encourage sustainable trade flows between Europe and the UK. In particular, meat prices were highly determinant of import streams. In this sense, EU carbon tariffs would lead to a high reduction in the quantity of meat imported by the UK from Europe, especially from Finland, Estonia, Czech Republic and Cyprus. The decrease in the quantity of meat and dairy imported from Europe would have positive environmental outcomes in the quantity of reduced UK embodied emissions from European countries, estimated at around 30.6 $MtCO_2$-eq. Regarding the nutritional profile, high drops of meat and dairy traded are characterised by a reduction in the level of some nutrients, like saturated fat, animal protein and sodium, as well as vegetable protein and fibre intakes.

5.3 Alternative policies scenarios

Overall, policymakers with the aim of regulating food consumption have the choice between command and control instruments, information provision and price-based approaches (Lorek and Spangenberg, 2010). In relation to the adverse effects of food consumption, command and control instruments are economically inefficient and have mainly been used in relation to cases where there is an acute threat to the life and health of the citizen (Edjabou and Smed, 2013). Information campaigns have been widely used to improve general health, such as to decrease smoking or to increase consumption of fruit and vegetables, but in relation to GHG emissions information campaigns are considered to have a limited effects (Edjabou and Smed, 2013). The lack of suitability of the two former policy instruments leaves price-based instruments as the most appropriate to reduce GHG emission from food consumption. In this study, environmental regulations were applied through two different scenarios: carbon taxation, scenario (A), and *Bonus-Malus* taxation, scenario (B), with a cost of £70/tCO_2-eq. In scenario (B), carbon taxes (*malus*) and subsidies (*bonus*) were applied to all the food groups including healthy and not healthy products. Different budget-neutral tax scenarios could bring major benefits in terms of nutritional and environmental outcomes. An option would be the implementations of the *bonus* part only to particular types of products, for example the healthier ones. This modification would incentivize households to substitute animal protein for vegetable protein and increase their intake of vitamins by improving the nutritional profile of the population. An example of this intervention was suggested by Briggs *et al.* (2013). They modelled two scenarios in order to account for and internalise the wider cost to society: the first taxes food groups with GHG emissions greater than the average and the second taxes high-GHG emission food groups and subsidises those with low emissions to create a revenue neutral scenario. Moreover, a redistribution of tax revenues via income-dependent or lump-sum transfers could be an alternative to reduce social inequalities (Klenert and Mattauch, 2016; Carattini;Carvalho and Fankhauser, 2018).

The present study provides emission estimates based on changes in the average diet of the entire population thereby assuming that all households respond to the tax induced price changes in the same manner, as in Wirsenius;Hedenus and Mohlin (2011) and Briggs *et al.* (2013). However, in practice households are likely to respond differently to the tax depending on how much food with a given tax rate they buy, whether they buy cheap or expensive products in the taxed categories and the resources available to them to compensate for the food price increases.

Kehlbacher *et al.* (2016) dealt with this issue by computing the impact of the tax at the level of the individual household in their sample. At the same time, they allowed for differences in responses across households to compute the distributional impacts of the policy. To analyse the distributional impacts they accounted for the fact that their data recorded purchases and not consumption over a two-week period. In this way, other policy interventions should consider grouping households according to socio-economic class. Additional assessments using micro level data would be needed to address these distributional issues, while also taking differences in diets, and thus exposure to diet-related health risks, into account (Latka *et al.*, 2021).

In order to observe more significant food consumption shifts after the implementation of carbon policies, it would be worthy disaggregating each food group into more specific categories. In the current study, the categories are quite broad and comprise different products with different nutritional and ecological impact. This further disaggregation will probably lead to more interesting substitutions within category after the application of policy interventions. Taxing beef products more than poultry and other meat foods might encourage replacements from red meat to white meat, although that it is not possible to observe this in the current study (Bonnet;Bouamra-Mechemache and Corre, 2018). The same would happen for other categories, like ready meals that include fish, meat and vegetable based foods. This applies also to cereals and dairy products. In addition, it would be correct to differentiate between processed and raw products, especially in the case of fruit and vegetables because of the different environmental impacts involved in their preparation methods.

Unintended health consequences can arise as the tax fails to take into account that some individuals may benefit from consuming emission intensive foods, such as milk. Equally, taxing foods according to their emission content can create perverse incentives with energy dense foods such as sweets and soft drinks attracting lower tax rates than more nutritious foods. In this context, the application of a sugar tax together with a carbon tax would be an option, as suggested by Briggs *et al.* (2016). This would address the problem of particular foods, like sugary drinks, which are good for the environment but bad for the health. In addition, more attention should be directed towards the nutritional implications of specific foods consumed. To assess the nutrition improvement arising from these consumption changes, the Nutrient Score could be calculated following the approach used by Latka *et al.* (2021) and Van Kernebeek *et al.* (2014). The health analysis in this study built a new approach by considering the health biomarkers as measures for individual health. Alternative health analysis should consider epidemiological methods, aiming to model the effects on mortality and deaths averted with comparative risks assessment methods, as the DIETRON model (Scarborough *et al.*, 2012;

Briggs *et al.*, 2013; Briggs *et al.*, 2016). This integration would be useful in order to compare these results with other studies in the literature.

Regarding the trade analysis, it is necessary to expand the present work and consider all the other food categories in order to get an overview of the entire food sector. In this way, it could be possible to observe shifts and redistributions among the different food groups. In other words, to understand if the carbon border tax would decrease UK imports of less sustainable products and increase trade in the more sustainable ones, like fruit and vegetables. This might also lead to an increase in the consumption of selected micro-nutrients that improve the nutritional quality of foods imported from the EU. At the same time, further research should investigate if a decrease in food imported from abroad could lead to an increase in UK local production of more environmental impactful products and the possibility of becoming a pollution haven (Monjon and Quirion, 2010; Atkinson *et al.*, 2011; Antimiani *et al.*, 2013).

Other scenarios should consider the implementations of carbon border taxes not only considering the embodied emissions, but also international freight transport, even with the data limitation issue. López *et al.* (2015) developed a multi-regional input-output model to evaluate the importance of international trade of agricultural products as well as their food-miles emissions on the proposed extended carbon footprint (ECF). The ECF includes total (direct and indirect, domestic and imported) carbon incorporated in the production and transport of products sold by sector as either final or intermediate goods and domestically or abroad. Further research should analyse the negative consequences of lower trade flows in terms of reduced welfare across countries (Larch and Wanner, 2017). Moreover, the consumers' interest in where their food come from is another issue that needs to be taken into account (López *et al.*, 2015).

5.4 Policy Implications

Three main implications of this research study for economic policy shall be highlighted. First, the findings obtained from this research suggest that *bonus-malus* interventions could be efficient tools for environmental policy, which can change consumption patterns in a cost-efficient way. In this sense, there are options to incentivise people to adopt healthier and more sustainable diets without dramatically affecting food prices. The redistribution of carbon revenues in the form of a price subsidy, as suggested in this study, can be a promising strategy in view of future policy interventions. As previously stated, it would be sensible to subsidise only particular types of products, i.e., fruit and vegetables, in order to observe healthier consumption patterns, whilst not penalizing low-income households. Policy makers should take this into account and consider similar types of scenarios to address the environmental challenges of food diets and at the same time the regressivity of these types of market-based instruments. Moreover, despite the modest changes achieved in terms of nutritional and health outcomes, this was the first study to consider the implications of more sustainable diets on particular health biomarkers at an individual level. More research should be proposed in this direction and more health indicators should be suggested in order to link the environmental and nutritional aspects of food consumption. Based on these health indicators, valuable information regarding the risk of particular diseases will be provided.

Second, the implementation of carbon taxes on food prices affecting the consumer side together with a carbon border mechanism in the producer side could be part of a global strategy targeting eco-friendly food choices. A coherent policy package incentivizing the consumption, production and trade of certain foods identified as beneficial should be designed to reach nutritional and sustainability objectives simultaneously, thereby also restricting freedom of choice to the least possible extent. Price at €70 tCO_2-eq may be enough to reduce the quantity of meat and dairy imported from abroad and to reduce the consumption of the most damaging environmental products. However, a higher carbon price would be required to improve the efficiency of the intervention and gain more environmental benefits. Despite the inefficiencies that arise with the tax, the revenues could be used to expedite low emissions innovations in food production. In the medium term, European countries would probably need to introduce clean development mechanisms, namely changes to their generation of energy, to offset the imported carbon tax in order to find alternative ways to sustain their growth. In this regard, environmental policies and supply side measures targeted at producers and the entire value chain should incentivise firm to replace technologies towards a greener production, in accordance with the Porther Hypothesis (Ranocchia and Lambertini, 2021). Furthermore, producers may be encouraged by new taxes or subsidies to invest in the development of more healthy alternative food products; a fat or sugar tax, for example, may induce producers to develop low-fat (low-sugar) versions of food originally high in fat/sugar content.

Third, acknowledging the previously mentioned modelling limitations, it appears that monetary instruments alone will not suffice in order to reach nutrition and sustainability objectives simultaneously. Complementary measures able to change behaviour of large consumer groups are needed alongside price signals. These could be a mix of the fiscal-interventions like information campaigns, product labelling or nudges or target group specific interventions to increase the awareness, acceptability and willingness of consumers to change to sustainable and healthy diets. The information provided in the eco-labels could push households to move their consumption strategies towards production with lower environmental damage. Also, adding transport to eco-labels of foods products could allow countries to reduce the impact of international freight transport or reduce the chemical inputs in the production of organic goods. The use of advertising campaigns aiming to inform consumer of the lowest emissions linked to proximity and seasonal consumption is advisable. Other ways of reducing food related emissions should also be considered such as the reduction of food waste in food processing, distribution, retail and the home (Kehlbacher et al., 2016). Further research on the interactions between price and non-price measures is needed. Whether in reality comparably high tax rates would be necessary to reach substantial demand shifts, changes in preference and substitution behaviour towards vegetarian diets would likely require less drastic price incentives (Latka *et al.*, 2021)

5.5 Limitations

The study presents some policy related limitations to be considered. It is important to keep in mind that the model was estimated on a UK sample of households. Thus, its policy implications should be limited to the UK context given that food price elasticities can vary substantially across countries and cultures. In addition, owing to the proliferation of international cuisines within the UK, policy efforts should be made to take these issues into account. A second limitation is that food demand models only include food items consumed at home and ignores all those foods consumed away from home. Food-away from home accounts for a large share of the UK food market. Excluding these items from the demand analysis may lead to imprecise estimates. Hence, the bad health and environmental consequences from consuming such nutrients can derive mostly from food-away-consumption rather than the food consumption at home. Carbon policies would need to be implemented also within bars and restaurants in order to achieve interesting results. Another issue that policy makers would face in implementing carbon regulations on foods is related to Brexit. New trade agreements have already been put in place and the imposition of further barriers on trade and carbon adjustment mechanisms could damage the relationship between the UK and the EU. Policy efforts should be made in order to take into account the different issues and promote the development of sustainable trade agreements after the UK has left the EU.

5.6 Conclusions

This research aimed to explore the impact of carbon taxation on diet, health and trade within the UK by quantitative simulations. Research findings indicate the potential of cost-efficient policies in predicting more sustainable food consumption behaviours, with slightly positive health outcomes. However, since the relationship between nutrition and sustainability results is still uncertain, more research is needed in order to find the best balance between nutrition, health and environment. Alternative policy interventions and health models are suggested from the findings of this research in order to influence further studies. New scenarios and various combinations thereof will give more insights into how to design the most appropriate taxation strategy for healthy and sustainable eating. Supply side strategies and technology improvements would need to be implemented in order to direct food production and consumption towards more sustainable and nutritional goals.

This study is a contribution to the growing literature that considers the challenges of public health and climate change. Many aspects of this study have shown the importance of targeting food products based on their emission contents. This could be seen as a starting point for future investigations aiming to increase awareness and actions.

5.7 Post-Note Chapter 5

The main implications of this PhD study showed how carbon taxation and, more specifically, *bonus-malus* interventions could be efficient tools to change consumption patterns in a more eco-friendly and nutritional way. Policy makers should consider the implementation of this policy by redistributing the economic revenues in the form of price subsidies. As previously stated, it would be sensible to subsidise only certain types of products to observe more nutritional shifts among the population. On the other hand, policy makers should consider how lab-grown meat would fit in this environmental design. This type of meat would have lower carbon footprint than conventional one – with a consequent lower carbon tax paid by the consumers. For this reason, it might be worthy to incentivise the consumption of this product rather than penalising it – especially for people who are in the process to reduce the consumption of traditional meat. Revenues from carbon taxation could be used to accelerate the production of lab grown meat in substitution of the traditional ones. At the same time, economic revenues could be generally used as incentives for firms to replace technologies towards a greener production and to expedite low emission innovations in food production. People that work at governmental level could also implement a combination of different taxes and subsidies that may induce producers to develop healthier and alternative food products. Government institutions and local authorities should work together to discuss the different aspects and come to a joint agreement before the development of the most accurate plan. In this regard, collaboration between different institutions, stakeholders, research bodies and academia that work for the food sector might be necessary to find the best strategy.

Policy makers should also consider the implementation of complementary measures in combination with market-based instruments to reach nutrition and sustainability objectives together. Information campaign, eco-labelling, nudges mechanism could increase awareness and willingness to change at population level. These and other strategies should be considered at governmental level and applied in the food sector in order to reach robust food consumption shifts.

5.7.1 Direction for future research

This PhD study was the first to consider the effects of more sustainable diets on health biomarkers at an individual level – body mass index, total cholesterol, glucose, and glycated haemoglobin. More research should be directed in this direction and more health indicators should be suggested to link the environmental and nutritional outcomes of food consumption. In this way, valuable information regarding the risk of diseases will be provided. Further research at academic level should also propose collaborations with health authorities to maximise the nutritional and health goals linked with this PhD study – to increase the value and the impact of the project. At the same time, an expansion of the current research project with a potential risk assessment model (e.g. DIETRON) would be worthwhile in order to consistently compare the results of this study with the current literature surrounding this topic.

Alongside the focus and attention on increasing the proportion of plants within our diets, relative to animals, far more consideration should be given to the type and quality of plant-based foods eaten. More research should be directed to policy tools that discourage the consumption of processed foods – to avoid the unintended health consequences of plant-based foods which contain high levels of sugars, fats, salts, which are often used to replicate the taste and texture of their meat counterparts. In this sense, more interest should be given to the 'more but better approach' to plant-based foods, encouraging greater biodiversity of fresh fruits, vegetables, wholegrains nuts and legumes using agroecological, regenerative and sustainable agricultural practices. On the other hand, 'less but better' approach to meat consumption should be followed. Better from a health, sustainability, and animal welfare perspective, supporting high welfare agroecological, regenerative, pastoral, organic livestock farming system which support the shifts from intensive factory farms towards those farming practices and principles that can build soil health, improve biodiversity, reduce global GHGs and improve farmer livelihoods.

At the same time, further research on the combination between price and non-price interventions at production and consumption level is needed in collaboration with policy makers and different stakeholders working in the food sector. Innovative research in the field should highlight the impact and the real-life consequences following the application of these environmental regulations. In this regard, quantitative analyses of large secondary dataset as well as qualitative research involving consumers could be proposed. A proper engagement with policy makers, the public and other food systems actors might be needed to achieve robust objectives and to maximise research impact and uptake. A deep and strong relationship with European partners outside the UK, including academic partners and the WHO would be ideal to address further issues at global level and to study new aspects of the trade analysis linked with this PhD study.

Many other aspects related to the food sector might be proposed for future research strategies. From food waste actions to food packaging issues, that should be implemented concurrently with carbon policies and measures.

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Appendices

Appendix A

Nutrient	Unit of measure	Nutrient	Unit of measure
Vegetable Protein	g	Glucose	g
Animal Protein	g	Fructose	g
Fat	g	Sucrose	g
Saturates	g	Maltose	g
Mono-unsaturates	g	Lactose	g
Poly-unsaturates	g	Other sugars	g
Carbohydrate	g	Total sugars	g
Energy - Kcal	kcal	Non-milk extr sugars	g
Energy - MJ	MJ	Alcohol	g
Calcium	mg	Fibre:Southgate	g
Iron	mg	Fibre:Englyst	g
Retinol	ug	Potassium	g
Carotene	ug	Magnesium	mg
Retinol equivalent	ug	Copper	mg
Thiamin	mg	Zinc	mg
Riboflavin	mg	Vitamin B6	mg
Nicotinic acid	mg	Vitamin B12	ug
Tryptophan	mg	Phosphorus	mg
Niacin Equivalent	mg	Manganese	mg
Vitamin C	mg	Biotin	ug
Vitamin D	ug	Pantothenic acid	mg
FOLATE	ug	Vitamin E	mg
Sodium	g	Cholesterol	mg
Starch	g		

Table A. 1: List of nutrients

Efscode	**Product name**	**Unit**	**Emissions (gCO2/100g)**	**Source**
1.1.4.1.3	UHT whole milk	ml	158	Tesco
1.1.4.1.2	Sterilised whole milk	ml	158	Tesco
1.1.4.1.1	Pasteurised or homogenised whole milk	ml	158	Tesco
1.1.4.1.5	Welfare milk	ml	158	Tesco
1.1.4.3.1	Condensed or evaporated milk	ml	310	Verge; et al 2013
1.1.4.3.2	Infant or baby milks – ready to drink	ml	310	Verge; et al 2013
1.1.4.3.3	Infant or baby milks – dried	ml	750	Flysjo A. et al, 2014
1.1.4.3.4	Instant dried milk	ml	750	Flysjo A. et al, 2014
1.1.4.4.1	Yoghurt	ml	196	Tesco
1.1.4.4.2	Fromage frais	ml	196	Tesco
1.1.4.2.1	Fully skimmed milk	ml	123	Tesco
1.1.4.2.2	Semi-skimmed milk	ml	141	Tesco
1.1.4.6.3	Dairy desserts – not frozen	ml	100	Flysjo A. et al, 2014
1.1.4.3.5	Dried milk products	ml	750	Flysjo A. et al, 2014
1.1.4.6.4	Milk drinks & other milks (replaced 200405 onwards)	ml	96	Tesco
1.1.4.6.1	Cream	ml	296	Tesco
1.1.4.5.1	Hard cheese – Cheddar type	grams	662	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.4.5.2	Hard cheese – Other UK or foreign equivalent	grams	662	Tesco
1.1.4.5.3	Hard cheese – Edam or other foreign	grams	662	Tesco
1.1.4.5.4	Cottage cheese	grams	180	Verge; et al 2013
1.1.4.5.5	Soft natural cheese	grams	662	Tesco
1.1.4.5.6	Processed cheese	grams	400	Drewnowsky et. Al, 2015
1.1.2.1.1	Beef joints – on the bone	grams	2397	Tesco
1.1.2.1.2	Beef joints – boned	grams	2397	Tesco
1.1.2.1.3	Beef steak – less expensive	grams	2397	Tesco
1.1.2.1.4	Beef steak – more expensive	grams	2397	Tesco
1.1.2.1.5	Minced beef	grams	2397	Tesco
1.1.2.1.6	All other beef and veal	grams	2397	Tesco
1.1.2.4.1	Mutton	grams	1413	Tesco
1.1.2.4.2	Lamb joints	grams	1413	Tesco
1.1.2.4.3	Lamb chops	grams	1413	Tesco
1.1.2.4.4	All other lamb	grams	1413	Tesco
1.1.2.2.1	Pork joints	grams	608	Tesco
1.1.2.2.2	Pork chops	grams	608	Tesco
1.1.2.2.3	Pork fillets and steaks	grams	608	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.2.2.4	All other pork	grams	608	Tesco
1.1.2.6.1	Ox liver	grams	2397	Tesco
1.1.2.6.2	Lambs liver	grams	1413	Tesco
1.1.2.6.3	Pigs liver	grams	608	Tesco
1.1.2.6.4	All other liver	grams	1472	Tesco
1.1.2.6.5	All offal other than liver	grams	700	Drewnowsky et. Al, 2015
1.1.2.3.1	Bacon and ham joints, uncooked	grams	608	Tesco
1.1.2.3.2	Bacon and ham rashers, uncooked	grams	608	Tesco
1.1.2.11.2	Ham and bacon	grams	608	Tesco
1.1.2.11.1	Cooked chicken and turkey	grams	996	Tesco
1.3.1.1.1	Takeaway chicken	grams	996	Tesco
1.1.2.10.1	Corned beef – canned or sliced	grams	9540	Tesco
1.1.2.11.3	Other cooked meat	grams	897	Tesco
1.1.2.10.2	Other canned meat and canned meat products	grams	476	Tesco
1.1.2.5.1	Chicken – whole or part	grams	305	Tesco
1.1.2.5.2	Turkey – whole or part	grams	717	Clune et al.,2017)

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.2.5.3	Poultry other than chicken or turkey	grams	540	Scarborough et al, 2014
1.1.2.7.1	Other fresh, chilled or frozen meat	grams	650	Tesco
1.1.2.8.1	Sausages, uncooked – pork	grams	608	Tesco
1.1.2.8.2	Sausages, uncooked – beef etc.	grams	2397	Tesco
1.1.2.12.2	Meat pies – ready to eat	grams	420	Tesco
1.1.2.12.1	Sausage rolls – ready to eat	grams	2610	Lukas M. et al 2016
1.1.2.12.3	Meat pies, pasties and puddings – frozen or not frozen	grams	796	Tesco
1.1.2.8.4	Burgers – frozen or not frozen	grams	2397	Tesco
1.1.2.13.1	Complete meat-based ready meals – frozen or not frozen	grams	895	Tesco
1.1.2.13.2	Other convenience meat products - frozen or not frozen	grams	650	Tesco
1.1.2.9.1	Pate	grams	460	Scarborough Peter et al, 2014

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.2.8.3	Delicatessen type sausages	grams	1472	Tesco
1.1.2.9.2	Meat pastes and spreads	grams	310	Ximena, Rivera, 2016
1.3.1.1.2	Takeaway meat pies and pasties	grams	796	Tesco
1.3.1.3.1	Takeaway burger and bun	grams	2397	Tesco
1.3.1.3.2	Takeaway kebabs	grams	460	Scarborough et al, 2014
1.3.1.3.3	Takeaway sausages and saveloys	grams	2610	Lukas M. et al 2016
1.3.1.4.1	Takeaway meat based meals	grams	895	Tesco
1.3.1.3.4	Takeaway miscellaneous meats	grams	796	Tesco
1.1.3.1.1	White fish, fresh or chilled	grams	280	Tesco
1.1.3.1.2	White fish, frozen	grams	325	(Ziegler et al, 2013)
1.1.3.2.3	Herrings and other blue fish, fresh or chilled	grams	351	Clune et al.,2017)
1.1.3.2.4	Herrings and other blue fish, frozen	grams	140	(Ziegler et al, 2013)
1.1.3.2.1	Salmon, fresh or chilled	grams	367	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.3.2.2	Salmon, frozen	grams	250	(Ziegler et al, 2013)
1.1.3.4.2	Blue fish, dried or salted or smoked	grams	94.2	Tesco
1.1.3.4.1	White fish, dried or salted or smoked	grams	182	Tesco
1.1.3.3.1	Shellfish, fresh or chilled	grams	139	Irribarren D, 2010
1.1.3.3.2	Shellfish, frozen	grams	950	Irribarren D, 2010
1.3.1.1.3	Takeaway fish	grams	201	Wallen A. et al 2004
1.1.3.5.1	Tinned salmon	grams	363	Tesco
1.1.3.5.2	Other tinned or bottled fish	grams	350	Hoolohan et al, 2013
1.1.3.6.1	Ready meals and other fish products - frozen or not frozen	grams	201	Wallen A. et al 2004
1.3.1.1.4	Takeaway fish products	grams	201	Wallen A. et al 2005
1.3.1.4.2	Takeaway fish based meals	grams	201	Wallen A. et al 2004
1.1.4.7.1	Eggs	number	450	Tesco
1.1.5.1.1	Butter	grams	950	Tesco
1.1.5.2.1	Soft margarine	grams	107	Tesco
1.1.5.2.2	Other margarine	grams	107	Tesco
1.1.5.5.1	Lard, cooking fat	grams	401	Scarborough et al, 2014
1.1.5.3.1	Olive Oil	ml	453	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.5.4.1	Other vegetable and salad oils	ml	107	Tesco
1.1.5.2.3	Reduced fat spreads	grams	107	Tesco
1.1.5.2.4	Low fat spreads	grams	107	Tesco
1.1.5.5.2	Suet and dripping	grams	401	Scarborough et al, 2014
1.1.4.6.2	Imitatation cream	grams	473	Scarborough et al, 2014
1.1.8.1.1	Sugar	grams	49	Tesco
1.1.8.2.1	Jams and fruit curds	grams	81	Wallen A. et al, 2004
1.1.8.2.2	Marmalade	grams	81	Wallen A. et al, 2005
1.1.8.3.1	Syrup, treacle	grams	99	Wallen A. et al, 2006
1.1.8.2.4	Honey	grams	68	Tesco
1.1.7.4.1	Potatoes - bought Jan-Aug, previous years crop	grams	87	Tesco
1.1.7.4.2	Potatoes - bought Jan-Aug, this years crop	grams	93	Tesco
1.1.7.4.3	Potatoes - bought Sep-Dec, current crop or new imported	grams	93	Tesco
1.1.7.2.1	Fresh cabbages	grams	22	How low can we go
1.1.7.2.2	Fresh brussels sprouts	grams	45	Tesco
1.1.7.2.3	Fresh cauliflower	grams	45	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.7.1.1	Lettuce and leafy salads	grams	45	Tesco
1.1.7.3.3	Fresh peas	grams	165	Tesco
1.1.7.3.4	Fresh beans	grams	43	Clune et al.,2017)
1.1.7.1.2	Other fresh green vegetables	grams	117	Tesco
1.1.7.5.1	Fresh carrots	grams	20	Clune et al.,2017)
1.1.7.5.2	Fresh turnips and swede	grams	29	Clune et al.,2017)
1.1.7.5.4	Other fresh root vegetables	grams	18	Clune et al.,2017)
1.1.7.5.3	Fresh onions, leeks and shallots	grams	43	Tesco
1.1.7.3.1	Fresh cucumbers	grams	133	Tesco
1.1.7.5.5	Fresh mushrooms	grams	480	Tesco
1.1.7.3.5	Fresh tomatoes	grams	59	Tesco
1.1.7.5.6	Fresh vegetable stewpack, stirfry pack etc.	grams	261	Tesco
1.1.7.1.3	Fresh stem vegetables	grams	254	Tesco
1.1.7.3.2	Fresh marrow, courgettes, aubergine and other vegetables	grams	117	Tesco
1.1.9.2.3	Fresh herbs	grams	57	Clune et al.,2017)

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.7.8.1	Tomatoes, canned or bottled	grams	117	Tesco
1.1.7.8.2	Peas, canned	grams	110	Tesco
1.1.7.8.3	Baked beans in sauce	grams	140	Tesco
1.1.7.8.4	Other canned beans and pulses	grams	136	Tesco
1.1.7.8.6	Other canned vegetables	grams	84	Tesco
1.1.7.7.2	Dried pulses, other than air-dried	grams	150	Nijdam et al 2012
1.1.7.7.1	Air-dried vegetables	grams	426	Hoolohan et al, 2013
1.1.7.8.7	Tomato puree and vegetable purees	ml	140	Scaroborough et al, 2014
1.2.2.5.1	Vegetable juices e.g. tomato juice, carrot juice	ml	140	Scaroborough et al, 2014
1.1.7.9.2	Chips - frozen or not frozen	grams	260	Tesco
1.3.1.2.1	Takeaway chips	grams	260	Tesco
1.1.7.9.1	Instant potato	grams	112	Wallen et. Al, 2004
1.1.7.8.5	Canned potatoes	grams	111	Tesco
1.1.8.6.1	Crisps and potato snacks	grams	155	Tesco
1.1.7.9.3	Other potato products - frozen or not frozen	grams	237	Wallen et. Al, 2004
1.1.7.6.1	Peas, frozen	grams	125	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.7.6.2	Beans, frozen	grams	225	Scaroborough et al, 2014
1.1.7.10.1	Ready meals and other vegetable products - frozen or not	grams	30	Garnett et Tara. 2006
1.3.1.5.1	All vegetable takeaway products	grams	273	Hoolohan et al, 2013
1.1.7.6.3	Other frozen vegetables	grams	306	Hoolohan et al, 2013
1.1.6.1.1	Fresh oranges	grams	39	Tesco
1.1.6.1.2	Other fresh citrus fruits	grams	39	Tesco
1.1.6.3.1	Fresh apples	grams	87	Tesco
1.1.6.3.2	Fresh pears	grams	31	Clune et al.,2017)
1.1.6.3.3	Fresh stone fruit	grams	38	Clune et al.,2017)
1.1.6.4.1	Fresh grapes	grams	84	Tesco
1.1.6.4.2	Other fresh soft fruit	grams	78	Tesco
1.1.6.2.1	Fresh bananas	grams	69	Tesco
1.1.6.5.1	Fresh melons	grams	51	Clune et al.,2017)
1.1.6.5.2	Other fresh fruit	grams	80	Clune et al.,2017)
1.1.6.8.1	Tinned peaches, pears and pineapples	grams	128	Hoolohan et al, 2013
1.1.6.8.2	All other tinned or bottled fruit	grams	128	Hoolohan et al, 2013
1.1.6.7.1	Dried fruit	grams	341	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.6.6.1	Frozen strawberries, apple slices and other frozen fruits	grams	277	Hoolohan et al, 2013
1.1.6.7.2	Nuts & edible seeds	grams	216	Tesco
1.1.6.7.3	Peanut butter	grams	473	Scarborough et al, 2014
1.2.2.4.1	Pure fruit juices	ml	99	Wallen A. et al, 2004
1.1.1.1.1	White bread, standard, unsliced	grams	92	Tesco
1.1.1.1.2	White bread, standard, sliced	grams	92	Tesco
1.1.1.1.3	White bread, premium, sliced and unsliced	grams	92	Tesco
1.1.1.1.4	White bread, soft grain, sliced and unsliced	grams	82	Tesco
1.1.1.2.1	Brown bread, sliced and unsliced	grams	82	Tesco
1.1.1.2.2	Wholemeal and granary bread, sliced and unsliced	grams	82	Tesco
1.1.1.3.1	Rolls - white, brown or wholemeal	grams	92	Tesco
1.1.1.3.2	Malt bread and fruit loaves	grams	175.5	Tesco and Hoolohan et al., 2013

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.1.3.3	Vienna and French bread	grams	92	Tesco
1.1.1.3.4	Starch reduced bread and rolls	grams	162.5	Scarborough et al, 2014
1.1.1.3.6	Other breads	grams	162.5	Scarborough et al, 2014
1.1.1.3.5	Sandwiches	grams	663	Scarborough et al, 2014
1.3.1.7.1	Sandwiches from takeaway	grams	663	Scarborough et al, 2015
1.3.1.2.4	Takeaway breads	grams	450	Scarborough et al, 2014
1.1.1.8.3	Flour	grams	50	Tesco
1.1.1.4.1	Buns, scones and teacakes	grams	91	Wallen A. et al, 2004
1.1.1.6.1	Cakes and pastries, not frozen	grams	188	Tesco
1.3.1.2.5	Takeaway pastries	grams	240	Masset, 2018
1.1.1.4.2	Crispbread	grams	82	Tesco
1.1.1.4.4	Sweet biscuits (not chocolate) and cereal bars	grams	100	Drewnowsky et. Al, 2015
1.1.1.4.5	Cream crackers and other unsweetened biscuits	grams	264	Wallen A. et al, 2004
1.1.1.4.3	Chocolate biscuits	grams	155	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.1.5.1	Oatmeal and oat products	grams	85	Tesco
1.1.1.5.2	Muesli	grams	466.7	Scarborough et al, 2014
1.1.1.5.3	High fibre breakfast cereals	grams	328	Tesco
1.1.1.5.4	Sweetened breakfast cereals	grams	497	Tesco
1.1.1.5.5	Other breakfast cereals	grams	317	Tesco
1.1.1.6.5	Canned or fresh carton custard	grams	140.8	Scarborough et al, 2014
1.1.1.6.6	All canned milk puddings	grams	491	Scarborough et al, 2014
1.1.1.6.4	Puddings	grams	120	Scarborough et al, 2014
1.1.1.8.1	Dried rice	grams	160	Tesco
1.1.1.8.2	Cooked rice	grams	160	Tesco
1.3.1.2.2	Takeaway rice	grams	160	Tesco
1.1.9.3.3	Invalid foods, slimming foods and sports foods	grams	123.2	Scarborough et al, 2014
1.1.9.3.2	Infant cereal foods	grams	467	Scarborough et al, 2014
1.1.1.6.2	Cakes and pastries - frozen	grams	400	Scarborough et al, 2014

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.1.7.1	Canned pasta	grams	670	Scarborough et al, 2014
1.1.1.7.2	Dried and fresh pasta	grams	322	Tesco
1.3.1.2.3	Takeaway pasta and noodles	grams	1130	Tesco
1.1.1.7.3	Pizzas - frozen and not frozen	grams	457	Tesco
1.3.1.6.1	Takeaway pizza	grams	457	Tesco
1.1.1.6.3	Cake, pudding and dessert mixes	grams	188	Tesco
1.1.8.6.2	Cereal snacks	grams	264	Jeswani et al. , 2015
1.1.1.7.4	Quiches and flans - frozen and not frozen	grams	408	Hoolohan et al, 2013
1.3.1.8.2	Takeaway crisps, savoury snacks, popcorn, popadums	grams	409	Hoolohan et al, 2013
1.1.1.7.5	Other cereal foods - frozen and not frozen	grams	434	Jeswani et al. , 2015
1.1.1.8.4	Other cereals	grams	173	Hoolohan et al, 2013
1.2.1.2.1	Tea	grams	1140	Tesco
1.2.1.1.1	Coffee beans and ground coffee	grams	3764	Tesco
1.2.1.1.2	Instant coffee	grams	40	Hassard, 2014
1.2.1.1.3	Coffee essences	ml	3746	Tesco
1.2.1.3.1	Cocoa and chocolate drinks	grams	14	Jeswani et al. , 2015

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.2.1.3.2	Malt drinks and chocolate versions of malted drinks	grams	933	Scarborough et al, 2014
1.2.2.1.1	Mineral or spring waters	ml	20	Tesco
1.1.9.3.1	Baby foods	grams	467	Scarborough et al, 2014
1.1.9.5.1	Soups - canned or cartons	grams	225	Tesco
1.1.9.5.2	Soups - dehydrated or powdered	grams	225	Tesco
1.3.1.8.5	Soups - from takeaway	grams	225	Tesco
1.3.1.8.6	Other takeaway food brought home	grams	94	Scarborough et al, 2014
1.1.9.1.3	Salad dressings	grams	260	Hoolohan et al, 2013
1.1.8.3.2	Other spreads and dresssings	grams	38	Scarborough et al, 2014
1.1.9.1.1	Pickles	grams	30	Garnett et Tara. 2006
1.1.9.1.2	Sauces	grams	482	Scarborough et al, 2014
1.3.1.8.4	Takeaway sauces and mayonnnais	grams	473	Scarborough et al
1.1.9.6.2	Stock cubes and meat and yeast extracts	grams	320	Scarborough et al, 2014

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.8.2.3	Jelly squares or crystals	grams	38	Scarborough et al, 2014
1.1.8.7.1	Ice cream tub or block	ml	64	Wallen A. et al, 2004
1.1.8.7.2	Ice cream cornets, choc-ices, lollies with ice cream	ml	64	Wallen A. et al, 2005
1.1.8.7.3	Ice lollies, sorbet, frozen mousse, frozen yoghurt	ml	64	Wallen A. et al, 2006
1.3.1.8.3	Takeaway ice cream, ice cream products, milkshakes	ml	164	Wallen A. et al, 2007
1.1.9.2.1	Salt	grams	22	Tesco
1.1.8.1.2	Artificial sweeteners		0	Scarborough et al, 2014
1.1.9.1.4	Vinegar		224	Bartocci et al, 2017
1.1.9.2.2	Spices and dried herbs		160	Scarborough et al, 2014
1.1.9.6.1	Bisto, gravy granules, stuffing mix, baking powder		473	Scarborough et al, 2014
1.1.9.7.1	Wine and beer making kits		20	Amienyo and Azapagic, 2016
1.2.1.2.2	Fruit teas, instant tea, herbal tea, rosehip tea		15.56	Azapagic, 2016

Efscode	**Product name**	**Unit**	**Emissions (gCO2/100g)**	**Source**
1.1.9.4.1	Soya and novel protein foods	grams	200	Scarborough et al, 2014
1.2.2.3.1	Soft drinks, concentrated, not low calorie	ml	28	Tesco
1.2.2.2.1	Soft drinks, not concentrated, not low calorie	ml	28	Tesco
1.2.2.3.2	Soft drinks, concentrated, low calorie	ml	23	Tesco
1.2.2.2.2	Soft drinks, not concentrated, low calorie	ml	23	Tesco
1.1.8.4.1	Chocolate bars - solid	grams	155	Tesco
1.1.8.4.2	Chocolate bars - filled	grams	147	Konstantas et al. 2018
1.1.8.5.1	Chewing gum	grams	38	Scarborough et al, 2014
1.1.8.5.2	Mints	grams	120	Scarborough et al, 2014
1.1.8.5.3	Boiled sweets	grams	38	Scarborough et al, 2014
1.1.8.5.4	Fudges, toffees, caramels	grams	120	Scarborough et al, 2014

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.3.1.8.1	Takeaway confectionery	grams	446	Hoolohan et al, 2013
1.4.3.1.1	Beers	ml	77	Tesco
1.4.3.1.2	Lagers and continental beers	ml	79	Tesco
1.4.2.1.4	Ciders and perry	ml	135	Hoolohan et al, 2013
1.4.2.1.2	Champagne, sparkling wines and wine with mixer	ml	167	Scarborough et al, 2014
1.4.2.1.1	Table wine (White wine)	ml	181	Rugani et al, 2013
1.4.2.1.1	Table wine (Red wine)	ml	145	Rugani et al, 2013
1.4.1.1.3	Spirits with mixer	ml	167	Scarborough et al, 2014
1.4.2.1.3	Fortified wines	ml	167	Scarborough et al, 2014
1.4.1.1.1	Spirits	ml	135.2	Saxe and Henrik, 2010
1.4.2.1.5	Alcopops	ml	72	Scarborough et al, 2014
1.1.7.1.4	Prepared lettuce salads	grams	240	Lukas et al. 2016
1.3.1.8.6	Tea and coffee from takeaway	ml	2298	Tesco

Efscode	Product name	Unit	Emissions (gCO2/100g)	Source
1.1.7.4.1	Fresh potatoes not specified elsewhere	grams	93	Tesco
1.1.7.4.2	Fresh new potatoes	grams	93	Tesco
1.1.7.4.4	Fresh baking potatoes	grams	118	Tesco
1.1.4.6.5	Non-dairy milk substitutes	ml	96	Tesco
1.1.4.6.4	Milk drinks & other milks	ml	123.2	Scarborough et al, 2014

Table A. 2: Emission values per each category listed in the LCF**

**Food products were aggregated in Stata by considering the different macro-categories. The GHGE values were averaged at group level by collapsing in Stata at food category level. No weighting parameter was used. In that case, we would have also needed a dynamic weight because the weight changes with the composition of the food basket.

Variables	Explanation
$\boldsymbol{z_1}$	Instrumental variable for cereal prices
$\boldsymbol{z_2}$	Instrumental variable for dairy prices
$\boldsymbol{z_3}$	Instrumental variable for drinks prices
$\boldsymbol{z_4}$	Instrumental variable for fats prices
$\boldsymbol{z_5}$	Instrumental variable for fish prices
$\boldsymbol{z_6}$	Instrumental variable for fruit prices
$\boldsymbol{z_7}$	Instrumental variable for meat prices
$\boldsymbol{z_8}$	Instrumental variable for potatoes prices
$\boldsymbol{z_9}$	Instrumental variable for ready meals prices
$\boldsymbol{z_{10}}$	Instrumental variable for sweets prices
$\boldsymbol{z_{11}}$	Instrumental variable for vegetables prices
$\boldsymbol{I_h}$	Instrumental variable for household expenditure (household income)

Table A. 3: Variables – 1st stage IV Control Function

Variables	Explanation
$\boldsymbol{p_1}$	Log of cereal prices
$\boldsymbol{p_2}$	Log of dairy prices
$\boldsymbol{p_3}$	Log of drinks prices
$\boldsymbol{p_4}$	Log of fats prices
$\boldsymbol{p_5}$	Log of fish prices
$\boldsymbol{p_6}$	Log of fruit prices
$\boldsymbol{p_7}$	Log of meat prices
$\boldsymbol{p_8}$	Log of potatoes prices
$\boldsymbol{p_9}$	Log of ready meals prices
$\boldsymbol{p_{10}}$	Log of sweets prices
$\boldsymbol{p_{11}}$	Log of vegetables prices

Table A. 4: Variables - 1st stage Probit

Food Group	Cereals	D&E	Drinks	F,O&S	Fish	Fruit	Meat	Potatoes	RM	Sweets	Veg.	Exp.
Cereals	-1.03***	.434***	.862***	.645***	.689***	.248***	1.09***	1.436***	1.35***	.948***	.824***	**1.18*** **
	(.025)	(.009)	(.001)	(.006)	(.006)	(.012)	(.001)	(.006)	(.006)	(.001)	(.002)	**(.001)**
D&E		-1.20***	1.15***	1.101***	.883***	.841***	1.38***	1.200***	.915***	1.001***	1.16***	**1.37*** **
		(.027)	(.001)	(.001)	(.002)	(.002)	(.004)	(.003)	(.001)	(.001)	(.002)	**(.003)**
Drinks			-.791***	.872***	.768***	.914***	.712***	.749***	.564***	.712***	1.05***	**1.09*** **
			(.009)	(.002)	(.004)	(.001)	(.004)	(.003)	(.007)	(.004)	(.001)	**(.001)**
F,O&S				-2.405***	1.03***	1.08***	1.164***	1.070***	.855***	.756***	.872***	**1.08*** **
				(.054)	(.001)	(.001)	(.002)	(.001)	(.002)	(.004)	(.002)	**(.001)**
Fish					-1.28***	.768***	.821***	.983***	.393***	.623***	.733***	**.777*** **
					(.023)	(.005)	(.003)	(.001)	(.015)	(.007)	(.005)	**(.003)**
Fruit						-1.73***	1.19***	.906***	.823***	1.097***	.912***	**1.32*** **
						(.026)	(.002)	(.001)	(.004)	(.002)	(.001)	**(.004)**
Meat							-1.714***	.845***	.829***	.868***	.542***	**.748*** **
							(.018)	(.002)	(.002)	(.001)	(.005)	**(.002)**
Potatoes								-4.86***	1.004***	.995***	.224***	**.986*** **
								(.054)	(.001)	(.001)	(.010)	**(.001)**
RM									-1.28***	.685***	.858***	**.474*** **
									(.015)	(.005)	(.003)	**(.006)**
Sweets										-1.61***	.716***	**.875*** **
										(.017)	(.003)	**(.001)**
Veg.											-1.78***	**1.307*** **
											(.027)	**(.002)**

Table A. 5: Mean compensated own, cross price elasticities of demand and expenditure - second aggregation (considering only endogeneity of expenditure)

Food Group	Budget Share (%)	Budget Share scenario (A) (%)	Budget Share scenario (B) (%)	Δ scenario (A) (%)	p-values Δ scenario A	Δ scenario (B) (%)	p-values Δ scenario B
Cereals	8.8	8.7	8.8	-1.1	-0.2	0.000	0.000
D&E	11.2	10.9	11.1	-2.9	-1.0	0.000	0.000
Drinks	16.3	16.0	16.1	-1.6	-1.1	0.000	0.000
F,O&S	4.0	4.0	4.0	-0.4	0.1	0.000	0.000
Fish	4.4	4.4	4.3	0.1	-2.0	0.038	0.000
Fruit	7.1	6.8	7.0	-4.4	-2.3	0.000	0.000
Meat	14.2	14.7	14.5	3.4	2.1	0.000	0.000
Potatoes	4.4	4.4	4.4	0.4	0.4	0.000	0.000
RM	9.6	10.4	10.0	8.2	4.7	0.000	0.000
Sweets	11.7	11.8	11.7	0.2	-0.5	0.000	0.000
Veg.	8.3	8.0	8.1	-3.5	-1.9	0.000	0.000

Table A. 6: Budget share changes in scenario (A) and (B) (considering only endogeneity of expenditure)

Appendix B

Stata Codes Almost Ideal Demand System Estimation And Simulation

```
*generate regional prices and substitute them when prices are missing

foreach var of varlist price_cereals price_diary_eggs price_drinks price_fats_spreads price_fish price_fruit
price_meat price_potatoes price_ready_meals price_sweets price_vegetables {
egen p_`var'_gorx = mean(`var'), by(Gorx)
}

foreach var of varlist price_cereals price_diary_eggs price_drinks price_fats_spreads price_fish price_fruit
price_meat price_potatoes price_ready_meals price_sweets price_vegetables {
replace `var' =  p_`var'_gorx if `var' == 0
}

*generate log of prices

gen lnp1 = ln( price_cereals )
gen lnp2 = ln( price_diary_eggs )
gen lnp3 = ln( price_drinks )
gen lnp4 = ln( price_fats_spreads)
gen lnp5 = ln(price_fish)
gen lnp6 = ln( price_fruit )
gen lnp7 = ln( price_meat )
gen lnp8 = ln( price_potatoes)
gen lnp9 = ln( price_ready_meals)
gen lnp10 = ln( price_sweets )
gen lnp11 = ln( price_vegetables)

*generate instruments for prices (prices of different months and regions)

*CEREALS

egen tot_exp_cer = sum( expenditureCEREALS )
egen tot_exp_cer_region = sum(expenditureCEREALS), by(Gorx month)
egen tot_quantity_cer = sum( quantityCEREALS )
egen tot_quantity_cer_region = sum( quantityCEREALS ) , by(Gorx month)
gen p_1 = (tot_exp_cer - tot_exp_cer_region)/(tot_quantity_cer -  tot_quantity_cer_region)
gen ln_p_1 = ln(p_1)
gen price_cereals_region = tot_exp_cer_region/tot_quantity_cer_region

DAIRY AND EGGS

egen tot_exp_dairy = sum( expenditureDIARY_EGGS )
egen tot_exp_dairy_region = sum( expenditureDIARY_EGGS), by(Gorx month)
egen tot_quantity_dairy = sum( quantityDIARY_EGGS )
egen tot_quantity_dairy_region = sum( quantityDIARY_EGGS), by(Gorx month)
gen p_2 = (tot_exp_dairy - tot_exp_dairy_region)/(tot_quantity_dairy - tot_quantity_dairy_region)
gen ln_p_2 = ln(p_2)
gen price_dairy_region = tot_exp_dairy_region/tot_quantity_dairy_region

*DRINKS

egen tot_exp_drinks = sum( expenditureDRINKS )
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx month)
egen tot_quantity_drinks = sum( quantityDRINKS )
```

```
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx month)
gen p_3 = (tot_exp_drinks - tot_exp_drinks_region)/(tot_quantity_drinks - tot_quantity_drinks_region)
gen ln_p_3 = ln(p_3)
gen price_drinks_region = tot_exp_drinks_region/tot_quantity_drinks_region

*FATS AND SPREADS

egen tot_exp_fats = sum( expenditureFATS_SPREAD_SAUCES )
egen tot_exp_fats_region = sum( expenditureFATS_SPREAD_SAUCES ), by(Gorx month)
egen tot_quantity_fats = sum( quantityFATS_SPREAD_SAUCES)
egen tot_quantity_fats_region = sum( quantityFATS_SPREAD_SAUCES) , by(Gorx month)
gen p_4 = (tot_exp_fats - tot_exp_fats_region)/(tot_quantity_fats - tot_quantity_fats_region)
gen ln_p_4= ln(p_4)
gen price_fats_region = tot_exp_fats_region/tot_quantity_fats_region

*FISH

egen tot_exp_fish = sum( expenditureFISH )
egen tot_exp_fish_region = sum( expenditureFISH ), by(Gorx month)
egen tot_quantity_fish = sum( quantityFISH )
egen tot_quantity_fish_region = sum( quantityFISH ) , by(Gorx month)
gen p_5 = (tot_exp_fish - tot_exp_fish_region )/(tot_quantity_fish - tot_quantity_fish_region )
gen ln_p_5= ln(p_5)
gen price_fish_region = tot_exp_fish_region/tot_quantity_fish_region

*FRUIT

egen tot_exp_fruit = sum( expenditureFRUIT )
egen tot_exp_fruit_region = sum( expenditureFRUIT ), by(Gorx month)
egen tot_quantity_fruit = sum( quantityFRUIT )
egen tot_quantity_fruit_regions = sum( quantityFRUIT ) , by(Gorx month)
gen p_6 = (tot_exp_fruit - tot_exp_fruit_region)/(tot_quantity_fruit - tot_quantity_fruit_regions)
gen ln_p_6= ln(p_6)
gen price_fruit_region = tot_exp_fruit_region/tot_quantity_fruit_regions

*MEAT

egen tot_exp_meat = sum( expenditureMEAT )
egen tot_exp_meat_region = sum( expenditureMEAT ), by(Gorx month)
egen tot_quantity_meat = sum( quantityMEAT )
egen tot_quantity_meat_region = sum( quantityMEAT ) , by(Gorx month)
gen p_7 = (tot_exp_meat - tot_exp_meat_region)/(tot_quantity_meat - tot_quantity_meat_region)
gen ln_p_7= ln(p_7)
gen price_meat_region = tot_exp_meat_region/tot_quantity_meat_region

*POTATOES

egen tot_exp_potatoes = sum( expenditurePOTATOES )
egen tot_exp_potatoes_region = sum( expenditurePOTATOES ), by(Gorx month)
egen tot_quantity_potatoes = sum( quantityPOTATOES )
egen tot_quantity_potatoes_regions = sum( quantityPOTATOES ) , by(Gorx month)

gen p_8 = (tot_exp_potatoes - tot_exp_potatoes_region)/(tot_quantity_potatoes -
tot_quantity_potatoes_regions)
gen ln_p_8= ln(p_8)
gen price_potatoes_region = tot_exp_potatoes_region/tot_quantity_potatoes_regions

*READY MEALS

egen tot_exp_ready = sum( expenditureREADY_MEALS )
egen tot_exp_ready_region = sum( expenditureREADY_MEALS ), by(Gorx month)
```

```
egen tot_quantity_ready = sum( quantityREADY_MEALS )
egen tot_quantity_ready_region = sum( quantityREADY_MEALS ) , by(Gorx month)
gen p_9 = (tot_exp_ready - tot_exp_ready_region)/(tot_quantity_ready - tot_quantity_ready_region)
gen ln_p_9= ln(p_9)
gen price_ready_region = tot_exp_ready_region/tot_quantity_ready_region

*SWEETS

egen tot_exp_sweets = sum( expenditureSWEETS )
egen tot_exp_sweets_region = sum( expenditureSWEETS ), by(Gorx month)
egen tot_quantity_sweets = sum( quantitySWEETS )
egen tot_quantity_sweets_regions = sum( quantitySWEETS ) , by(Gorx month)
gen p_10 = (tot_exp_sweets - tot_exp_sweets_region)/(tot_quantity_sweets - tot_quantity_sweets_regions)
gen ln_p_10= ln(p_10)
gen price_sweets_region = tot_exp_sweets_region/tot_quantity_sweets_regions

*VEGETABLES

egen tot_exp_veg = sum( expenditureVEGETABLES )
egen tot_exp_veg_region = sum( expenditureVEGETABLES ), by(Gorx month)
egen tot_quantity_veg = sum( quantityVEGETABLES )
egen tot_quantity_veg_region = sum( quantityVEGETABLES ) , by(Gorx month)
gen p_11 = (tot_exp_veg - tot_exp_veg_region)/(tot_quantity_veg - tot_quantity_veg_region)
gen ln_p_11= ln(p_11)
gen price_veg_region = tot_exp_veg_region/tot_quantity_veg_region

*gen Stone Price Index

gen lnP_Index =
[(w1*lnp1)+(w2*lnp2)+(w3*lnp3)+(w4*lnp4)+(w5*lnp5)+(w6*lnp6)+(w7*lnp7)+(w8*lnp8)+(w9*l
np9)+(w10*lnp10)+(w11*lnp11)]

*gen household expenditure

gen hh_expenditure = expenditureCEREALS + expenditureDIARY_EGGS + expenditureDRINKS
+expenditureFATS_SPREAD_SAUCES + expenditureFISH + expenditureFRUIT + expenditureMEAT +
expenditurePOTATOES + expenditureREADY_MEALS + expenditureSWEETS + expenditureVEGETABLES

gen ln_hh_expenditure = ln(hh_expenditure)

*gen real expenditure

gen lnm = ln(hh_expenditure/exp(lnP_Index))

*generate covariates at household level

global covariates size age_HRP sex_oldest

*gen log of income as instrument

gen ln_income = ln(income_pence)

*First stage control function (IV) for each price and expenditure

reg lnp1 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp1, res
test ln_p_1

reg lnp2 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp2, res
test ln_p_2
```

```
reg lnp3 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp3, res
test ln_p_3

reg lnp4 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp4, res
test ln_p_4

reg lnp5 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp5, res
test ln_p_5

reg lnp6 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp6, res
test ln_p_6

reg lnp7 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp7, res
test ln_p_7

reg lnp8 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp8, res
test ln_p_8

reg lnp9 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp9, res
test ln_p_9

reg lnp10 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp10, res
test ln_p_10

reg lnp11 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict res_lnp11, res
test ln_p_11

reg ln_hh_expenditure ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11
ln_income $covariates
predict res_hh_expenditure, res
test ln_income

*gen probability that each food category was purchased

gen dw1=1 if w1>0
replace dw1=0 if w1==0

gen dw2=1 if w2>0
replace dw2=0 if w2==0

gen dw3=1 if w3>0
replace dw3=0 if w3==0

gen dw4=1 if w4>0
```

```
replace dw4=0 if w4==0

gen dw5=1 if w5>0
replace dw5=0 if w5==0

gen dw6=1 if w6>0
replace dw6=0 if w6==0

gen dw7=1 if w7>0
replace dw7=0 if w7==0

gen dw8=1 if w8>0
replace dw8=0 if w8==0

gen dw9=1 if w9>0
replace dw9=0 if w9==0

gen dw10=1 if w10>0
replace dw10=0 if w10==0

gen dw11=1 if w11>0
replace dw11=0 if w11==0

*Fist stage Probit estimation for sample selection and generation of Inverse Mills Ratio

probit dw1 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb1
gen imr1 = normalden(xb1)/normal(xb1)
gen imr1c=(normalden(xb1)/(1-normal(xb1)))
replace imr1=imr1c if w1==0

probit dw2 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb2
gen imr2 = normalden(xb2)/normal(xb2)
gen imr2c=(normalden(xb2)/(1-normal(xb2)))
replace imr2=imr2c if w2==0

probit dw3 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb3
gen imr3 = normalden(xb3)/normal(xb3)
gen imr3c=(normalden(xb3)/(1-normal(xb3)))
replace imr3=imr3c if w3==0

probit dw4 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb4
gen imr4 = normalden(xb4)/normal(xb4)
gen imr4c=(normalden(xb4)/(1-normal(xb4)))
replace imr4=imr4c if w4==0

probit dw5 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb5
gen imr5 = normalden(xb5)/normal(xb5)
gen imr5c=(normalden(xb5)/(1-normal(xb5)))
replace imr5=imr5c if w5==0

probit dw6 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb6
gen imr6 = normalden(xb6)/normal(xb6)
gen imr6c=(normalden(xb6)/(1-normal(xb6)))
replace imr6=imr6c if w6==0

probit dw7 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
```

```
predict xb7
gen imr7 = normalden(xb7)/normal(xb7)
gen imr7c=(normalden(xb7)/(1-normal(xb7)))
replace imr7=imr7c if w7==0

probit dw8 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb8
gen imr8 = normalden(xb8)/normal(xb8)
gen imr8c=(normalden(xb8)/(1-normal(xb8)))
replace imr8=imr8c if w8==0

probit dw9 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb9
gen imr9 = normalden(xb9)/normal(xb9)
gen imr9c=(normalden(xb9)/(1-normal(xb9)))
replace imr9=imr9c if w9==0

probit dw10 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb10
gen imr10 = normalden(xb10)/normal(xb10)
gen imr10c=(normalden(xb10)/(1-normal(xb10)))
replace imr10=imr10c if w10==0

probit dw11 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb11
gen imr11 = normalden(xb11)/normal(xb11)
gen imr11c=(normalden(xb11)/(1-normal(xb11)))
replace imr11=imr11c if w11==0

*restriction AIDS

gen p11 = (lnp11 - lnp1)
gen p2 = (lnp2 - lnp1)
gen p3 = (lnp3 - lnp1)
gen p4 = (lnp4 - lnp1)
gen p5 = (lnp5 - lnp1)
gen p6 = (lnp6 - lnp1)
gen p7 = (lnp7 - lnp1)
gen p8 = (lnp8 - lnp1)
gen p9 = (lnp9 - lnp1)
gen p10 = (lnp10 - lnp1)

*AIDS ESTIMATION

nlsur (w2=
{_cons2}+{p22}*p2+{p23}*p3+{p24}*p4+{p25}*p5+{p26}*p6+{p27}*p7+{p28}*p8+{p29}*p9+{p210}
*p10+{p211}*p11+{b2}*lnm+{x2:$covariates}+{z2:imr2 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3
res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w3 =
{_cons3}+{p23}*p2+{p33}*p3+{p34}*p4+{p35}*p5+{p36}*p6+{p37}*p7+{p38}*p8+{p39}*p9+{p310}
*p10+{p311}*p11+{b3}*lnm+{x3:$covariates}+{z3: imr3 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3
res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w4 =
{_cons4}+{p24}*p2+{p34}*p3+{p44}*p4+{p45}*p5+{p46}*p6+{p47}*p7+{p48}*p8+{p49}*p9+{p410}
*p10+{p411}*p11+{b4}*lnm+{x4:$covariates}+{z4:imr4 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3
res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w5 =
{_cons5}+{p25}*p2+{p35}*p3+{p45}*p4+{p55}*p5+{p56}*p6+{p57}*p7+{p58}*p8+{p59}*p9+{p510}
*p10+{p511}*p11+{b5}*lnm+{x5:$covariates}+{z5:imr5 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3
res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
```

(w6 =
{_cons6}+{p26}*p2+{p36}*p3+{p46}*p4+{p56}*p5+{p66}*p6+{p67}*p7+{p68}*p8+{p69}*p9+{p610}*p10+{p611}*p11+{b6}*lnm+{x6:$covariates}+{z6: imr6 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w7 =
{_cons7}+{p27}*p2+{p37}*p3+{p47}*p4+{p57}*p5+{p67}*p6+{p77}*p7+{p78}*p8+{p79}*p9+{p710}*p10+{p711}*p11+{b7}*lnm+{x7:$covariates}+{z7:imr7 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w8 =
{_cons8}+{p28}*p2+{p38}*p3+{p48}*p4+{p58}*p5+{p68}*p6+{p78}*p7+{p88}*p8+{p89}*p9+{p810}*p10+{p811}*p11+{b8}*lnm+{x8:$covariates}+{z8:imr8 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w9 =
{_cons9}+{p29}*p2+{p39}*p3+{p49}*p4+{p59}*p5+{p69}*p6+{p79}*p7+{p89}*p8+{p99}*p9+{p910}*p10+{p911}*p11+{b9}*lnm+{x9:$covariates}+{z9:imr9 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w10 =
{_cons10}+{p210}*p2+{p310}*p3+{p410}*p4+{p510}*p5+{p610}*p6+{p710}*p7+{p810}*p8+{p910}*p9+{p1010}*p10+{p1011}*p11+{b10}*lnm+{x10:$covariates}+{z10:imr10 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w11{_cons11}+{p211}*p2+{p311}*p3+{p411}*p4+{p511}*p5+{p611}*p6+{p711}*p7+{p811}*p8+{p911}*p9+{p1011}*p10+{p1111}*p11+{b11}*lnm+{x11:$covariates}+{z11:imr11 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11}), variables (w2 w3 w4 w5 w6 w7 w8 w9 w10 w11 p2 p3 p4 p5 p6 p7 p8 p9 p10 p11 lnm imr2 imr3 imr3 imr4 imr5 imr6 imr7 imr8 imr9 imr10 imr11 res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11 res_hh_expenditure $covariates)

*predict initial budget share from the model

predict w_dairy, equation(#1)

predict w_drinks, equation(#2)

predict w_fats, equation(#3)

predict w_fish, equation(#4)

predict w_fruit, equation(#5)

predict w_meat, equation(#6)

predict w_potatoes, equation(#7)

predict w_ready, equation(#8)

predict w_sweets, equation(#9)

predict w_veg, equation(#10)

gen w_cereals = 1 -
(w_dairy+w_drinks+w_fats+w_fish+w_fruit+w_meat+w_potatoes+w_ready+w_sweets+w_veg)

*estimate the coefficients from the missing equation

nlcom
(lnp_w2_w2:[p22]_cons)(lnp_w2_w3:[p23]_cons)(lnp_w2_w4:[p24]_cons)(lnp_w2_w5:[p25]_cons)(lnp_w2_w6:[p26]_cons)(lnp_w2_w7:[p27]_cons)(lnp_w2_w8:[p28]_cons)(lnp_w2_w9:[p29]_cons)(lnp_w2_w10:[p210]_cons)(lnp_w2_w11:[p211]_cons)(lnp_w3_w3:[p33]_cons)(lnp_w3_w4:[p34]_cons)(lnp_w3_w5:[p35]_cons)(lnp_w3_w6:[p36]_cons)(lnp_w3_w7:[p37]_cons)(lnp_w3_w8:[p38]_cons)(lnp_w3_w9:[p39]_cons)(lnp_w3_w10:[p310]_cons)(lnp_w3_w11:[p311]_cons)(lnp_w4_w4:[p44]_cons)(lnp_w4_w5:[p45]_cons)(lnp_w4_w6:[p46]_cons)(lnp_w4_w7:[p47]_cons)(lnp_w4_w8:[p48]_cons)(lnp_w4_w9:[p49]_cons)(lnp_w4_w10:[p410]_cons)(lnp_w4_w11:[p411]_cons)(lnp_w5_w5:[p55]_cons)(lnp_w5_w6:[p56]_cons)(lnp_w

5_w7:[p57]_cons)(lnp_w5_w8:[p58]_cons)(lnp_w5_w9:[p59]_cons)(lnp_w5_w10:[p510]_cons)(lnp_w5_w11:[p511]_cons)(lnp_w6_w6:[p66]_cons)(lnp_w6_w7:[p67]_cons)(lnp_w6_w8:[p68]_cons)(lnp_w6_w9:[p69]_cons)(lnp_w6_w10:[p610]_cons)(lnp_w6_w11:[p611]_cons)(lnp_w7_w7:[p77]_cons)(lnp_w7_w8:[p78]_cons)(lnp_w7_w9:[p79]_cons)(lnp_w7_w10:[p710]_cons)(lnp_w7_w11:[p711]_cons)(lnp_w8_w8:[p88]_cons)(lnp_w8_w9:[p89]_cons)(lnp_w8_w10:[p810]_cons)(lnp_w8_w11:[p811]_cons)(lnp_w9_w9:[p99]_cons)(lnp_w9_w10:[p910]_cons)(lnp_w9_w11:[p911]_cons)(lnp_w10_w10:[p1010]_cons)(lnp_w10_w11:[p1011]_cons)(lnp_w11_w11:[p1111]_cons)(lnp_w1_w2:0-[p22]_cons-[p23]_cons-[p24]_cons-[p25]_cons-[p26]_cons-[p27]_cons-[p28]_cons-[p29]_cons-[p210]_cons-[p211]_cons)(lnp_w1_w3:0-[p23]_cons-[p33]_cons-[p34]_cons-[p35]_cons-[p36]_cons-[p37]_cons-[p38]_cons-[p39]_cons-[p310]_cons-[p311]_cons)(lnp_w1_w4:0-[p24]_cons-[p34]_cons-[p44]_cons-[p45]_cons-[p46]_cons-[p47]_cons-[p48]_cons-[p49]_cons-[p410]_cons-[p411]_cons)(lnp_w1_w5:0-[p25]_cons-[p35]_cons-[p45]_cons-[p55]_cons-[p56]_cons-[p57]_cons-[p58]_cons-[p59]_cons-[p510]_cons-[p511]_cons)(lnp_w1_w6:0-[p26]_cons-[p36]_cons-[p46]_cons-[p56]_cons-[p66]_cons-[p67]_cons-[p68]_cons-[p69]_cons-[p610]_cons-[p611]_cons)(lnp_w1_w7:0-[p27]_cons-[p37]_cons-[p47]_cons-[p57]_cons-[p67]_cons-[p77]_cons-[p78]_cons-[p79]_cons-[p710]_cons-[p711]_cons)(lnp_w1_w8:0-[p28]_cons-[p38]_cons-[p48]_cons-[p58]_cons-[p68]_cons-[p78]_cons-[p88]_cons-[p89]_cons-[p810]_cons-[p811]_cons)(lnp_w1_w9:0-[p29]_cons-[p39]_cons-[p49]_cons-[p59]_cons-[p69]_cons-[p79]_cons-[p89]_cons-[p99]_cons-[p910]_cons-[p911]_cons)(lnp_w1_w10:0-[p210]_cons-[p310]_cons-[p410]_cons-[p510]_cons-[p610]_cons-[p710]_cons-[p810]_cons-[p910]_cons-[p1010]_cons-[p1011]_cons)(lnp_w1_w11:0-[p211]_cons-[p311]_cons-[p411]_cons-[p511]_cons-[p611]_cons-[p711]_cons-[p811]_cons-[p911]_cons-[p1011]_cons-[p1111]_cons)(b2:[b2]_cons)(b3:[b3]_cons)(b4:[b4]_cons)(b5:[b5]_cons)(b6:[b6]_cons)(b7:[b7]_cons)(b8:[b8]_cons)(b9:[b9]_cons)(b10:[b10]_cons)(b11:[b11]_cons)(lnp_w1_w1:0-(0-[p22]_cons-[p23]_cons-[p24]_cons-[p25]_cons-[p26]_cons-[p27]_cons-[p28]_cons-[p29]_cons-[p210]_cons-[p211]_cons)-(0-[p23]_cons-[p33]_cons-[p34]_cons-[p35]_cons-[p36]_cons-[p37]_cons-[p38]_cons-[p39]_cons-[p310]_cons-[p311]_cons)-(0-[p24]_cons-[p34]_cons-[p44]_cons-[p45]_cons-[p46]_cons-[p47]_cons-[p48]_cons-[p49]_cons-[p410]_cons-[p411]_cons)-(0-[p25]_cons-[p35]_cons-[p45]_cons-[p55]_cons-[p56]_cons-[p57]_cons-[p58]_cons-[p59]_cons-[p510]_cons-[p511]_cons)-(0-[p26]_cons-[p36]_cons-[p46]_cons-[p56]_cons-[p66]_cons-[p67]_cons-[p68]_cons-[p69]_cons-[p610]_cons-[p611]_cons)-(0-[p27]_cons-[p37]_cons-[p47]_cons-[p57]_cons-[p67]_cons-[p77]_cons-[p78]_cons-[p79]_cons-[p710]_cons-[p711]_cons)-(0-[p28]_cons-[p38]_cons-[p48]_cons-[p58]_cons-[p68]_cons-[p78]_cons-[p88]_cons-[p89]_cons-[p810]_cons-[p811]_cons)-(0-[p29]_cons-[p39]_cons-[p49]_cons-[p59]_cons-[p69]_cons-[p79]_cons-[p89]_cons-[p99]_cons-[p910]_cons-[p911]_cons)-(0-[p210]_cons-[p310]_cons-[p410]_cons-[p510]_cons-[p610]_cons-[p710]_cons-[p810]_cons-[p910]_cons-[p1010]_cons-[p1011]_cons)-(0-[p211]_cons-[p311]_cons-[p411]_cons-[p511]_cons-[p611]_cons-[p711]_cons-[p811]_cons-[p911]_cons-[p1011]_cons-[p1111]_cons))(_cons1:1-[_cons2]_cons-[_cons3]_cons-[_cons4]_cons-[_cons5]_cons-[_cons6]_cons-[_cons7]_cons-[_cons8]_cons-[_cons9]_cons-[_cons10]_cons-[_cons11]_cons)(b1: 0-[b2]_cons-[b3]_cons-[b4]_cons-[b5]_cons-[b6]_cons-[b7]_cons-[b8]_cons-[b9]_cons-[b10]_cons-[b11]_cons)(x1_size: 0-[x2_size]_cons-[x3_size]_cons-[x4_size]_cons-[x5_size]_cons-[x6_size]_cons-[x7_size]_cons-[x8_size]_cons-[x9_size]_cons-[x10_size]_cons-[x11_size]_cons)(x1_age_HRP: 0-[x2_age_HRP]_cons-[x3_age_HRP]_cons-[x4_age_HRP]_cons-[x5_age_HRP]_cons-[x6_age_HRP]_cons-[x7_age_HRP]_cons-[x8_age_HRP]_cons-[x9_age_HRP]_cons-[x10_age_HRP]_cons-[x11_age_HRP]_cons)(x1_sex: 0-[x2_sex_oldest]_cons-[x3_sex_oldest]_cons-[x4_sex_oldest]_cons-[x5_sex_oldest]_cons-[x6_sex_oldest]_cons-[x7_sex_oldest]_cons-[x8_sex_oldest]_cons-[x9_sex_oldest]_cons-[x10_sex_oldest]_cons-[x11_sex_oldest]_cons)(z1_res_lnp1: 0 -[z2_res_lnp1]_cons-[z3_res_lnp1]_cons-[z4_res_lnp1]_cons-[z5_res_lnp1]_cons-[z6_res_lnp1]_cons-[z7_res_lnp1]_cons-[z8_res_lnp1]_cons-[z9_res_lnp1]_cons-[z10_res_lnp1]_cons-[z11_res_lnp1]_cons)(z1_res_lnp2: 0- [z2_res_lnp2]_cons-[z3_res_lnp2]_cons-[z4_res_lnp2]_cons-[z5_res_lnp2]_cons-[z6_res_lnp2]_cons-[z7_res_lnp2]_cons-[z8_res_lnp2]_cons-[z9_res_lnp2]_cons-[z10_res_lnp2]_cons-[z11_res_lnp2]_cons)(z1_res_lnp3: 0 - [z2_res_lnp3]_cons-[z3_res_lnp3]_cons-[z4_res_lnp3]_cons-[z5_res_lnp3]_cons-[z6_res_lnp3]_cons-[z7_res_lnp3]_cons-[z8_res_lnp3]_cons-[z9_res_lnp3]_cons-[z10_res_lnp3]_cons -[z11_res_lnp3]_cons)(z1_res_lnp4: 0- [z2_res_lnp4]_cons-[z3_res_lnp4]_cons-[z4_res_lnp4]_cons-[z5_res_lnp4]_cons-[z6_res_lnp4]_cons-[z7_res_lnp4]_cons-[z8_res_lnp4]_cons-[z9_res_lnp4]_cons-[z10_res_lnp4]_cons -[z11_res_lnp4]_cons)(z1_res_lnp5: 0-[z2_res_lnp5]_cons-[z3_res_lnp5]_cons-[z4_res_lnp5]_cons-[z5_res_lnp5]_cons-[z6_res_lnp5]_cons-[z7_res_lnp5]_cons-[z8_res_lnp5]_cons-[z9_res_lnp5]_cons-[z10_res_lnp5]_cons -[z11_res_lnp5]_cons)(z1_res_lnp6: 0-[z2_res_lnp6]_cons-[z3_res_lnp6]_cons-[z4_res_lnp6]_cons-

```
[z5_res_lnp6]_cons-[z6_res_lnp6]_cons-[z7_res_lnp6]_cons-[z8_res_lnp6]_cons-[z9_res_lnp6]_cons-
[z10_res_lnp6]_cons-[z11_res_lnp6]_cons)(z1_res_lnp7: 0-[z2_res_lnp7]_cons-[z3_res_lnp7]_cons-
[z4_res_lnp7]_cons-[z5_res_lnp7]_cons-[z6_res_lnp7]_cons-[z7_res_lnp7]_cons-[z8_res_lnp7]_cons-
[z9_res_lnp7]_cons-[z10_res_lnp7]_cons-[z11_res_lnp7]_cons)(z1_res_lnp8: 0-[z2_res_lnp8]_cons-
[z3_res_lnp8]_cons-[z4_res_lnp8]_cons-[z5_res_lnp8]_cons-[z6_res_lnp8]_cons-[z7_res_lnp8]_cons-
[z8_res_lnp8]_cons-[z9_res_lnp8]_cons-[z10_res_lnp8]_cons-[z11_res_lnp8]_cons)(z1_res_lnp9: 0 -
[z2_res_lnp9]_cons-[z3_res_lnp9]_cons-[z4_res_lnp9]_cons-[z5_res_lnp9]_cons-[z6_res_lnp9]_cons-
[z7_res_lnp9]_cons-[z8_res_lnp9]_cons-[z9_res_lnp9]_cons-[z10_res_lnp9]_cons -
[z11_res_lnp9]_cons)(z1_res_lnp10: 0-[z2_res_lnp10]_cons-[z3_res_lnp10]_cons-[z4_res_lnp10]_cons-
[z5_res_lnp10]_cons-[z6_res_lnp10]_cons-[z7_res_lnp10]_cons-[z8_res_lnp10]_cons-[z9_res_lnp10]_cons-
[z10_res_lnp10]_cons-[z11_res_lnp10]_cons)(z1_res_lnp11: 0-[z2_res_lnp11]_cons-[z3_res_lnp11]_cons-
[z4_res_lnp11]_cons-[z5_res_lnp11]_cons-[z6_res_lnp11]_cons-[z7_res_lnp11]_cons-[z8_res_lnp11]_cons-
[z9_res_lnp11]_cons-[z10_res_lnp11]_cons-[z11_res_lnp11]_cons)(z1_res_hh_expenditure: 0 -
[z2_res_hh_expenditure]_cons-[z3_res_hh_expenditure]_cons-[z4_res_hh_expenditure]_cons-
[z5_res_hh_expenditure]_cons-[z6_res_hh_expenditure]_cons-[z7_res_hh_expenditure]_cons-
[z8_res_hh_expenditure]_cons-[z9_res_hh_expenditure]_cons-[z10_res_hh_expenditure]_cons-
[z11_res_hh_expenditure]_cons), post
```

```
*predict own/cross price and expenditure elasticities
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```
predictnl own_w1 = 1+(_b[lnp_w1_w1]/(w1^2))-(1/w1), se(own_w1_se)
predictnl e_w1_w2 = 1+(_b[lnp_w1_w2]/(w1*w2)), se(e_w1_w2_se)
predictnl e_w1_w3 = 1+(_b[lnp_w1_w3]/(w1*w3)), se(e_w1_w3_se)
predictnl e_w1_w4 = 1+(_b[lnp_w1_w4]/(w1*w4)), se(e_w1_w4_se)
predictnl e_w1_w5 = 1+(_b[lnp_w1_w5]/(w1*w5)), se(e_w1_w5_se)
predictnl e_w1_w6 = 1+(_b[lnp_w1_w6]/(w1*w6)), se(e_w1_w6_se)
predictnl e_w1_w7 = 1+(_b[lnp_w1_w7]/(w1*w7)), se(e_w1_w7_se)
predictnl e_w1_w8 = 1+(_b[lnp_w1_w8]/(w1*w8)), se(e_w1_w8_se)
predictnl e_w1_w9 = 1+(_b[lnp_w1_w9]/(w1*w9)), se(e_w1_w9_se)
predictnl e_w1_w10 = 1+(_b[lnp_w1_w10]/(w1*w10)), se(e_w1_w10_se)
predictnl e_w1_w11 = 1+(_b[lnp_w1_w11]/(w1*w11)), se(e_w1_w11_se)
predictnl own_w2 = 1+(_b[lnp_w2_w2]/(w2^2))-(1/w2), se(own_w2_se)
predictnl e_w2_w3 = 1+(_b[lnp_w2_w3]/(w2*w3)), se(e_w2_w3_se)
predictnl e_w2_w4 = 1+(_b[lnp_w2_w4]/(w2*w4)), se(e_w2_w4_se)
predictnl e_w2_w5 = 1+(_b[lnp_w2_w5]/(w2*w5)), se(e_w2_w5_se)
predictnl e_w2_w6 = 1+(_b[lnp_w2_w6]/(w2*w6)), se(e_w2_w6_se)
predictnl e_w2_w7 = 1+(_b[lnp_w2_w7]/(w2*w7)), se(e_w2_w7_se)
predictnl e_w2_w8 = 1+(_b[lnp_w2_w8]/(w2*w8)), se(e_w2_w8_se)
predictnl e_w2_w9 = 1+(_b[lnp_w2_w9]/(w2*w9)), se(e_w2_w9_se)
predictnl e_w2_w10 = 1+(_b[lnp_w2_w10]/(w2*w10)), se(e_w2_w10_se)
predictnl e_w2_w11 = 1+(_b[lnp_w2_w11]/(w2*w11)), se(e_w2_w11_se)
predictnl own_w3 = 1+(_b[lnp_w3_w3]/(w3^2))-(1/w3), se(own_w3_se)
predictnl e_w3_w4 = 1+(_b[lnp_w3_w4]/(w3*w4)), se(e_w3_w4_se)
predictnl e_w3_w5 = 1+(_b[lnp_w3_w5]/(w3*w5)), se(e_w3_w5_se)
predictnl e_w3_w6 = 1+(_b[lnp_w3_w6]/(w3*w6)), se(e_w3_w6_se)
predictnl e_w3_w7 = 1+(_b[lnp_w3_w7]/(w3*w7)), se(e_w3_w7_se)
predictnl e_w3_w8 = 1+(_b[lnp_w3_w8]/(w3*w8)), se(e_w3_w8_se)
predictnl e_w3_w9 = 1+(_b[lnp_w3_w9]/(w3*w9)), se(e_w3_w9_se)
predictnl e_w3_w10 = 1+(_b[lnp_w3_w10]/(w3*w10)), se(e_w3_w10_se)
predictnl e_w3_w11 = 1+(_b[lnp_w3_w11]/(w3*w11)), se(e_w3_w11_se)
predictnl own_w4 = 1+(_b[lnp_w4_w4]/(w4^2))-(1/w4), se(own_w4_se)
predictnl e_w4_w5 = 1+(_b[lnp_w4_w5]/(w4*w5)), se(e_w4_w5_se)
predictnl e_w4_w6 = 1+(_b[lnp_w4_w6]/(w4*w6)), se(e_w4_w6_se)
predictnl e_w4_w7 = 1+(_b[lnp_w4_w7]/(w4*w7)), se(e_w4_w7_se)
predictnl e_w4_w8 = 1+(_b[lnp_w4_w8]/(w4*w8)), se(e_w4_w8_se)
predictnl e_w4_w9 = 1+(_b[lnp_w4_w9]/(w4*w9)), se(e_w4_w9_se)
predictnl e_w4_w10 = 1+(_b[lnp_w4_w10]/(w4*w10)), se(e_w4_w10_se)
```

```
predictnl e_w4_w11 = 1+(_b[lnp_w4_w11]/(w4*w11)), se(e_w4_w11_se)
predictnl own_w5 = 1+(_b[lnp_w5_w5]/(w5^2))-(1/w5), se(own_w5_se)
predictnl e_w5_w6 = 1+(_b[lnp_w5_w6]/(w5*w6)), se(e_w5_w6_se)
predictnl e_w5_w7 = 1+(_b[lnp_w5_w7]/(w5*w7)), se(e_w5_w7_se)
predictnl e_w5_w8 = 1+(_b[lnp_w5_w8]/(w5*w8)), se(e_w5_w8_se)
predictnl e_w5_w9 = 1+(_b[lnp_w5_w9]/(w5*w9)), se(e_w5_w9_se)
predictnl e_w5_w10 = 1+(_b[lnp_w5_w10]/(w5*w10)), se(e_w5_w10_se)
predictnl e_w5_w11 = 1+(_b[lnp_w5_w11]/(w5*w11)), se(e_w5_w11_se)
predictnl own_w6 = 1+(_b[lnp_w6_w6]/(w6^2))-(1/w6), se(own_w6_se)
predictnl e_w6_w7 = 1+(_b[lnp_w6_w7]/(w6*w7)), se(e_w6_w7_se)
predictnl e_w6_w8 = 1+(_b[lnp_w6_w8]/(w6*w8)), se(e_w6_w8_se)
predictnl e_w6_w9 = 1+(_b[lnp_w6_w9]/(w6*w9)), se(e_w6_w9_se)
predictnl e_w6_w10 = 1+(_b[lnp_w6_w10]/(w6*w10)), se(e_w6_w10_se)
predictnl e_w6_w11 = 1+(_b[lnp_w6_w11]/(w6*w11)), se(e_w6_w11_se)
predictnl own_w7 = 1+(_b[lnp_w7_w7]/(w7^2))-(1/w7), se(own_w7_se)
predictnl e_w7_w8 = 1+(_b[lnp_w7_w8]/(w7*w8)), se(e_w7_w8_se)
predictnl e_w7_w9 = 1+(_b[lnp_w7_w9]/(w7*w9)), se(e_w7_w9_se)
predictnl e_w7_w10 = 1+(_b[lnp_w7_w10]/(w7*w10)), se(e_w7_w10_se)
predictnl e_w7_w11 = 1+(_b[lnp_w7_w11]/(w7*w11)), se(e_w7_w11_se)
predictnl own_w8 = 1+(_b[lnp_w8_w8]/(w8^2))-(1/w8), se(own_w8_se)
predictnl e_w8_w9 = 1+(_b[lnp_w8_w9]/(w8*w9)), se(e_w8_w9_se)
predictnl e_w8_w10 = 1+(_b[lnp_w8_w10]/(w8*w10)), se(e_w8_w10_se)
predictnl e_w8_w11 = 1+(_b[lnp_w8_w11]/(w8*w11)), se(e_w8_w11_se)
predictnl own_w9 = 1+(_b[lnp_w9_w9]/(w9^2))-(1/w9), se(own_w9_se)
predictnl e_w9_w10 = 1+(_b[lnp_w9_w10]/(w9*w10)), se(e_w9_w10_se)
predictnl e_w9_w11 = 1+(_b[lnp_w9_w11]/(w9*w11)), se(e_w9_w11_se)
predictnl own_w10 = 1+(_b[lnp_w10_w10]/(w10^2))-(1/w10), se(own_w10_se)
predictnl e_w10_w11 = 1+(_b[lnp_w10_w11]/(w10*w11)), se(e_w10_w11_se)
predictnl own_w11 = 1+(_b[lnp_w11_w11]/(w11^2))-(1/w11), se(own_w11_se)
predictnl expenditure_w1 = 1+(_b[b1]/w1), se(expenditure_w1_se)
predictnl expenditure_w2 = 1+(_b[b2]/w2), se(expenditure_w2_se)
predictnl expenditure_w3 = 1+(_b[b3]/w3), se(expenditure_w3_se)
predictnl expenditure_w4 = 1+(_b[b4]/w4), se(expenditure_w4_se)
predictnl expenditure_w5 = 1+(_b[b5]/w5), se(expenditure_w5_se)
predictnl expenditure_w6 = 1+(_b[b6]/w6), se(expenditure_w6_se)
predictnl expenditure_w7 = 1+(_b[b7]/w7), se(expenditure_w7_se)
predictnl expenditure_w8 = 1+(_b[b8]/w8), se(expenditure_w8_se)
predictnl expenditure_w9 = 1+(_b[b9]/w9), se(expenditure_w9_se)
predictnl expenditure_w10 = 1+(_b[b10]/w10), se(expenditure_w10_se)
predictnl expenditure_w11 = 1+(_b[b11]/w11), se(expenditure_w11_se)

mean own_w1 [aweight = 1/(own_w1_se^2) ]
mean e_w1_w2 [aweight = 1/(e_w1_w2_se^2)]
mean e_w1_w3 [aweight = 1/(e_w1_w3_se^2)]
mean e_w1_w4 [aweight = 1/(e_w1_w4_se^2)]
mean e_w1_w5 [aweight = 1/(e_w1_w5_se^2)]
mean e_w1_w6 [aweight = 1/(e_w1_w6_se^2)]
mean e_w1_w7 [aweight = 1/(e_w1_w7_se^2)]
mean e_w1_w8 [aweight = 1/(e_w1_w8_se^2)]
mean e_w1_w9 [aweight = 1/(e_w1_w9_se^2)]
mean e_w1_w10 [aweight = 1/(e_w1_w10_se^2)]
mean e_w1_w11 [aweight = 1/(e_w1_w11_se^2)]
mean own_w2 [aweight = 1/(own_w2_se^2)]
mean e_w2_w3 [aweight = 1/(e_w2_w3_se^2)]
mean e_w2_w4 [aweight = 1/(e_w2_w4_se^2)]
mean e_w2_w5 [aweight = 1/(e_w2_w5_se^2)]
mean e_w2_w6 [aweight = 1/(e_w2_w6_se^2)]
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mean e_w2_w7 [aweight = 1/(e_w2_w7_se^2)]
mean e_w2_w8 [aweight = 1/(e_w2_w8_se^2)]
mean e_w2_w9 [aweight = 1/(e_w2_w9_se^2)]
mean e_w2_w10 [aweight = 1/(e_w2_w10_se^2)]
mean e_w2_w11 [aweight = 1/(e_w2_w11_se^2)]
mean own_w3 [aweight = 1/(own_w3_se^2)]
mean e_w3_w4 [aweight = 1/(e_w3_w4_se^2)]
mean e_w3_w5 [aweight = 1/(e_w3_w5_se^2)]
mean e_w3_w6 [aweight = 1/(e_w3_w6_se^2)]
mean e_w3_w7 [aweight = 1/(e_w3_w7_se^2)]
mean e_w3_w8 [aweight = 1/(e_w3_w8_se^2)]
mean e_w3_w9 [aweight = 1/(e_w3_w9_se^2)]
mean e_w3_w10 [aweight = 1/(e_w3_w10_se^2)]
mean e_w3_w11 [aweight = 1/(e_w3_w11_se^2)]
mean own_w4 [aweight = 1/(own_w4_se^2)]
mean e_w4_w5 [aweight = 1/(e_w4_w5_se^2)]
mean e_w4_w6 [aweight = 1/(e_w4_w6_se^2)]
mean e_w4_w7 [aweight = 1/(e_w4_w7_se^2)]
mean e_w4_w8 [aweight = 1/(e_w4_w8_se^2)]
mean e_w4_w9 [aweight = 1/(e_w4_w9_se^2)]
mean e_w4_w10 [aweight = 1/(e_w4_w10_se^2)]
mean e_w4_w11 [aweight = 1/(e_w4_w11_se^2)]
mean own_w5 [aweight = 1/(own_w5_se^2)]
mean e_w5_w6 [aweight = 1/(e_w5_w6_se^2)]
mean e_w5_w7 [aweight = 1/(e_w5_w7_se^2)]
mean e_w5_w8 [aweight = 1/(e_w5_w8_se^2)]
mean e_w5_w9 [aweight = 1/(e_w5_w9_se^2)]
mean e_w5_w10 [aweight = 1/(e_w5_w10_se^2)]
mean e_w5_w11 [aweight = 1/(e_w5_w11_se^2)]
mean own_w6 [aweight = 1/(own_w6_se^2) ]
mean e_w6_w7 [aweight = 1/(e_w6_w7_se^2)]
mean e_w6_w8 [aweight = 1/(e_w6_w8_se^2)]
mean e_w6_w9 [aweight = 1/(e_w6_w9_se^2)]
mean e_w6_w10 [aweight = 1/(e_w6_w10_se^2)]
mean e_w6_w11 [aweight = 1/(e_w6_w11_se^2)]
mean own_w7 [aweight = 1/(own_w7_se^2)]
mean e_w7_w8 [aweight = 1/(e_w7_w8_se^2)]
mean e_w7_w9 [aweight = 1/(e_w7_w9_se^2)]
mean e_w7_w10 [aweight = 1/(e_w7_w10_se^2)]
mean e_w7_w11 [aweight = 1/(e_w7_w11_se^2)]
mean own_w8 [aweight = 1/(own_w8_se^2) ]
mean e_w8_w9 [aweight = 1/(e_w8_w9_se^2)]
mean e_w8_w10 [aweight = 1/(e_w8_w10_se^2)]
mean e_w8_w11 [aweight = 1/(e_w8_w11_se^2)]
mean own_w9 [aweight = 1/(own_w9_se^2)]
mean e_w9_w10 [aweight = 1/(e_w9_w10_se^2)]
mean e_w9_w11 [aweight = 1/(e_w9_w11_se^2)]
mean own_w10 [aweight = 1/(own_w10_se^2)]
mean e_w10_w11 [aweight = 1/(e_w10_w11_se^2)]
mean own_w11 [aweight = 1/(own_w11_se^2)]
mean expenditure_w1 [aweight = 1/(expenditure_w1_se)^2]
mean expenditure_w2 [aweight = 1/(expenditure_w2_se)^2]
mean expenditure_w3 [aweight = 1/(expenditure_w3_se)^2]
mean expenditure_w4 [aweight = 1/(expenditure_w4_se)^2]
mean expenditure_w5 [aweight = 1/(expenditure_w5_se)^2]
mean expenditure_w6 [aweight = 1/(expenditure_w6_se)^2]
mean expenditure_w7 [aweight = 1/(expenditure_w7_se)^2]
```

```
mean expenditure_w8 [aweight = 1/(expenditure_w8_se)^2]
mean expenditure_w9 [aweight = 1/(expenditure_w9_se)^2]
mean expenditure_w10 [aweight = 1/(expenditure_w10_se)^2]
mean expenditure_w11 [aweight = 1/(expenditure_w11_se)^2]

*gen carbon tax per emission grams (£70/tonne CO2)

gen k_cereals = 0.007*emission_grams_cereals
gen k_dairy = 0.007*emission_grams_dairy
gen k_drinks = 0.007*emission_grams_drinks
gen k_fats = 0.007*emission_grams_fats
gen k_fish = 0.007*emission_grams_fish
gen k_fruit = 0.007*emission_grams_fruit
gen k_meat = 0.007*emission_grams_meat
gen k_potatoes = 0.007*emission_grams_potatoes
gen k_readymeals = 0.007*emission_grams_readymeals
gen k_sweets = 0.007*emission_grams_sweets
gen k_vegetables = 0.007*emission_grams_vegetables

*gen taxed prices

gen p_cereals_taxed = k_cereals+price_cereals
gen p_dairy_taxed = k_dairy + price_diary_eggs
gen p_drinks_taxed = price_drinks + (k_drinks + 0.2* k_drinks)
gen p_fats_taxed = k_fats + price_fats_spreads
gen p_fish_taxed = k_fish + price_fish
gen p_fruit_taxed = k_fruit+ price_fruit
gen p_meat_taxed = k_meat + price_meat
gen p_potatoes_taxed = k_potatoes+price_potatoes
gen p_ready_meals_taxed = price_ready_meals + (k_readymeals + 0.2*k_readymeals)
gen p_sweets_taxed = price_sweets + ( k_sweets + 0.2* k_sweets )
gen p_vegetables_taxed = k_vegetables+price_vegetables

*gen log of taxed prices

foreach v in p_cereals_taxed p_dairy_taxed p_drinks_taxed p_fats_taxed p_fish_taxed p_fruit_taxed
p_meat_taxed p_potatoes_taxed p_ready_meals_taxed p_sweets_taxed p_vegetables_taxed      {
gen ln`v' = ln(`v')
}

rename lnp_cereals_taxed lnp1t
rename lnp_dairy_taxed lnp2t
rename lnp_drinks_taxed lnp3t
rename lnp_fats_taxed lnp4t
rename lnp_fish_taxed lnp5t
rename lnp_fruit_taxed lnp6t
rename lnp_meat_taxed lnp7t
rename lnp_potatoes_taxed lnp8t
rename lnp_ready_meals_taxed lnp9t
rename lnp_sweets_taxed lnp10t
rename lnp_vegetables_taxed lnp11t

*gen Stone Price Index for taxed prices

gen lnP2_Index =
[(w1*lnp1t)+(w2*lnp2t)+(w3*lnp3t)+(w4*lnp4t)+(w5*lnp5t)+(w6*lnp6t)+(w7*lnp7t)+(w8*lnp8t)+
(w9*lnp9t)+(w10*lnp10t)+(w11*lnp11t)]

*gen real expenditure for taxed prices
```

```
gen lnm2 = ln(hh_expenditure/exp(lnP2_Index))

*Simulation model. Estimate the AIDS. Then replace the prices with the taxed ones. Then predict budget shares after taxation

nlsur (w2 =
{_cons2}+{p22}*p2+{p23}*p3+{p24}*p4+{p25}*p5+{p26}*p6+{p27}*p7+{p28}*p8+{p29}*p9+{p210}*p10+{p211}*p11+{b2}*lnm+{x2:$covariates}+{z2:imr2 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w3 =
{_cons3}+{p23}*p2+{p33}*p3+{p34}*p4+{p35}*p5+{p36}*p6+{p37}*p7+{p38}*p8+{p39}*p9+{p310}*p10+{p311}*p11+{b3}*lnm+{x3:$covariates}+{z3: imr3 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w4 =
{_cons4}+{p24}*p2+{p34}*p3+{p44}*p4+{p45}*p5+{p46}*p6+{p47}*p7+{p48}*p8+{p49}*p9+{p410}*p10+{p411}*p11+{b4}*lnm+{x4:$covariates}+{z4:imr4 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w5 =
{_cons5}+{p25}*p2+{p35}*p3+{p45}*p4+{p55}*p5+{p56}*p6+{p57}*p7+{p58}*p8+{p59}*p9+{p510}*p10+{p511}*p11+{b5}*lnm+{x5:$covariates}+{z5:imr5 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w6 =
{_cons6}+{p26}*p2+{p36}*p3+{p46}*p4+{p56}*p5+{p66}*p6+{p67}*p7+{p68}*p8+{p69}*p9+{p610}*p10+{p611}*p11+{b6}*lnm+{x6:$covariates}+{z6: imr6 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w7 =
{_cons7}+{p27}*p2+{p37}*p3+{p47}*p4+{p57}*p5+{p67}*p6+{p77}*p7+{p78}*p8+{p79}*p9+{p710}*p10+{p711}*p11+{b7}*lnm+{x7:$covariates}+{z7:imr7 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w8 =
{_cons8}+{p28}*p2+{p38}*p3+{p48}*p4+{p58}*p5+{p68}*p6+{p78}*p7+{p88}*p8+{p89}*p9+{p810}*p10+{p811}*p11+{b8}*lnm+{x8:$covariates}+{z8:imr8 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w9 =
{_cons9}+{p29}*p2+{p39}*p3+{p49}*p4+{p59}*p5+{p69}*p6+{p79}*p7+{p89}*p8+{p99}*p9+{p910}*p10+{p911}*p11+{b9}*lnm+{x9:$covariates}+{z9:imr9 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w10 =
{_cons10}+{p210}*p2+{p310}*p3+{p410}*p4+{p510}*p5+{p610}*p6+{p710}*p7+{p810}*p8+{p910}*p9+{p1010}*p10+{p1011}*p11+{b10}*lnm+{x10:$covariates}+{z10:imr10 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11})
(w11 =
{_cons11}+{p211}*p2+{p311}*p3+{p411}*p4+{p511}*p5+{p611}*p6+{p711}*p7+{p811}*p8+{p911}*p9+{p1011}*p10+{p1111}*p11+{b11}*lnm+{x11:$covariates}+{z11:imr11 res_hh_expenditure res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11}),variables (w2 w3 w4 w5 w6 w7 w8 w9 w10 w11 p2 p3 p4 p5 p6 p7 p8 p9 p10 p11 lnm imr2 imr3 imr3 imr4 imr5 imr6 imr7 imr8 imr9 imr10 imr11 res_lnp1 res_lnp2 res_lnp3 res_lnp4 res_lnp5 res_lnp6 res_lnp7 res_lnp8 res_lnp9 res_lnp10 res_lnp11 res_hh_expenditure $covariates)

*replace the prices with the new taxed prices

rename p2 p2_old
gen p2 = p2t

rename p3 p3_old
gen p3 = p3t

rename p4 p4_old
```

```
gen p4 = p4t

rename p5 p5_old
gen p5 = p5t

rename p6 p6_old
gen p6 = p6t

rename p7 p7_old
gen p7 = p7t

rename p8 p8_old
gen p8 = p8t

rename p9 p9_old
gen p9 = p9t

rename p10 p10_old
gen p10 = p10t

rename p11 p11_old
gen p11 = p11t

rename lnm lnm_old
gen lnm = lnm2

*predict budget shares after taxation

predict w_dairy_tax, equation(#1)

predict w_drinks_tax, equation(#2)

predict w_fats_tax, equation(#3)

predict w_fish_tax, equation(#4)

predict w_fruit_tax, equation(#5)

predict w_meat_tax, equation(#6)

predict w_potatoes_tax, equation(#7)

predict w_ready_tax, equation(#8)

predict w_sweets_tax, equation(#9)

predict w_veg_tax, equation(#10)

gen w_cereals_tax = 1 -
(w_dairy_tax+w_drinks_tax+w_fats_tax+w_fish_tax+w_fruit_tax+w_meat_tax+w_potatoes_tax+w_ready_
tax+w_sweets_tax+w_veg_tax)

*simulate household expenditure after carbon taxation; replace prices with the taxed ones

reg ln_hh_expenditure lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnp11 ln_income $covariates

rename lnp1 lnp1_old

gen lnp1 = lnp1t

rename lnp2 lnp2_old

gen lnp2 = lnp2t

rename lnp3 lnp3_old

gen lnp3 = lnp3t
```

```
rename lnp4 lnp4_old

gen lnp4 = lnp4t

rename lnp5 lnp5_old

gen lnp5 = lnp5t

rename lnp6 lnp6_old

gen lnp6 = lnp6t

rename lnp7 lnp7_old

gen lnp7 = lnp7t

rename lnp8 lnp8_old

gen lnp8 = lnp8t

rename lnp9 lnp9_old

gen lnp9 = lnp9t

rename lnp10 lnp10_old

gen lnp10 = lnp10t

rename lnp11 lnp11_old

gen lnp11 = lnp11t

predict ln_hh_exp_tax

gen hh_exp_tax = exp(ln_hh_exp_tax)

*generate variation in household expenditure before and after carbon taxation to use for the bonus price

gen change_expenditure = (hh_exp_tax - hh_exp)/ hh_exp

*gen expenditure and quantities after tax

gen expenditure_cereals_tax = w_cereals_tax*hh_exp_tax
gen expenditure_dairy_tax = w_dairy_tax*hh_exp_tax
gen expenditure_drinks_tax = w_drinks_tax*hh_exp_tax
gen expenditure_fats_tax = w_fats_tax*hh_exp_tax
gen expenditure_fish_tax = w_fish_tax*hh_exp_tax
gen expenditure_fruit_tax = w_fruit_tax*hh_exp_tax
gen expenditure_meat_tax = w_meat_tax*hh_exp_tax
gen expenditure_potatoes_tax = w_potatoes_tax*hh_exp_tax
gen expenditure_ready_meals_tax =w_ready_tax*hh_exp_tax
gen expenditure_sweet_tax = w_sweets_tax*hh_exp_tax
gen expenditure_vegetables_tax = w_veg_tax*hh_exp_tax

gen quantity_cereals_taxed = expenditure_cereals_tax/p_cereals_taxed
gen quantity_dairy_taxed = expenditure_dairy_tax/p_dairy_taxed
gen quantity_drinks_taxed = expenditure_drinks_tax/p_drinks_taxed
gen quantity_fats_taxed = expenditure_fats_tax/p_fats_taxed
gen quantity_fish_taxed = expenditure_fish_tax/p_fish_taxed
gen quantity_fruit_taxed = expenditure_fruit_tax/p_fruit_taxed
gen quantity_meat_taxed = expenditure_meat_tax/p_meat_taxed
gen quantity_potatoes_taxed = expenditure_potatoes_tax/p_potatoes_taxed
gen quantity_readymeals_taxed = expenditure_ready_meals_tax/p_ready_meals_taxed
gen quantity_sweets_taxed = expenditure_sweet_tax/p_sweets_taxed
gen quantity_vegetables_taxed = expenditure_vegetables_tax/p_vegetables_taxed
```

*gen prices after bonus malus taxation

```
gen p_bonus_cereals = p_cereals_taxed *(1 - change_expenditure )
gen p_bonus_dairy = p_dairy_taxed * (1 - change_expenditure )
gen p_bonus_drinks = p_drinks_taxed * (1 - change_expenditure )
gen p_bonus_fats = p_fats_taxed*(1-change_expenditure)
gen p_bonus_fish = p_fish_taxed*(1-change_expenditure)
gen p_bonus_fruit = p_fruit_taxed * (1 - change_expenditure )
gen p_bonus_meat = p_meat_taxed * (1 - change_expenditure )
gen p_bonus_potatoes = p_potatoes_taxed * (1 - change_expenditure)
gen p_bonus_readymeals = p_ready_meals_taxed*(1-change_expenditure)
gen p_bonus_sweets = p_sweets_taxed*(1-change_expenditure)
gen p_bonus_vegetables = p_vegetables_taxed*(1-change_expenditure)
```

*the same simulation codes were used to simulate new budget shares, quantities and expenditures after Bonus Mauls interventions

```
*use health dataset

*gen quantities for each food group

gen quantityCEREALS = BROWNGRANARYANDWHEATGERMBREAD + HIGHFIBREBREAKFASTCEREALS
+ OTHERBREAD + OTHERBREAKFASTCEREALS + PASTARICEANDOTHERCEREALS + WHITEBREAD +
WHOLEMEALBREAD

gen quantityPOTATOES = CHIPSFRIEDROASTPOTATOESANDPOTATO +
OTHERPOTATOESPOTATOSALADSDISHES

gen quantityDIARY_EGGS = CHEDDARCHEESE + ONEPERCENTMILK + CHEESE +
OTHERMILKANDCREAM + SEMISKIMMEDMILK + SKIMMEDMILK +
YOGURTFROMAGEFRAISANDDAIRYDESSER + COTTAGECHEESE +OTHERCHEESE + WHOLEMILK +
EGGSANDEGGDISHES + BUTTER

gen quantityFRUIT = FRUIT + NUTSANDSEEDS

gen quantityVEGETABLES = SALADANDOTHERRAWVEGETABLES + VEGETABLESNOTRAW

gen quantityMEAT = BACONANDHAM + BEEFVEALANDDISHES  + CHICKENANDTURKEYDISHES +
COATEDCHICKEN + LAMBANDDISHES + LIVERDISHES + OTHERMEATANDMEATPRODUCTS +
SAUSAGES

gen quantityFISH = OILYFISH + OTHERWHITEFISHSHELLFISHFISHDISHE + PORKANDDISHES  +
WHITEFISHCOATEDORFRIED

gen quantityREADY_MEALS = MEATPIESANDPASTRIES + BURGERSANDKEBABS +
CRISPSANDSAVOURYSNACKS

gen quantitySWEETS = BISCUITS + BUNSCAKESPASTRIESFRUITPIES + CHOCOLATECONFECTIONERY +
ICECREAM + PUDDINGS + SUGARCONFECTIONERY + SUGARSPRESERVESANDSWEETSPREADS

gen quantityDRINKS = BEERLAGERCIDERPERRY + FRUITJUICE + SOFTDRINKSLOWCALORIE +
SOFTDRINKSNOTLOWCALORIE + SPIRITSANDLIQUEURS + TEACOFFEEANDWATER + WINE

gen quantityFATS_SPREAD_SAUCES =  PUFAMARGARINEOILS  +
REDUCEDFATSPREADNOTPOLYUNSATURAT + REDUCEDFATSPREADPOLYUNSATURATED +
OTHERMARGARINEFATSANDOILS + LOWFATSPREADNOTPOLYUNSATURATED +
SAVOURYSAUCESPICKLESGRAVIESCONDI

*gen weightded prices from the Living Cost and Food Survey

gen p_cereals = .235011
gen p_dairy = .1525098
gen p_drinks = .1875187
gen p_fats = .3782077
gen p_fish = .9218737
gen p_fruit = .2470811
gen p_meat = .6333167
gen p_potatoes = .1834737
gen p_readymeals = .6062601
gen p_vegetables = .2148936
gen p_sweets = .4254794

*gen expenditure for each food group

gen expenditureCEREALS = quantityCEREALS*p_cereals
```

```
gen expenditureDIARY_EGGS = quantityDIARY_EGGS*p_dairy
gen expenditureDRINKS = quantityDRINKS*p_drinks
gen expenditureFATS_SPREAD_SAUCES = quantityFATS_SPREAD_SAUCES*p_fats
gen expenditureFISH = quantityFISH*p_fish
gen expenditureFRUIT = quantityFRUIT*p_fruit
gen expenditureMEAT = quantityMEAT*p_meat
gen expenditurePOTATOES = quantityPOTATOES*p_potatoes
gen expenditureREADY_MEALS = quantityREADY_MEALS * p_readymeals
gen expenditureVEGETABLES = quantityVEGETABLES*p_vegetables
gen expenditureSWEETS = quantitySWEETS*p_sweets

*gen household expenditure assuming that children eat half amount compared to adults

*CEREALS
gen exp_cereals_adults = expenditureCEREALS*NumAdult if AdChild == 1
gen exp_cereals_childs = (expenditureCEREALS/2)*NumChild if AdChild == 1
replace exp_cereals_childs = (expenditureCEREALS)*NumChild if AdChild == 2
replace exp_cereals_adults = (2*expenditureCEREALS)*NumAdult if AdChild == 2
gen exp_cereals_fam = ((exp_cereals_adults+exp_cereals_childs)/4)*365

*DAIRY
gen exp_dairy_adults = expenditureDIARY_EGGS*NumAdult if AdChild == 1
gen exp_dairy_childs = (expenditureDIARY_EGGS/2)*NumChild if AdChild == 1
replace exp_dairy_childs = (expenditureDIARY_EGGS)*NumChild if AdChild == 2
replace exp_dairy_adults = (2*expenditureDIARY_EGGS)*NumAdult if AdChild == 2
gen exp_dairy_fam = ((exp_dairy_adults+exp_dairy_childs)/4)*365

*DRINKS
gen exp_drinks_adults = expenditureDRINKS*NumAdult if AdChild == 1
gen exp_drinks_childs = (expenditureDRINKS/2)*NumChild if AdChild == 1
replace exp_drinks_childs = (expenditureDRINKS)*NumChild if AdChild == 2
replace exp_drinks_adults = (2*expenditureDRINKS)*NumAdult if AdChild == 2
gen exp_drinks_fam = ((exp_drinks_adults+exp_drinks_childs)/4)*365

*FATS
gen exp_fats_adults = expenditureFATS_SPREAD_SAUCES*NumAdult if AdChild == 1
gen exp_fats_childs = (expenditureFATS_SPREAD_SAUCES*2)*NumChild if AdChild == 1
replace exp_fats_childs = (expenditureFATS_SPREAD_SAUCES)*NumChild if AdChild == 2
replace exp_fats_adults = (2*expenditureFATS_SPREAD_SAUCES)*NumAdult if AdChild == 2
gen exp_fats_fam = ((exp_fats_adults+exp_fats_childs)/4)*365

*FISH
gen exp_fish_adults = expenditureFISH*NumAdult if AdChild == 1
gen exp_fish_childs = (expenditureFISH/2)*NumChild if AdChild == 1
replace exp_fish_childs = (expenditureFISH)*NumChild if AdChild == 2
replace exp_fish_adults = (2*expenditureFISH)*NumAdult if AdChild == 2
gen exp_fish_fam = ((exp_fish_adults+exp_fish_childs)/4)*365

*FRUIT
gen exp_fruit_adults = expenditureFRUIT*NumAdult if AdChild == 1
gen exp_fruit_childs = (expenditureFRUIT/2)*NumChild if AdChild == 1
replace exp_fruit_childs = (expenditureFRUIT)*NumChild if AdChild == 2
replace exp_fruit_adults = (2*expenditureFRUIT)*NumAdult if AdChild == 2
gen exp_fruit_fam = ((exp_fruit_adults+exp_fruit_childs)/4)*365

*MEAT
gen exp_meat_adults = expenditureMEAT*NumAdult if AdChild == 1
gen exp_meat_childs = (expenditureMEAT/2)*NumChild if AdChild == 1
replace exp_meat_childs = (expenditureMEAT)*NumChild if AdChild == 2
replace exp_meat_adults = (2*expenditureMEAT)*NumAdult if AdChild == 2
gen exp_meat_fam = ((exp_meat_adults+exp_meat_childs)/4)*365
```

```
*POTATOES
gen exp_potatoes_adults = expenditurePOTATOES*NumAdult if AdChild == 1
gen exp_potatoes_childs = (expenditurePOTATOES/2)*NumChild if AdChild == 1
replace exp_potatoes_childs = (expenditurePOTATOES)*NumChild if AdChild == 2
replace exp_potatoes_adults = (2*expenditurePOTATOES)*NumAdult if AdChild == 2
gen exp_potatoes_fam = ((exp_potatoes_adults+exp_potatoes_childs)/4)*365

*READY MEALS
gen exp_ready_adults = expenditureREADY_MEALS*NumAdult if AdChild == 1
gen exp_ready_childs = (expenditureREADY_MEALS/2)*NumChild if AdChild == 1
replace exp_ready_childs = (expenditureREADY_MEALS)*NumChild if AdChild == 2
replace exp_ready_adults = (2*expenditureREADY_MEALS)*NumAdult if AdChild == 2
gen exp_ready_fam = ((exp_ready_adults+exp_ready_childs)/4)*365

*SWEETS
gen exp_sweets_adults = expenditureSWEETS*NumAdult if AdChild == 1
gen exp_sweets_childs = (expenditureSWEETS/2)*NumChild if AdChild == 1
replace exp_sweets_childs = (expenditureSWEETS)*NumChild if AdChild == 2
replace exp_sweets_adults = (2*expenditureSWEETS)*NumAdult if AdChild == 2
gen exp_sweets_fam = ((exp_sweets_adults+exp_sweets_childs)/4)*365

*VEGETABLES
gen exp_veg_adults = expenditureVEGETABLES*NumAdult if AdChild == 1
gen exp_veg_childs = (expenditureVEGETABLES/2)*NumChild if AdChild == 1
replace exp_veg_childs = (expenditureVEGETABLES)*NumChild if AdChild == 2
replace exp_veg_adults = (2*expenditureVEGETABLES)*NumAdult if AdChild == 2
gen exp_veg_fam = ((exp_veg_adults+exp_veg_childs)/4)*365

gen log_cereals = log( exp_cereals_fam )

gen log_dairy = log( exp_dairy_fam )

gen log_drinks = log( exp_drinks_fam )

gen log_fats = log( exp_fats_fam )

gen log_fish = log( exp_fish_fam )

gen log_fruit = log( exp_fruit_fam )

gen log_meat = log( exp_meat_fam )

gen log_ready = log( exp_ready_fam )

gen log_sweets = log( exp_sweets_fam )

gen log_veg = log( exp_veg_fam )

gen log_potatoes = log( exp_potatoes_fam )

*gen log of HbA1c  (first health measure)

gen log_A1c = log(A1C_mmol_mol)

reg log_A1c log_cereals log_dairy log_drinks log_fats log_fish log_fruit log_meat log_potatoes log_sweets
log_ready log_veg log_income DMHSize MFPSex MFPAge, vce(robust)

predict log_A1c_hat

gen A1c_hat = exp(log_A1c_hat)
```

```
sum A1c_hat
clear

*use dataset of diet

scalar define s_drinks = _b[ log_drinks ]

scalar define s_cereals = _b[ log_cereals ]

scalar define s_age = _b[MFPAge]

scalar define s_sex = _b[MFPSex]

scalar define s_size = _b[DMHSize]

scalar define s_cons = _b[_cons]

scalar define s_dairy = _b[ log_dairy ]

scalar define s_fruit = _b[ log_fruit ]

scalar define s_veg = _b[ log_veg ]

scalar define s_fats = _b[ log_fats ]

scalar define s_meat = _b[ log_meat ]

scalar define s_fish = _b[ log_fish ]

scalar define s_potatoes = _b[ log_potatoes ]

scalar define s_readymeals = _b[ log_ready ]

scalar define s_sweets = _b[ log_sweets ]

scalar define s_income = _b[log_income]

*generate year expenditure

gen exp_day_cereal = (expenditure_cereals /14)*365
gen log_cereal = log(exp_day_cereal)

gen exp_day_dairy = (expenditure_dairy /14)*365
gen log_dairy = log(exp_day_dairy)

gen exp_day_drinks = (expenditure_drinks /14)*365
gen log_drinks = log(exp_day_drinks)

gen exp_day_fruit = (expenditure_fruit /14)*365
gen log_fruit = log(exp_day_fruit)

gen exp_day_fish = (expenditure_fish /14)*365
gen log_fish = log(exp_day_fish)

gen exp_day_veg = (expenditure_vegetables /14)*365
gen log_veg = log(exp_day_veg)

gen exp_day_meat = (expenditure_meat /14)*365
gen log_meat = log(exp_day_meat)
```

```
gen exp_day_potatoes = (expenditure_potatoes /14)*365
gen log_potatoes = log(exp_day_potatoes)

gen exp_day_fats = (expenditure_fats /14)*365
gen log_fats = log(exp_day_fats)

gen exp_day_readymeals = (expenditure_ready_meals /14)*365
gen log_ready = log(exp_day_readymeals)

gen exp_day_sweets = (expenditure_sweet /14)*365
gen log_sweets = log(exp_day_sweets)

gen exp_day_cereals_tax = (expenditure_cereals_tax/14)*365
gen log_cereals_tax = log(exp_day_cereals_tax)

gen exp_day_dairy_tax = (expenditure_dairy_tax /14)*365
gen log_dairy_tax = log(exp_day_dairy_tax)

gen exp_day_drink_tax = (expenditure_drinks_tax /14)*365
gen log_drink_tax = log(exp_day_drink_tax)

gen exp_day_fruit_tax = (expenditure_fruit_tax /14)*365
gen log_fruit_tax = log(exp_day_fruit_tax)

gen exp_day_fat_tax = (expenditure_fats_tax /14)*365
gen log_fat_tax = log(exp_day_fat_tax)

gen exp_day_meat_tax = (expenditure_meat_tax /14)*365
gen log_meat_tax = log(exp_day_meat_tax)

gen exp_day_potatoes_tax = (expenditure_potatoes_tax /14)*365
gen log_potatoes_tax = log(exp_day_potatoes_tax)

gen exp_day_veg_tax = (expenditure_vegetables_tax /14)*365
gen log_veg_tax = log(exp_day_veg_tax)

gen exp_day_sweets_tax = (expenditure_sweet_tax /14)*365
gen log_sweet_tax = log(exp_day_sweets_tax)

gen exp_day_readymeal_tax = (expenditure_ready_meals_tax /14)*365
gen log_readymeal_tax = log(exp_day_readymeal_tax)

gen exp_day_fish_tax = (expenditure_fish_tax /14)*365
gen log_fish_tax = log(exp_day_fish_tax)

gen exp_day_cereals_bonus = (expenditure_cereals_bonus/14)*365
gen log_cereal_bonus = log(exp_day_cereals_bonus)

gen exp_day_dairy_bonus = (expenditure_dairy_bonus /14)*365
gen log_dairy_bonus = log(exp_day_dairy_bonus)

gen exp_day_drink_bonus = (expenditure_drinks_bonus /14)*365
gen log_drinks_bonus = log(exp_day_drink_bonus)

gen exp_day_fruit_bonus = (expenditure_fruit_bonus /14)*365
gen log_fruit_bonus = log(exp_day_fruit_bonus)

gen exp_day_fat_bonus = (expenditure_fats_bonus /14)*365
gen log_fat_bonus = log(exp_day_fat_bonus)

gen exp_day_meat_bonus = (expenditure_meat_bonus/14)*365
```

```
gen log_meat_bonus = log(exp_day_meat_bonus)

gen exp_day_potatoes_bonus = (expenditure_potatoes_bonus /14)*365
gen log_potatoes_bonus = log(exp_day_potatoes_bonus)

gen exp_day_veg_bonus = (expenditure_vegetables_bonus /14)*365
gen log_veg_bonus = log(exp_day_veg_bonus)

gen exp_day_sweets_bonus = (expenditure_sweet_bonus/14)*365
gen log_sweets_bonus = log(exp_day_sweets_bonus)

gen exp_day_fish_bonus = (expenditure_fish_bonus /14)*365
gen log_fish_bonus = log(exp_day_fish_bonus)

gen exp_day_ready_meals_bonus = (expenditure_ready_meals_bonus /14)*365
gen log_ready_bonus = log(exp_day_ready_meals_bonus)

gen log_income  = log(income_pence)

*gen HbA1c  based on the parameters obtained from the health dataset

gen log_A1c_tax = s_cons + s_cereals*log_cereals_tax + s_dairy*log_dairy_tax + s_drinks*log_drink_tax +
s_fruit*log_fruit_tax + s_fish* log_fish_tax + s_veg*log_veg_tax + s_meat*log_meat_tax +
s_potatoes*log_potatoes_tax + s_fats*log_fat_tax + s_readymeals*log_readymeal_tax +
s_sweets*log_sweet_tax + s_size*size+ s_age*age_HRP + s_sex*sex_oldest + s_income*log_income

gen log_A1c_bonus = s_cons + s_cereals*log_cereal_bonus + s_dairy*log_dairy_bonus +
s_drinks*log_drinks_bonus + s_fruit*log_fruit_bonus + s_fish*log_fish_bonus + s_veg*log_veg_bonus +
s_meat*log_meat_bonus + s_potatoes*log_potatoes_bonus + s_fats*log_fat_bonus +
s_readymeals*log_ready_bonus + s_sweets*log_sweets_bonus + s_size*size + s_age*age_HRP +
s_sex*sex_oldest + s_income*log_income

gen log_A1c_before = s_cons + s_cereals*log_cereal + s_dairy*log_dairy + s_drinks*log_drinks +
s_fruit*log_fruit + s_fish*log_fish + s_veg*log_veg + s_meat*log_meat + s_potatoes*log_potatoes +
s_fats*log_fats + s_readymeals*log_ready + s_sweets*log_sweets + s_size*size + s_age*age_HRP +
s_sex*sex_oldest + s_income*log_income

gen A1c_before = exp(log_A1c_before)
gen A1c_tax = exp(log_A1c_tax)
gen A1c_bonus  = exp(log_A1c_bonus)


**do the same for the other health indicators  (BMI, Cholesterol and Glucose)
```

```
*generate European regions
generate region = 0
*British Isles
replace region = 1 if REPORTER == "GB"
replace region = 1 if REPORTER == "IE"
*Western Europe
replace region = 2 if REPORTER == "FR"
replace region = 2 if REPORTER == "DE"
replace region = 2 if REPORTER == "BW"
replace region = 2 if REPORTER == "BE"
replace region = 2 if REPORTER == "NL"
replace region = 2 if REPORTER == "LU"
replace region = 2 if REPORTER == "AU"
replace region = 2 if REPORTER == "AT"
*Northern Europe
replace region = 3 if REPORTER == "DK"
replace region = 3 if REPORTER == "FI"
replace region = 3 if REPORTER == "SE"
*Eastern Europe
replace region = 4 if REPORTER == "PL"
replace region = 4 if REPORTER == "BG"
replace region = 4 if REPORTER == "CZ"
replace region = 4 if REPORTER == "HR"
replace region = 4 if REPORTER == "SI"
replace region = 4 if REPORTER == "SK"
replace region = 4 if REPORTER == "LT"
replace region = 4 if REPORTER == "LV"
replace region = 4 if REPORTER == "EE"
replace region = 4 if REPORTER == "RO"
replace region = 4 if REPORTER == "HU"
*Southern Europe
replace region = 5 if REPORTER == "IT"
```

```
replace region = 5 if REPORTER == "ES"

replace region = 5 if REPORTER == "PT"

replace region = 5 if REPORTER == "GR"

replace region = 5 if REPORTER == "CY"

replace region = 5 if REPORTER == "MT"

*generate regional prices

foreach var of varlist price_meat price_dairy price_fish price_veg price_fruit price_cereals price_sugar
price_beverages price_misc price_coffee {
egen p_region`var' = mean(`var'), by(region)
}

*replace local prices with regional prices when missing

foreach var of varlist price_meat price_dairy price_fish price_veg price_fruit price_cereals price sugar
price_beverages price_misc price_coffee {
replace `var' =  p_region`var' if `var' == .
}

*generate importer and exporter fixed effects

tab REPORTER, gen (imp)

tab PARTNER, gen (exp)

* generate taxed prices

gen p_bev_taxed = price_beverages + k_bev
gen p_misc_taxed = price_misc + k_misc
gen p_sugars_taxed = price_sugar + k_sugar
gen p_fruit_taxed = price_fruit + k_fruit
gen p_veg_taxed = price_veg + k_veg
gen p_cereals_taxed = price_cereals + k_cereals
gen p_coffee_taxed = price_coffee + k_coffee
gen p_meat_taxed = price_meat + k_meat
gen p_dairy_taxed = price_dairy + k_dairy
gen p_fish_taxed = price_fish + k_fish

gen lnpt2 = ln(p_dairy_taxed)

gen lnpt3 = ln(p_meat_taxed)

gen ln_T_dairy = ln(DAIRY_QUANTITY+1)

gen ln_T_meat = ln(MEAT_QUANTITY+1)

*Gravity model estimation for dairy products

eststo:ivreg2 ln_trade_dairy ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep
ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg),
endog(ln_price_dairy)

eststo:ivreg2 ln_T_dairy ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep
ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg),
endog(ln_price_dairy)

eststo: ivtobit ln_trade_dairy ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep
ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg), ll vce(robust)
```

eststo:ivpoisson cfunction DAIRY_QUANTITY ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg), vce(robust)

eststo:ivpoisson cfunction DAIRY_QUANTITY ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg) if DAIRY_QUANTITY > 0, vce(robust)

*Gravity model estimation for dairy products

eststo:ivreg2 ln_trade_meat ln_distance contig comlang_off ln_farm_number_rep ln_livestock_rep ln_utilised_rep imp1-imp28 exp1-exp28 year (ln_price_meat = ln_price_pig), endog(ln_price_meat)

eststo:ivreg2 ln_T_meat ln_distance contig comlang_off ln_farm_number_rep ln_livestock_rep ln_utilised_rep imp1-imp28 exp1-exp28 year (ln_price_meat = ln_price_pig), endog(ln_price_meat)

eststo: ivtobit ln_trade_meat ln_distance contig comlang_off ln_farm_number_rep ln_livestock_rep ln_utilised_rep imp1-imp28 exp1-exp28 year (ln_price_meat = ln_price_pig), vce(robust)

eststo:ivpoisson cfunction MEAT_QUANTITY ln_distance contig comlang_off imp1-imp28 exp1-exp28 year ln_farm_number_rep ln_livestock_rep ln_utilised_rep (ln_price_meat = ln_price_pig), vce(robust)

eststo:ivpoisson cfunction MEAT_QUANTITY ln_distance contig comlang_off imp1-imp28 exp1-exp28 year ln_farm_number_rep ln_livestock_rep ln_utilised_rep (ln_price_meat = ln_price_pig) if MEAT_QUANTITY>0 , vce(robust)

*Simulation

*OLS ivreg dairy

ivreg2 ln_trade_dairy ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg), endog(ln_price_dairy)

rename ln_price_dairy ln_p_old

gen ln_price_dairy = lnpt2

predict ln_dairy_tax, xb

gen dairy_tax = exp(ln_dairy_tax)

drop ln_price_dairy

rename ln_p_old ln_price_dairy

ivreg2 ln_trade_dairy ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg), endog(ln_price_dairy)

predict ln_dairy_hat, xb

gen dairy_hat = exp(ln_dairy_hat)

gen diff = (dairy_tax- dairy_hat)/dairy_hat

* OLS ivreg meat

ivreg2 ln_trade_meat ln_distance contig comlang_off ln_farm_number_rep ln_livestock_rep ln_utilised_rep imp1-imp28 exp1-exp28 year (ln_price_meat = ln_price_pig), endog(ln_price_meat)

rename ln_price_meat ln_p_old

gen ln_price_meat = lnpt3

predict ln_meat_tax, xb

gen meat_tax = exp(ln_meat_tax)

```
drop ln_price_meat

rename ln_p_old ln_price_meat

ivreg2 ln_trade_meat ln_distance contig comlang_off ln_farm_number_rep ln_livestock_rep ln_utilised_rep
imp1-imp28 exp1-exp28 year (ln_price_meat = ln_price_pig), endog(ln_price_meat)

predict ln_meat_hat, xb

gen meat_hat = exp(ln_meat_hat)

gen diff = (meat_tax- meat_hat)/meat_hat

*ivpoisson control function dairy

ivpoisson cfunction DAIRY_QUANTITY ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep
ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg), vce(robust)

rename ln_price_dairy ln_p_old

gen ln_price_dairy = lnpt2

predict exp_dairy_tax, xb

gen dairy_tax = exp(exp_dairy_tax)

drop ln_price_dairy

rename ln_p_old ln_price_dairy

ivpoisson cfunction DAIRY_QUANTITY ln_distance contig comlang_off ln_utilised_rep ln_livestock_rep
ln_farm_number_rep imp1-imp28 exp1-exp28 year (ln_price_dairy = ln_inst ln_price_egg), vce(robust)

predict exp_dairy_hat, xb

gen dairy_hat = exp(exp_dairy_hat)

gen diff = (dairy_tax - dairy_hat)/dairy_hat

* ivpoisson control function  meat

ivpoisson cfunction MEAT_QUANTITY ln_distance contig comlang_off imp1-imp28 exp1-exp28 year
ln_farm_number_rep ln_livestock_rep ln_utilised_rep (ln_price_meat = ln_price_pig), vce(robust)

rename ln_price_meat ln_p_old

gen ln_price_meat = lnpt3

predict exp_meat_tax, xb

gen meat_tax = exp(exp_meat_tax)

drop ln_price_meat

rename ln_p_old ln_price_meat

ivpoisson cfunction MEAT_QUANTITY ln_distance contig comlang_off imp1-imp28 exp1-exp28 year
ln_farm_number_rep ln_livestock_rep ln_utilised_rep (ln_price_meat = ln_price_pig), vce(robust)

predict exp_meat_hat, xb

gen meat_hat = exp(exp_meat_hat)

gen diff = (meat_tax - meat_hat)/meat_hat
```

Appendix C

Stata Codes Endogeneity Instruments

<u>Endogeneity of Prices and Expenditure</u>

```
*covariates are all the exogeneous variables in the model
**prices of the same regions without mine, as instruments for prices
*carbs
egen tot_exp_carb = sum( expenditureCARBOHYDRATES ), by(Gorx)
egen tot_quantity_carb = sum( quantityCARBOHYDRATES ) , by(Gorx)
gen p_1 = (tot_exp_carb - expenditureCARBOHYDRATES)/(tot_quantity_carb -quantityCARBOHYDRATES)
gen ln_p_1 = ln(p_1)
reg lnp1 ln_p_1 $covariates
predict res_lnp1, res
*dairy
egen tot_exp_diary = sum( expenditureDIARY ), by(Gorx)
egen tot_quantity_diary = sum( quantityDIARY ) , by(Gorx)
gen p_2 = (tot_exp_diary - expenditureDIARY)/(tot_quantity_diary - quantityDIARY)
gen ln_p_2 = ln(p_2)
reg lnp2 ln_p_2 $covariates
predict res_lnp2, res
*drinks
egen tot_exp_drinks = sum( expenditureDRINKS ), by(Gorx)
egen tot_quantity_drinks = sum( quantityDRINKS ) , by(Gorx)
gen p_3 = (tot_exp_drinks - expenditureDRINKS)/(tot_quantity_drinks - quantityDRINKS)
gen ln_p_3 = ln(p_3)
reg lnp3 ln_p_3 $covariates
predict res_lnp3, res
*fruit and vegetables
egen tot_exp_fruitveg = sum( expenditureFRUIT_VEGETABLES ), by(Gorx)
egen tot_quantity_fruitveg = sum( quantityFRUIT_VEGETABLES) , by(Gorx)
gen p_4 = (tot_exp_fruitveg - expenditureFRUIT_VEGETABLES)/(tot_quantity_fruitveg -
quantityFRUIT_VEGETABLES)
gen ln_p_4= ln(p_4)
reg lnp4 ln_p_4 $covariates
predict res_lnp4, residuals
*oil
egen tot_exp_oil = sum( expenditureOIL ), by(Gorx)
egen tot_quantity_oil = sum( quantityOIL ) , by(Gorx)
gen p_5 = (tot_exp_oil - expenditureOIL)/(tot_quantity_oil - quantityOIL)
gen ln_p_5= ln(p_5)
reg lnp5 ln_p_5 $covariates
predict res_lnp5, residuals
*proteins
egen tot_exp_proteins = sum( expenditurePROTEINS ), by(Gorx)
egen tot_quantity_proteins = sum( quantityPROTEINS ) , by(Gorx)
gen p_6 = (tot_exp_proteins - expenditurePROTEINS)/(tot_quantity_proteins - quantityPROTEINS)
gen ln_p_6= ln(p_6)
reg lnp6 ln_p_6 $covariates
predict res_lnp6, residuals
*others
egen tot_exp_others = sum( expenditureOTHERS ), by(Gorx)
egen tot_quantity_others = sum( quantityOTHERS ) , by(Gorx)
```

```
gen p_7 = (tot_exp_others - expenditureOTHERS)/(tot_quantity_others - quantityOTHERS)
gen ln_p_7= ln(p_7)
reg lnp7 ln_p_7 $covariates
predict res_lnp7, residuals
*income as instrument for expenditure
gen ln_income = ln(income_pence)
gen ln_hh_expenditure = ln( hh_expenditure )
reg ln_hh_expenditure ln_income $covariates
predict res_hh_expenditure, res
```

Defra prices used and Hausman Instruments

```
gen lnP_Index = [(w1*lnp1)+(w2*lnp2)+(w3*lnp3)+(w4*lnp4)+(w5*lnp5)+(w6*lnp6)+(w7*lnp7)]
gen lnm = ln(hh_expenditure/exp(lnP_Index))
*carbs
egen tot_exp_carb = sum( expenditureCARBOHYDRATES ), by(Gorx)
egen tot_quantity_carb = sum( quantityCARBOHYDRATES ) , by(Gorx)
gen p_1 = (tot_exp_carb - expenditureCARBOHYDRATES)/(tot_quantity_carb -
quantityCARBOHYDRATES)
gen ln_p_1 = ln(p_1)
*dairy
egen tot_exp_diary = sum( expenditureDIARY ), by(Gorx)
egen tot_quantity_diary = sum( quantityDIARY ) , by(Gorx)
gen p_2 = (tot_exp_diary - expenditureDIARY)/(tot_quantity_diary - quantityDIARY)
gen ln_p_2 = ln(p_2)
*drinks
egen tot_exp_drinks = sum( expenditureDRINKS ), by(Gorx)
egen tot_quantity_drinks = sum( quantityDRINKS ) , by(Gorx)
gen p_3 = (tot_exp_drinks - expenditureDRINKS)/(tot_quantity_drinks - quantityDRINKS)
gen ln_p_3 = ln(p_3)

gen p_4 = 0.058 if Gorx == 1
replace p_4 =0.06 if Gorx == 2
replace p_4 = 0.09 if Gorx == 3
replace p_4 = 0.100 if Gorx ==4
replace p_4 = 0.103 if Gorx == 5
replace p_4 = 0.107 if Gorx == 6
replace p_4 = 0.12 if Gorx == 7
replace p_4 = 0.11 if Gorx == 8
replace p_4 = 0.105 if Gorx == 9
replace p_4 = 0.09 if Gorx == 10
replace p_4 = 0.07 if Gorx == 11
replace p_4 = 0.05 if Gorx == 12
gen ln_p_4 = ln(p_4)

*oil
egen tot_exp_oil = sum( expenditureOIL ), by(Gorx)
egen tot_quantity_oil = sum( quantityOIL ) , by(Gorx)
gen p_5 = (tot_exp_oil - expenditureOIL)/(tot_quantity_oil - quantityOIL)
gen ln_p_5= ln(p_5)

gen p_6 = 0.253 if Gorx == 1
replace p_6 = 0.251 if Gorx == 2
replace p_6 = 0.257 if Gorx == 3
replace p_6 = 0.248 if Gorx ==4
replace p_6 = 0.231 if Gorx == 5
replace p_6 = 0.242 if Gorx == 6
```

```
replace p_6 = 0.222 if Gorx == 7
replace p_6 = 0.221 if Gorx == 8
replace p_6 = 0.224 if Gorx == 9
replace p_6 = 0.218 if Gorx == 10
replace p_6 = 0.220 if Gorx == 11
replace p_6 = 0.228 if Gorx == 12
gen ln_p_6 = ln(p_6)
*others
egen tot_exp_others = sum( expenditureOTHERS ), by(Gorx)
egen tot_quantity_others = sum( quantityOTHERS ) , by(Gorx)
gen p_7 = (tot_exp_others - expenditureOTHERS)/(tot_quantity_others - quantityOTHERS)
gen ln_p_7= ln(p_7)
```

<u>Average other regions as instruments</u>

```
egen p_diary_gorx = mean( p_diary) , by(Gorx)
egen p_carb_gorx = mean( p_carb) , by(Gorx)
egen p_drinks_gorx = mean( p_drinks) , by(Gorx)
egen p_fruitveg_gorx = mean( p_fruitveg) , by(Gorx)
egen p_oil_gorx = mean( p_oil) , by(Gorx)
egen p_prot_gorx = mean( p_proteins) , by(Gorx)
egen p_others_gorx = mean( p_others) , by(Gorx)

gen p_1 = [sum(p_carb_gorx) - p_carb_gorx]/5024
gen p_2 = [sum(p_dairy_gorx)- p_dairy_gorx]/5024
gen p_3 = [sum(p_drinks_gorx)- p_drinks_gorx]/5024
gen p_4 = [sum(p_fruitveg_gorx)- p_fruitveg_gorx]/5024
gen p_5 = [sum(p_oil_gorx)- p_oil_gorx]/5024
gen p_6 = [sum(p_proteins_gorx)- p_proteins_gorx]/5024
gen p_7 = [sum(p_others_gorx)-p_others_gorx]/5024
```

<u>Hausman Instruments and nlcom used for the elasticities</u>

```
*global covariates size age_HRP sex_oldest
*carbs
egen tot_exp_carb = sum( expenditureCARBOHYDRATES )
egen tot_exp_carb_region = sum(expenditureCARBOHYDRATES), by(Gorx)
egen tot_quantity_carb = sum( quantityCARBOHYDRATES )
egen tot_quantity_carb_region = sum( quantityCARBOHYDRATES ) , by(Gorx)
gen p_1 = (tot_exp_carb - tot_exp_carb_region)/(tot_quantity_carb -  tot_quantity_carb_region)
gen ln_p_1 = ln(p_1)
*dairy
egen tot_exp_dairy = sum( expenditureDIARY )
egen tot_exp_dairy_region = sum( expenditureDIARY ), by(Gorx)
egen tot_quantity_dairy = sum( quantityDIARY )
egen tot_quantity_dairy_region = sum( quantityDIARY ), by(Gorx)
gen p_2 = (tot_exp_dairy - tot_exp_dairy_region)/(tot_quantity_dairy - tot_quantity_dairy_region)
gen ln_p_2 = ln(p_2)
*drinks
egen tot_exp_drinks = sum( expenditureDRINKS )
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx)
egen tot_quantity_drinks = sum( quantityDRINKS )
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx)
gen p_3 = (tot_exp_drinks - tot_exp_drinks_region)/(tot_quantity_drinks - tot_quantity_drinks_region)
gen ln_p_3 = ln(p_3)
*fruitveg
egen tot_exp_fruitveg = sum( expenditureFRUIT_VEGETABLES )
```

```
egen tot_exp_fruitveg_region = sum( expenditureFRUIT_VEGETABLES ), by(Gorx)
egen tot_quantity_fruitveg = sum( quantityFRUIT_VEGETABLES)
egen tot_quantity_fruitveg_region = sum( quantityFRUIT_VEGETABLES) , by(Gorx)
gen p_4 = (tot_exp_fruitveg - tot_exp_fruitveg_region)/(tot_quantity_fruitveg -
tot_quantity_fruitveg_region)
gen ln_p_4= ln(p_4)
*oil
egen tot_exp_oil = sum( expenditureOIL )
egen tot_exp_oil_region = sum( expenditureOIL ), by(Gorx)
egen tot_quantity_oil = sum( quantityOIL )
egen tot_quantity_oil_region = sum( quantityOIL ) , by(Gorx)
gen p_5 = (tot_exp_oil - tot_exp_oil_region )/(tot_quantity_oil - tot_quantity_oil_region )
gen ln_p_5= ln(p_5)
*proteins
egen tot_exp_proteins = sum( expenditurePROTEINS )
egen tot_exp_proteins_region = sum( expenditurePROTEINS ), by(Gorx)
egen tot_quantity_proteins = sum( quantityPROTEINS )
egen tot_quantity_proteins_regions = sum( quantityPROTEINS ) , by(Gorx)
gen p_6 = (tot_exp_proteins - tot_exp_proteins_region)/(tot_quantity_proteins -
tot_quantity_proteins_regions)
gen ln_p_6= ln(p_6)
*others
egen tot_exp_others = sum( expenditureOTHERS )
egen tot_exp_others_region = sum( expenditureOTHERS ), by(Gorx)
egen tot_quantity_others = sum( quantityOTHERS )
egen tot_quantity_others_region = sum( quantityOTHERS ) , by(Gorx)
gen p_7 = (tot_exp_others - tot_exp_others_region)/(tot_quantity_others - tot_quantity_others_region)
gen ln_p_7= ln(p_7)

quietly sum w1
 scalar w1_mean = r(mean)
quietly sum w2
 scalar w2_mean = r(mean)
quietly sum w3
 scalar w3_mean = r(mean)
quietly sum w4
 scalar w4_mean = r(mean)
quietly sum w5
 scalar w5_mean = r(mean)
quietly sum w6
 scalar w6_mean = r(mean)
quietly sum w7
 scalar w7_mean = r(mean)

nlcom (own_w1: 1+(_b[lnp_w1_w1]/(w1_mean^2))-(1/w1_mean))/*
   */(e_w1_w2 : 1+(_b[lnp_w1_w2]/(w1_mean*w2_mean)))/*
         */(e_w1_w3 : 1+(_b[lnp_w1_w3]/(w1_mean*w3_mean)))/*
         */(e_w1_w4 : 1+(_b[lnp_w1_w4]/(w1_mean*w4_mean)))/*
         */(e_w1_w5 : 1+(_b[lnp_w1_w5]/(w1_mean*w5_mean)))/*
         */(e_w1_w6 : 1+(_b[lnp_w1_w6]/(w1_mean*w6_mean)))/*
         */(e_w1_w7 : 1+(_b[lnp_w1_w7]/(w1_mean*w7_mean)))

nlcom (own_w2: 1+(_b[lnp_w2_w2]/(w2_mean^2))-(1/w2_mean))/*
   */(e_w2_w3 : 1+(_b[lnp_w2_w3]/(w2_mean*w3_mean)))/*
         */(e_w2_w4 : 1+(_b[lnp_w2_w4]/(w2_mean*w4_mean)))/*
         */(e_w2_w5 : 1+(_b[lnp_w2_w5]/(w2_mean*w5_mean)))/*
         */(e_w2_w6 : 1+(_b[lnp_w2_w6]/(w2_mean*w6_mean)))/*
```

```
*/(e_w2_w7 : 1+(_b[lnp_w2_w7]/(w2_mean*w7_mean)))

nlcom (own_w3: 1+(_b[lnp_w3_w3]/(w3_mean^2))-(1/w3_mean))/*
  */(e_w3_w4 : 1+(_b[lnp_w3_w4]/(w3_mean*w4_mean)))/*
        */(e_w3_w5 : 1+(_b[lnp_w3_w5]/(w3_mean*w5_mean)))/*
        */(e_w3_w6 : 1+(_b[lnp_w3_w6]/(w3_mean*w6_mean)))/*
        */(e_w3_w7 : 1+(_b[lnp_w3_w7]/(w3_mean*w7_mean)))

nlcom (own_w4 : 1+(_b[lnp_w4_w4]/(w4_mean^2))-(1/w4_mean))/*
  */(e_w4_w5 : 1+(_b[lnp_w4_w5]/(w4_mean*w5_mean)))/*
        */(e_w4_w6 : 1+(_b[lnp_w4_w6]/(w4_mean*w6_mean)))/*
        */(e_w4_w7 : 1+(_b[lnp_w4_w7]/(w4_mean*w7_mean)))

nlcom (own_w5 : 1+(_b[lnp_w5_w5]/(w5_mean^2))-(1/w5_mean))/*
  */(e_w5_w6 : 1+(_b[lnp_w5_w6]/(w5_mean*w6_mean)))/*
        */(e_w5_w7 : 1+(_b[lnp_w5_w7]/(w5_mean*w7_mean)))/*

nlcom (own_w6 : 1+(_b[lnp_w6_w6]/(w6_mean^2))-(1/w6_mean))/*
  */(e_w6_w7 : 1+(_b[lnp_w6_w7]/(w6_mean*w7_mean)))

nlcom (own_w7 : 1+(_b[lnp_w7_w7]/(w7_mean^2))-(1/w7_mean))
```

<u>Prices of the same region, year, and month without me</u>

```
#carbohydrates
egen tot_exp_carb = sum( expenditureCARBOHYDRATES ), by(Gorx Year month)
egen tot_quantity_carb = sum( quantityCARBOHYDRATES ) , by(Gorx Year month)
gen exp_1 = tot_exp_carb - expenditureCARBOHYDRATES
gen quantity_1 = tot_quantity_carb - quantityCARBOHYDRATES
gen p_1 = (exp_1/quantity_1)
gen ln_p_1 = ln(p_1)
reg lnp1 ln_p_1
predict res_lnp1, residuals
#diary
egen tot_exp_diary = sum( expenditureDIARY ), by(Gorx Year month)
egen tot_quantity_diary = sum( quantityDIARY ) , by(Gorx Year month)
gen exp_2 = tot_exp_diary - expenditureDIARY
gen quantity_2 = tot_quantity_diary - quantityDIARY
gen p_2 = (exp_2/quantity_2)
gen ln_p_2 = ln(p_2)
reg lnp2 ln_p_2
predict res_lnp2, residuals
#drinks
egen tot_exp_drinks = sum( expenditureDRINKS ), by(Gorx Year month)
egen tot_quantity_drinks = sum( quantityDRINKS ) , by(Gorx Year month)
gen exp_3 = tot_exp_drinks - expenditureDRINKS
gen quantity_3 = tot_quantity_drinks - quantityDRINKS
gen p_3 = (exp_3/quantity_3)
gen ln_p_3= ln(p_3)
reg lnp3 ln_p_3
predict res_lnp3, residuals
#fruitveg
egen tot_exp_fruitveg = sum( expenditureFRUIT_VEGETABLES ), by(Gorx Year month)
egen tot_quantity_fruitveg = sum( quantityFRUIT_VEGETABLES) , by(Gorx Year month)
gen exp_4 = tot_exp_fruitveg - expenditureFRUIT_VEGETABLES
gen quantity_4 = tot_quantity_fruitveg - quantityFRUIT_VEGETABLES
gen p_4 = (exp_4/quantity_4)
```

```
gen ln_p_4= ln(p_4)
reg lnp4 ln_p_4
predict res_lnp4, residuals
#oil
egen tot_exp_oil = sum( expenditureOIL ), by(Gorx Year month)
egen tot_quantity_oil = sum( quantityOIL ) , by(Gorx Year month)
gen exp_5 = tot_exp_oil - expenditureOIL
gen quantity_5 = tot_quantity_oil - quantityOIL
gen p_5 = (exp_5/quantity_5)
gen ln_p_5= ln(p_5)
reg lnp5 ln_p_5
predict res_lnp5, residuals
#proteins
egen tot_exp_proteins = sum( expenditurePROTEINS ), by(Gorx Year month)
egen tot_quantity_proteins = sum( quantityPROTEINS ) , by(Gorx Year month)
gen exp_6 = tot_exp_proteins - expenditurePROTEINS
gen quantity_6 = tot_quantity_proteins - quantityPROTEINS
gen p_6 = (exp_6/quantity_6)
gen ln_p_6= ln(p_6)
reg lnp6 ln_p_6
predict res_lnp6, residuals
#others
egen tot_exp_others = sum( expenditureOTHERS ), by(Gorx Year month)
egen tot_quantity_others = sum( quantityOTHERS ) , by(Gorx Year month)
gen exp_7 = tot_exp_others - expenditureOTHERS
gen quantity_7 = tot_quantity_others - quantityOTHERS
gen p_7 = (exp_7/quantity_7)
gen ln_p_7= ln(p_7)
reg lnp7 ln_p_7
predict res_lnp7, residuals
gen ln_income = ln(income)
gen ln_hh_expenditure = ln( hh_expenditure )
reg ln_hh_expenditure ln_income
predict res_hh_expenditure, res
```

<u>Instruments prices of the same region without my price</u>

```
egen tot_exp_carb_region = sum(expenditureCARBOHYDRATES), by(Gorx)
egen tot_quantity_carb_region = sum( quantityCARBOHYDRATES ) , by(Gorx)
gen p_1 = (tot_exp_carb_region - expenditureCARBOHYDRATES)/(tot_quantity_carb_region -
quantityCARBOHYDRATES)
gen ln_p_1 = ln(p_1)
egen tot_exp_dairy_region = sum( expenditureDIARY ), by(Gorx)
egen tot_quantity_dairy_region = sum( quantityDIARY ), by(Gorx)
gen p_2 = (tot_exp_dairy_region - expenditureDIARY)/(tot_quantity_dairy_region - quantityDIARY )
gen ln_p_2 = ln(p_2)
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx)
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx)
gen p_3 = (tot_exp_drinks_region - expenditureDRINKS)/(tot_quantity_drinks_region - quantityDRINKS)
gen ln_p_3 = ln(p_3)
egen tot_exp_fruitveg_region = sum( expenditureFRUIT_VEGETABLES ), by(Gorx)
egen tot_quantity_fruitveg_region = sum( quantityFRUIT_VEGETABLES) , by(Gorx)
gen p_4 = (tot_exp_fruitveg_region - expenditureFRUIT_VEGETABLES)/(tot_quantity_fruitveg_region -
quantityFRUIT_VEGETABLES)
gen ln_p_4= ln(p_4)
egen tot_exp_oil_region = sum( expenditureOIL ), by(Gorx)
egen tot_quantity_oil_region = sum( quantityOIL ) , by(Gorx)
```

```
gen p_5 = (tot_exp_oil_region - expenditureOIL )/(tot_quantity_oil_region - quantityOIL)
gen ln_p_5= ln(p_5)
egen tot_exp_proteins_region = sum( expenditurePROTEINS ), by(Gorx)
egen tot_quantity_proteins_regions = sum( quantityPROTEINS ) , by(Gorx)
gen p_6 = (tot_exp_proteins_region - expenditurePROTEINS)/(tot_quantity_proteins_regions -
quantityPROTEINS)
gen ln_p_6= ln(p_6)
egen tot_exp_others_region = sum( expenditureOTHERS ), by(Gorx)
egen tot_quantity_others_region = sum( quantityOTHERS ) , by(Gorx)
gen p_7 = (tot_exp_others_region - expenditureOTHERS )/(tot_quantity_others_region - quantityOTHERS)
gen ln_p_7= ln(p_7)

* test endogeneity of prices with Hausman test
reg lnp1 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp1, res
test ln_p_1
reg lnp2 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp2, res
test ln_p_2
reg lnp3 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp3, res
test ln_p_3
reg lnp4 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp4, residuals
test ln_p_4
reg lnp5 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp5, residuals
test ln_p_5
reg lnp6 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp6, residuals
test ln_p_6
reg lnp7 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_lnp7, residuals
test ln_p_7
gen ln_hh_expenditure = ln( hh_expenditure )
reg ln_hh_expenditure ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income $covariates
predict res_hh_expenditure, res
test ln_income
*ivregress
ivregress 2sls w1 size age_HRP sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
ivregress 2sls w2 size age_HRP sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
ivregress 2sls w3 size age_HRP sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
ivregress 2sls w4 size age_HRP sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
ivregress 2sls w5 size age_HR  sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
ivregress 2sls w6 size age_HRP sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
ivregress 2sls w7 size age_HRP sex_oldest (lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnm = ln_p_1 ln_p_2 ln_p_3
ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_income)
```

<u>Regional prices and other regions prices as instruments</u>

```
* I replaced individual prices with regional monthly prices
```

```
egen p_cereals_gorx = mean( price_cereals) , by(Gorx month)
egen p_dairy_gorx = mean( price_diary_eggs) , by(Gorx month)
egen p_drinks_gorx = mean( price_drinks) , by(Gorx month)
egen p_fats_gorx = mean( price_fats_spreads) , by(Gorx month)
egen p_fish_gorx = mean( price_fish) , by(Gorx month)
egen p_fruit_gorx = mean( price_fruit) , by(Gorx month)
egen p_meat_gorx = mean( price_meat) , by(Gorx month )
egen p_potatoes_gorx = mean( price_potatoes) , by(Gorx month)
egen p_ready_meals_gorx = mean( price_ready_meals) , by(Gorx month)
egen p_sweets_gorx = mean( price_sweets) , by(Gorx month)
egen p_vegetables_gorx = mean( price_vegetables) , by(Gorx month)

replace price_cereals = p_cereals_gorx
replace price_diary_eggs = p_dairy_gorx
replace price_drinks = p_drinks_gorx
replace price_fruit = p_fruit_gorx
replace price_fish = p_fish_gorx
replace price_meat = p_meat_gorx
replace price_fats_spreads = p_fats_gorx
replace price_potatoes = p_potatoes_gorx
replace price_ready_meals = p_ready_meals_gorx
replace price_sweets = p_sweets_gorx
replace price_vegetables = p_vegetables_gorx

*I created as instruments price of other regions
*cereals
egen tot_exp_cer = sum( expenditureCEREALS )
egen tot_exp_cer_region = sum(expenditureCEREALS), by(Gorx)
egen tot_quantity_cer = sum( quantityCEREALS )
egen tot_quantity_cer_region = sum( quantityCEREALS ) , by(Gorx)
gen p_1 = (tot_exp_cer - tot_exp_cer_region)/(tot_quantity_cer -  tot_quantity_cer_region)
gen ln_p_1 = ln(p_1)
gen price_cereals_region = tot_exp_cer_region/tot_quantity_cer_region
*dairy
egen tot_exp_dairy = sum( expenditureDIARY_EGGS )
egen tot_exp_dairy_region = sum( expenditureDIARY_EGGS), by(Gorx)
egen tot_quantity_dairy = sum( quantityDIARY_EGGS )
egen tot_quantity_dairy_region = sum( quantityDIARY_EGGS), by(Gorx)
gen p_2 = (tot_exp_dairy - tot_exp_dairy_region)/(tot_quantity_dairy - tot_quantity_dairy_region)
gen ln_p_2 = ln(p_2)
gen price_dairy_region = tot_exp_dairy_region/tot_quantity_dairy_region
*drinks
egen tot_exp_drinks = sum( expenditureDRINKS )
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx)
egen tot_quantity_drinks = sum( quantityDRINKS )
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx)
gen p_3 = (tot_exp_drinks - tot_exp_drinks_region)/(tot_quantity_drinks - tot_quantity_drinks_region)
gen ln_p_3 = ln(p_3)
gen price_drinks_region = tot_exp_drinks_region/tot_quantity_drinks_region
*fats
egen tot_exp_fats = sum( expenditureFATS_SPREAD_SAUCES )
egen tot_exp_fats_region = sum( expenditureFATS_SPREAD_SAUCES ), by(Gorx)
egen tot_quantity_fats = sum( quantityFATS_SPREAD_SAUCES)
egen tot_quantity_fats_region = sum( quantityFATS_SPREAD_SAUCES) , by(Gorx)
gen p_4 = (tot_exp_fats - tot_exp_fats_region)/(tot_quantity_fats - tot_quantity_fats_region)
gen ln_p_4= ln(p_4)
gen price_fats_region = tot_exp_fats_region/tot_quantity_fats_region
```

```
*fish
egen tot_exp_fish = sum( expenditureFISH )
egen tot_exp_fish_region = sum( expenditureFISH ), by(Gorx)
egen tot_quantity_fish = sum( quantityFISH )
egen tot_quantity_fish_region = sum( quantityFISH ) , by(Gorx)
gen p_5 = (tot_exp_fish - tot_exp_fish_region )/(tot_quantity_fish - tot_quantity_fish_region )
gen ln_p_5= ln(p_5)
gen price_fish_region = tot_exp_fish_region/tot_quantity_fish_region
*fruit
egen tot_exp_fruit = sum( expenditureFRUIT )
egen tot_exp_fruit_region = sum( expenditureFRUIT ), by(Gorx)
egen tot_quantity_fruit = sum( quantityFRUIT )
egen tot_quantity_fruit_regions = sum( quantityFRUIT ) , by(Gorx)
gen p_6 = (tot_exp_fruit - tot_exp_fruit_region)/(tot_quantity_fruit - tot_quantity_fruit_regions)
gen ln_p_6= ln(p_6)
gen price_fruit_region = tot_exp_fruit_region/tot_quantity_fruit_regions
*meat
egen tot_exp_meat = sum( expenditureMEAT )
egen tot_exp_meat_region = sum( expenditureMEAT ), by(Gorx)
egen tot_quantity_meat = sum( quantityMEAT )
egen tot_quantity_meat_region = sum( quantityMEAT ) , by(Gorx)
gen p_7 = (tot_exp_meat - tot_exp_meat_region)/(tot_quantity_meat - tot_quantity_meat_region)
gen ln_p_7= ln(p_7)
gen price_meat_region = tot_exp_meat_region/tot_quantity_meat_region
*potatoes
egen tot_exp_potatoes = sum( expenditurePOTATOES )
egen tot_exp_potatoes_region = sum( expenditurePOTATOES ), by(Gorx)
egen tot_quantity_potatoes = sum( quantityPOTATOES )
egen tot_quantity_potatoes_regions = sum( quantityPOTATOES ) , by(Gorx)
gen p_8 = (tot_exp_potatoes - tot_exp_potatoes_region)/(tot_quantity_potatoes -
tot_quantity_potatoes_regions)
gen ln_p_8= ln(p_8)
gen price_potatoes_region = tot_exp_potatoes_region/tot_quantity_potatoes_regions
*ready meals
egen tot_exp_ready = sum( expenditureREADY_MEALS )
egen tot_exp_ready_region = sum( expenditureREADY_MEALS ), by(Gorx)
egen tot_quantity_ready = sum( quantityREADY_MEALS )
egen tot_quantity_ready_region = sum( quantityREADY_MEALS ) , by(Gorx)
gen p_9 = (tot_exp_ready - tot_exp_ready_region)/(tot_quantity_ready - tot_quantity_ready_region)
gen ln_p_9= ln(p_9)
gen price_ready_region = tot_exp_ready_region/tot_quantity_ready_region
*sweets
egen tot_exp_sweets = sum( expenditureSWEETS )
egen tot_exp_sweets_region = sum( expenditureSWEETS ), by(Gorx)
egen tot_quantity_sweets = sum( quantitySWEETS )
egen tot_quantity_sweets_regions = sum( quantitySWEETS ) , by(Gorx)
gen p_10 = (tot_exp_sweets - tot_exp_sweets_region)/(tot_quantity_sweets - tot_quantity_sweets_regions)
gen ln_p_10= ln(p_10)
gen price_sweets_region = tot_exp_sweets_region/tot_quantity_sweets_regions
*vegetables
egen tot_exp_veg = sum( expenditureVEGETABLES )
egen tot_exp_veg_region = sum( expenditureVEGETABLES ), by(Gorx)
egen tot_quantity_veg = sum( quantityVEGETABLES )
egen tot_quantity_veg_region = sum( quantityVEGETABLES ) , by(Gorx)
gen p_11 = (tot_exp_veg - tot_exp_veg_region)/(tot_quantity_veg - tot_quantity_veg_region)
gen ln_p_11= ln(p_11)
gen price_veg_region = tot_exp_veg_region/tot_quantity_veg_region
```

Same month and other region prices

```
gen lnP_Index = [(w1*lnp1)+(w2*lnp2)+(w3*lnp3)+(w4*lnp4)+(w5*lnp5)+(w6*lnp6)+(w7*lnp7)]
gen lnm = ln(hh_expenditure/exp(lnP_Index))
global covariates size age_HRP sex_oldest
*carbs
egen tot_exp_carb = sum( expenditureCARBOHYDRATES ), by(month)
egen tot_exp_carb_region = sum(expenditureCARBOHYDRATES), by(Gorx month)
egen tot_quantity_carb = sum( quantityCARBOHYDRATES ), by(month)
egen tot_quantity_carb_region = sum( quantityCARBOHYDRATES ) , by(Gorx month)
gen p_1 = (tot_exp_carb - tot_exp_carb_region)/(tot_quantity_carb - tot_quantity_carb_region)
gen ln_p_1 = ln(p_1)
*dairy
egen tot_exp_dairy = sum( expenditureDIARY ), by(month)
egen tot_exp_dairy_region = sum( expenditureDIARY ), by(Gorx month)
egen tot_quantity_dairy = sum( quantityDIARY ), by(month)
egen tot_quantity_dairy_region = sum( quantityDIARY ), by(Gorx month)
gen p_2 = (tot_exp_dairy - tot_exp_dairy_region)/(tot_quantity_dairy - tot_quantity_dairy_region)
gen ln_p_2 = ln(p_2)
*drinks
egen tot_exp_drinks = sum( expenditureDRINKS ), by(month)
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx month)
egen tot_quantity_drinks = sum( quantityDRINKS ), by(month)
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx month)
gen p_3 = (tot_exp_drinks - tot_exp_drinks_region)/(tot_quantity_drinks - tot_quantity_drinks_region)
gen ln_p_3 = ln(p_3)
 *fruitveg
egen tot_exp_fruitveg = sum( expenditureFRUIT_VEGETABLES ), by(month)
egen tot_exp_fruitveg_region = sum( expenditureFRUIT_VEGETABLES ), by(Gorx month)
egen tot_quantity_fruitveg = sum( quantityFRUIT_VEGETABLES), by(month)
egen tot_quantity_fruitveg_region = sum( quantityFRUIT_VEGETABLES) , by(Gorx month)
gen p_4 = (tot_exp_fruitveg - tot_exp_fruitveg_region)/(tot_quantity_fruitveg -
tot_quantity_fruitveg_region)
gen ln_p_4= ln(p_4)
*oil
egen tot_exp_oil = sum( expenditureOIL ), by(month)
egen tot_exp_oil_region = sum( expenditureOIL ), by(Gorx month)
egen tot_quantity_oil = sum( quantityOIL ), by(month)
egen tot_quantity_oil_region = sum( quantityOIL ) , by(Gorx month)
gen p_5 = (tot_exp_oil - tot_exp_oil_region )/(tot_quantity_oil - tot_quantity_oil_region )
gen ln_p_5= ln(p_5)
*proteins
egen tot_exp_proteins = sum( expenditurePROTEINS ), by(month)
egen tot_exp_proteins_region = sum( expenditurePROTEINS ), by(Gorx month)
egen tot_quantity_proteins = sum( quantityPROTEINS ), by(month)
egen tot_quantity_proteins_regions = sum( quantityPROTEINS ) , by(Gorx month)
gen p_6 = (tot_exp_proteins - tot_exp_proteins_region)/(tot_quantity_proteins -
tot_quantity_proteins_regions)
gen ln_p_6= ln(p_6)
*others
egen tot_exp_others = sum( expenditureOTHERS ), by(month)
egen tot_exp_others_region = sum( expenditureOTHERS ), by(Gorx month)
egen tot_quantity_others = sum( quantityOTHERS ), by(month)
egen tot_quantity_others_region = sum( quantityOTHERS ) , by(Gorx month)
gen p_7 = (tot_exp_others - tot_exp_others_region)/(tot_quantity_others - tot_quantity_others_region)
```

gen ln_p_7= ln(p_7)

Prices in the same month as instruments

```
*carbs
egen tot_exp_carb = sum( expenditureCARBOHYDRATES ), by(month)
egen tot_quantity_carb = sum( quantityCARBOHYDRATES ) , by(month)
gen p_1 = (tot_exp_carb - expenditureCARBOHYDRATES)/(tot_quantity_carb - quantityCARBOHYDRATES)
gen ln_p_1 = ln(p_1)
*dairy
egen tot_exp_diary = sum( expenditureDIARY ), by(month)
egen tot_quantity_diary = sum( quantityDIARY ) , by(month)
gen p_2 = (tot_exp_diary - expenditureDIARY)/(tot_quantity_diary - quantityDIARY)
gen ln_p_2 = ln(p_2)
*drinks
egen tot_exp_drinks = sum( expenditureDRINKS ), by(month)
egen tot_quantity_drinks = sum( quantityDRINKS ) , by(month)
gen p_3 = (tot_exp_drinks - expenditureDRINKS)/(tot_quantity_drinks - quantityDRINKS)
gen ln_p_3 = ln(p_3)
*fruitveg
egen tot_exp_fruitveg = sum( expenditureFRUIT_VEGETABLES ), by(month)
egen tot_quantity_fruitveg = sum( quantityFRUIT_VEGETABLES) , by(month)
gen p_4 = (tot_exp_fruitveg - expenditureFRUIT_VEGETABLES)/(tot_quantity_fruitveg - quantityFRUIT_VEGETABLES)
gen ln_p_4= ln(p_4)
*oil
egen tot_exp_oil = sum( expenditureOIL ), by(month)
egen tot_quantity_oil = sum( quantityOIL ) , by(month)
gen p_5 = (tot_exp_oil - expenditureOIL)/(tot_quantity_oil - quantityOIL)
gen ln_p_5= ln(p_5)
*proteins
egen tot_exp_proteins = sum( expenditurePROTEINS ), by(month)
egen tot_quantity_proteins = sum( quantityPROTEINS ) , by(month)
gen p_6 = (tot_exp_proteins - expenditurePROTEINS)/(tot_quantity_proteins - quantityPROTEINS)
gen ln_p_6= ln(p_6)
*others
egen tot_exp_others = sum( expenditureOTHERS ), by(month)
egen tot_quantity_others = sum( quantityOTHERS ) , by(month)
gen p_7 = (tot_exp_others - expenditureOTHERS)/(tot_quantity_others - quantityOTHERS)
gen ln_p_7= ln(p_7)
```

Prices in the same region as instrument

```
*carbs
egen tot_exp_carb_region = sum(expenditureCARBOHYDRATES), by(Gorx)
egen tot_quantity_carb_region = sum( quantityCARBOHYDRATES ) , by(Gorx)
gen p_1 = (tot_exp_carb_region - expenditureCARBOHYDRATES)/(tot_quantity_carb_region - quantityCARBOHYDRATES)
gen ln_p_1 = ln(p_1)
*dairy
egen tot_exp_dairy_region = sum( expenditureDIARY ), by(Gorx)
egen tot_quantity_dairy_region = sum( quantityDIARY ), by(Gorx)
gen p_2 = (tot_exp_dairy_region - expenditureDIARY)/(tot_quantity_dairy_region - quantityDIARY )
gen ln_p_2 = ln(p_2)
*drinks
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx)
```

```
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx)
gen p_3 = (tot_exp_drinks_region - expenditureDRINKS)/(tot_quantity_drinks_region - quantityDRINKS)
gen ln_p_3 = ln(p_3)
*fruitveg
egen tot_exp_fruitveg_region = sum( expenditureFRUIT_VEGETABLES ), by(Gorx)
egen tot_quantity_fruitveg_region = sum( quantityFRUIT_VEGETABLES) , by(Gorx)
gen p_4 = (tot_exp_fruitveg_region - expenditureFRUIT_VEGETABLES)/(tot_quantity_fruitveg_region -
quantityFRUIT_VEGETABLES)
gen ln_p_4= ln(p_4)
*oil
egen tot_exp_oil_region = sum( expenditureOIL ), by(Gorx)
egen tot_quantity_oil_region = sum( quantityOIL ) , by(Gorx)
gen p_5 = (tot_exp_oil_region - expenditureOIL )/(tot_quantity_oil_region - quantityOIL)
gen ln_p_5= ln(p_5)
*proteins
egen tot_exp_proteins_region = sum( expenditurePROTEINS ), by(Gorx)
egen tot_quantity_proteins_regions = sum( quantityPROTEINS ) , by(Gorx)
gen p_6 = (tot_exp_proteins_region - expenditurePROTEINS)/(tot_quantity_proteins_regions -
quantityPROTEINS)
gen ln_p_6= ln(p_6)
*others
egen tot_exp_others_region = sum( expenditureOTHERS ), by(Gorx)
egen tot_quantity_others_region = sum( quantityOTHERS ) , by(Gorx)
gen p_7 = (tot_exp_others_region - expenditureOTHERS )/(tot_quantity_others_region - quantityOTHERS)
gen ln_p_7= ln(p_7)
```

Stata Codes Alternative Simulation Methods

Simulation with residuals

```
gen w1t= cons1 + p11*lnp1t + p12*lnp2t + p13*lnp3t + p14*lnp4t + p15*lnp5t + p16*lnp6t +
p17*lnp7t + p18*lnp8t + p19*lnp9t + p110*lnp10t + p111*lnp11t + b1*lnm2 + size1*size +
age1*age_HRP + sex1*sex_oldest + res_w1
gen w2t= cons2 + p12*lnp1t + p22*lnp2t + p23*lnp3t + p24*lnp4t + p25*lnp5t + p26*lnp6t +
p27*lnp7t + p28*lnp8t + p29*lnp9t + p210*lnp10t + p211*lnp11t + b2*lnm2 + size2*size +
age2*age_HRP + sex2*sex_oldest + res_w2
gen w3t= cons3 + p13*lnp1t + p23*lnp2t + p33*lnp3t + p34*lnp4t + p35*lnp5t + p36*lnp6t +
p37*lnp7t + p38*lnp8t + p39*lnp9t + p310*lnp10t + p311*lnp11t + b3*lnm2 + size3*size +
age3*age_HRP + sex3*sex_oldest + res_w3
gen w4t= cons4 + p14*lnp1t + p24*lnp2t + p34*lnp3t + p44*lnp4t + p45*lnp5t + p46*lnp6t +
p47*lnp7t + p48*lnp8t + p49*lnp9t + p410*lnp10t + p411*lnp11t + b4*lnm2 + size4*size +
age4*age_HRP + sex4*sex_oldest + res_w4
gen w5t= cons5 + p15*lnp1t + p25*lnp2t + p35*lnp3t + p45*lnp4t + p55*lnp5t + p56*lnp6t +
p57*lnp7t + p58*lnp8t + p59*lnp9t + p510*lnp10t + p511*lnp11t + b5*lnm2 + size5*size +
age5*age_HRP + sex5*sex_oldest + res_w5
gen w6t= cons6 + p16*lnp1t + p26*lnp2t + p36*lnp3t + p46*lnp4t + p56*lnp5t + p66*lnp6t +
p67*lnp7t + p68*lnp8t + p69*lnp9t + p610*lnp10t + p611*lnp11t + b6*lnm2 + size6*size +
age6*age_HRP + sex6*sex_oldest + res_w6
gen w7t= cons7 + p17*lnp1t + p27*lnp2t + p37*lnp3t + p47*lnp4t + p57*lnp5t + p67*lnp6t +
p77*lnp7t + p78*lnp8t + p79*lnp9t + p710*lnp10t + p711*lnp11t + b7*lnm2 + size7*size +
age7*age_HRP + sex7*sex_oldest + res_w7
gen w8t= cons8 + p18*lnp1t + p28*lnp2t + p38*lnp3t + p48*lnp4t + p58*lnp5t + p68*lnp6t +
p78*lnp7t + p88*lnp8t + p89*lnp9t + p810*lnp10t + p811*lnp11t + b8*lnm2 + size8*size +
age8*age_HRP + sex8*sex_oldest + res_w8
gen w9t= cons9 + p19*lnp1t + p29*lnp2t + p39*lnp3t + p49*lnp4t + p59*lnp5t + p69*lnp6t +
p79*lnp7t + p89*lnp8t + p99*lnp9t + p910*lnp10t + p911*lnp11t + b9*lnm2 + size9*size +
age9*age_HRP + sex9*sex_oldest + res_w9
gen w10t= cons10 + p110*lnp1t + p210*lnp2t + p310*lnp3t + p410*lnp4t + p510*lnp5t + p610*lnp6t
+ p710*lnp7t + p810*lnp8t + p910*lnp9t + p1010*lnp10t + p1011*lnp11t + b10*lnm2 + size10*size +
age10*age_HRP + sex10*sex_oldest + res_w10
gen w11t = cons11 + p111*lnp1t + p211*lnp2t + p311*lnp3t + p411*lnp4t + p511*lnp5t + p611*lnp6t
+ p711*lnp7t + p811*lnp8t + p911*lnp9t + p1011*lnp10t + p1111*lnp11t + b11*lnm2 + size11*size +
age11*age_HRP + sex11*sex_oldest + res_w11
gen ln_hh_expenditurет = s_cons + s_income*ln_income + s_lnp1*lnp1t + s_lnp2*lnp2t + s_lnp3*lnp3t +
s_lnp4*lnp4t + s_lnp5*lnp5t + s_lnp6*lnp6t + s_lnp7*lnp7t + s_lnp8*lnp8t + s_lnp9*lnp9t +
s_lnp10*lnp10t + s_lnp11*lnp11t + s_size*size + s_age*age_HRP + s_sex* sex_oldest +
res_hh_expenditure
```

Postfile simulation

```
*I am using eatwell dataset for simulation. It includes log of prices taxed, P Index and real expenditure
after taxation

program myprog3, rclass
version 15.1
set obs 5024

gen e1=rnormal()
gen e2=rnormal()
gen e3=rnormal()
gen e4=rnormal()
gen e5=rnormal()
```

```
gen e6=rnormal()
gen e7=rnormal()

gen w1t = cons1 + p11*lnp1t + p12*lnp2t + p13*lnp3t + p14*lnp4t + p15*lnp5t + p16*lnp6t +
p17*lnp7t + b1*lnm2 + size1*size + age1*age_HRP + sex1*sex_oldest + e1
gen w2t = cons2 + p12*lnp1t + p22*lnp2t + p23*lnp3t + p24*lnp4t + p25*lnp5t + p26*lnp6t +
p27*lnp7t + b2*lnm2 + size2*size + age2*age_HRP + sex2*sex_oldest + e2
gen w3t = cons3 + p13*lnp1t + p23*lnp2t + p33*lnp3t + p34*lnp4t + p35*lnp5t + p36*lnp6t +
p37*lnp7t + b3*lnm2 + size3*size + age3*age_HRP + sex3*sex_oldest + e3
gen w4t = cons4 + p14*lnp1t + p24*lnp2t + p34*lnp3t + p44*lnp4t + p45*lnp5t + p46*lnp6t +
p47*lnp7t + b4*lnm2 + size4*size + age4*age_HRP + sex4*sex_oldest + e4
gen w5t = cons5 + p15*lnp1t + p25*lnp2t + p35*lnp3t + p45*lnp4t + p55*lnp5t + p56*lnp6t +
p57*lnp7t + b5*lnm2 + size5*size + age5*age_HRP + sex5*sex_oldest + e5
gen w6t = cons6 + p16*lnp1t + p26*lnp2t + p36*lnp3t + p46*lnp4t + p56*lnp5t + p66*lnp6t +
p67*lnp7t + b6*lnm2 + size6*size + age6*age_HRP + sex6*sex_oldest + e6
gen w7t = cons7 + p17*lnp1t + p27*lnp2t + p37*lnp3t + p47*lnp4t + p57*lnp5t + p67*lnp6t +
p77*lnp7t + b7*lnm2 + size7*size + age7*age_HRP + sex7*sex_oldest + e7

sum w1t
  scalar w1t=r(w1t)

sum w2t
  scalar w2t=r(w2t)

sum w3t
  scalar w3t=r(w3t)

sum w4t
  scalar w4t=r(w4t)

sum w5t
  scalar w5t=r(w4t)

sum w6t
  scalar w6t=r(w5t)

sum w7t
  scalar w7t=r(w6t)

end

simulate w1t=r(w1t) w2t=r(w2t) w3t=r(w3t) w4t=r(w4t) w5t=r(w5t) w6t=r(w6t) w7t=r(w7t) ,
reps(10): myprog3

program myprog2, rclass
version 15.1
set obs 5017

gen e1=rnormal()
gen w1t = cons1 + p11*lnp1t + p12*lnp2t + p13*lnp3t + p14*lnp4t + p15*lnp5t + p16*lnp6t +
p17*lnp7t + b1*lnm2 + size1*size + age1*age_HRP + sex1*sex_oldest + e1
sum w1t
return scalar w1t_mean=r(mean)
gen e2=rnormal()
gen w2t = cons2 + p12*lnp1t + p22*lnp2t + p23*lnp3t + p24*lnp4t + p25*lnp5t + p26*lnp6t +
p27*lnp7t + b2*lnm2 + size2*size + age2*age_HRP + sex2*sex_oldest + e2
sum w2t
```

```
return scalar w2t_mean=r(mean)
gen e3=rnormal()
gen w3t = cons3 + p13*lnp1t + p23*lnp2t + p33*lnp3t + p34*lnp4t + p35*lnp5t + p36*lnp6t +
p37*lnp7t + b3*lnm2 + size3*size + age3*age_HRP + sex3*sex_oldest + e3
sum w3t
return scalar w3t_mean=r(mean)
gen e4=rnormal()
gen w4t = cons4 + p14*lnp1t + p24*lnp2t + p34*lnp3t + p44*lnp4t + p45*lnp5t + p46*lnp6t +
p47*lnp7t + b4*lnm2 + size4*size + age4*age_HRP + sex4*sex_oldest + e4
sum w4t
return scalar w4t_mean=r(mean)
gen e5=rnormal()
gen w5t = cons5 + p15*lnp1t + p25*lnp2t + p35*lnp3t + p45*lnp4t + p55*lnp5t + p56*lnp6t +
p57*lnp7t + b5*lnm2 + size5*size + age5*age_HRP + sex5*sex_oldest + e5
sum w5t
return scalar w5t_mean=r(mean)
gen e6=rnormal()
gen w6t = cons6 + p16*lnp1t + p26*lnp2t + p36*lnp3t + p46*lnp4t + p56*lnp5t + p66*lnp6t +
p67*lnp7t + b6*lnm2 + size6*size + age6*age_HRP + sex6*sex_oldest + e6
sum w6t
return scalar w6t_mean=r(mean)
gen e7=rnormal()
gen w7t = cons7 + p17*lnp1t + p27*lnp2t + p37*lnp3t + p47*lnp4t + p57*lnp5t + p67*lnp6t +
p77*lnp7t + b7*lnm2 + size7*size + age7*age_HRP + sex7*sex_oldest + e7
sum w7t
return scalar w7t_mean=r(mean)

drop e1 e2 e3 e4 e5 e6 e7 w1t w2t w3t w4t w5t w6t w7t

end

simulate w1t_mean=r(w1t_mean) w2t_mean=r(w2t_mean) w3t_mean=r(w3t_mean)
w4t_mean=r(w4t_mean) w5t_mean=r(w5t_mean) w6t_mean=r(w6t_mean) w7t_mean=r(w7t_mean) ,
reps(10): myprog2
```

Stata Codes Health Simulation with Quantity

Haemoglobin

```
drop if A1C_mmol_mol < 0

reg A1C_mmol_mol quantity_cereals quantity_dairy quantity_drinks quantity_fish quantity_fruit
quantity_meat quantity_fats quantity_potatoes quantity_ready_meals quantity_sweets quantity_vegetables
MFPAge MFPSex DMHSize, vce(robust)

clear
use "D:\DOCUMENT H\H__ - Copy\Stata\Preparation
Dataset\Dataset\2015_2016Q1\Aggregations\CATEGORIES_FINAL\New
folder\reshape_complete_nopulses_results_celine.dta"

estimates table

scalar define s_drinks = _b[quantity_drinks]
scalar define s_cereals = _b[quantity_cereals]
scalar define s_age = _b[MFPAge]
scalar define s_sex = _b[MFPSex]
scalar define s_size = _b[DMHSize]

scalar define s_cons = _b[_cons]
scalar define s_dairy = _b[ quantity_dairy ]
scalar define s_fruit = _b[ quantity_fruit ]
scalar define s_veg = _b[ quantity_vegetables ]
scalar define s_fats = _b[ quantity_fats ]
scalar define s_meat = _b[ quantity_meat ]
scalar define s_fish = _b[ quantity_fish ]
scalar define s_potatoes = _b[ quantity_potatoes ]
scalar define s_readymeals = _b[ quantity_ready_meals ]
scalar define s_sweets = _b[ quantity_sweets ]
gen quantity_day_cereal = quantity_cereals /14
gen quantity_day_dairy = quantity_dairy /14
gen quantity_day_drinks = quantity_drinks /14
gen quantity_day_fruit = quantity_fruit /14
gen quantity_day_fish = quantity_fish /14
gen quantity_day_vegetables = quantity_vegetables /14
gen quantity_day_meat = quantity_meat /14
gen quantity_day_potatoes = quantity_potatoes /14
gen quantity_day_fats = quantity_fats /14
gen quantity_day_sweets = quantity_sweets /14
gen quantity_day_readymeals = quantity_readymeals /14

gen quantity_day_cereals_tax = quantity_cereals_taxed/14
gen quantity_day_dairy_tax = quantity_dairy_taxed /14
gen quantity_day_drink_tax = quantity_drinks_taxed /14
gen quantity_day_fruit_tax = quantity_fruit_taxed /14
gen quantity_day_fat_tax = quantity_fats_taxed /14
gen quantity_day_meat_tax = quantity_meat_taxed /14
gen quantity_day_potatoes_tax = quantity_potatoes_taxed /14
gen quantity_day_veg_tax = quantity_vegetabkes_taxed /14
gen quantity_day_sweets_tax = quantity_sweets_taxed /14
gen quantity_day_readymeal_tax = quantity_readymeals_taxed /14
gen quantity_day_fish_tax = quantity_fish_taxed /14
```

```
gen quantity_day_cereals_bonus = quantity_cereals_bonus/14
gen quantity_day_dairy_bonus = quantity_dairy_bonus /14
gen quantity_day_drink_bonus = quantity_drinks_bonus /14
gen quantity_day_fruit_bonus = quantity_fruit_bonus /14
gen quantity_day_fat_bonus = quantity_fats_bonus /14
gen quantity_day_meat_bonus = quantity_meat_bonus/14
gen quantity_day_potatoes_bonus = quantity_potatoes_bonus /14
gen quantity_day_sweets_bonus = quantity_sweets_bonus/14
gen quantity_day_readymeal_bonus = quantity_readymeals_bonus /14
gen quantity_day_fish_bonus = quantity_fish_bonus /14
gen quantity_day_veg_bonus = quantity_vegetabkes_bonus /14

gen A1c_before = s_cons + s_cereals*quantity_day_cereal + s_dairy*quantity_day_dairy +
s_drinks*quantity_day_drinks + s_fruit*quantity_day_fruit + s_fish* quantity_day_fish + s_veg*
quantity_day_vegetables + s_meat*quantity_day_meat + s_potatoes*quantity_day_potatoes +
s_fats*quantity_day_fats + s_readymeals*quantity_day_readymeals + s_sweets*quantity_day_sweets +
s_size*size + s_age*age_HRP + s_sex*sex_oldest

gen A1c_tax = s_cons + s_cereals*quantity_day_cereals_tax + s_dairy*quantity_day_dairy_tax +
s_drinks*quantity_day_drink_tax + s_fruit*quantity_day_fruit_tax + s_fish* quantity_day_fish_tax + s_veg*
quantity_day_veg_tax + s_meat*quantity_day_meat_tax + s_potatoes*quantity_day_potatoes_tax +
s_fats*quantity_day_fat_tax + s_readymeals*quantity_day_readymeal_tax +
s_sweets*quantity_day_sweets_tax + s_size*size+ s_age*age_HRP + s_sex*sex_oldest

gen A1c_bonus = s_cons + s_cereals*quantity_day_cereals_bonus + s_dairy*quantity_day_dairy_bonus +
s_drinks*quantity_day_drink_bonus + s_fruit*quantity_day_fruit_bonus + s_fish* quantity_day_fish_bonus
+ s_veg*quantity_day_veg_bonus + s_meat*quantity_day_meat_bonus +
s_potatoes*quantity_day_potatoes_bonus + s_fats*quantity_day_fat_bonus +
s_readymeals*quantity_day_ready_meals_bonus + s_sweets*quantity_day_sweets_bonus + s_size*size +
s_age*age_HRP + s_sex*sex_oldest

sum A1c_before A1c_tax A1c_bonus

ttest A1c_before == A1c_tax
ttest A1c_before == A1c_bonus
```

<u>Body Mass Index</u>

```
drop if bmival < 0
drop if AdChild == 2

reg bmival quantity_cereals quantity_dairy quantity_drinks quantity_fish quantity_fruit quantity_meat
quantity_fats quantity_potatoes quantity_ready_meals quantity_sweets quantity_vegetables MFPAge
MFPSex DMHSize, vce(robust)
predict bmi_before

clear

use "D:\DOCUMENT H\H__ - Copy\Stata\Preparation
Dataset\Dataset\2015_2016Q1\Aggregations\CATEGORIES_FINAL\New
folder\reshape_complete_nopulses_results_celine.dta"

estimates table
scalar define s_drinks = _b[quantity_drinks]
scalar define s_cereals = _b[quantity_cereals]
scalar define s_age = _b[MFPAge]
```

```
scalar define s_sex = _b[MFPSex]
scalar define s_size = _b[DMHSize]

scalar define s_cons = _b[_cons]
scalar define s_dairy = _b[ quantity_dairy ]
scalar define s_fruit = _b[ quantity_fruit ]
scalar define s_veg = _b[ quantity_vegetables ]
scalar define s_fats = _b[ quantity_fats ]
scalar define s_meat = _b[ quantity_meat ]
scalar define s_fish = _b[ quantity_fish ]
scalar define s_potatoes = _b[ quantity_potatoes ]
scalar define s_readymeals = _b[ quantity_ready_meals ]
scalar define s_sweets = _b[ quantity_sweets ]

gen quantity_day_cereal = quantity_cereals /14
gen quantity_day_dairy = quantity_dairy /14
gen quantity_day_drinks = quantity_drinks /14
gen quantity_day_fruit = quantity_fruit /14
gen quantity_day_fish = quantity_fish /14
gen quantity_day_vegetables = quantity_vegetables /14
gen quantity_day_meat = quantity_meat /14
gen quantity_day_potatoes = quantity_potatoes /14
gen quantity_day_fats = quantity_fats /14
gen quantity_day_sweets = quantity_sweets /14
gen quantity_day_readymeals = quantity_readymeals /14

gen quantity_day_cereals_tax = quantity_cereals_taxed/14
gen quantity_day_dairy_tax = quantity_dairy_taxed /14
gen quantity_day_drink_tax = quantity_drinks_taxed /14
gen quantity_day_fruit_tax = quantity_fruit_taxed /14
gen quantity_day_fat_tax = quantity_fats_taxed /14
gen quantity_day_meat_tax = quantity_meat_taxed /14
gen quantity_day_potatoes_tax = quantity_potatoes_taxed /14
gen quantity_day_veg_tax = quantity_vegetabkes_taxed /14
gen quantity_day_sweets_tax = quantity_sweets_taxed /14
gen quantity_day_readymeal_tax = quantity_readymeals_taxed /14
gen quantity_day_fish_tax = quantity_fish_taxed /14

gen quantity_day_cereals_bonus = quantity_cereals_bonus/14
gen quantity_day_dairy_bonus = quantity_dairy_bonus /14
gen quantity_day_drink_bonus = quantity_drinks_bonus /14
gen quantity_day_fruit_bonus = quantity_fruit_bonus /14
gen quantity_day_fat_bonus = quantity_fats_bonus /14
gen quantity_day_meat_bonus = quantity_meat_bonus/14
gen quantity_day_potatoes_bonus = quantity_potatoes_bonus /14
gen quantity_day_sweets_bonus = quantity_sweets_bonus/14
gen quantity_day_readymeal_bonus = quantity_readymeals_bonus /14
gen quantity_day_fish_bonus = quantity_fish_bonus /14
gen quantity_day_veg_bonus = quantity_vegetabkes_bonus /14

gen bmi_before = s_cons + s_cereals*quantity_day_cereal + s_dairy*quantity_day_dairy +
s_drinks*quantity_day_drinks + s_fruit*quantity_day_fruit + s_fish* quantity_day_fish + s_veg*
quantity_day_vegetables + s_meat*quantity_day_meat + s_potatoes*quantity_day_potatoes +
s_fats*quantity_day_fats + s_readymeals*quantity_day_readymeals + s_sweets*quantity_day_sweets +
s_size*size + s_age*age_HRP + s_sex*sex_oldest
```

gen bmi_tax = s_cons + s_cereals*quantity_day_cereals_tax + s_dairy*quantity_day_dairy_tax + s_drinks*quantity_day_drink_tax + s_fruit*quantity_day_fruit_tax + s_fish* quantity_day_fish_tax + s_veg* quantity_day_veg_tax + s_meat*quantity_day_meat_tax + s_potatoes*quantity_day_potatoes_tax + s_fats*quantity_day_fat_tax + s_readymeals*quantity_day_readymeal_tax + s_sweets*quantity_day_sweets_tax + s_size*size+ s_age*age_HRP + s_sex*sex_oldest

gen bmi_bonus = s_cons + s_cereals*quantity_day_cereals_bonus + s_dairy*quantity_day_dairy_bonus + s_drinks*quantity_day_drink_bonus + s_fruit*quantity_day_fruit_bonus + s_fish* quantity_day_fish_bonus + s_veg*quantity_day_veg_bonus + s_meat*quantity_day_meat_bonus + s_potatoes*quantity_day_potatoes_bonus + s_fats*quantity_day_fat_bonus + s_readymeals*quantity_day_readymeal_bonus + s_sweets*quantity_day_sweets_bonus + s_size*size + s_age*age_HRP + s_sex*sex_oldest

ttest bmi_before == bmi_tax
ttest bmi_before == bmi_bonus

Cholesterol

drop if Chol < 0
reg Chol quantity_cereals quantity_dairy quantity_drinks quantity_fish quantity_fruit quantity_meat quantity_fats quantity_potatoes quantity_ready_meals quantity_sweets quantity_vegetables MFPAge MFPSex DMHSize, vce(robust)

clear

use "D:\DOCUMENT H\H__ - Copy\Stata\Preparation Dataset\Dataset\2015_2016Q1\Aggregations\CATEGORIES_FINAL\New folder\reshape_complete_nopulses_results_celine.dta"

estimates table

scalar define s_drinks = _b[quantity_drinks]
scalar define s_cereals = _b[quantity_cereals]
scalar define s_age = _b[MFPAge]
scalar define s_sex = _b[MFPSex]
scalar define s_size = _b[DMHSize]

scalar define s_cons = _b[_cons]
scalar define s_dairy = _b[quantity_dairy]
scalar define s_fruit = _b[quantity_fruit]
scalar define s_veg = _b[quantity_vegetables]
scalar define s_fats = _b[quantity_fats]
scalar define s_meat = _b[quantity_meat]
scalar define s_fish = _b[quantity_fish]
scalar define s_potatoes = _b[quantity_potatoes]
scalar define s_readymeals = _b[quantity_ready_meals]
scalar define s_sweets = _b[quantity_sweets]

gen quantity_day_cereal = quantity_cereals /14
gen quantity_day_dairy = quantity_dairy /14
gen quantity_day_drinks = quantity_drinks /14
gen quantity_day_fruit = quantity_fruit /14
gen quantity_day_fish = quantity_fish /14
gen quantity_day_vegetables = quantity_vegetables /14
gen quantity_day_meat = quantity_meat /14
gen quantity_day_potatoes = quantity_potatoes /14
gen quantity_day_fats = quantity_fats /14

```
gen quantity_day_sweets = quantity_sweets /14
gen quantity_day_readymeals = quantity_readymeals /14

gen quantity_day_cereals_tax = quantity_cereals_taxed/14
gen quantity_day_dairy_tax = quantity_dairy_taxed /14
gen quantity_day_drink_tax = quantity_drinks_taxed /14
gen quantity_day_fruit_tax = quantity_fruit_taxed /14
gen quantity_day_fat_tax = quantity_fats_taxed /14
gen quantity_day_meat_tax = quantity_meat_taxed /14
gen quantity_day_potatoes_tax = quantity_potatoes_taxed /14
gen quantity_day_veg_tax = quantity_vegetabkes_taxed /14
gen quantity_day_sweets_tax = quantity_sweets_taxed /14
gen quantity_day_readymeal_tax = quantity_readymeals_taxed /14
gen quantity_day_fish_tax = quantity_fish_taxed /14

gen quantity_day_cereals_bonus = quantity_cereals_bonus/14
gen quantity_day_dairy_bonus = quantity_dairy_bonus /14
gen quantity_day_drink_bonus = quantity_drinks_bonus /14
gen quantity_day_fruit_bonus = quantity_fruit_bonus /14
gen quantity_day_fat_bonus = quantity_fats_bonus /14
gen quantity_day_meat_bonus = quantity_meat_bonus/14
gen quantity_day_potatoes_bonus = quantity_potatoes_bonus /14
gen quantity_day_sweets_bonus = quantity_sweets_bonus/14
gen quantity_day_readymeal_bonus = quantity_readymeals_bonus /14
gen quantity_day_fish_bonus = quantity_fish_bonus /14
gen quantity_day_veg_bonus = quantity_vegetabkes_bonus /14

gen Chol_tax = s_cons + s_cereals*quantity_day_cereals_tax + s_dairy*quantity_day_dairy_tax +
s_drinks*quantity_day_drink_tax + s_fruit*quantity_day_fruit_tax + s_fish* quantity_day_fish_tax + s_veg*
quantity_day_veg_tax + s_meat*quantity_day_meat_tax + s_potatoes*quantity_day_potatoes_tax +
s_fats*quantity_day_fat_tax + s_readymeals*quantity_day_readymeal_tax +
s_sweets*quantity_day_sweets_tax + s_size*size+ s_age*age_HRP + s_sex*sex_oldest

gen Chol_before = s_cons + s_cereals*quantity_day_cereal + s_dairy*quantity_day_dairy +
s_drinks*quantity_day_drinks + s_fruit*quantity_day_fruit + s_fish* quantity_day_fish + s_veg*
quantity_day_vegetables + s_meat*quantity_day_meat + s_potatoes*quantity_day_potatoes +
s_fats*quantity_day_fats + s_readymeals*quantity_day_readymeals + s_sweets*quantity_day_sweets +
s_size*size + s_age*age_HRP + s_sex*sex_oldest

gen Chol_bonus = s_cons + s_cereals*quantity_day_cereals_bonus + s_dairy*quantity_day_dairy_bonus +
s_drinks*quantity_day_drink_bonus + s_fruit*quantity_day_fruit_bonus + s_fish* quantity_day_fish_bonus
+ s_veg*quantity_day_veg_bonus + s_meat*quantity_day_meat_bonus +
s_potatoes*quantity_day_potatoes_bonus + s_fats*quantity_day_fat_bonus +
s_readymeals*quantity_day_readymeal_bonus + s_sweets*quantity_day_sweets_bonus + s_size*size +
s_age* age_HRP + s_sex*sex_oldest

ttest Chol_before == Chol_tax
ttest Chol_before == Chol_bonus

use "D:\DOCUMENT H\H__ - Copy\NDNS\NDNS 2008-
2017\6533stata_EBC74014799029E8914B6BFBC7D58F9B_V1\UKDA-6533-
stata\stata\stata11_se\health_food_nutrient_quantity.dta"
```

<u>Glucose</u>

```
drop if Glucose < 0
```

```
reg Glucose quantity_cereals quantity_dairy quantity_drinks quantity_fish quantity_fruit quantity_meat
quantity_fats quantity_potatoes quantity_ready_meals quantity_sweets quantity_vegetables MFPAge
MFPSex DMHSize, vce(robust)
predict Glucose_before

clear

use "D:\DOCUMENT H\H__ - Copy\Stata\Preparation
Dataset\Dataset\2015_2016Q1\Aggregations\CATEGORIES_FINAL\New
folder\reshape_complete_nopulses_results_jonas.dta"

estimates table

scalar define s_drinks = _b[quantity_drinks]
scalar define s_cereals = _b[quantity_cereals]
scalar define s_age = _b[MFPAge]
scalar define s_sex = _b[MFPSex]
scalar define s_size = _b[DMHSize]

scalar define s_cons = _b[_cons]
scalar define s_dairy = _b[ quantity_dairy ]
scalar define s_fruit = _b[ quantity_fruit ]
scalar define s_veg = _b[ quantity_vegetables ]
scalar define s_fats = _b[ quantity_fats ]
scalar define s_meat = _b[ quantity_meat ]
scalar define s_fish = _b[ quantity_fish ]
scalar define s_potatoes = _b[ quantity_potatoes ]
scalar define s_readymeals = _b[ quantity_ready_meals ]
scalar define s_sweets = _b[ quantity_sweets ]

gen quantity_day_cereal = quantity_cereals /14
gen quantity_day_dairy = quantity_dairy /14
gen quantity_day_drinks = quantity_drinks /14
gen quantity_day_fruit = quantity_fruit /14
gen quantity_day_fish = quantity_fish /14
gen quantity_day_vegetables = quantity_vegetables /14
gen quantity_day_meat = quantity_meat /14
gen quantity_day_potatoes = quantity_potatoes /14
gen quantity_day_fats = quantity_fats /14
gen quantity_day_sweets = quantity_sweets /14
gen quantity_day_readymeals = quantity_readymeals /14

gen quantity_day_cereals_tax = quantity_cereals_taxed/14
gen quantity_day_dairy_tax = quantity_dairy_taxed /14
gen quantity_day_drink_tax = quantity_drinks_taxed /14
gen quantity_day_fruit_tax = quantity_fruit_taxed /14
gen quantity_day_fat_tax = quantity_fats_taxed /14
gen quantity_day_meat_tax = quantity_meat_taxed /14
gen quantity_day_potatoes_tax = quantity_potatoes_taxed /14
gen quantity_day_veg_tax = quantity_vegetabkes_taxed /14
gen quantity_day_sweets_tax = quantity_sweets_taxed /14
gen quantity_day_readymeal_tax = quantity_readymeals_taxed /14
gen quantity_day_fish_tax = quantity_fish_taxed /14

gen quantity_day_cereals_bonus = quantity_cereals_bonus/14
gen quantity_day_dairy_bonus = quantity_dairy_bonus /14
gen quantity_day_drink_bonus = quantity_drinks_bonus /14
```

```
gen quantity_day_fruit_bonus = quantity_fruit_bonus /14
gen quantity_day_fat_bonus = quantity_fats_bonus /14
gen quantity_day_meat_bonus = quantity_meat_bonus/14
gen quantity_day_potatoes_bonus = quantity_potatoes_bonus /14
gen quantity_day_sweets_bonus = quantity_sweets_bonus/14
gen quantity_day_readymeal_bonus = quantity_readymeals_bonus /14
gen quantity_day_fish_bonus = quantity_fish_bonus /14
gen quantity_day_veg_bonus = quantity_vegetabkes_bonus /14

gen Glucose_tax = s_cons + s_cereals*quantity_day_cereals_tax + s_dairy*quantity_day_dairy_tax +
s_drinks*quantity_day_drink_tax + s_fruit*quantity_day_fruit_tax + s_fish* quantity_day_fish_tax + s_veg*
quantity_day_veg_tax + s_meat*quantity_day_meat_tax + s_potatoes*quantity_day_potatoes_tax +
s_fats*quantity_day_fat_tax + s_readymeals*quantity_day_readymeal_tax +
s_sweets*quantity_day_sweets_tax + s_size*size+ s_age*age_HRP + s_sex*sex_oldest

gen Glucose_bonus = s_cons + s_cereals*quantity_day_cereals_bonus + s_dairy*quantity_day_dairy_bonus
+ s_drinks*quantity_day_drink_bonus + s_fruit*quantity_day_fruit_bonus + s_fish*
quantity_day_fish_bonus + s_veg*quantity_day_veg_bonus + s_meat*quantity_day_meat_bonus +
s_potatoes*quantity_day_potatoes_bonus + s_fats*quantity_day_fat_bonus +
s_readymeals*quantity_day_ready_meals_bonus + s_sweets*quantity_day_sweets_bonus + s_size*size +
s_age*age_HRP + s_sex*sex_oldest

ttest Glucose_before == Glucose_tax
ttest Glucose_before == Glucose_bonus
```

Stata Codes Infrequence Purchase Model and Sample Selection

<u>Infrequence Purchase Model</u>

```
gen P Index and real expenditure

gen lnP_Index =
[(w1*lnp1)+(w2*lnp2)+(w3*lnp3)+(w4*lnp4)+(w5*lnp5)+(w6*lnp6)+(w7*lnp7)+(w8*lnp8)+(w9*l
np9)+(w10*lnp10)+(w11*lnp11)+(w12*lnp12)]
gen lnm = ln(hh_expenditure/exp(lnP_Index))

*homogeneity restriction
I take as a reference p2 because is the category with less 0

gen p1 = (lnp1 -lnp2)
gen p3 = (lnp3 -lnp2)
gen p4 = (lnp4 -lnp2)
gen p5 = (lnp5 -lnp2)
gen p6 = (lnp6 -lnp2)
gen p7 = (lnp7 -lnp2)
gen p8 = (lnp8 -lnp2)
gen p9 = (lnp9 -lnp2)
gen p10 = (lnp10 -lnp2)
gen p11 = (lnp11 -lnp2)
gen p12 = (lnp12 -lnp2)

*gen dependent variable for probit
gen d = (w1>0)
gen y = w1

*then you do the same for all the other budget shares

probit d p1 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12 lnm children age_HRP
mat bprobit=e(b)
tobit y p1 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12 lnm children age_HRP, ll(0)
mat btobit=e(b)

program define ipm
version 10
args lnf theta1 theta2 theta3
tempvar d p z p0 p1
quietly gen double `d'=$ML_y1>0
quietly gen double `p'=normprob(`theta3')
quietly gen double `z'=(`p'*($ML_y1)-`theta1')/(`theta2')
quietly gen double `p0'=1-(`p'*normprob(-`z'))
quietly gen double `p1'=((`p')^2)*normalden(`z')/`theta2'
quietly replace `lnf'=(1-`d')*ln(`p0')+`d'*ln(`p1')
end

mat b=btobit,bprobit
ml model lf ipm (y = p1 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12 lnm children age_HRP) () (d = p1 p3 p4 p5 p6
p7 p8 p9 p10 p11 p12 lnm children age_HRP)
ml init b, copy
ml maximize
```

Control function and Inverse Mills Ratio

```
egen tot_exp_cer = sum( expenditureCEREALS )
egen tot_exp_cer_region = sum(expenditureCEREALS), by(Gorx month)
egen tot_quantity_cer = sum( quantityCEREALS )
egen tot_quantity_cer_region = sum( quantityCEREALS ) , by(Gorx month)
gen p_1 = (tot_exp_cer - tot_exp_cer_region)/(tot_quantity_cer -  tot_quantity_cer_region)
gen ln_p_1 = ln(p_1)
gen price_cereals_region = tot_exp_cer_region/tot_quantity_cer_region

egen tot_exp_dairy = sum( expenditureDIARY_EGGS )
egen tot_exp_dairy_region = sum( expenditureDIARY_EGGS), by(Gorx month)
egen tot_quantity_dairy = sum( quantityDIARY_EGGS )
egen tot_quantity_dairy_region = sum( quantityDIARY_EGGS), by(Gorx month)
gen p_2 = (tot_exp_dairy - tot_exp_dairy_region)/(tot_quantity_dairy - tot_quantity_dairy_region)
gen ln_p_2 = ln(p_2)
gen price_dairy_region = tot_exp_dairy_region/tot_quantity_dairy_region

egen tot_exp_drinks = sum( expenditureDRINKS )
egen tot_exp_drinks_region = sum( expenditureDRINKS ), by(Gorx month)
egen tot_quantity_drinks = sum( quantityDRINKS )
egen tot_quantity_drinks_region = sum( quantityDRINKS ) , by(Gorx month)
gen p_3 = (tot_exp_drinks - tot_exp_drinks_region)/(tot_quantity_drinks - tot_quantity_drinks_region)
gen ln_p_3 = ln(p_3)
gen price_drinks_region = tot_exp_drinks_region/tot_quantity_drinks_region

egen tot_exp_fats = sum( expenditureFATS_SPREAD_SAUCES )
egen tot_exp_fats_region = sum( expenditureFATS_SPREAD_SAUCES ), by(Gorx month)
egen tot_quantity_fats = sum( quantityFATS_SPREAD_SAUCES)
egen tot_quantity_fats_region = sum( quantityFATS_SPREAD_SAUCES) , by(Gorx month)
gen p_4 = (tot_exp_fats - tot_exp_fats_region)/(tot_quantity_fats - tot_quantity_fats_region)
gen ln_p_4= ln(p_4)
gen price_fats_region = tot_exp_fats_region/tot_quantity_fats_region

egen tot_exp_fish = sum( expenditureFISH )
egen tot_exp_fish_region = sum( expenditureFISH ), by(Gorx month)
egen tot_quantity_fish = sum( quantityFISH )
egen tot_quantity_fish_region = sum( quantityFISH ) , by(Gorx month)
gen p_5 = (tot_exp_fish - tot_exp_fish_region )/(tot_quantity_fish - tot_quantity_fish_region )
gen ln_p_5= ln(p_5)
gen price_fish_region = tot_exp_fish_region/tot_quantity_fish_region

egen tot_exp_fruit = sum( expenditureFRUIT )
egen tot_exp_fruit_region = sum( expenditureFRUIT ), by(Gorx month)
egen tot_quantity_fruit = sum( quantityFRUIT )
egen tot_quantity_fruit_regions = sum( quantityFRUIT ) , by(Gorx month)
gen p_6 = (tot_exp_fruit - tot_exp_fruit_region)/(tot_quantity_fruit - tot_quantity_fruit_regions)
gen ln_p_6= ln(p_6)
gen price_fruit_region = tot_exp_fruit_region/tot_quantity_fruit_regions

egen tot_exp_meat = sum( expenditureMEAT )
egen tot_exp_meat_region = sum( expenditureMEAT ), by(Gorx month)
egen tot_quantity_meat = sum( quantityMEAT )
egen tot_quantity_meat_region = sum( quantityMEAT ) , by(Gorx month)
gen p_7 = (tot_exp_meat - tot_exp_meat_region)/(tot_quantity_meat - tot_quantity_meat_region)
gen ln_p_7= ln(p_7)
gen price_meat_region = tot_exp_meat_region/tot_quantity_meat_region
```

```
egen tot_exp_potatoes = sum( expenditurePOTATOES )
egen tot_exp_potatoes_region = sum( expenditurePOTATOES ), by(Gorx month)
egen tot_quantity_potatoes = sum( quantityPOTATOES )
egen tot_quantity_potatoes_regions = sum( quantityPOTATOES ) , by(Gorx month)
gen p_8 = (tot_exp_potatoes - tot_exp_potatoes_region)/(tot_quantity_potatoes -
tot_quantity_potatoes_regions)
gen ln_p_8= ln(p_8)
gen price_potatoes_region = tot_exp_potatoes_region/tot_quantity_potatoes_regions

egen tot_exp_ready = sum( expenditureREADY_MEALS )
egen tot_exp_ready_region = sum( expenditureREADY_MEALS ), by(Gorx month)
egen tot_quantity_ready = sum( quantityREADY_MEALS )
egen tot_quantity_ready_region = sum( quantityREADY_MEALS ) , by(Gorx month)
gen p_9 = (tot_exp_ready - tot_exp_ready_region)/(tot_quantity_ready - tot_quantity_ready_region)
gen ln_p_9= ln(p_9)
gen price_ready_region = tot_exp_ready_region/tot_quantity_ready_region

egen tot_exp_sweets = sum( expenditureSWEETS )
egen tot_exp_sweets_region = sum( expenditureSWEETS ), by(Gorx month)
egen tot_quantity_sweets = sum( quantitySWEETS )
egen tot_quantity_sweets_regions = sum( quantitySWEETS ) , by(Gorx month)
gen p_10 = (tot_exp_sweets - tot_exp_sweets_region)/(tot_quantity_sweets - tot_quantity_sweets_regions)
gen ln_p_10= ln(p_10)
gen price_sweets_region = tot_exp_sweets_region/tot_quantity_sweets_regions

egen tot_exp_veg = sum( expenditureVEGETABLES )
egen tot_exp_veg_region = sum( expenditureVEGETABLES ), by(Gorx month)
egen tot_quantity_veg = sum( quantityVEGETABLES )
egen tot_quantity_veg_region = sum( quantityVEGETABLES ) , by(Gorx month)
gen p_11 = (tot_exp_veg - tot_exp_veg_region)/(tot_quantity_veg - tot_quantity_veg_region)
gen ln_p_11= ln(p_11)
gen price_veg_region = tot_exp_veg_region/tot_quantity_veg_region

reg ln_hh_expenditure ln_income ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10
ln_p_11 $covariates
predict xb_hh
gen hh_exp_xb = exp(xb_hh)
test ln_income

reg lnp1 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp1_hat
test ln_p_1

reg lnp2 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp2_hat
test ln_p_2

reg lnp3 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp3_hat
test ln_p_3

reg lnp4 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
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```
predict lnp4_hat
test ln_p_4

reg lnp5 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp5_hat
test ln_p_5

reg lnp6 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp6_hat
test ln_p_6

reg lnp7 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp7_hat
test ln_p_7

reg lnp8 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp8_hat
test ln_p_8

reg lnp9 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp9_hat
test ln_p_9

reg lnp10 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp10_hat
test ln_p_10

reg lnp11 ln_p_1 ln_p_2 ln_p_3 ln_p_4 ln_p_5 ln_p_6 ln_p_7 ln_p_8 ln_p_9 ln_p_10 ln_p_11 ln_income
$covariates
predict lnp11_hat
test ln_p_11

gen lnP_Index =
[(w1*lnp1_hat)+(w2*lnp2_hat)+(w3*lnp3_hat)+(w4*lnp4_hat)+(w5*lnp5_hat)+(w6*lnp6_hat)+(w7*l
np7_hat)+(w8*lnp8_hat)+(w9*lnp9_hat)+(w10*lnp10_hat)+(w11*lnp11_hat)]
gen lnm = ln(hh_exp_xb/exp(lnP_Index))

gen dw1=1 if w1>0
replace dw1=0 if w1==0
gen dw2=1 if w2>0
replace dw2=0 if w2==0
gen dw3=1 if w3>0
replace dw3=0 if w3==0
gen dw4=1 if w4>0
replace dw4=0 if w4==0
gen dw5=1 if w5>0
replace dw5=0 if w5==0
gen dw6=1 if w6>0
replace dw6=0 if w6==0
gen dw7=1 if w7>0
replace dw7=0 if w7==0
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gen dw8=1 if w8>0
replace dw8=0 if w8==0
gen dw9=1 if w9>0
replace dw9=0 if w9==0
gen dw10=1 if w10>0
replace dw10=0 if w10==0
gen dw11=1 if w11>0
replace dw11=0 if w11==0

probit dw1 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb1
gen imr1 = normalden(xb1)/normal(xb1)
gen imr1c=(normalden(xb1)/(1-normal(xb1)))
replace imr1=imr1c if w1==0

probit dw2 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb2
gen imr2 = normalden(xb2)/normal(xb2)
gen imr2c=(normalden(xb2)/(1-normal(xb2)))
replace imr2=imr2c if w2==0

probit dw3 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb3
gen imr3 = normalden(xb3)/normal(xb3)
gen imr3c=(normalden(xb3)/(1-normal(xb3)))
replace imr3=imr3c if w3==0

probit dw4 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb4
gen imr4 = normalden(xb4)/normal(xb4)
gen imr4c=(normalden(xb4)/(1-normal(xb4)))
replace imr4=imr4c if w4==0

probit dw5 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb5
gen imr5 = normalden(xb5)/normal(xb5)
gen imr5c=(normalden(xb5)/(1-normal(xb5)))
replace imr5=imr5c if w5==0

probit dw6 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb6
gen imr6 = normalden(xb6)/normal(xb6)
gen imr6c=(normalden(xb6)/(1-normal(xb6)))
replace imr6=imr6c if w6==0

probit dw7 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb7
gen imr7 = normalden(xb7)/normal(xb7)
gen imr7c=(normalden(xb7)/(1-normal(xb7)))
replace imr7=imr7c if w7==0

probit dw8 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb8
gen imr8 = normalden(xb8)/normal(xb8)
gen imr8c=(normalden(xb8)/(1-normal(xb8)))
replace imr8=imr8c if w8==0
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probit dw9 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb9
gen imr9 = normalden(xb9)/normal(xb9)
gen imr9c=(normalden(xb9)/(1-normal(xb9)))
replace imr9=imr9c if w9==0

probit dw10 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb10
gen imr10 = normalden(xb10)/normal(xb10)
gen imr10c=(normalden(xb10)/(1-normal(xb10)))
replace imr10=imr10c if w10==0

probit dw11 lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates
predict xb11
gen imr11 = normalden(xb11)/normal(xb11)
gen imr11c=(normalden(xb11)/(1-normal(xb11)))
replace imr11=imr11c if w11==0

gen p1 = (lnp1_hat - lnp11_hat)
gen p2 = (lnp2_hat - lnp11_hat)
gen p3 = (lnp3_hat - lnp11_hat)
gen p4 = (lnp4_hat - lnp11_hat)
gen p5 = (lnp5_hat - lnp11_hat)
gen p6 = (lnp6_hat - lnp11_hat)
gen p7 = (lnp7_hat - lnp11_hat)
gen p8 = (lnp8_hat - lnp11_hat)
gen p9 = (lnp9_hat - lnp11_hat)
gen p10= (lnp10_hat - lnp11_hat)

nlsur (w1 =
{_cons1}+{p11}*p1+{p12}*p2+{p13}*p3+{p14}*p4+{p15}*p5+{p16}*p6+{p17}*p7+{p18}*p8+{p19}*
p9+{p110}*p10+{b1}*lnm+{x1:$covariates})(w2 =
{_cons2}+{p12}*p1+{p22}*p2+{p23}*p3+{p24}*p4+{p25}*p5+{p26}*p6+{p27}*p7+{p28}*p8+{p29}*
p9+{p210}*p10+{b2}*lnm+{x2:$covariates}+{z2:imr2})(w3 =
{_cons3}+{p13}*p1+{p23}*p2+{p33}*p3+{p34}*p4+{p35}*p5+{p36}*p6+{p37}*p7+{p38}*p8+{p39}*
p9+{p310}*p10+{b3}*lnm+{x3:$covariates}+{z3:imr3})(w4 =
{_cons4}+{p14}*p1+{p24}*p2+{p34}*p3+{p44}*p4+{p45}*p5+{p46}*p6+{p47}*p7+{p48}*p8+{p49}*
p9+{p410}*p10+{b4}*lnm+{x4:$covariates}+{z4:imr4})(w5 =
{_cons5}+{p15}*p1+{p25}*p2+{p35}*p3+{p45}*p4+{p55}*p5+{p56}*p6+{p57}*p7+{p58}*p8+{p59}*
p9+{p510}*p10+{b5}*lnm+{x5:$covariates}+{z5:imr5})(w6 =
{_cons6}+{p16}*p1+{p26}*p2+{p36}*p3+{p46}*p4+{p56}*p5+{p66}*p6+{p67}*p7+{p68}*p8+{p69}*
p9+{p610}*p10+{b6}*lnm+{x6:$covariates}+{z6:imr6})(w7 =
{_cons7}+{p17}*p1+{p27}*p2+{p37}*p3+{p47}*p4+{p57}*p5+{p67}*p6+{p77}*p7+{p78}*p8+{p79}*
p9+{p710}*p10+{b7}*lnm+{x7:$covariates}+{z7:imr7})(w8 =
{_cons8}+{p18}*p1+{p28}*p2+{p38}*p3+{p48}*p4+{p58}*p5+{p68}*p6+{p78}*p7+{p88}*p8+{p89}*
p9+{p810}*p10+{b8}*lnm+{x8:$covariates}+{z8:imr8})(w9 =
{_cons9}+{p19}*p1+{p29}*p2+{p39}*p3+{p49}*p4+{p59}*p5+{p69}*p6+{p79}*p7+{p89}*p8+{p99}*
p9+{p910}*p10+{b9}*lnm+{x9:$covariates}+{z9:imr9})(w10 =
{_cons10}+{p110}*p1+{p210}*p2+{p310}*p3+{p410}*p4+{p510}*p5+{p610}*p6+{p710}*p7+{p810}*
p8+{p910}*p9+{p1010}*p10+{b10}*lnm+{x10:$covariates}+{z10:imr10}),variables (w1 w2 w3 w4 w5
w6 w7 w8 w9 w10 p1 p2 p3 p4 p5 p6 p7 p8 p9 p10 lnm imr2 imr3 imr4 imr5 imr6 imr7 imr8 imr9 imr10
$covariates)

nlcom
(lnp_w1_w1:[p11]_cons)(lnp_w1_w2:[p12]_cons)(lnp_w1_w3:[p13]_cons)(lnp_w1_w4:[p14]_cons)(lnp_w
1_w5:[p15]_cons)(lnp_w1_w6:[p16]_cons)(lnp_w1_w7:[p17]_cons)(lnp_w1_w8:[p18]_cons)(lnp_w1_w9:[
p19]_cons)(lnp_w1_w10:[p110]_cons)(lnp_w2_w2:[p22]_cons)(lnp_w2_w3:[p23]_cons)(lnp_w2_w4:[p24
```

]_cons)(lnp_w2_w5:[p25]_cons)(lnp_w2_w6:[p26]_cons)(lnp_w2_w7:[p27]_cons)(lnp_w2_w8:[p28]_cons)(lnp_w2_w9:[p29]_cons)(lnp_w2_w10:[p210]_cons)(lnp_w3_w3:[p33]_cons)(lnp_w3_w4:[p34]_cons)(lnp_w3_w5:[p35]_cons)(lnp_w3_w6:[p36]_cons)(lnp_w3_w7:[p37]_cons)(lnp_w3_w8:[p38]_cons)(lnp_w3_w9:[p39]_cons)(lnp_w3_w10:[p310]_cons)(lnp_w4_w4:[p44]_cons)(lnp_w4_w5:[p45]_cons)(lnp_w4_w6:[p46]_cons)(lnp_w4_w7:[p47]_cons)(lnp_w4_w8:[p48]_cons)(lnp_w4_w9:[p49]_cons)(lnp_w4_w10:[p410]_cons)(lnp_w5_w5:[p55]_cons)(lnp_w5_w6:[p56]_cons)(lnp_w5_w7:[p57]_cons)(lnp_w5_w8:[p58]_cons)(lnp_w5_w9:[p59]_cons)(lnp_w5_w10:[p510]_cons)(lnp_w6_w6:[p66]_cons)(lnp_w6_w7:[p67]_cons)(lnp_w6_w8:[p68]_cons)(lnp_w6_w9:[p69]_cons)(lnp_w6_w10:[p610]_cons)(lnp_w7_w7:[p77]_cons)(lnp_w7_w8:[p78]_cons)(lnp_w7_w9:[p79]_cons)(lnp_w7_w10:[p710]_cons)(lnp_w8_w8:[p88]_cons)(lnp_w8_w9:[p89]_cons)(lnp_w8_w10:[p810]_cons)(lnp_w9_w9:[p99]_cons)(lnp_w9_w10:[p910]_cons)(lnp_w10_w10:[p1010]_cons)(lnp_w11_w1:0-[p11]_cons-[p12]_cons-[p13]_cons-[p14]_cons-[p15]_cons-[p16]_cons-[p17]_cons-[p18]_cons-[p19]_cons-[p110]_cons)(lnp_w11_w2:0-[p12]_cons-[p22]_cons-[p23]_cons-[p24]_cons-[p25]_cons-[p26]_cons-[p27]_cons-[p28]_cons-[p29]_cons-[p210]_cons)(lnp_w11_w3:0-[p13]_cons-[p23]_cons-[p33]_cons-[p34]_cons-[p35]_cons-[p36]_cons-[p37]_cons-[p38]_cons-[p39]_cons-[p310]_cons)(lnp_w11_w4:0-[p14]_cons-[p24]_cons-[p34]_cons-[p44]_cons-[p45]_cons-[p46]_cons-[p47]_cons-[p48]_cons-[p49]_cons-[p410]_cons)(lnp_w11_w5:0-[p15]_cons-[p25]_cons-[p35]_cons-[p45]_cons-[p55]_cons-[p56]_cons-[p57]_cons-[p58]_cons-[p59]_cons-[p510]_cons)(lnp_w11_w6:0-[p16]_cons-[p26]_cons-[p36]_cons-[p46]_cons-[p56]_cons-[p66]_cons-[p67]_cons-[p68]_cons-[p69]_cons-[p610]_cons)(lnp_w11_w7:0-[p17]_cons-[p27]_cons-[p37]_cons-[p47]_cons-[p57]_cons-[p67]_cons-[p77]_cons-[p78]_cons-[p79]_cons-[p710]_cons)(lnp_w11_w8:0-[p18]_cons-[p28]_cons-[p38]_cons-[p48]_cons-[p58]_cons-[p68]_cons-[p78]_cons-[p88]_cons-[p89]_cons-[p810]_cons)(lnp_w11_w9:0-[p19]_cons-[p29]_cons-[p39]_cons-[p49]_cons-[p59]_cons-[p69]_cons-[p79]_cons-[p89]_cons-[p99]_cons-[p910]_cons)(lnp_w11_w10:0-[p110]_cons-[p210]_cons-[p310]_cons-[p410]_cons-[p510]_cons-[p610]_cons-[p710]_cons-[p810]_cons-[p910]_cons-[p1010]_cons)(b1:[b1]_cons)(b2:[b2]_cons)(b3:[b3]_cons)(b4:[b4]_cons)(b5:[b5]_cons)(b6:[b6]_cons)(b7:[b7]_cons)(b8:[b8]_cons)(b9:[b9]_cons)(b10:[b10]_cons)(lnp_w11_w11:0-(0-[p11]_cons-[p12]_cons-[p13]_cons-[p14]_cons-[p15]_cons-[p16]_cons-[p17]_cons-[p18]_cons-[p19]_cons-[p110]_cons)-(0-[p12]_cons-[p22]_cons-[p23]_cons-[p24]_cons-[p25]_cons-[p26]_cons-[p27]_cons-[p28]_cons-[p29]_cons-[p210]_cons)-(0-[p13]_cons-[p23]_cons-[p33]_cons-[p34]_cons-[p35]_cons-[p36]_cons-[p37]_cons-[p38]_cons-[p39]_cons-[p310]_cons)-(0-[p14]_cons-[p24]_cons-[p34]_cons-[p44]_cons-[p45]_cons-[p46]_cons-[p47]_cons-[p48]_cons-[p49]_cons-[p410]_cons)-(0-[p15]_cons-[p25]_cons-[p35]_cons-[p45]_cons-[p55]_cons-[p56]_cons-[p57]_cons-[p58]_cons-[p59]_cons-[p510]_cons)-(0-[p16]_cons-[p26]_cons-[p36]_cons-[p46]_cons-[p56]_cons-[p66]_cons-[p67]_cons-[p68]_cons-[p69]_cons-[p610]_cons)-(0-[p17]_cons-[p27]_cons-[p37]_cons-[p47]_cons-[p57]_cons-[p67]_cons-[p77]_cons-[p78]_cons-[p79]_cons-[p710]_cons)-(0-[p18]_cons-[p28]_cons-[p38]_cons-[p48]_cons-[p58]_cons-[p68]_cons-[p78]_cons-[p88]_cons-[p89]_cons-[p810]_cons)-(0-[p19]_cons-[p29]_cons-[p39]_cons-[p49]_cons-[p59]_cons-[p69]_cons-[p79]_cons-[p89]_cons-[p99]_cons-[p910]_cons)-(0-[p110]_cons-[p210]_cons-[p310]_cons-[p410]_cons-[p510]_cons-[p610]_cons-[p710]_cons-[p810]_cons-[p910]_cons-[p1010]_cons))(_cons11:1-[_cons1]_cons-[_cons2]_cons-[_cons3]_cons-[_cons4]_cons-[_cons5]_cons-[_cons6]_cons-[_cons7]_cons-[_cons8]_cons-[_cons9]_cons-[_cons10]_cons)(b11: 0-[b1]_cons-[b2]_cons-[b3]_cons-[b4]_cons-[b5]_cons-[b6]_cons-[b7]_cons-[b8]_cons-[b9]_cons-[b10]_cons)(x11_size: 0-[x1_size]_cons-[x2_size]_cons-[x3_size]_cons-[x4_size]_cons-[x5_size]_cons-[x6_size]_cons-[x7_size]_cons-[x8_size]_cons-[x9_size]_cons-[x10_size]_cons)(x11_age_HRP: 0-[x1_age_HRP]_cons-[x2_age_HRP]_cons-[x3_age_HRP]_cons-[x4_age_HRP]_cons-[x5_age_HRP]_cons-[x6_age_HRP]_cons-[x7_age_HRP]_cons-[x8_age_HRP]_cons-[x9_age_HRP]_cons-[x10_age_HRP]_cons)(x11_sex: 0-[x1_sex_oldest]_cons-[x2_sex_oldest]_cons-[x3_sex_oldest]_cons-[x4_sex_oldest]_cons-[x5_sex_oldest]_cons-[x6_sex_oldest]_cons-[x7_sex_oldest]_cons-[x8_sex_oldest]_cons-[x9_sex_oldest]_cons-[x10_sex_oldest]_cons)(z11_imr11: 0-[z2_imr2]_cons-[z3_imr3]_cons-[z4_imr4]_cons-[z5_imr5]_cons-[z6_imr6]_cons-[z7_imr7]_cons-[z8_imr8]_cons-[z9_imr9]_cons-[z10_imr10]_cons, post

Sample selection

*gen P_Index and real expenditure
gen lnP_Index =
[(w1*lnp1)+(w2*lnp2)+(w3*lnp3)+(w4*lnp4)+(w5*lnp5)+(w6*lnp6)+(w7*lnp7)+(w8*lnp8)+(w9*lnp9)+(w10*lnp10)+(w11*lnp11)+(w12*lnp12)]
gen lnm = ln(hh_expenditure/exp(lnP_Index))

```
global covariates size age_HRP sex_oldest

*household expenditure endogeneity
reg ln_hh_expenditure ln_income lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnp11 lnp12
$covariates
predict res_hh_expenditure, res

scalar define s_income = _b[ln_income]
scalar define s_lnp1 = _b[lnp1]
scalar define s_lnp2 = _b[lnp2]
scalar define s_lnp3 = _b[lnp3]
scalar define s_lnp4 = _b[lnp4]
scalar define s_lnp5 = _b[lnp5]
scalar define s_lnp6 = _b[lnp6]
scalar define s_lnp7 = _b[lnp7]
scalar define s_lnp8 = _b[lnp8]
scalar define s_lnp9 = _b[lnp9]
scalar define s_lnp10 = _b[lnp10]
scalar define s_lnp11 = _b[lnp11]
scalar define s_lnp12 = _b[lnp12]
scalar define s_size = _b[size]
scalar define s_age = _b[age_HRP]
scalar define s_sex = _b[sex_oldest]
scalar define s_cons = _b[_cons]

*homogeneity restrictions
gen p1 = (lnp1 - lnp11)

gen p2 = (lnp2 - lnp11)

gen p3 = (lnp3 - lnp11)

gen p4 = (lnp4 - lnp11)

gen p5 = (lnp5 - lnp11)

gen p6 = (lnp6 - lnp11)

gen p7 = (lnp7 - lnp11)

gen p8 = (lnp8 - lnp11)

gen p9 = (lnp9 - lnp11)

gen p10 = (lnp10 - lnp11)

gen d_cereals=1 if w1>0
replace d_cereals=0 if w1==0
gen d_dairy=1 if w2>0
replace d_dairy=0 if w2==0
gen d_drinks=1 if w3>0
replace d_drinks=0 if w3==0
gen d_fats=1 if w4>0
replace d_fats=0 if w4==0
gen d_fish=1 if w5>0
replace d_fish=0 if w5==0
```

```
gen d_fruit=1 if w6>0
replace d_fruit=0 if w6==0
gen d_meat=1 if w7>0
replace d_meat=0 if w7==0
gen d_pot=1 if w8>0
replace d_pot=0 if w8==0
gen d_ready=1 if w9>0
replace d_ready=0 if w9==0
gen d_sweets=1 if w10>0
replace d_sweets=0 if w10==0
gen d_veg=1 if w11>0
replace d_veg=0 if w11==0

xi:mvprobit (d_dairy = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_drinks = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_fats = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_fish = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_fruit = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_meat = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_pot = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_ready = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_sweets = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)(d_veg = lnp1 lnp2 lnp3 lnp4 lnp5 lnp6 lnp7 lnp8 lnp9 lnp10 lnm $covariates)

mvppred xb

*gen Inverse Mills Ratio
gen imr_dairy = normalden(xb1)/normal(xb1)
gen imr_drinks = normalden(xb2)/normal(xb2)
gen imr_fats = normalden(xb3)/normal(xb3)
gen imr_fish = normalden(xb4)/normal(xb4)
gen imr_fruit = normalden(xb5)/normal(xb5)
gen imr_meat = normalden(xb6)/normal(xb6)
gen imr_pot = normalden(xb7)/normal(xb7)
gen imr_ready = normalden(xb8)/normal(xb8)
gen imr_sweets= normalden(xb9)/normal(xb9)
gen imr_veg = normalden(xb10)/normal(xb10)

drop xb*

nlsur (w1 =
{_cons1}+{p11}*p1+{p12}*p2+{p13}*p3+{p14}*p4+{p15}*p5+{p16}*p6+{p17}*p7+{p18}*p8+{p19}*p9+{p110}*p10+{b1}*lnm+{x1:$covariates}+{z1:res_hh_expenditure})
    (w2 =
{_cons2}+{p12}*p1+{p22}*p2+{p23}*p3+{p24}*p4+{p25}*p5+{p26}*p6+{p27}*p7+{p28}*p8+{p29}*p9+{p210}*p10+{b2}*lnm+{x2:$covariates}+{imr_2}*imr_dairy+{z2:res_hh_expenditure})
        (w3 =
{_cons3}+{p13}*p1+{p23}*p2+{p33}*p3+{p34}*p4+{p35}*p5+{p36}*p6+{p37}*p7+{p38}*p8+{p39}*p9+{p310}*p10+{b3}*lnm+{x3:$covariates}+{imr_3}*imr_drinks+{z3:res_hh_expenditure})
        (w4 =
{_cons4}+{p14}*p1+{p24}*p2+{p34}*p3+{p44}*p4+{p45}*p5+{p46}*p6+{p47}*p7+{p48}*p8+{p49}*p9+{p410}*p10+{b4}*lnm+{x4:$covariates}+{imr_4}*imr_fats+{z4:res_hh_expenditure})
        (w5 =
{_cons5}+{p15}*p1+{p25}*p2+{p35}*p3+{p45}*p4+{p55}*p5+{p56}*p6+{p57}*p7+{p58}*p8+{p59}*p9+{p510}*p10+{b5}*lnm+{x5:$covariates}+{imr_5}*imr_fish+{z5:res_hh_expenditure})
        (w6 =
{_cons6}+{p16}*p1+{p26}*p2+{p36}*p3+{p46}*p4+{p56}*p5+{p66}*p6+{p67}*p7+{p68}*p8+{p69}*p9+{p610}*p10+{b6}*lnm+{x6:$covariates}+{imr_6}*imr_fruit+{z6:res_hh_expenditure})
```

```
	(w7 =
{_cons7}+{p17}*p1+{p27}*p2+{p37}*p3+{p47}*p4+{p57}*p5+{p67}*p6+{p77}*p7+{p78}*p8+{p79}*
p9+{p710}*p10+{b7}*lnm+{x7:$covariates}+{imr_7}*imr_meat+{z7:res_hh_expenditure})
	(w8 =
{_cons8}+{p18}*p1+{p28}*p2+{p38}*p3+{p48}*p4+{p58}*p5+{p68}*p6+{p78}*p7+{p88}*p8+{p89}*
p9+{p810}*p10+{b8}*lnm+{x8:$covariates}+{imr_8}*imr_pot+{z8:res_hh_expenditure})
	(w9 =
{_cons9}+{p19}*p1+{p29}*p2+{p39}*p3+{p49}*p4+{p59}*p5+{p69}*p6+{p79}*p7+{p89}*p8+{p99}*
p9+{p910}*p10+{b9}*lnm+{x9:$covariates}+{imr_9}*imr_ready+{z9:res_hh_expenditure})
	(w10 =
{_cons10}+{p110}*p1+{p210}*p2+{p310}*p3+{p410}*p4+{p510}*p5+{p610}*p6+{p710}*p7+{p810}*
p8+{p910}*p9+{p1010}*p10+{b10}*lnm+{x10:$covariates}+{imr_10}*imr_sweets+{z10:res_hh_expen
diture}),variables (w1 w2 w3 w4 w5 w6 w7 w8 w9 w10 p1 p2 p3 p4 p5 p6 p7 p8 p9 p10 lnm
res_hh_expenditure imr_dairy imr_drinks imr_fats imr_fish imr_fruit imr_meat imr_pot imr_ready
imr_sweets $covariates)

scalar define imr_2 = [imr_dairy]_cons
scalar define imr_3 = [imr_drinks]_cons
scalar define imr_4 = [imr_fats]_cons
scalar define imr_5 = [imr_fish]_cons
scalar define imr_6 = [imr_fruit]_cons
scalar define imr_7 = [imr_meat]_cons
scalar define imr_8 = [imr_potatoes]_cons
scalar define imr_9 = [imr_ready]_cons
scalar define imr_10 = [imr_sweets]_cons

scalar define cons1 = [_cons1]_cons
scalar define size1 = [x1_size]_cons
scalar define age1 = [x1_age_HRP]_cons
scalar define sex1 = [x1_sex_oldest]_cons
scalar define cons2 = [_cons2]_cons
scalar define size2 = [x2_size]_cons
scalar define age2 = [x2_age_HRP]_cons
scalar define sex2 = [x2_sex_oldest]_cons
scalar define cons3 = [_cons3]_cons
scalar define size3 = [x3_size]_cons
scalar define age3 = [x3_age_HRP]_cons
scalar define sex3 = [x3_sex_oldest]_cons
scalar define cons4 = [_cons4]_cons
scalar define size4 = [x4_size]_cons
scalar define age4 = [x4_age_HRP]_cons
scalar define sex4 = [x4_sex_oldest]_cons
scalar define cons5 = [_cons5]_cons
scalar define size5 = [x5_size]_cons
scalar define age5 = [x5_age_HRP]_cons
scalar define sex5 = [x5_sex_oldest]_cons
scalar define cons6 = [_cons6]_cons
scalar define size6 = [x6_size]_cons
scalar define age6 = [x6_age_HRP]_cons
scalar define sex6 = [x6_sex_oldest]_cons
scalar define cons7 = [_cons7]_cons
scalar define size7 = [x7_size]_cons
scalar define age7 = [x7_age_HRP]_cons
scalar define sex7 = [x7_sex_oldest]_cons
scalar define cons8 = [_cons8]_cons
scalar define size8 = [x8_size]_cons
scalar define age8 = [x8_age_HRP]_cons
```

```
scalar define sex8 = [x8_sex_oldest]_cons
scalar define cons9 = [_cons9]_cons
scalar define size9 = [x9_size]_cons
scalar define age9 = [x9_age_HRP]_cons
scalar define sex9 = [x9_sex_oldest]_cons
scalar define cons10 = [_cons10]_cons
scalar define size10 = [x10_size]_cons
scalar define age10 = [x10_age_HRP]_cons
scalar define sex10 = [x10_sex_oldest]_cons

nlcom
(lnp_w1_w1:[p11]_cons)(lnp_w1_w2:[p12]_cons)(lnp_w1_w3:[p13]_cons)(lnp_w1_w4:[p14]_cons)(lnp_w1_w5:[p15]_cons)(lnp_w1_w6:[p16]_cons)(lnp_w1_w7:[p17]_cons)(lnp_w1_w8:[p18]_cons)(lnp_w1_w9:[p19]_cons)(lnp_w1_w10:[p110]_cons)(lnp_w1_w11:[p111]_cons)(lnp_w2_w2:[p22]_cons)(lnp_w2_w3:[p23]_cons)(lnp_w2_w4:[p24]_cons)(lnp_w2_w5:[p25]_cons)(lnp_w2_w6:[p26]_cons)(lnp_w2_w7:[p27]_cons)(lnp_w2_w8:[p28]_cons)(lnp_w2_w9:[p29]_cons)(lnp_w2_w10:[p210]_cons)(lnp_w2_w11:[p211]_cons)(lnp_w3_w3:[p33]_cons)(lnp_w3_w4:[p34]_cons)(lnp_w3_w5:[p35]_cons)(lnp_w3_w6:[p36]_cons)(lnp_w3_w7:[p37]_cons)(lnp_w3_w8:[p38]_cons)(lnp_w3_w9:[p39]_cons)(lnp_w3_w10:[p310]_cons)(lnp_w3_w11:[p311]_cons)(lnp_w4_w4:[p44]_cons)(lnp_w4_w5:[p45]_cons)(lnp_w4_w6:[p46]_cons)(lnp_w4_w7:[p47]_cons)(lnp_w4_w8:[p48]_cons)(lnp_w4_w9:[p49]_cons)(lnp_w4_w10:[p410]_cons)(lnp_w4_w11:[p411]_cons)(lnp_w5_w5:[p55]_cons)(lnp_w5_w6:[p56]_cons)(lnp_w5_w7:[p57]_cons)(lnp_w5_w8:[p58]_cons)(lnp_w5_w9:[p59]_cons)(lnp_w5_w10:[p510]_cons)(lnp_w5_w11:[p511]_cons)(lnp_w6_w6:[p66]_cons)(lnp_w6_w7:[p67]_cons)(lnp_w6_w8:[p68]_cons)(lnp_w6_w9:[p69]_cons)(lnp_w6_w10:[p610]_cons)(lnp_w6_w11:[p611]_cons)(lnp_w7_w7:[p77]_cons)(lnp_w7_w8:[p78]_cons)(lnp_w7_w9:[p79]_cons)(lnp_w7_w10:[p710]_cons)(lnp_w7_w11:[p711]_cons)(lnp_w8_w8:[p88]_cons)(lnp_w8_w9:[p89]_cons)(lnp_w8_w10:[p810]_cons)(lnp_w8_w11:[p811]_cons)(lnp_w9_w9:[p99]_cons)(lnp_w9_w10:[p910]_cons)(lnp_w9_w11:[p911]_cons)(lnp_w10_w10:[p1010]_cons)(lnp_w10_w11:[p1011]_cons)(lnp_w11_w11:[p1111]_cons)(lnp_w12_w1:0-[p11]_cons-[p12]_cons-[p13]_cons-[p14]_cons-[p15]_cons-[p16]_cons-[p17]_cons-[p18]_cons-[p19]_cons-[p110]_cons-[p111]_cons)(lnp_w12_w2:0-[p12]_cons-[p22]_cons-[p23]_cons-[p24]_cons-[p25]_cons-[p26]_cons-[p27]_cons-[p28]_cons-[p29]_cons-[p210]_cons-[p211]_cons)(lnp_w12_w3:0-[p13]_cons-[p23]_cons-[p33]_cons-[p34]_cons-[p35]_cons-[p36]_cons-[p37]_cons-[p38]_cons-[p39]_cons-[p310]_cons-[p311]_cons)(lnp_w12_w4:0-[p14]_cons-[p24]_cons-[p34]_cons-[p44]_cons-[p45]_cons-[p46]_cons-[p47]_cons-[p48]_cons-[p49]_cons-[p410]_cons-[p411]_cons)(lnp_w12_w5:0-[p15]_cons-[p25]_cons-[p35]_cons-[p45]_cons-[p55]_cons-[p56]_cons-[p57]_cons-[p58]_cons-[p59]_cons-[p510]_cons-[p511]_cons)(lnp_w12_w6:0-[p16]_cons-[p26]_cons-[p36]_cons-[p46]_cons-[p56]_cons-[p66]_cons-[p67]_cons-[p68]_cons-[p69]_cons-[p610]_cons-[p611]_cons)(lnp_w12_w7:0-[p17]_cons-[p27]_cons-[p37]_cons-[p47]_cons-[p57]_cons-[p67]_cons-[p77]_cons-[p78]_cons-[p79]_cons-[p710]_cons-[p711]_cons)(lnp_w12_w8:0-[p18]_cons-[p28]_cons-[p38]_cons-[p48]_cons-[p58]_cons-[p68]_cons-[p78]_cons-[p88]_cons-[p89]_cons-[p810]_cons-[p811]_cons)(lnp_w12_w9:0-[p19]_cons-[p29]_cons-[p39]_cons-[p49]_cons-[p59]_cons-[p69]_cons-[p79]_cons-[p89]_cons-[p99]_cons-[p910]_cons-[p911]_cons)(lnp_w12_w10:0-[p110]_cons-[p210]_cons-[p310]_cons-[p410]_cons-[p510]_cons-[p610]_cons-[p710]_cons-[p810]_cons-[p910]_cons-[p1010]_cons-[p1011]_cons)(lnp_w12_w11:0-[p111]_cons-[p211]_cons-[p311]_cons-[p411]_cons-[p511]_cons-[p611]_cons-[p711]_cons-[p811]_cons-[p911]_cons-[p1011]_cons-[p1111]_cons)(b1:[b1]_cons)(b2:[b2]_cons)(b3:[b3]_cons)(b4:[b4]_cons)(b5:[b5]_cons)(b6:[b6]_cons)(b7:[b7]_cons)(b8:[b8]_cons)(b9:[b9]_cons)(b10:[b10]_cons)(b11:[b11]_cons)(lnp_w12_w12:0-(0-[p11]_cons-[p12]_cons-[p13]_cons-[p14]_cons-[p15]_cons-[p16]_cons-[p17]_cons-[p18]_cons-[p19]_cons-[p110]_cons-[p111]_cons)-(0-[p12]_cons-[p22]_cons-[p23]_cons-[p24]_cons-[p25]_cons-[p26]_cons-[p27]_cons-[p28]_cons-[p29]_cons-[p210]_cons-[p211]_cons)-(0-[p13]_cons-[p23]_cons-[p33]_cons-[p34]_cons-[p35]_cons-[p36]_cons-[p37]_cons-[p38]_cons-[p39]_cons-[p310]_cons-[p311]_cons)-(0-[p14]_cons-[p24]_cons-[p34]_cons-[p44]_cons-[p45]_cons-[p46]_cons-[p47]_cons-[p48]_cons-[p49]_cons-[p410]_cons-[p411]_cons)-(0-[p15]_cons-[p25]_cons-[p35]_cons-[p45]_cons-[p55]_cons-[p56]_cons-[p57]_cons-[p58]_cons-[p59]_cons-[p510]_cons-[p511]_cons)-(0-[p16]_cons-[p26]_cons-[p36]_cons-[p46]_cons-[p56]_cons-[p66]_cons-[p67]_cons-[p68]_cons-[p69]_cons-[p610]_cons-[p611]_cons)-(0-[p17]_cons-[p27]_cons-[p37]_cons-[p47]_cons-[p57]_cons-[p67]_cons-[p77]_cons-[p78]_cons-[p79]_cons-[p710]_cons-[p711]_cons)-(0-[p18]_cons-[p28]_cons-[p38]_cons-[p48]_cons-[p58]_cons-[p68]_cons-[p78]_cons-[p88]_cons-[p89]_cons-[p810]_cons-[p811]_cons)-(0-[p19]_cons-[p29]_cons-[p39]_cons-
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[p49]_cons-[p59]_cons-[p69]_cons-[p79]_cons-[p89]_cons-[p99]_cons-[p910]_cons-[p911]_cons)-(0-
[p110]_cons-[p210]_cons-[p310]_cons-[p410]_cons-[p510]_cons-[p610]_cons-[p710]_cons-[p810]_cons-
[p910]_cons-[p1010]_cons-[p1011]_cons)-(0-[p111]_cons-[p211]_cons-[p311]_cons-[p411]_cons-
[p511]_cons-[p611]_cons-[p711]_cons-[p811]_cons-[p911]_cons-[p1011]_cons-
[p1111]_cons))(_cons12:1-[_cons1]_cons-[_cons2]_cons-[_cons3]_cons-[_cons4]_cons-[_cons5]_cons-
[_cons6]_cons-[_cons7]_cons-[_cons8]_cons-[_cons9]_cons-[_cons10]_cons-[_cons11]_cons)(b12: 0-
[b1]_cons-[b2]_cons-[b3]_cons-[b4]_cons-[b5]_cons-[b6]_cons-[b7]_cons-[b8]_cons-[b9]_cons-[b10]_cons-
[b11]_cons)(x12_size: 0-[x1_size]_cons-[x2_size]_cons-[x3_size]_cons-[x4_size]_cons-[x5_size]_cons-
[x6_size]_cons-[x7_size]_cons-[x8_size]_cons-[x9_size]_cons-[x10_size]_cons-
[x11_size]_cons)(x12_age_HRP: 0-[x1_age_HRP]_cons-[x2_age_HRP]_cons-[x3_age_HRP]_cons-
[x4_age_HRP]_cons-[x5_age_HRP]_cons-[x6_age_HRP]_cons-[x7_age_HRP]_cons-[x8_age_HRP]_cons-
[x9_age_HRP]_cons-[x10_age_HRP]_cons-[x11_age_HRP]_cons)(x12_sex: 0-[x1_sex_oldest]_cons-
[x2_sex_oldest]_cons-[x3_sex_oldest]_cons-[x4_sex_oldest]_cons-[x5_sex_oldest]_cons-
[x6_sex_oldest]_cons-[x7_sex_oldest]_cons-[x8_sex_oldest]_cons-[x9_sex_oldest]_cons-
[x10_sex_oldest]_cons-[x11_sex_oldest]_cons)(imr_10: 0-[imr_1]_cons - [imr_2]_cons -[imr_3]_cons -
[imr_4]_cons -[imr_5]_cons -[imr_6]_cons - [imr_7]_cons -[imr_8]_cons - [imr_9]_cons - [imr_10]_cons -
[imr_11]_cons), post

gen xb_11 = cons11 + p111*lnp1 + p211*lnp2 + p311*lnp3 + p411*lnp4 + p511*lnp5 + p611*lnp6 +
p711*lnp7 + p811*lnp8 + p911*lnp9 + p1011*lnp10 + p1111*lnp11 + b11*lnm + size11*size +
age11*age_HRP + sex11*sex_oldest

predict res_11, res

*gen elasticities

predictnl own_w1 = 1+(_b[lnp_w1_w1]/(w1^2))-(1/w1), se(own_w1_se)
predictnl e_w1_w2 = 1+(_b[lnp_w1_w2]/(w1*w2)), se(e_w1_w2_se)
predictnl e_w1_w3 = 1+(_b[lnp_w1_w3]/(w1*w3)), se(e_w1_w3_se)
predictnl e_w1_w4 = 1+(_b[lnp_w1_w4]/(w1*w4)), se(e_w1_w4_se)
predictnl e_w1_w5 = 1+(_b[lnp_w1_w5]/(w1*w5)), se(e_w1_w5_se)
predictnl e_w1_w6 = 1+(_b[lnp_w1_w6]/(w1*w6)), se(e_w1_w6_se)
predictnl e_w1_w7 = 1+(_b[lnp_w1_w7]/(w1*w7)), se(e_w1_w7_se)
predictnl e_w1_w8 = 1+(_b[lnp_w1_w8]/(w1*w8)), se(e_w1_w8_se)
predictnl e_w1_w9 = 1+(_b[lnp_w1_w9]/(w1*w9)), se(e_w1_w9_se)
predictnl e_w1_w10 = 1+(_b[lnp_w1_w10]/(w1*w10)), se(e_w1_w10_se)
predictnl e_w1_w11 = 1+(_b[lnp_w11_w11]/(w1*w11)), se(e_w1_w11_se)
predictnl own_w2 = 1+(_b[lnp_w2_w2]/(w2^2))-(1/w2), se(own_w2_se)
predictnl e_w2_w3 = 1+(_b[lnp_w2_w3]/(w2*w3)), se(e_w2_w3_se)
predictnl e_w2_w4 = 1+(_b[lnp_w2_w4]/(w2*w4)), se(e_w2_w4_se)
predictnl e_w2_w5 = 1+(_b[lnp_w2_w5]/(w2*w5)), se(e_w2_w5_se)
predictnl e_w2_w6 = 1+(_b[lnp_w2_w6]/(w2*w6)), se(e_w2_w6_se)
predictnl e_w2_w7 = 1+(_b[lnp_w2_w7]/(w2*w7)), se(e_w2_w7_se)
predictnl e_w2_w8 = 1+(_b[lnp_w1_w8]/(w1*w8)), se(e_w2_w8_se)
predictnl e_w2_w9 = 1+(_b[lnp_w2_w9]/(w2*w9)), se(e_w2_w9_se)
predictnl e_w2_w10 = 1+(_b[lnp_w2_w10]/(w2*w10)), se(e_w2_w10_se)
predictnl e_w2_w11 = 1+(_b[lnp_w11_w2]/(w2*w11)), se(e_w2_w11_se)
predictnl own_w3 = 1+(_b[lnp_w3_w3]/(w3^2))-(1/w3), se(own_w3_se)
predictnl e_w3_w4 = 1+(_b[lnp_w3_w4]/(w3*w4)), se(e_w3_w4_se)
predictnl e_w3_w5 = 1+(_b[lnp_w3_w5]/(w3*w5)), se(e_w3_w5_se)
predictnl e_w3_w6 = 1+(_b[lnp_w3_w6]/(w3*w6)), se(e_w3_w6_se)
predictnl e_w3_w7 = 1+(_b[lnp_w3_w7]/(w3*w7)), se(e_w3_w7_se)
predictnl e_w3_w8 = 1+(_b[lnp_w3_w8]/(w3*w8)), se(e_w3_w8_se)
predictnl e_w3_w9 = 1+(_b[lnp_w3_w9]/(w3*w9)), se(e_w3_w9_se)
predictnl e_w3_w10 = 1+(_b[lnp_w3_w10]/(w3*w10)), se(e_w3_w10_se)
predictnl e_w3_w11 = 1+(_b[lnp_w11_w3]/(w3*w11)), se(e_w3_w11_se)
predictnl own_w4 = 1+(_b[lnp_w4_w4]/(w4^2))-(1/w4), se(own_w4_se)
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predictnl e_w4_w5 = 1+(_b[lnp_w4_w5]/(w4*w5)), se(e_w4_w5_se)
predictnl e_w4_w6 = 1+(_b[lnp_w4_w6]/(w4*w6)), se(e_w4_w6_se)
predictnl e_w4_w7 = 1+(_b[lnp_w4_w7]/(w4*w7)), se(e_w4_w7_se)
predictnl e_w4_w8 = 1+(_b[lnp_w4_w8]/(w4*w8)), se(e_w4_w8_se)
predictnl e_w4_w9 = 1+(_b[lnp_w4_w9]/(w4*w9)), se(e_w4_w9_se)
predictnl e_w4_w10 = 1+(_b[lnp_w4_w10]/(w4*w10)), se(e_w4_w10_se)
predictnl e_w4_w11 = 1+(_b[lnp_w11_w4]/(w4*w11)), se(e_w4_w11_se)
predictnl own_w5 = 1+(_b[lnp_w5_w5]/(w5^2))-(1/w5), se(own_w5_se)
predictnl e_w5_w6 = 1+(_b[lnp_w5_w6]/(w5*w6)), se(e_w5_w6_se)
predictnl e_w5_w7 = 1+(_b[lnp_w5_w7]/(w5*w7)), se(e_w5_w7_se)
predictnl e_w5_w8 = 1+(_b[lnp_w5_w8]/(w5*w8)), se(e_w5_w8_se)
predictnl e_w5_w9 = 1+(_b[lnp_w5_w9]/(w5*w9)), se(e_w5_w9_se)
predictnl e_w5_w10 = 1+(_b[lnp_w5_w10]/(w5*w10)), se(e_w5_w10_se)
predictnl e_w5_w11 = 1+(_b[lnp_w11_w5]/(w5*w11)), se(e_w5_w11_se)
predictnl own_w6 = 1+(_b[lnp_w6_w6]/(w6^2))-(1/w6), se(own_w6_se)
predictnl e_w6_w7 = 1+(_b[lnp_w6_w7]/(w6*w7)), se(e_w6_w7_se)
predictnl e_w6_w8 = 1+(_b[lnp_w6_w8]/(w6*w8)), se(e_w6_w8_se)
predictnl e_w6_w9 = 1+(_b[lnp_w6_w9]/(w6*w9)), se(e_w6_w9_se)
predictnl e_w6_w10 = 1+(_b[lnp_w6_w10]/(w6*w10)), se(e_w6_w10_se)
predictnl e_w6_w11 = 1+(_b[lnp_w11_w6]/(w6*w11)), se(e_w6_w11_se)
predictnl own_w7 = 1+(_b[lnp_w7_w7]/(w7^2))-(1/w7), se(own_w7_se)
predictnl e_w7_w8 = 1+(_b[lnp_w7_w8]/(w7*w8)), se(e_w7_w8_se)
predictnl e_w7_w9 = 1+(_b[lnp_w7_w9]/(w7*w9)), se(e_w7_w9_se)
predictnl e_w7_w10 = 1+(_b[lnp_w7_w10]/(w7*w10)), se(e_w7_w10_se)
predictnl e_w7_w11 = 1+(_b[lnp_w11_w7]/(w7*w11)), se(e_w7_w11_se)
predictnl own_w8 = 1+(_b[lnp_w8_w8]/(w8^2))-(1/w8), se(own_w8_se)
predictnl e_w8_w9 = 1+(_b[lnp_w8_w9]/(w8*w9)), se(e_w8_w9_se)
predictnl e_w8_w10 = 1+(_b[lnp_w8_w10]/(w8*w10)), se(e_w8_w10_se)
predictnl e_w8_w11 = 1+(_b[lnp_w11_w8]/(w8*w11)), se(e_w8_w11_se)
predictnl own_w9 = 1+(_b[lnp_w9_w9]/(w9^2))-(1/w9), se(own_w9_se)
predictnl e_w9_w10 = 1+(_b[lnp_w9_w10]/(w9*w10)), se(e_w9_w10_se)
predictnl e_w9_w11 = 1+(_b[lnp_w11_w9]/(w9*w11)), se(e_w9_w11_se)
predictnl own_w10 = 1+(_b[lnp_w10_w10]/(w10^2))-(1/w10), se(own_w10_se)
predictnl e_w10_w11 = 1+(_b[lnp_w11_w10]/(w10*w11)), se(e_w10_w11_se)
predictnl own_w11 = 1+(_b[lnp_w11_w11]/(w11^2))-(1/w11), se(own_w11_se)

predictnl expenditure_w1 = 1+(_b[b1]/w1), se(expenditure_w1_se)
predictnl expenditure_w2 = 1+(_b[b2]/w2), se(expenditure_w2_se)
predictnl expenditure_w3 = 1+(_b[b3]/w3), se(expenditure_w3_se)
predictnl expenditure_w4 = 1+(_b[b4]/w4), se(expenditure_w4_se)
predictnl expenditure_w5 = 1+(_b[b5]/w5), se(expenditure_w5_se)
predictnl expenditure_w6 = 1+(_b[b6]/w6), se(expenditure_w6_se)
predictnl expenditure_w7 = 1+(_b[b7]/w7), se(expenditure_w7_se)
predictnl expenditure_w8 = 1+(_b[b8]/w8), se(expenditure_w8_se)
predictnl expenditure_w9 = 1+(_b[b9]/w9), se(expenditure_w9_se)
predictnl expenditure_w10 = 1+(_b[b10]/w10), se(expenditure_w10_se)
predictnl expenditure_w11 = 1+(_b[b11]/w11), se(expenditure_w11_se)

mean own_w1 [aweight = 1/(own_w1_se^2) ]
estimates table, star(.05 .01 .001)
mean e_w1_w2 [aweight = 1/(e_w1_w2_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w3 [aweight = 1/(e_w1_w3_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w4 [aweight = 1/(e_w1_w4_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w5 [aweight = 1/(e_w1_w5_se^2)]
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estimates table, star(.05 .01 .001)
mean e_w1_w6 [aweight = 1/(e_w1_w6_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w7 [aweight = 1/(e_w1_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w8 [aweight = 1/(e_w1_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w9 [aweight = 1/(e_w1_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w10 [aweight = 1/(e_w1_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w1_w11 [aweight = 1/(e_w1_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w2 [aweight = 1/(own_w2_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w3 [aweight = 1/(e_w2_w3_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w4 [aweight = 1/(e_w2_w4_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w5 [aweight = 1/(e_w2_w5_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w6 [aweight = 1/(e_w2_w6_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w7 [aweight = 1/(e_w2_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w8 [aweight = 1/(e_w2_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w9 [aweight = 1/(e_w2_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w10 [aweight = 1/(e_w2_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w2_w11 [aweight = 1/(e_w2_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w3 [aweight = 1/(own_w3_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w4 [aweight = 1/(e_w3_w4_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w5 [aweight = 1/(e_w3_w5_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w6 [aweight = 1/(e_w3_w6_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w7 [aweight = 1/(e_w3_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w8 [aweight = 1/(e_w3_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w9 [aweight = 1/(e_w3_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w10 [aweight = 1/(e_w3_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w3_w11 [aweight = 1/(e_w3_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w4 [aweight = 1/(own_w4_se^2)]
estimates table, star(.05 .01 .001)
mean e_w4_w5 [aweight = 1/(e_w4_w5_se^2)]
estimates table, star(.05 .01 .001)
mean e_w4_w6 [aweight = 1/(e_w4_w6_se^2)]
estimates table, star(.05 .01 .001)
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```
mean e_w4_w7 [aweight = 1/(e_w4_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w4_w8 [aweight = 1/(e_w4_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w4_w9 [aweight = 1/(e_w4_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w4_w10 [aweight = 1/(e_w4_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w4_w11 [aweight = 1/(e_w4_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w5 [aweight = 1/(own_w5_se^2)]
estimates table, star(.05 .01 .001)
mean e_w5_w6 [aweight = 1/(e_w5_w6_se^2)]
estimates table, star(.05 .01 .001)
mean e_w5_w7 [aweight = 1/(e_w5_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w5_w8 [aweight = 1/(e_w5_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w5_w9 [aweight = 1/(e_w5_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w5_w10 [aweight = 1/(e_w5_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w5_w11 [aweight = 1/(e_w5_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w6 [aweight = 1/(own_w6_se^2) ]
estimates table, star(.05 .01 .001)
mean e_w6_w7 [aweight = 1/(e_w6_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w6_w8 [aweight = 1/(e_w6_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w6_w9 [aweight = 1/(e_w6_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w6_w10 [aweight = 1/(e_w6_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w6_w11 [aweight = 1/(e_w6_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w7 [aweight = 1/(own_w7_se^2)]
estimates table, star(.05 .01 .001)
mean e_w7_w8 [aweight = 1/(e_w7_w8_se^2)]
estimates table, star(.05 .01 .001)
mean e_w7_w9 [aweight = 1/(e_w7_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w7_w10 [aweight = 1/(e_w7_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w7_w11 [aweight = 1/(e_w7_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w8 [aweight = 1/(own_w8_se^2) ]
estimates table, star(.05 .01 .001)
mean e_w8_w9 [aweight = 1/(e_w8_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w8_w10 [aweight = 1/(e_w8_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w8_w11 [aweight = 1/(e_w8_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w9 [aweight = 1/(own_w9_se^2)]
estimates table, star(.05 .01 .001)
mean e_w9_w10 [aweight = 1/(e_w9_w10_se^2)]
```

```
estimates table, star(.05 .01 .001)
mean e_w9_w11 [aweight = 1/(e_w9_w11_se^2)]
estimates table, star(.05 .01 .001)
mean own_w10 [aweight = 1/(own_w10_se^2)]
estimates table, star(.05 .01 .001)
mean e_w10_w11 [aweight = 1/(e_w10_w11_se^2)]
estimates table, star(.05 .01 .001)
mean e_w10_w12 [aweight = 1/(e_w10_w12_se^2)]
estimates table, star(.05 .01 .001)
mean own_w11 [aweight = 1/(own_w11_se^2)]
estimates table, star(.05 .01 .001)
mean expenditure_w1 [aweight = 1/(expenditure_w1_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w2 [aweight = 1/(expenditure_w2_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w3 [aweight = 1/(expenditure_w3_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w4 [aweight = 1/(expenditure_w4_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w5 [aweight = 1/(expenditure_w5_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w6 [aweight = 1/(expenditure_w6_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w7 [aweight = 1/(expenditure_w7_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w8 [aweight = 1/(expenditure_w8_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w9 [aweight = 1/(expenditure_w9_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w10 [aweight = 1/(expenditure_w10_se)^2]
estimates table, star(.05 .01 .001)
mean expenditure_w11 [aweight = 1/(expenditure_w11_se)^2]
estimates table, star(.05 .01 .001)

replace k_cereals = 0 if k_cereals ==.
replace k_dairy = 0 if k_dairy ==.
replace k_drinks = 0 if k_drinks == .
replace k_fats=0 if k_fats == 0
replace k_fats=0 if k_fats == .
replace k_fruit = 0 if k_fruit ==.
replace k_meat = 0 if k_meat ==.
replace k_potatoes = 0 if k_potatoes ==.
replace k_pulses = 0 if k_pulses == .
replace k_readymeals = 0 if k_readymeals==.
replace k_sweets = 0 if k_sweets ==.
replace k_vegetables = 0 if k_vegetables ==.

*gen price taxed

gen p_cereals_taxed = k_cereals+price_cereals
gen p_dairy_taxed = k_dairy + price_diary_eggs
gen p_drinks_taxed = k_drinks + price_drinks
gen p_fats_taxed = k_fats + price_fats_spreads
gen p_fish_taxed = k_fish + price_fish
gen p_fruit_taxed = k_fruit+ price_fruit
gen p_meat_taxed = k_meat + price_meat
gen p_potatoes_taxed = k_potatoes+price_potatoes
```

```
gen p_pulses_taxed = k_pulses+price_pulses
gen p_ready_meals_taxed = k_readymeals + price_ready_meals
gen p_sweets_taxed = k_sweets+price_sweets
gen p_vegetables_taxed = k_vegetables+price_vegetables

gen p_drinks_taxed2 = price_drinks + (k_drinks + 0.2* k_drinks)
gen p_sweets_taxed2 = price_sweets + ( k_sweets + 0.2* k_sweets )
gen p_ready_meals_taxed2 = price_ready_meals + (k_readymeals + 0.2*k_readymeals)

foreach v in p_cereals_taxed p_dairy_taxed p_drinks_taxed2 p_fats_taxed p_fish_taxed p_fruit_taxed
p_meat_taxed p_potatoes_taxed p_pulses_taxed p_ready_meals_taxed2 p_sweets_taxed2
p_vegetables_taxed       {
 gen ln`v' = ln(`v')
}

rename lnp_cereals_taxed lnp1t
rename lnp_dairy_taxed lnp2t
rename lnp_drinks_taxed2 lnp3t
rename lnp_fats_taxed lnp4t
rename lnp_fish_taxed lnp5t
rename lnp_fruit_taxed lnp6t
rename lnp_meat_taxed lnp7t
rename lnp_potatoes_taxed lnp8t
rename lnp_pulses_taxed lnp9t
rename lnp_ready_meals_taxed2 lnp10t
rename lnp_sweets_taxed2 lnp11t
rename lnp_vegetables_taxed lnp12t

gen lnP2_Index =
[(w1*lnp1t)+(w2*lnp2t)+(w3*lnp3t)+(w4*lnp4t)+(w5*lnp5t)+(w6*lnp6t)+(w7*lnp7t)+(w8*lnp8t)+
(w9*lnp9t)+(w10*lnp10t)+(w11*lnp11t)+(w12*lnp12t)]
gen lnm2 = ln(hh_expenditure/exp(lnP2_Index))

*simulation
*1 caso
gen e1=rnormal()
gen e2=rnormal()
gen e3=rnormal()
gen e4=rnormal()
gen e5=rnormal()
gen e6=rnormal()
gen e7=rnormal()
gen e8=rnormal()
gen e9=rnormal()
gen e10=rnormal()
gen e11=rnormal()
gen e12=rnormal()

gen w1t= p1_cons + p1_1*lnp1t + p1_2*lnp2t + p1_3*lnp3t + p1_4*lnp4t + p1_5*lnp5t + p1_6*lnp6t +
p1_7*lnp7t + p1_8*lnp8t + p1_9*lnp9t + p1_10*lnp10t + p1_11*lnp11t + p1_12*lnp12t + b1*lnm2 +
p1_size*size + p1_age*age_HRP + p1_sex*sex_oldest + imr_1*imr_w1 + e1
gen w2t= p2_cons + p2_1*lnp1t + p2_2*lnp2t + p2_3*lnp3t + p2_4*lnp4t + p2_5*lnp5t + p2_6*lnp6t +
p2_7*lnp7t + p2_8*lnp8t + p2_9*lnp9t + p2_10*lnp10t + p2_11*lnp11t + p2_12*lnp12t + b2*lnm2 +
p2_size*size + p2_age*age_HRP + p2_sex*sex_oldest + imr_2*imr_w2 +e1
gen w3t= p3_cons + p3_1*lnp1t + p3_2*lnp2t + p3_3*lnp3t + p3_4*lnp4t + p3_5*lnp5t + p3_6*lnp6t +
p3_7*lnp7t + p3_8*lnp8t + p3_9*lnp9t + p3_10*lnp10t + p3_11*lnp11t + p3_12*lnp12t + b3*lnm2 +
p3_size*size + p3_age*age_HRP + p3_sex*sex_oldest + imr_3*imr_w3 + e1
```

```
gen w4t= p4_cons + p4_1*lnp1t + p4_2*lnp2t + p4_3*lnp3t + p4_4*lnp4t + p4_5*lnp5t + p4_6*lnp6t +
p4_7*lnp7t + p4_8*lnp8t + p4_9*lnp9t + p4_10*lnp10t + p4_11*lnp11t + p4_12*lnp12t + b4*lnm2 +
p4_size*size + p4_age*age_HRP + p4_sex*sex_oldest + imr_4*imr_w4 + e1
gen w5t= p5_cons + p5_1*lnp1t + p5_2*lnp2t + p5_3*lnp3t + p5_4*lnp4t + p5_5*lnp5t + p5_6*lnp6t +
p5_7*lnp7t + p5_8*lnp8t + p5_9*lnp9t + p5_10*lnp10t + p5_11*lnp11t + p5_12*lnp12t + b5*lnm2 +
p5_size*size + p5_age*age_HRP + p5_sex*sex_oldest + imr_5*imr_w5 + e1
gen w6t= p6_cons + p6_1*lnp1t + p6_2*lnp2t + p6_3*lnp3t + p6_4*lnp4t + p6_5*lnp5t + p6_6*lnp6t +
p6_7*lnp7t + p6_8*lnp8t + p6_9*lnp9t + p6_10*lnp10t + p6_11*lnp11t + p6_12*lnp12t + b6*lnm2 +
p6_size*size + p6_age*age_HRP + p6_sex*sex_oldest + imr_6*imr_w6 + e1
gen w7t= p7_cons + p7_1*lnp1t + p7_2*lnp2t + p7_3*lnp3t + p7_4*lnp4t + p7_5*lnp5t + p7_6*lnp6t +
p7_7*lnp7t + p7_8*lnp8t + p7_9*lnp9t + p7_10*lnp10t + p7_11*lnp11t + p7_12*lnp12t + b7*lnm2 +
p7_size*size + p7_age*age_HRP + p7_sex*sex_oldest + imr_7*imr_w7 + e1
gen w8t= p8_cons + p8_1*lnp1t + p8_2*lnp2t + p8_3*lnp3t + p8_4*lnp4t + p8_5*lnp5t + p8_6*lnp6t +
p8_7*lnp7t + p8_8*lnp8t + p8_9*lnp9t + p8_10*lnp10t + p8_11*lnp11t + p8_12*lnp12t + b8*lnm2 +
p8_size*size + p8_age*age_HRP + p8_sex*sex_oldest + imr_8*imr_w8 +e1
gen w9t= p9_cons + p9_1*lnp1t + p9_2*lnp2t + p9_3*lnp3t + p9_4*lnp4t + p9_5*lnp5t + p9_6*lnp6t +
p9_7*lnp7t + p9_8*lnp8t + p9_9*lnp9t + p9_10*lnp10t + p9_11*lnp11t + p9_12*lnp12t + b9*lnm2 +
p9_size*size + p9_age*age_HRP + p9_sex*sex_oldest + imr_9*imr_w9 +e1
gen w10t= p10_cons + p10_1*lnp1t + p10_2*lnp2t + p10_3*lnp3t + p10_4*lnp4t + p10_5*lnp5t +
p10_6*lnp6t + p10_7*lnp7t + p10_8*lnp8t + p10_9*lnp9t + p10_10*lnp10t + p10_11*lnp11t +
p10_12*lnp12t + b10*lnm2 + p10_size*size + p10_age*age_HRP + p10_sex*sex_oldest +
imr_10*imr_w10+e1
gen w11t= p11_cons + p11_1*lnp1t + p11_2*lnp2t + p11_3*lnp3t + p11_4*lnp4t + p11_5*lnp5t +
p11_6*lnp6t + p11_7*lnp7t + p11_8*lnp8t + p11_9*lnp9t + p11_10*lnp10t + p11_11*lnp11t +
p11_12*lnp12t + b11*lnm2 + p11_size*size + p11_age*age_HRP + p11_sex*sex_oldest +
imr_11*imr_w11+e1
gen w12t= p12_cons + p1_12*lnp1t + p2_12*lnp2t + p3_12*lnp3t + p4_12*lnp4t + p5_12*lnp5t +
p6_12*lnp6t + p7_12*lnp7t + p8_12*lnp8t + p9_12*lnp9t + p10_12*lnp10t + p11_12*lnp11t +
p12_12*lnp12t + b12*lnm2 + p12_size*size + p12_age*age_HRP + p12_sex*sex_oldest +
imr_12*imr_w12+e1
```