# FOOD WASTE, THE DOUBLE-BURDEN OF MALNUTRITION, AND THE SUSTAINABILITY OF THE GLOBAL FOOD SYSTEM

by

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*Para mi familia y esos amigos que son como familia, mi gran inspiración y mayor motivación*

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# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# ABSTRACT

Sustainably meeting the food demands of a growing population based on finite resources while protecting the environment is one of the great challenges of humanity in the coming decades. This dissertation combines three essays that examine how future patterns of global food consumption will affect human health, and how the food system changes driven by the ongoing global nutrition transition will affect the environment. The production of food needed to meet a growing population combined with changes in food consumption patterns are placing unprecedented levels of stress on the planet's scarce natural resources. In this context, while the existing literature has mainly focused on increasing production, the magnitude of loss and waste is too large to be ignored. The first essay contributes to the literature by examining the linkages between consumers' food waste at the national level on the one hand, and global food security and environmental health on the other hand. Absent significant behavioral changes or successful policy interventions, food waste will nearly double by 2050. Emerging economies are likely to play a key role in driving this growth in global food waste. Further findings indicate that the global benefits of food waste mitigation are greatly enhanced in the context of a more open international trade regime. Yet even as food loss and waste has been undernutrition and overweight/obesity levels have also been increasing. Together, these trends form a triple challenge for food security, global sustainability and human health. In the second essay I examine the role of the excessive calorie availability as an historical driver of adult BMI. I find that, in part driven by excess in calorie availability, individuals in more recent cohorts are overweight or obese earlier and for larger proportions of their lifespan than those in earlier cohorts. This highlights the potential for unintended health consequences of agricultural and trade policies directed at increasing calorie supplies. In the third essay I introduce a novel framework that extends the UN-FAO's methodology for assessing undernutrition to also assess the extent of overconsumption and obesity. This framework allows for examination of the dynamics of the double burden of malnutrition between 2015 and 2050. Specifically, this framework shows how shifting towards healthier and more sustainable food consumption levels and reducing food waste could synergistically address multiple health and environmental burdens.

# CHAPTER 1. INTRODUCTION

Sustainably meeting the food demands of a growing population based on finite resources while protecting the environment is one of the great challenges of humanity in the coming decades. Current trends in population and consumption preferences will continue boosting demand for food for at least another 40 years (Godfray et al. 2010). In this context, increasing food supplies as well as decreasing food losses and waste are key to meeting these challenges. While the existing literature has mainly focused on increasing production, the magnitude of loss and waste is too large to be ignored (Irfanoglu et al. 2014; FAO 2019b) especially when an increasing number of people around the world suffer from food insecurity and different forms of malnutrition (FAO 2021). Roughly, one-third of the edible parts of global food produced for human consumption is estimated to be lost or wasted (FAO 2015), and these losses have been valued at 1 trillion USD (FAO 2013). Resources used in the production of food that ends up being lost and wasted accounts for almost one-fourth of the overall global cropland and fertilizer use (Kummu et al. 2012) contributing around 3.3 Gigatonnes of CO2-equivalent methane emissions (FAO 2013).

Food lost and wasted also presents a social dilemma, given the persistence of global hunger. Food waste at the consumer level in industrialized countries (222 million tons) is almost as high as the total net food production in Sub Saharan Africa (230 million tons) (FAO 2015). Yet even as food loss and waste is rising, the global population facing chronic food deprivation has also been increasing, growing from 804 million in 2016 to around 821 million in 2017 (FAO 2019c). Food waste is concentrated in the industrialized countries, where more than 40% of the food losses and waste occur at retail and consumer (households and retails) levels (FAO 2015) and private households are responsible for the largest share (Monier 2010). Responding to these apparent contradictions, food loss and waste has received growing attention from policymakers, as well as from academics, at local, regional, and global levels. Indeed, it is included as part of the United Nation's 2030 Agenda for Sustainable Development.

Simultaneously, over the past century, rising incomes and increased urbanization have altered food consumption worldwide. Nutrition transitions currently underway in low- and middle-income countries are characterized by increases in the overall and proportional consumption of animal fats and protein (Miljkovic and Mostad 2007), refined grains, and added sugar (Malik, Willett, and Hu 2013; Tilman and Clark 2014) which have been implicated in rising rates of obesity

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and diabetes worldwide (Chopra, Galbraith, and Darnton-Hill 2002). Economic transitions, from preindustrial agrarian food systems towards industrialized food systems characterized by capital-intensive production and processing transform the allocation and functions of labor within food supply chains (Finkelstein et al., 2005; Popkin, 2001), reducing average physical activity levels. As a result, the balance between energy intake and energy expenditure has tipped over time, concomitant with observed increases in rates of overweight and obesity virtually everywhere (Hall et al., 2011; Swinburn et al., 2011; Thomas et al., 2011).

The global prevalence of obesity among adults more than doubled between 1980 and 2014 and rates of childhood overweight and obesity are increasing in most regions of the world (FAO, 2017a). The ratio of overweight to underweight individuals is increasing globally in step with improvements in per capita incomes (Abarca-Gómez et al. 2017; Abdullah 2015). Further, the double burden associated with the simultaneous presentation of poor nutrition, both at low and high levels of calorie consumption, continues to increase in the poorest low-income and middle-income countries (Popkin et al., 2020; Rutter, 2011; Siddiqui & Donato, 2020). In 2016, 41 million children under five years of age were overweight, and in the same year the Food and Agriculture Organization of the United Nations (FAO) estimated 3.4 million deaths annually due to overweight and obesity (FAO 2017a). By 2030, one in three individuals in the global population is projected to be overweight or obese (FAO 2017b), outnumbering those with normal weight. At the same time, food insecurity is expected to follow a similar upward trend. The prevalence rate of undernourishment reached 8.9% of the global population (nearly 690 million of people) in 2019 and by 2030 10% (840 million of people) will be unable to meet a diet with the minimum caloric requirements for a healthy life (FAO 2020). The coexistence of undernutrition and overweight/obesity constitutes an unprecedented challenge to global health. Effectively responding to this requires a better understanding of the dynamics of these phenomena (Popkin et al., 2020; Webb & Block, 2012) .

These developments have serious consequences for health, as childhood and adult obesity are major risk factors for non-communicable diseases, such as cardiovascular disease (Scherer and Hill 2016), diabetes (Scherer & Hill, 2016; Verma & Hussain, 2017), and some types of cancer (Avgerinos et al. 2019; Williams 2013). These trends in food consumption also threaten the environment (Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson, et al. 2018; Willett et al. 2019). Currently the food system accounts

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for around one third of the global greenhouse gas emissions (GHG) (IPCC 2019; Crippa et al. 2021) and dietary trends are expected to be a major contributor to an estimated 80 per cent increase in global agricultural GHG emissions from food production and to global land clearing towards the mid-21st century (Tilman & Clark, 2014). Addressing the global challenge posed by this diet-environment–health trilemma is a high priority for society (Tilman & Clark, 2014; Willett et al., 2019).

This dissertation combines three essays that examines how future patterns of global food consumption will affect human health, and how the agricultural changes needed to support the ongoing global nutrition transition will affect the environment. Specifically, the dissertation focuses on the quantitative linkages among the waste and the excessive intake of food and its influences on human health and environmental sustainability. The essays are motivated on the current trends and patterns in the global food system, where a growing demand combined with changes in consumption patterns are placing unprecedented levels of stress on the planet's scarce natural resources. In this context, consumers' food waste as well as overweight and obesity are rapidly growing especially in low- and middle-income countries. At the same time, an important share of the global population still suffers hunger Indeed, the coexistence of global overweight and obesity, as well as consumers undernutrition and overweight/obesity constitutes an unprecedented challenge to global health. Effectively responding to this requires a better understanding of the dynamics of the underlying phenomena.

The first essay, presented in Chapter 2, titled "Global food waste across the income spectrum: Implications for food prices, production and resource use" addresses the quantitative linkages between food waste, food security, and environmental sustainability, at global scale. Based on the energy balance equation widely used un the nutrition literature, I develop a new panel database on household food waste at the national level based on the Energy Balance equation, including adjustments for changes in body weight over time. I use this to characterize the non-linear relationship between per capita income and the share of food availability wasted. By incorporating this relationship into a global partial equilibrium model of the agricultural sector, I develop future trajectories of household food waste. I find that, in the absence of policies or behavioral changes, emerging economies particularly China and South Asia are likely to play a key role in determining global food waste at mid-century. More generally, the interaction between food waste reduction measures and trade policies is a novel contribution of this chapter. Trade policies which increase agricultural market integration have the potential to amplify the benefits of food waste reductions for food security (by facilitating the accessibility to food in the most vulnerable regions) and for reduce pressure on natural resources. This chapter also highlights the importance of developing new measurement methods for food waste that can be rapidly deployed across the globe. Measurement is the foundation of international action and there is a need for approaches which can be readily implemented with existing data sources and incorporated into quantitative models to explore impacts and consequences of mitigation measures. The data base which I have developed represents a new step the direction of having a global, internationally comparable data set on food waste.

In the second essay, presented in Chapter 3, titled "Excess calorie availability and adult BMI: a cohort analysis of patterns and trends for 156 countries from 1890 to 2015", I study the association between increases in food energy supply and changes in body mass index (BMI) across countries and time. Although changes in diets, lifestyles, and food environments have been implicated in the rise in BMIs in most countries, the specific role of excess calorie availability (ECA) and the cohort mechanisms that underlie patterns and trends in BMI are poorly understood. In this study I examine these relationships for 156 countries over the past century. By constructing a pseudo-panel dataset from repeated cross-sectional data, I developed an econometric model that allows identifying these relationships across time and countries. I find a positive association between ECA and BMI and a strengthening of this correlation over successive generations. Consequently, more recent cohorts reach adulthood with higher BMIs and become overweight and obese at younger ages. These results provide a number of policy-relevant insights. First, the findings highlight how some standard agricultural and trade policies oriented toward reducing hunger by increasing calorie supplies might have unintended consequences for undesirable overweight, obesity, and health-related outcomes (Law 2019). In light of current trends in food supply, these findings are of particular importance for developing countries already dealing with the complexities of a rising malnutrition double burden. Second, as the world continues to push toward increasing the supply of food to alleviate hunger among those still facing food insecurity, there is a simultaneous need to underscore and address, through policy and education, the importance of nutrition and diet quality, including the production, promotion and availability of affordable healthy diets, to avoid intensification of the already worrisome trends in adult BMI.

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In the third essay, presented in Chapter 4, titled "Confronting the double burden of malnutrition yields health and environmental benefits" I introduce a novel framework that extends the UN-FAO's methodology for assessing undernutrition to also encompass excessive calorie consumption and its association with the evolution of adult Body Mass Indexes (BMI). By incorporating these relationships into a global partial equilibrium model of the food sector (SIMPLE), I develop future trajectories of age-, sex-, and cohort specific adult BMI across major world regions over the next three decades. This allows for an examination of the dynamics of the double burden of malnutrition between 2015 and 2050. I find that the excessive consumption of calories will play a key role in driving rising BMI levels, particularly in emerging economies. As a consequence of reaching higher levels of BMI at younger ages, future cohorts will increase their exposure to the health risks attributable to overweight and obesity, including coronary heart disease (CHD), stroke, site-specific cancers, and type 2 diabetes (T2DM) I use this framework to shed light on the health, food, and environmental security impacts of changing food consumption behavior. A key finding is that environmental benefits of shifting consumption patterns are dominated by food waste reductions as opposed to changes in dietary composition. I extend the existing literature on this topic by disaggregating, for the first time, three elements of the linkage from food purchasing behavior and the environment: changes in the composition of food consumption to achieve a more balanced diet, reductions in overall food intake, and reductions in food waste. I examine the relative contribution of each subcomponent to environmental sustainability, revealing that the food waste component of what has been dubbed in the literature 'dietary changes' represents the largest contributor to the environmental benefits of shifting food purchases to a more sustainable level.

The three essays in this dissertation advance the current state of knowledge in the literature exploring the trade-offs and synergies arising out of the competing demands on the planet's finite resources (such as water, land, clean air, biodiversity etc.), as well as potential pathways for sustainable development in the coming decades. Specifically, the outcomes from this dissertation provide several policy-relevant insights on the challenges related to the excessive consumption of food (understood as the gap between current food consumption levels), the environmental sustainability, and attributable weight-related diseases to current trends on adult BMI.

The rest of the document is organized as follows: in Chapter 2, I introduce a novel food waste index that is traceable across time and countries to then use it for the estimation of systematic underlying relationships between income and caloric waste. By incorporating these relationships into a global partial equilibrium model of the food sector, I turn then to explore the quantitative linkages between food waste, resource use, and caloric undernutrition. The Chapter 2 concludes with a discussion of the main findings and the limitations of the study, pointing on potential avenues for future research. Chapter 3 starts with a review of the existent literature on current trends and patterns on adults BMI attributable weight-related diseases. I then develop a country-level pseudo-panel dataset on excessive calorie availability (ECA) to explore its role as a historical driver of overweight and obesity globally. In the section “Results” in this chapter I examine the specific correlations of ECA, as well as cohort and age effects, with observed changes on adult BMI during recent decades. Chapter 3 concludes with a summary main findings and potential implications of the study, pointing on a number of policy-relevant insights. Chapter 4 starts with a review of current trends and patterns on the ongoing malnutrition double burden, especially relevant in low- and middle-income countries. I then provide a novel framework to simultaneously analyze both ends of the caloric distribution by extending the widely used FAO’s Prevalence of Undernourishment (PoU) methodology. By incorporating these relationships into a global partial equilibrium model of the food sector, I turn then to explore the potential multiple dividends (i.e., health and environmental benefits) of policies oriented to mitigate consumers’ food waste, and to prevent overweight and obesity. Chapter 4 concludes with a review of the main findings in the study as well as pointing to some potential policy implications. Finally, in the Chapter 5 I present a summarize of the main findings and potential conclusions resulting from the studies undertaken through the three essays in this dissertation.

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# CHAPTER 2. GLOBAL FOOD WASTE ACROSS THE INCOME SPECTRUM: IMPLICATIONS FOR FOOD PRICES, PRODUCTION, AND RESOURCE USE



**Motivation and rationale:** There are few examples in the existing literature that address the quantitative linkages between food waste, food security, and environmental sustainability, at global scale. Here I develop a new panel database on household food waste at the national level based on the energy balance equation, including adjustments for changes in body weight over time. I use this to characterize the non-linear relationship between per capita income and the share of food availability wasted. By incorporating this relationship into a global partial equilibrium model of the agricultural sector (SIMPLE), I develop future trajectories of household food waste. I find that the emerging economies, particularly China and South Asia, are likely to play a key role in determining global food waste at mid-century. I also present several counterfactual scenarios that shed light on the implications for environmental and food security of limiting future growth in food waste. I find that the global impacts of these alternative pathways are greatly enhanced in the context of a more open international trade regime.

## 2.1 Introduction

In this chapter, I contribute to the literature by providing a novel framework to better understand the linkages between consumer's food waste at the national level on the one hand, and global food security and environmental health on the other hand. I begin with a newly constructed panel data set on per capita daily uneaten calories using a basic energy balance equation. Given the lack of data on food waste the present chapter also contributes by providing a global, internationally comparable data set on food waste. This allows for an empirical examination of the underlying systematic relationships between per capita income and the share of food waste in total food availability (*SFW*: the ratio of uneaten calories divided by purchased calories, a unit-free proportion). This statistical relationship allows us to incorporate food waste into a global partial equilibrium model of the agricultural sector. With this framework in hand, I undertake projections of future food waste as well as analysis of the food security and environmental impacts of alternative scenarios in which future food waste is limited.

One barrier to reducing food loss and waste is the lack of data at the national and international level. Responding to this deficiency, FAO has developed the Food Loss Index to estimate how much food is lost in production or in the supply chain before it reaches the retail level. According to FAO 2019, 14% of food is lost through the supply chain before reaching the retail level. However, little is known about how much food is wasted by consumers (households and/or retailers). As a result this lack of data, there are few credible studies of the linkages between consumers' food waste, food security, and environmental health (Hall et al. 2009a; M. Verma et al. 2017; 2020). Despite the attempt to develop a systematic framework for food loss and waste based on the life cycle of a typical food item by Bellemare et al. (2017), in general, the inconsistency of measures of food loss and waste has contributed to the absence of a coherent policy framework towards sustainable food consumption (Reisch, Eberle, and Lorek 2013; Bellemare et al. 2017).

The present study follows the definition proposed by the High-Level Panel of Experts on Food Security and Nutrition (HLPE 2014): "food loss and waste (FLW) refer to a decrease, at all stages of the food chain from harvest to consumption in mass, of food that was originally intended for human consumption, regardless of the cause". The proposed definition HLPE (2014) distinguishes between food losses (FL) "occurring *before the consumption level* regardless of the cause" and food waste (FW), "*occurring at the consumption level* regardless of the cause" (emphasis added). This distinction between loss and waste is essential for the current study since I focus solely on food waste at consumers (households and retailers) level.

The chapter is organized as follows. I start with a review of the current literature on food waste, focusing specifically on the regional and global scale implications. I then introduce the new international data set on food waste which forms the basis for a novel methodology for estimating the underlying relationship between per capita income and food waste. This allows me to incorporate food waste into a global partial equilibrium model of the agricultural sector. In the section "Results" I start by performing an historical validation of the model for the period 2006-2013. I then turn to a business-as-usual (BAU) projection of global food waste to 2050. Finally, I evaluate the impact on food security and the environment of mitigating in food waste, emphasizing the key role for international market integration. The chapter concludes with a discussion of the findings and the limitations on the present study, pointing on potential avenues for future research.

## 2.2 Literature Review and Knowledge Gap

The Food and Agriculture Organization of the United Nations (FAO) reports the Food Balance Sheets (FBS), which is the most extensive global database on countries' food systems. The FBS report annual data about domestic food supply (e.g., production, imports, and stock changes), and domestic food utilization (e.g., feed, seed, processing, export, etc.). FAO's methodology is not free of criticism (Hall et al. 2009a; Svedberg 1999b). It is believed to underestimate food availability in developing countries, particularly in rural areas where unreported subsistence production represents an important share of the households' consumption bundle (Hawkesworth et al. (2010). Additionally, before the last revision of the methodology (FAO 2019a) one of the components of the FBS (often stocks) would take on the outstanding unbalanced amount thereby inheriting all the statistical errors. The revised methodology reported by FAO mitigates some of those inaccuracies (FAO 2019a) by improving the estimates of the specific modules through the supply chain (e.g., stocks, food, feed, loss, etc.). In the revised methodology, imputations for the FBS components not reported by countries are generated by dedicated modules and then a balancing mechanism proportionally spread the imbalances out among all the components (FAO 2019a). The new food loss module reports essential information of losses across the whole food value chain up to and excluding the retail level. However, the information related to food waste at the consumer level is still being revised (FAO 2019a). Despite its limitations, FAO's is the most widely used global database for food availability at country level. Based on the FBS Kummu et al. (2012) examine the relationship between crop-based food loss and waste throughout the entire supply chain and environmental sustainability. The authors estimate the potential resource savings and the impact on food supply from a hypothetical reduction on food waste. They find that around one quarter of the produced food (614 kcal/cap/day) is lost within the food supply chain, accounting for close to one quarter of the total resources used (fresh water, cropland and fertilizer).

There are several examples in the existing literature of country-based studies attempting to quantify the magnitude of food waste at the consumers (households and retail) level. Most of them focus on developed regions. Monier et al. (2010) provides a comprehensive meta-analysis data base for food waste in the European Union (EU) based mostly on data from the EUROSTAT database as well as through literature review. They find that total food waste in the EU27 (the EU except for the United Kingdom –UK--) in 2006 added up to 181 kg per capita per year (corresponding to 12 percent of the total EU food production). From which the 42 percent is generated by households (adding up to 23.3 million of tons). They also provide evidence of significant variability in per capita waste among the EU countries, with the highest food waste per capita generated in the Netherlands, Belgium and Cyprus. Thyberg et al. (2015) offer a meta-analysis and synthesis of state, county, and regional studies from 1989 and 2013 within the United States (US) based on the weight of food disposed in Municipal Solid Waste (MSW) in the US. They find that the aggregate food waste disposal rate per person per day was 0.615 pounds (leading to an estimate of 35.5 million tons of food waste disposed annually in the US). The proportion of food waste in the overall MSW increased significantly during the 25 years analyzed in this study. The authors also find evidence of significant variations in per capita food waste across different regions.

Using a different framework, moving from quantifying weight to quantifying calories, Hall et al. (2009) developed a detailed mathematical model relating changes in body weight and food intake. This model allows the authors to calculate the energy content of food waste in the US, from the difference between the US food supply for consumption in kilocalories per capita per day (kcal/cap/day) and their estimations of food intake (kcal/cap/day). Their results show that per capita daily caloric waste in the US has increased by 50% since 1974, reaching around 1400 kcal/cap/day (around 40% of the available calories) by the year 2013.

There are few examples in the existing literature addressing the linkages between the reductions in food waste at the household level, on the one hand, and global food security and environmental sustainability, on the other. A key reason for this literature gap is the absence of reliable data on food waste at the national level (Hall et al. 2009; Xue et al. 2017; FAO 2019b). The range of methods applied to quantify food waste also differs greatly from country to country (Xue et al. 2017; FAO 2019b) making comparisons or integrated analyses nearly impossible. Indeed, there is not one unique definition of food waste. The absence of such a standard has contributed to a dearth of comparable data (Parfitt, Barthel, and Macnaughton 2010; Bellemare et al. 2017) leading to poorly informed efforts attempting to reduce food waste (Bellemare et al. 2017).

We can classify methods for quantifying food waste into two groups, those based on energy metrics (e.g. kcal) (Kummu et al. 2012; Hall et al. 2009a; Hiç et al. 2016) and those based on weight metrics (e.g. kg, ton) (Monier et al. 2010; Thyberg, Tonjes, and Gurevitch 2015). The former has the advantages of accounting for variation on nutritional content within each food type, providing information regarding the nutritional value of the food wasted (Lipinski et al. 2013) while also presenting a better opportunity for comparability across countries. Hiç et al. (2016) extend the methodology proposed in Hall et al. (2009) to calculate surplus in energy availability for 73 countries, linking the latter with Greenhouse Gas (GHG) emissions. Their results show how, given small changes in global energy requirement relative to large changes in food availability the food surplus has increased particularly rapidly in emerging economies (India and China). They also forecast a global food surplus of 850 kcal/cap/day by 2050, leading to an increase in associated GHG emissions in the range of 1.9 to 2.5 Gt Co2 equivalent/year. Springmann et al. (2018), analyze the environmental effects of the food system as well as options for mitigating those effects, including food waste and loss reductions, towards 2050. However, they base their analysis on current estimates of food waste, not on future projections. They find that, in the absence of yield improvements, technical change and moderating measures, the food system's broad effects on the environment could increase by 50–90%. The authors conclude that such a scenario would cause humanity to violate the planetary safe operating space. They also conclude that a synergistic combination of sustainability measures, including cutting food waste by 75%, will be needed to avoid serious environmental damages.

There are also some studies which have sought to evaluate the economic implications of food waste and its mitigation using applied general and partial equilibrium frameworks. Irfanoglu et al. (2014) explore the impacts of reducing food losses and waste on global food security, trade, greenhouse gas emissions, and land use by using the Simplified International Model of Crop Prices, Land Use and the Environment (SIMPLE) model (Baldos and Hertel 2013). In this study the food waste is incorporated by including a household production function in the model, and the food waste is computed as the difference between food purchased and food consumed. However, they do not offer a methodology for projecting the future evolution of food waste. Britz et al. (2014) analyze the potential effects of food waste reduction on the whole economy incorporating food waste reduction related costs in a regional computable general equilibrium (CGE) model. They point out that, under certain circumstances, the attempts to reduce food waste might cause severe loss of competitiveness for the agriculture and food production sectors. Hertel and Baldos (2016b) examine the implications of a range of policy initiatives aimed at improving food security and environmental outcomes, including reductions in post-harvest losses in SSA and reductions in food waste in the wealthy economies. Their study uses the SIMPLE model as a framework, first in the context of historically segmented markets for the global food economy, and secondly in a hypothetical future world of fully integrated crop commodity markets. Their study is the first to point out the potential interaction of the policies to reduce food waste and loss with trade policies.

Verma et al. (2020) present a cross section data set with country-specific metrics of per capita daily caloric waste for 70 countries by extending the energy-balance equation presented in Hall et al. (2009). Their study starts by exploring the relationship between food waste, income, and prices concluding in an estimation of the affluence elasticity of waste (a metric for the influence of per capita income on food wasted). A limitation in this study is the absence of a time series component which stems from the fact that they do not consider changes in body weight in the energy balance equations. This limits the applicability of their study in examining the long-term underlying systematic relationships between income, food availability, and food waste. All of these model-based studies: Verma et al. (2020), Britz et al. (2014), Hiç et al. (2016), Irfanoglu, et al. (2014), Hertel and Baldos (2016b) and Springmann et al.(2018), fail to provide a systematic analysis of the long-term relationship between national per capita income growth and food waste.

The present research differs from the aforementioned studies in a number of important ways. I start by extending the methodology used in Hall et al. (2009), Hiç et al. (2016), and Verma et al. (2020), to calculate daily caloric per capita waste by incorporating changes in body weight into the analysis and extending coverage to a time series encompassing 95% of the world's population. This results in a new panel data set of country-specific average daily per capita calories wasted from 1975 to 2014 for 158 countries. While previous studies have focused on the implications of reducing current levels of food waste (Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson, et al. 2018), I use these data to estimate a model of food waste evolution across the development spectrum which allows for more accurate projections of consumer food waste. These estimates are then incorporated into a global model to shed light on how food waste affects food security and environmental health towards 2050. Finally, I analyze several counterfactual scenarios on how limiting future evolution of food waste would

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affect food security and the pressure on environmental resources, paying special attention to how these impacts are influenced by the extent of international market integration.

## 2.3 Food Waste Measurement Methodology and the Long-Term Relationship with Income

### 2.3.1 A New Panel Data Set for Global Food Waste

I begin by creating a consistent, international panel database building on the energy balance equation. Since food waste at the country level is not directly observed at present, it must be inferred from other observables, including food availability (FA), estimates of physical activity levels (PAL) and basal metabolic rates (BMR), and changes in Body Mass Index (BMI). This leads to the following system of equations for deducing food waste:

$$Energy\ expenditure = Physical\ activity\ level*Basal\ Metabolic\ Rate \tag{2.1}$$

$$Food\ Intake = \Delta\ Body\ weight*\rho + Energy\ Expenditure \tag{2.2}$$

$$Food\ Waste = Food\ Available - Food\ Intake \tag{2.3}$$

In Equation 2.2 $\rho$ is a parameter which converts changes (increases) in body weight to excessive intake of calories based on the energy balance equations (Hall et al. 2011). Following this approach, the uneaten calories at household level are quantified as the difference between the available calories (kcal/cap/day) and the caloric intake (kcal/cap/day). Country-specific food availability (kcal/cap/day) is obtained from the FAO Food Balance Sheets (FAO/WHO 2017) over the period 1975-2013. The country-specific average Energy Expenditure are calculated from the product of country-specific BMR and the country-specific PAL. The composite BMR, for an average person in each country, is a function of countries' demographics (age, average weight, and sex) retrieved from World Bank Database (World Bank 2018). PAL based on different lifestyles retrieved from (FAO/WHO 2001). I extend Verma et al. (2020) by incorporating the increment of body weight into this equation. The country-specific average increase $\Delta Body\ weight$ ($BW$) was obtained from the differences in BMI reported for the years 1975, 1985,1995, 2005, and 2014 (Abarca-Gómez et al. 2017) and country-specific average height for male and female from NCD Risk Factor Collaboration (Risk and Collaboration 2016). The increment in body weight is converted to energy (Kcal/cap/day) by applying a weight change model (Hall et al. 2011). Finally, by assuming a uniform intertemporal distribution of changes on energy expenditure due to changes on average weight, I can calculate country-specific average annual energy daily intake for the period 1975-2013. This extension is critical to permit estimation of the underlying long-term relationships between income, prices, food availability, and food waste.

Previous evidence suggests that per capita income plays a key role in the evolution of food waste, both due to an increase in food purchases per capita and an increase in the opportunity cost of household labor (Xue et al. 2017). Previous studies suggest this relationship to be nonlinear, wherein the responsiveness of food waste to changes in income is high for developing countries and falls as nations become richer. Here, I use the newly constructed data set to explore this relationship in greater depth.

I find it useful to focus on the share of food waste in a country's total food supply, as opposed to the absolute level of waste (M. Verma et al. 2020; Carmona-Garcia et al. 2017; Xue et al. 2017; Zhou and Yu 2014). I define the Share of Food Waste (*SFW*) as the ratio of daily per capita calories wasted over the per capita calorie availability. Then I compare the evolution of the SFW across income regions, as well as across countries over time. **Figure 2.1** presents an illustration of the findings based on a subset of 18 countries in the data set, chosen to represent a variety of geographic regions as well as different levels of development.

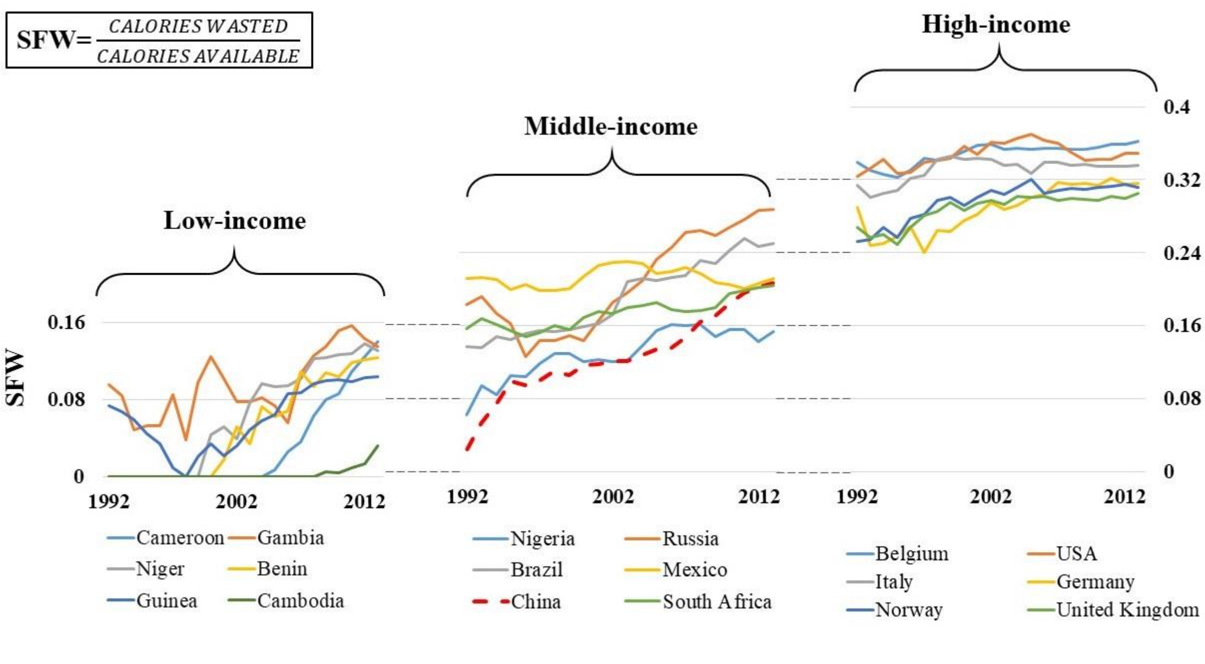


**Figure 2.1. The Share of Food Waste (SFW) across the income spectrum.**
Using a subset of 18 countries (selected from the 158 used in the present study) grouped by income levels according to World Bank Classification 2018.

A first point to be observed in **Figure 2.1** is that, *on average*, the per capita daily energy supply has exceeded the requirements for most of the countries in the sample since 1992. That is also true at the global level, where the gap between the calories available and required, for an average person, have firmly increased in the recent decades (**Figure A.1**). The global *SFW* has increased from 0.11 to 0.17 over the 1992-2013 period. Of course, it should be noted that this does not mean that every person is obtaining sufficient calories, due to the wide distribution of caloric intake within each country. Understanding the intra-country distribution of food (food accessibility), is beyond the scope of this study given the level of aggregation in this approach. A second observation is that, in low-income countries, *SFW* rises rapidly as per capita incomes increase. Middle-income countries illustrate a transition period during which the absolute amount of food waste rises rapidly, while the rate of growth slows. Finally, high-income countries appear to converge to a relatively stable level of *SFW*. In this sample of 18 countries (**Figure 2.1**), *SFW* ends up stabilizing in the range between 29% and 36%. The UK is at the low end of this range – perhaps indicative of the strong emphasis placed on reducing food waste in the UK starting in 2007 (Defra 2007). On the other hand, the US is near the top of this group, peaking around 37% in 2004, consistent with figure reported in Hall et al. (2009), before dropping to 34.6% by the year 2013. Of course, a steady share of food waste in total availability is not equivalent to constant per capita food waste, since availability, as well as body mass have continued to rise in most regions.

The consistency of the results with those of Hall et al. (2009) is important, as it provides an indirect channel for validating the approach taken, which is inspired by those authors. In their paper, focusing only on the US, Hall et al. (2009) compare their estimates of total food waste to data on US municipal solid food waste and find a close correspondence. Their estimates move closely over time with the observed data on municipal food waste, although their predictions of food waste are consistently above the solid food waste time series. This makes sense for several reasons. Firstly, not all waste goes to municipal dumps. And secondly, the solid food waste observations are likely underestimates of the true values of municipal waste. An additional source of indirect validation of the approach taken in this chapter comes from the fact that it suggests a leveling off of food waste at higher income levels that is consistent with the findings in the extensive literature review on food waste measurement and data provided by Xue et al. (2017) along with evidence that the income elasticity of calories purchased and wasted decreases with rising incomes (Zhou and Yu 2014; M. Verma et al. 2020).

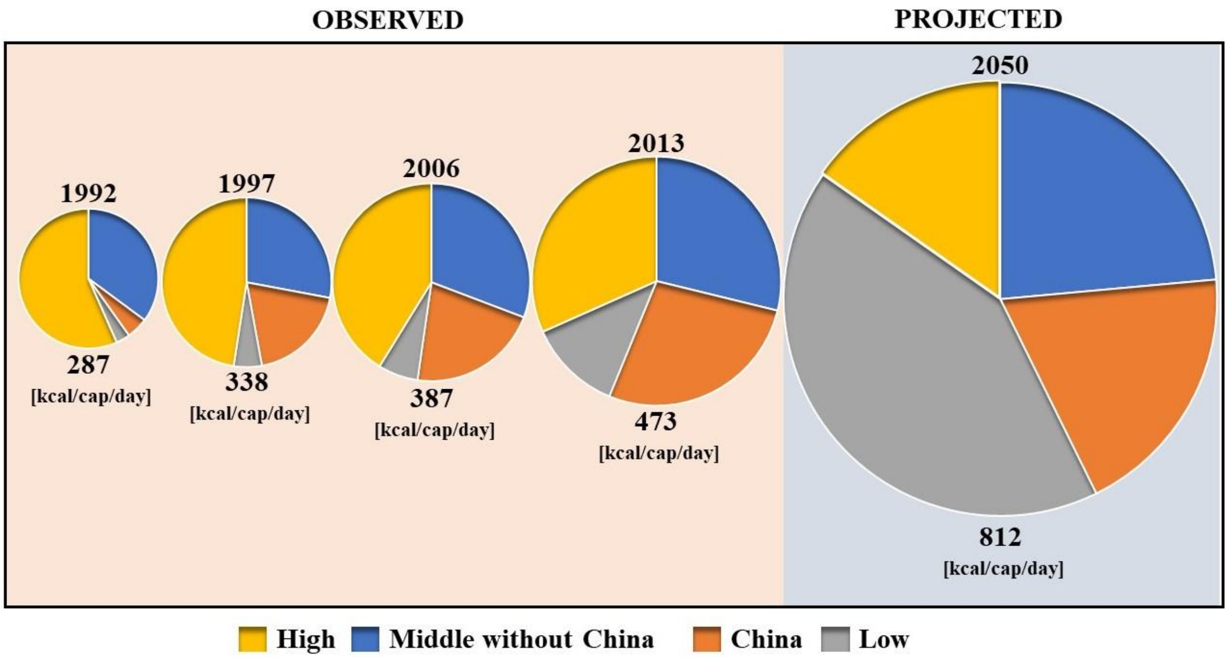


**Figure 2.2. Aggregates the food waste data from all 158 countries in the data set to the global level.** Showing the observed contribution of major country groupings to global, per capita food waste over the period 1992 to 2013 as well as the projections towards 2050 (see Results below).

**Figure 2.2** aggregates the food waste data from all 158 countries in the data set to the global level, showing the contribution of major country groupings to global, per capita food waste over the period 1992 to 2013. The size of the "pies" correspond to how the estimated "global" per capita food waste has increased in this sample of countries since 1992 – starting at 287 kcal/capita/day and rising to 473 by 2013, with a projected 72% increase reaching 812 kcal/capita/day by the 2050 (see Section 4 below). This global estimate is somewhat lower than that of Hiç et al. (2016), who project waste of 850 kcal/capita/day by mid-century.

The changes in the relative shares within the pie show how the middle-income countries' contribution to global food waste has come to dominate this total. (It should be noted that the "share" here is a different concept than the *SFW* in the presented in **Figure 2.1**.) On the one hand, the high-income regions--population weighted--share of the 287 kcal (during 1992) was 57% and decreased 25 percentage points to reach 32% of the global 473 kcal wasted during 2013. On the other hand, China's share of global food waste increased from 5% during 1992 to 27% of the global total in 2013. These findings are consistent with previous studies estimating food waste via this caloric methodology (Hall et al. 2009a; Hiç et al. 2016; M. Verma et al. 2020). The observed changes in relative contributions to the composite global daily caloric waste, leading to a dominant role of middle-income countries, follow from the rapid increases in population and income in developing countries where food comprises a large share of the average households' budget (Barrett and Dorosh 1996); in contrast, the share of budget expended on food in developed countries such as US can be less than 10% (US EPA 2016). Additionally, it can be observed that China plays a critical role in global food waste given its large population.

Having examined the historical evolution of food waste, I now turn to future projections. This will entail several steps: first estimating the relationship between food waste and income, then incorporating it into an economic model and finally making projections based on future growth in income, population, technology, and food waste policies.

### ***Estimating a Model of Food Waste Response to Income Growth***

Given the apparent difference in behavior of *SFW* with respect to income growth amongst the low, middle and high income countries, I first test for structural breaks in the data set using the Chow test (Chow 1960). **Table 2.1** summarizes the results[1]. The large F statistic leads us to conclude that there are structural breaks in this relationship across the three income groupings, which suggests that I need to consider a non-linear functional form (**Figure A.2**) that allows for different responses of *SFW* to income at different income levels.

**Table 2.1. Summary statistics and test for structural breaks**

| | **GDPpc** | **SFW** |
|---|---|---|
| **Observations** | 3466 | 3466 |
| **Mean** | 11329 | 0.1243 |
| **Min** | 162 | 0.0001 |
| **Max** | 111968 | 0.3698 |
| **Structural test** | F (3, 3462) = 1081 | Prob>F = 0 |

*Note: the type of non-linear relationship between the share of food waste in total food availability and per capita income suggested by* **Figure 2.1** *is evidenced in many social and economic processes.*

[1] *Please find the* ***Figure A.2*** *in which I illustrate the observed data points of Share of Food Waste (SFW) data across the income spectrum and the SFW projections obtained through the linear function estimation. That figure illustrates how a lineal approximation to model the relationship between income and food waste would over-project SFW for higher levels of income.*

The response variable, in this case *SFW*, starts out rather flat, and at a low level. At low per capita income, food is relatively expensive and represents a large share of households' budgets (Barrett and Dorosh 1996). They cannot afford to waste food and the opportunity cost of the time involved in food procurement, preparation and storage is relatively low (Lusk and Ellison 2017). Furthermore, the nature of diets at low-income levels – predominantly staples – is such that storage is easier. Food waste begins to grow as household incomes rise, diets diversify to include perishable fruits, vegetables and meats (Popkin 1994), and wages rise, increasing the opportunity cost of time spent on food procurement and preparation (Lusk and Ellison 2017). Increased away-from-home food consumption likely plays a role here as well as previous studies suggest that consumers are more likely to save food when eating at home when compared with eating away-from-home (Asioli, Pinpart, and Balcombe 2019). **Figure 2.1** shows that this acceleration is particularly striking as countries move into the middle-income category. This growth in the overall share of food waste plateaus at high income levels when households have made the transition to a modern, industrialized economy. As consumers reach the affluent stage, a further increase of income would likely have no significant impact on calorie purchasing (including wasted calories). Rather, calorie purchases (including waste) are expected to enter a stage of stasis (Zhou and Yu 2014).

The S-shaped curve suggested by **Figure 2.1** is quite similar to that found in the technology adoption literature where adoption rates start out slowly before reaching a 'take off' stage at which point the technology starts spreading at an increasing rate until it gradually levels off (Griliches 1957; Jarvis 1981). Usually these patterns of change in adoption rates are modelled through a logistic function (Nin et al. 2004; Ludena et al. 2007a; Polson and Spencer 1991). The logistic function has the advantage of being parsimonious, yet flexible enough to capture the essential features in these relationships, enabling the capture of convex as well as concave curvatures at different income levels. I find this flexibility essential to capture both the broad trends as well as the regional eccentricities (i.e., due to different regulations, cultural differences, and/or relative prices of food with respect to non-food items in the market) in the response on food waste as the income evolves. The logistic functional form used here postulates the following relationship between per capita income and *SFW*:

$$SFW_i = \frac{\gamma}{1+ e^{-\alpha-\beta * GDP\_pc_i}} \qquad (2.4)$$

`

The parameters γ, α, and β govern the shape of the logistic function. The value of β determines the speed of change in the function; a higher value implies a faster approach of *SFW* to the upper asymptote of the function γ. The parameter α governs the midpoint ascent, indirectly determining where the function starts to increase. After applying the standard logarithmic transformation, and including an *i.i.d.* error term, the estimating form of the equation becomes:

$$Y_i = \log\left(\frac{SFW_i}{\gamma - SFW_i}\right) = \alpha + \beta * GDP\_pc_i + \varepsilon_i \tag{2.5}$$

For a given value of γ, one may calculate the value of the left-hand side of the equation (2.4). Then α and β may be found by least-squares regression under the classical ordinary least squares (OLS) assumptions (Nin et al. 2004; Ludena et al. 2007a). By iterating through this process, the value of γ may also be determined according to the criterion of minimizing the sum of squares of the residuals. There are several approaches for this, from systematic procedures to estimating the upper asymptote of the function such as the Golden Section Search and Fibonacci Search (Vardavas 1989) to running numerous regressions, each with a different value for γ. Results from the latter procedure are reported in the **Table 2.2**. The confidence intervals of the two parameters estimated (α and β) show that these parameters are rather precisely estimated. These confidence intervals will also be employed when attaching error bars to the projections of future food waste.

**Table 2.2. OLS estimations for parameters in the logistic function**

| | Coef. | [95% Conf. Interval] |
|---|---|---|
| α | -1.821084 | [-1.873587 -1.76858] |
| β | 0.0000367 | [0.0000341 0.0000393] |
| γ | 0.3201 | - |

**Figure 2.3** plots this estimated logistic function, along with the data points in the sample. As can be seen from that figure, while it seems that most countries follow this same general pattern of food waste as incomes rise, at any given income level *SFW* varies quite a bit. This is hardly surprising, as there are many other factors determining food waste beyond income (Chalak et al. 2016). These country-specific factors, as well as the economic modeling approach taken in Section 4 below, lead us to aggregate the data into regions and then re-calibrate the logistic function parameters to better reflect regional variation in the parameters governing equation 5.

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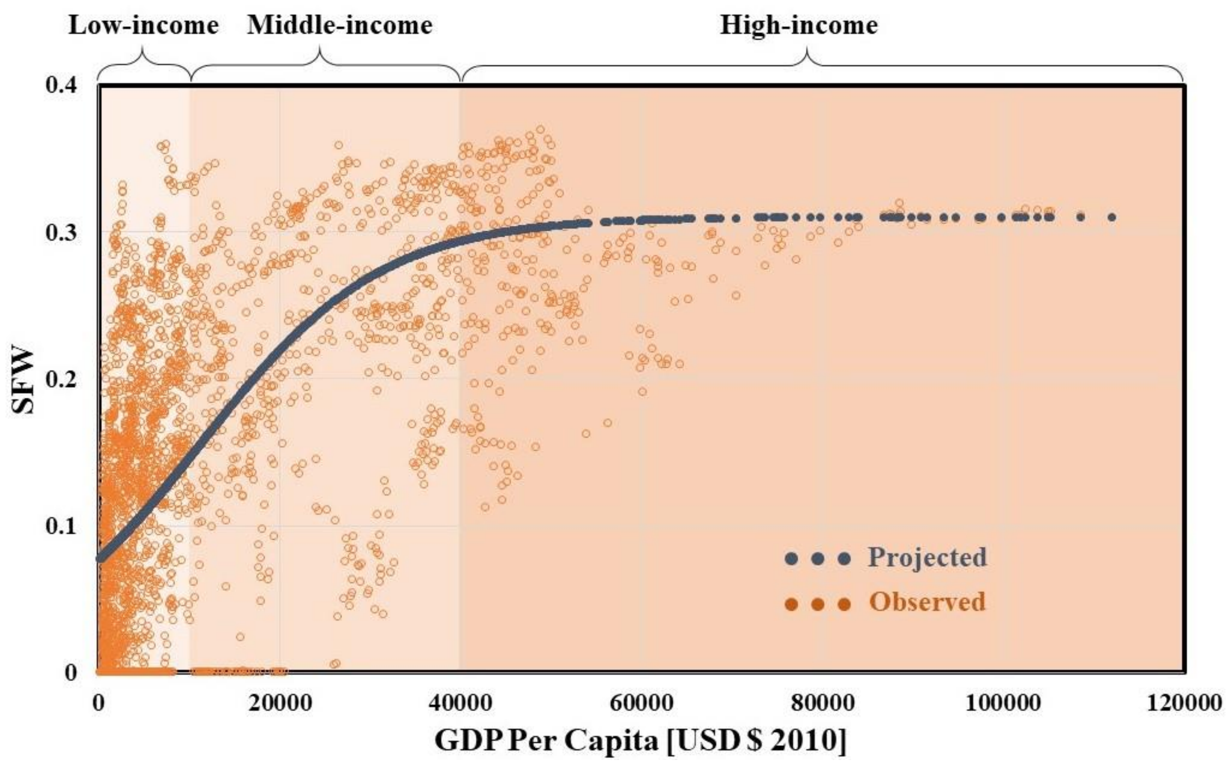


**Figure 2.3. The observed and projected data points of Share of Food Waste (SFW).**
Data across the income spectrum and the SFW projections obtained through the logistic function estimation previously described in this section.

***Regional Aggregation and Calibration***

In order to project future food waste, I aggregate countries to the regional level and then calibrate the regional parameters to reproduce the 2006 benchmark. While there is a cost to losing country-specific detail, this aggregation permits us to incorporate the projections of the share of food waste into a validated model of global partial equilibrium model of the agricultural sector. With this in hand I can project the level of food waste in 2050, as well as analyzing the consequences of alternative pathways for the reduction of future food waste. Regional aggregation is also useful given the eccentricity of individual countries and potential reporting errors to the FAO. In anticipation of the economic projections to be undertaken in Section 4 below, I have chosen to aggregate countries to the geographic 15 regions in an economic model (**Figure 2.4**). This allows to capture the changes in food waste through a large portion of the income spectrum over this period (see

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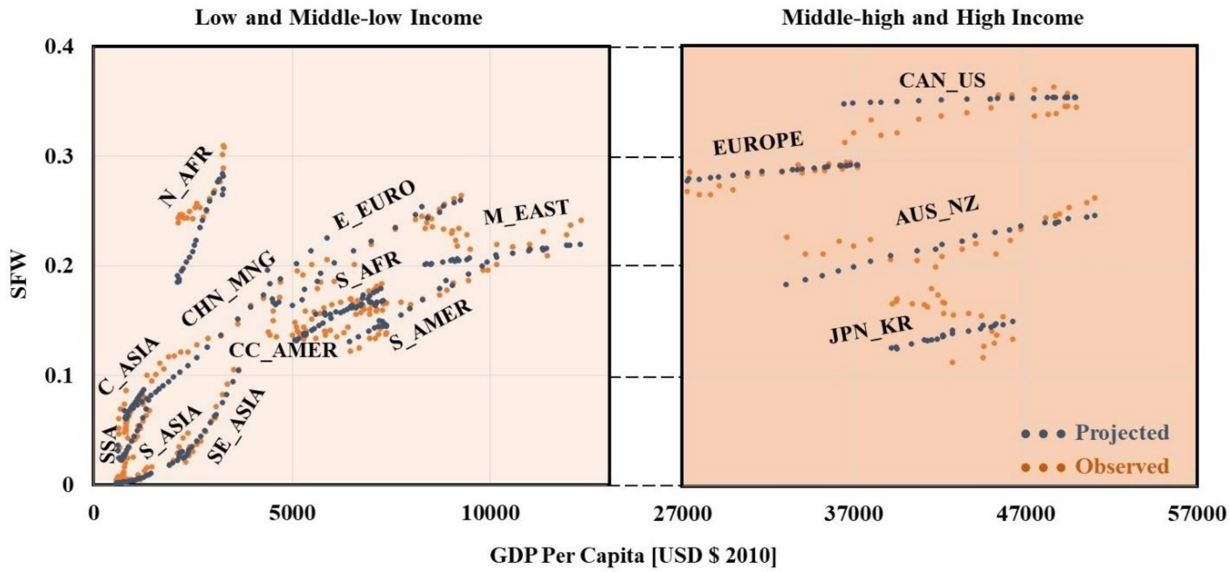


**Figure A.3** for a compiled version of **Figure 2.4**), while avoiding dealing with the inevitable country-specific eccentricities that arise in such a data set.

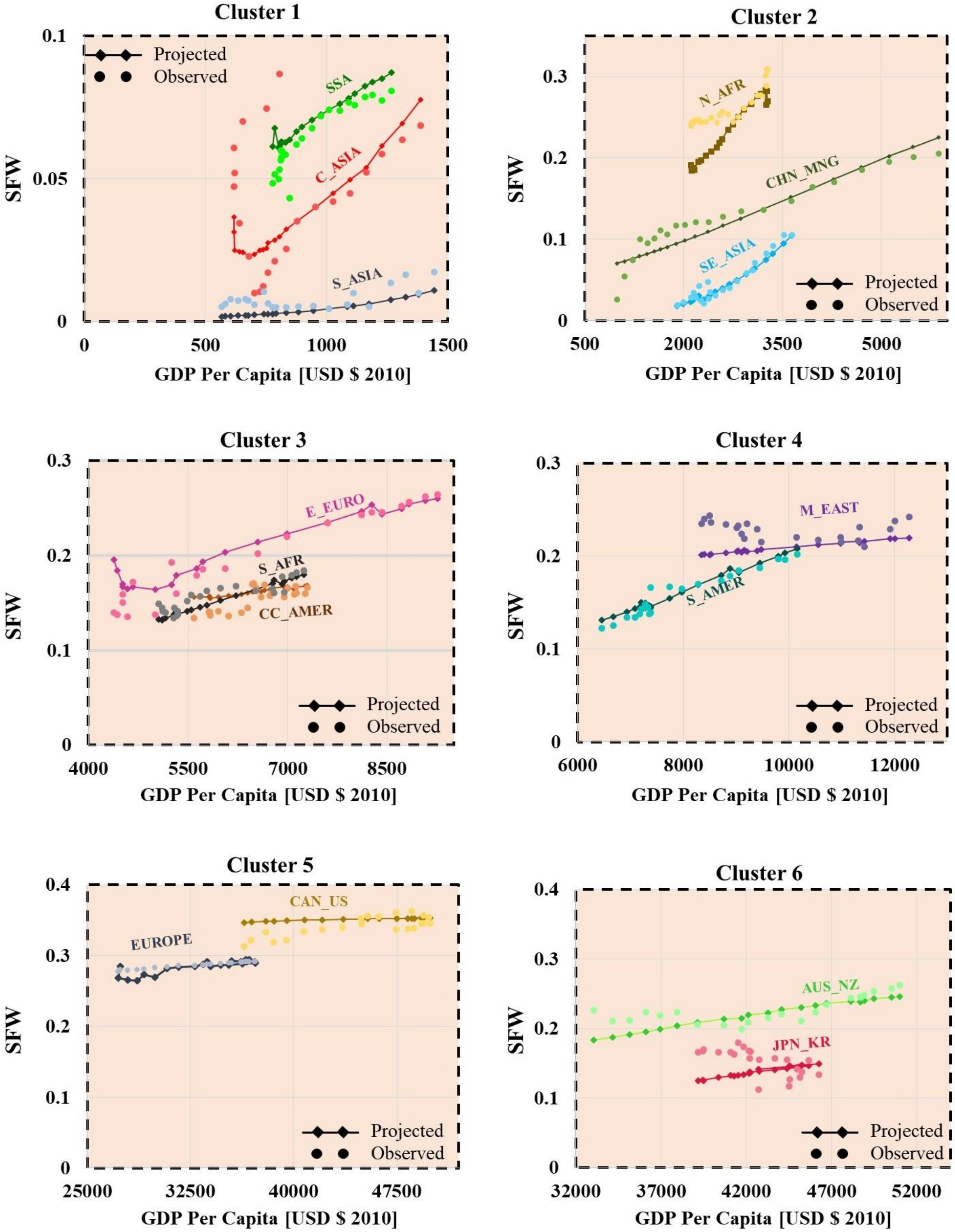


**Figure 2.4. The logistic projections and observed levels of SFW.**

The logistic function projections (points connected via the solid lines) and the observed levels of SFW collapsing the data points through weighted-population averages into 15 regions across the 22 annual data points (SFW & income for 1992-2013) for each region.

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This particular aggregation into 15 regions has the additional advantage of matching with the global model SIMPLE[2] which I use for future projections. Calibration involves adjusting the logistic function parameters for each region while requiring this function pass through the year 2006 benchmark data set used in Section 4 and based on FAO (FAO/WHO 2017) and World Bank (World Bank 2018) data. This calibration procedure minimizes the deviation across the entire series from the original estimates in **Table 2.1** (illustrated in **Figure 2.3**). I use the year 2006 as benchmark in anticipation of the economic projections to be undertaken in Section 4. **Figure 2.4** plots the aggregated regional data points, along with outputs from the region-specific logistic functions (i.e., projections) for each year over the sample period. The significant shifts in these functions across regions illustrates the importance of the calibration step for capturing regional variation in the share of food waste and matching observed data as well as undertaking global projections.

***Future Evolution of SFW***

**Figure 2.5** puts these region-specific *SFW* functions in the context of a timeline starting in 1992 and continuing through the period of observation (up to 2013) and forward to 2050 using income projections to be discussed below. Error bars for the projected food waste shares were obtained through a bounding analysis using the lower and upper bounds from the confidence intervals in **Table 2.2**. From this figure, several points emerge. Firstly, the calibrated logistic functions now track individual regions' evolving food waste quite closely. Secondly, there is very little 'action' in the high-income countries, where the share of food waste is not expected to change significantly in the absence of targeted policies. Thirdly, the most dramatic changes between 2013 and 2050 are expected in South Asia, where the economy is starting out at a very low level of food waste, but high-income growth over the next three decades is expected to boost *SFW* to nearly one-third. Finally, based on the error bars in **Figure 2.5**, the most developed regions (US/Canada,

[2] The Simplified International Model of Crop Prices, Land Use and the Environment (SIMPLE) model is a global partial equilibrium model of the agriculture sector For a detailed explanation on the SIMPLE model, see the textbook by (Hertel and Baldos 2016). The SIMPLE model is designed to capture the major socio-economic forces at work in determining food consumption (crops, livestock and processed foods), cropland use, output, prices and nutritional attainment. The SIMPLE model focuses on a few key relationships related to global agriculture, keeping it as simple as possible while capturing the important drivers of global agricultural change. In order to avoid frequent criticism of general or partial equilibrium models, identification problems when involving too many behavioral parameters since each estimation implies an error SIMPLE focuses only on the relationships that are considered essential. However, the authors acknowledge that there is a trade-off in this decision. With the risk of becoming too simple which might lead to introducing other errors.

Europe), already at a high level of *SFW*, as well as the middle-income ones (China and South America), present significantly less sensitivity to changes in the parameters shaping the function. However, the uncertainties in the projected calculations are greater in the low and lower middle-income regions (i.e., Sub Saharan Africa and South Asia) – particularly during the transition period to high income levels. It is also important to note that I base the projections in the observed values of food waste through the income spectrum. While the model attempts to capture the regional eccentricities, it does not capture changes in food waste beyond what has been observed in the period up to 2013 (e.g., potential decreases in food waste through increase of awareness). Below, I will explore the potential effects on resource use and food security of freezing the food waste (among other scenarios) in the results session.

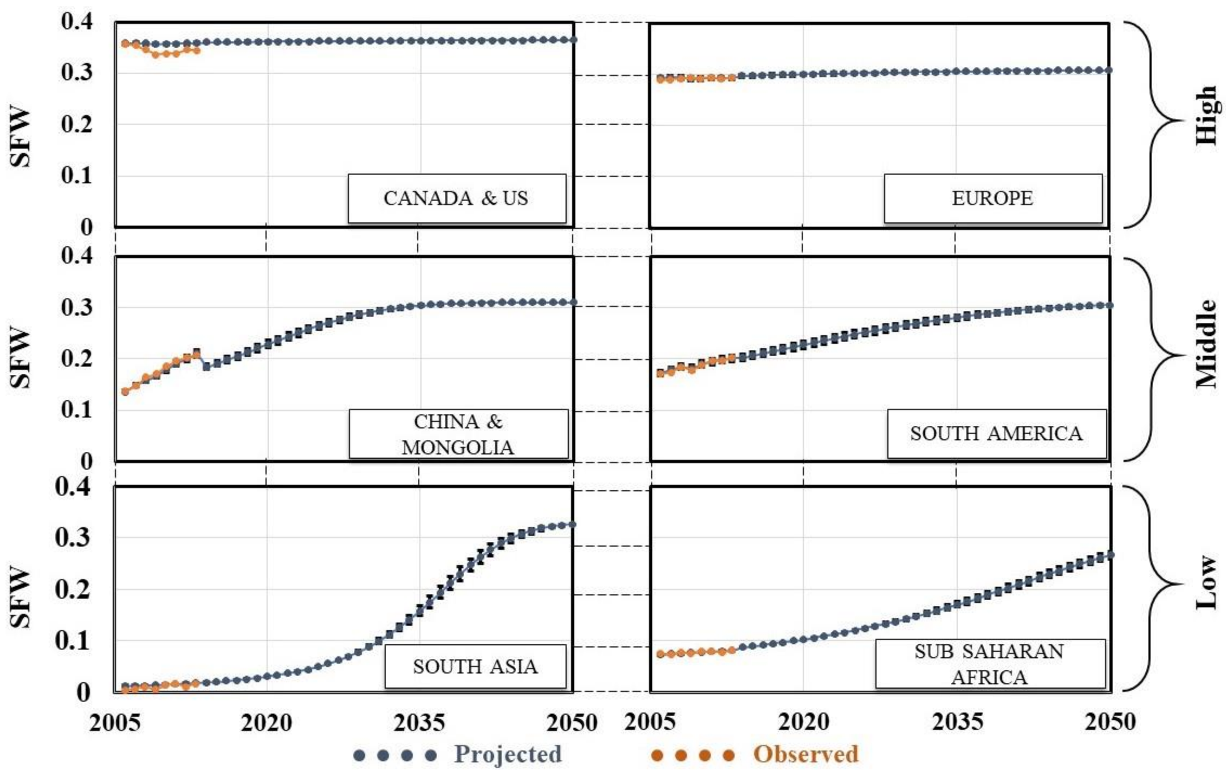


**Figure 2.5. SFW observed between 2006-2013 and projected towards 2050.**
This figure includes 6 of the 15 regions in the study (the remaining regions' figures are reported in the **Figure A.4**). The top two panels present two high-income regions, the ones in the middle two middle-income regions and the two at the bottom present lower income regions (according to World Bank 2018 classification of countries by income).

## 2.4 Incorporating the SFW into a Global Partial Equilibrium Model of the Agriculture Sector

In order to convert the region-specific SFW functions reported in **Table 2.2**, into projections of global food waste, I require projections of income per capita and total food availability for each of the 15 regions. It is common in agricultural models to treat income as exogenous, and so I, too, adopt a partial equilibrium approach, taking income growth from other global modeling activities, while assuming limited feedback from food waste to national income. In an ideal world, I would have data on food waste by type of food commodity – i.e., a different *SFW* function for each food type. However, given the aggregate data set which I have been able to develop, I am forced to assume that the share of food waste in total availability is the same across all food types. This is clearly a limitation which should be relaxed in future work, as improved data become available.

Given this aggregate approach to food waste, I do not require an extremely detailed model of food consumption. Rather, I focus on obtaining accurate, long run projections of total food consumption and total calories available, by region. One partial equilibrium model suitable for such purposes is the SIMPLE model (a Simplified International Model of Prices, Land use and the Environment). It is attractive for the purposes in this chapter since it has been subjected to historical validation with respect to long run evolution of crop output, prices, land use and caloric undernutrition (Hertel and Baldos 2016b;  Baldos and Hertel 2016; 2013; Baldos and Hertel 2014).

The SIMPLE model includes three production activities in each of 15 regions: 1) an aggregate crop sector; 2) livestock; and 3) processed food, whereby the latter two utilize crop and non-crop inputs to produce food products for consumers. Food demand responds to changing prices and income through the incorporation of income and price elasticicities which vary as a function of regional income per capita. These relationships are obtained from a cross-country analysis of purchasing patterns (Muhammad et al. 2011), and that vary by food commodity (crop, livestock, and processed foods).

The crops sector employs land and non-land inputs via a Constant Elasticity of Substitution (CES) production function and the use of inputs is governed by the extensive and intensive margins of factor supply. The crop commodity is a composite of all 175 crops in the FAOSTAT database, weighted by relative prices to produce output measured in corn-equivalent tons. Crops are traded internationally and consumed directly as well as indirectly through their use in livestock and processed food production. For a detailed exposition, see the textbook by Hertel and Baldos

(2016a). The model is parsimonious and open source. As with the *SFW* data set, SIMPLE is based on FAO data.

## 2.5 Results

### 2.5.1 Model Validation

As in Baldos and Hertel (2014) who used SIMPLE to examine changes in undernourishment over time, I start the analysis by evaluating how well the model projects *SFW* outcomes over an historical period, in this case, 2006–2013 (7-years). Often studies that use economic models to project future outcomes are not validated against history, yet this is a critical step. Additionally, this historical assessment provides valuable inputs for examining changes in the future. The historical projections in **Figure 2.6** are most accurate at the global level; the projections are less accurate at the regional level, which is consistent with previous studies attempting to validate global agricultural models (Baldos and Hertel 2014; McCalla and Revoredo 2001). Those authors find that food availability and price projections become less accurate with greater levels of disaggregation.

At the regional level, the framework underpredicts the growth in food waste in China, while over-predicting 2013 food waste in the US. Re-examination of the US time series for SFW in **Figure 2.1**, it can be seen that the food waste share jumped up around 2006 and then dropped to its level in the early 2000's by 2013. The model is not capable of capturing this cyclical behavior. In the case of the low-income region in **Figure 2.6** – SSA, the model does reasonably well over the historical period, while anticipating a significant rise by 2050.

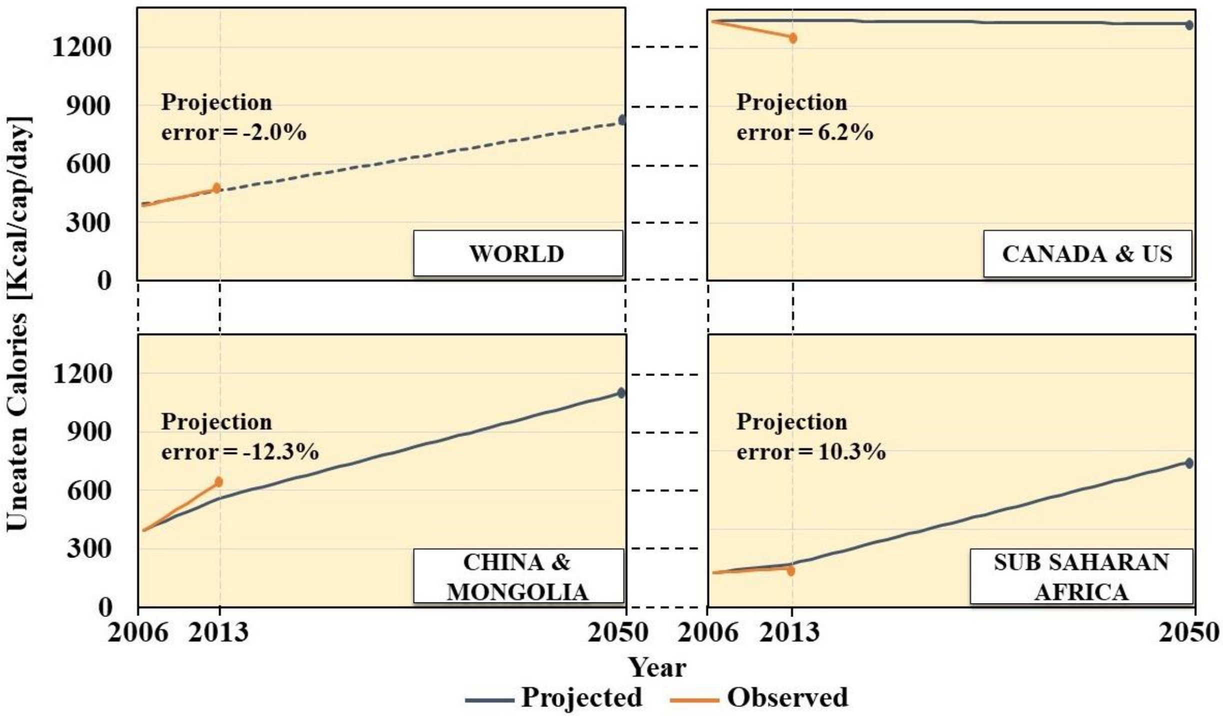


**Figure 2.6. Observed uneaten calories and model projections from 2013 to 2050.**
The panels plot observed uneaten calories (kcal/cap/day) in 2006 and 2013, and model projections for 2013 and 2050 obtained from the baseline simulation starting in 2006. Projection errors (% difference between model projected and observed values for 2016) are reported.

### 2.5.2 Future Projections

***Baseline***

The projections of uneaten calories to 2050 in **Figure 2.6** rely on incorporation of equation (2.4)--albeit with the regionally calibrated parameters—into the SIMPLE model which produces estimates of total caloric availability and purchases. SIMPLE is projected forward with exogenous shocks to population, per capita incomes, total factor productivity (TFP) growth, and biofuel consumption. Growth rates for population and income were derived from the Shared Socioeconomic Pathways (Fricko et al. 2017). The Shared Socioeconomic Pathways (SSPs) create a framework for global studies, usually focused on environmental outcomes, to explore how the future can evolve under a consistent set of assumptions. They cover a wide range of hypothetical future states of the world by providing five different narratives. Here I the use the SSP 2 as the reference in the baseline projections. Given its description of a "middle-of-the-road" state of nature, the SSP 2 is natural starting point to further explore integrated solutions for achieving societal objectives to reduce pressure on environmental resources (Fricko et al. 2017). In the projections, TFP growth rates are based on the historical estimates from (Ludena et al. 2007a) and (Fuglie 2012). The growth in global biofuel consumption is from the document published in the World Energy Outlook (IEA 2008; IEA 2012 ) (shocks are reported in **Table D.1**. See Appendix D for details).

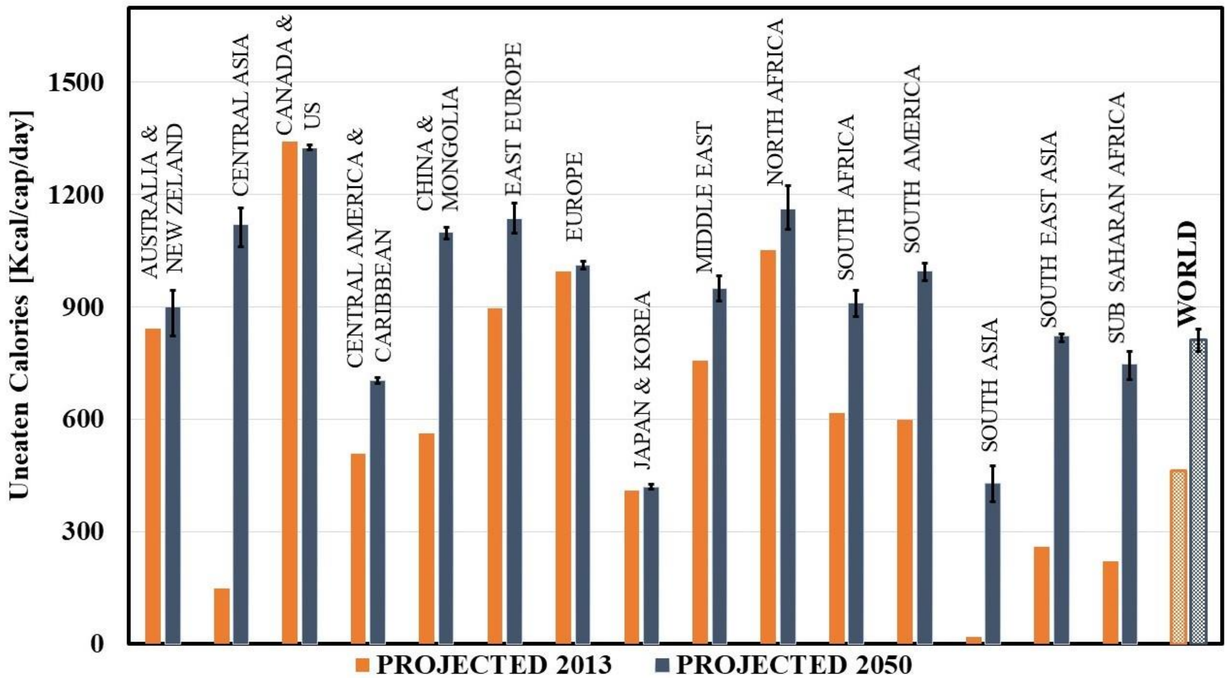


**Figure 2.7. Projected uneaten calories 2013 and towards 2050.**

Error bars were obtained following the same process described above in the document. The upper (lower) bound corresponds to the projected uneaten calories while using the upper (lower) bounds from the 95% CI for the region-specific α and β.

**Figure 2.7** reports projections for uneaten calories in 2013 and 2050, using a modeling framework. In the absence of significant policy interventions or behavioral changes, food waste is expected to increase substantially by 2050. Globally, *SFW* is expected to increase from 0.17 (17% of calories purchased are uneaten) to 0.26 in 2050. Daily uneaten calories are expected to nearly double going from 473 (kcal/cap/day) in 2013 to 812 (kcal/cap/day) in 2050. The largest per capita increases in food waste are expected to arise in the emerging markets where population and income will likely increase most. This is consistent with Engel's law, since is also expected that the share of budget expended on food would also be higher than in developing regions and since the increasing purchases of food may lead to the increase in the excessive intake and waste of calories. In rich countries the *SFW* seems to have levelled off, so that middle income countries, particularly

China and lower income regions as South Asia, Southeast Asia, and Sub Saharan Africa are expected to dominate future global food waste (see the rightmost pie chart in **Figure 2.2** – 2050). Note that China's share of the global food waste declines from 2013 to 2050, as its food waste growth is outpaced by that of South and Central Asia, and Sub Saharan Africa. Additionally, the uncertainties on food waste projections are heterogenous across regions. The framework used in this study allows for systematic investigation of the impacts of variations in the key inputs on driving the results simulation results (Appendix D). In the case of the results on food waste, the systematic sensitivity analysis was driven by sampling from the estimated distributions for the 3 key region-specific parameters ($\gamma$, $\alpha$, and $\beta$) that govern the shape of the logistic function capturing the underlying relationship between income and caloric waste (equation 2.4). Specifically, in this analysis, the Gaussian quadrature approach to systematic sensitivity analysis draws parameters from the previously estimated distributions and produces 95% confidence intervals for the model results. I find that the regions already presenting higher levels of food waste have lower uncertainties. On the other hand, regions at earlier stages on the transition towards higher levels of food waste, present larger uncertainties.

***Examining the Consequences of Alternative Waste Reduction Pathways***

In the light of these results, I turn the attention to the likely implications for land use and food security of curbing future trajectories of food waste, as well as examining their interactions with trade policies. I start by exploring the food security and land impacts of rolling back *SFW* in all regions, except for the poorest one – SSA, to 0.20 (*SFW* = 0.20 scenario)[3]. The second experiment explores the impact of freezing *SFW* in all regions, except for SSA, at their values in 2020 (*SFW*=2020 scenario). Finally, I consider the impact of a somewhat less stringent scenario wherein of the *SFW* freeze is not implemented until 2030 (*SFW*=2030 scenario).

Each of these three experiments is undertaken against the backdrop of two different levels of global market integration (segmented vs. fully integrated markets) to shed light on the interactions of initiatives attempting to reduce food waste with trade policies. The different scenarios projected are the result of changing assumptions with respect to the future evolution of the global economy. The segmented markets specification is designed to reproduce current conditions, in which domestic agricultural markets are imperfectly linked to world markets due to

[3] From **Figure 2.5** we can see that SSA only rises above 0.20 at the end of the projected period.

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domestic and border policies as well as trade and transport costs. The underlying idea in the segmented markets model is to reflect restricted accessibility to global markets. Not all consumers can buy goods in the global markets and not all producers are able to sell into the world market. The relative prices of domestic and international commodities, as well as the national market share of the domestically produced and of the international good, enter into a Constant Elasticity of Substitution demand function. Greater accessibility to global markets implies a larger elasticity of substitution between the domestic and the international good. This, in turn, results in less potential for deviation between local and international prices. When global market access is restricted for many households the implied elasticity of substitution is small and the potential for discrepancies between international and local prices is greater. The segmented markets version is also the specification used in the validation exercise described above and discussed in more detail in Hertel and Baldos (2016b). In contrast, the integrated markets version of the model assumes that all the consumers and producers can buy or sell in the global market, implying a unique equilibrium global price for crop. The integrated markets scenario is designed to reflect a future world in which global supply chains and enhanced trade infrastructure effectively remove barriers to trade and the world price and domestic price is equated for crop commodities.

**Figure 2.8** presents key results from these six experiments (three policies x two trade regimes). Results are reported as deviations from the 2050 baseline due to the three different food waste reduction scenarios. I focus here on the implications for global cropland use, undernourishment headcount (in million, the quantity of people below the minimum caloric intake level for a healthy life), and prevalence of undernourishment (% of population whose caloric intake is below the minimum for a healthy life).

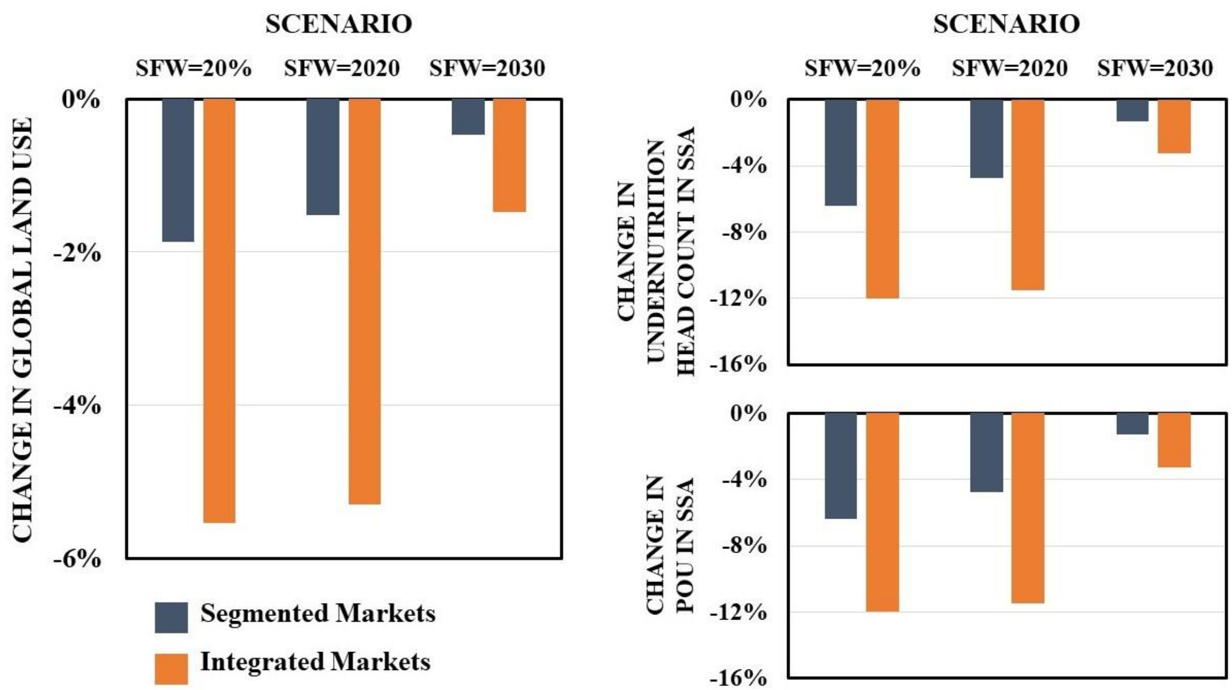


**Figure 2.8. Results on counterfactual scenarios for food security and resource use.**
The panel on the left reports the reduction on land use and the panels on the right report reductions in undernourishment headcount and in the prevalence of undernourishment (PoU) within SSA (% difference with respect to the baseline) resulting from limiting future trajectories on food waste (freezing SFW at 20%, 2020-, and 2030-year's level) under different assumptions of market integration (segmented markets vs fully integrated international agricultural markets).

As expected, under all food waste scenarios global cropland area declines, as does undernourishment. However, even under the most extreme scenario (SFW = 0.20), the declines are rather modest as long as international markets are segmented. For example, the decline in cropland area in 2050 is less than 2%. This changes rather dramatically when international agricultural markets are assumed to be fully integrated. In this case, the decline in food demand in the rich countries is more fully transmitted across the globe, with stronger declines in land use and also in SSA undernourishment. (By mid-century, the projections suggest that this is where most of the world's remaining undernourishment will reside.) Therefore, I conclude that trade policies and food policies can be highly complementary, with greater trade integration enhancing the food and environmental benefits of reducing food waste.

Freezing the share of food waste at 2020 levels is nearly as effective as the across-the-board, 0.20 target. However, the *SFW*=2030 scenario for freezing the share of food waste a decade later results in considerably lower impacts on the use of natural resources. This highlights the importance of moving quickly to limit the growth in food waste to the rate of growth of food availability. This must be done before most of the world's population begins exceeding the 0.20 threshold if this scenario is going to contribute to improved food and environmental security.

## 2.6 Discussion and Limitations

The global pattern of food waste is evolving rapidly. There is an increasing gap between the average caloric supply and the average energy requirements. Under current trends, and in the absence of policy interventions or significant behavioral changes, I can expect that the global calories wasted at consumers level will nearly double by 2050. Per capita uneaten calories at the consumers level have leveled off in rich countries; however, this category is growing rapidly in middle income countries, and it is these countries that will drive future global changes. By the estimates in this chapter, China already dominates global food waste, but in the next three decades, it will be joined by South Asia and other lower income regions where rapid growth in food waste due to rising incomes, diversifying diets, and growing population could have a dramatic impact on the global total.

Previous studies have shown that mitigation of current levels of food waste offers one potential pathway for contributing to global environmental goals. Combined with other efforts, limiting food waste is an avenue to remaining within the planet's 'safe operating space' for land, water availability and quality & GHGs (Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, and Carlson 2018). By modeling the evolution of food waste with per capita incomes, I am able to explore a richer set of (more realistic) scenarios than in previous studies which have typically abstracted from future growth in food waste (Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, and Carlson 2018). I consider two cases wherein the share of food waste in food availability is frozen. Undertaking such a policy in 2020 would have a strong impact on global resource use and food security – particularly if accompanied by greater trade integration. However, if such measures are delayed until 2030, and if trade frictions lead to greater market segmentation, then this food waste mitigation pathway will likely have far more modest food and environmental security benefits.

More generally, the interaction between food waste reduction measures and trade policies is a novel contribution of this chapter. Trade policies which increase agricultural market integration have the potential to amplify the benefits of food waste reductions for food security (by facilitating the accessibility to food in the most vulnerable regions) and for reduce pressure on natural resources.

This chapter also highlights the importance of developing new measurement methods for food waste that can be rapidly deployed across the globe. Measurement is the foundation of international action and there is a need for approaches which can be readily implemented with existing data sources and incorporated into quantitative models to explore impacts and consequences of mitigation measures. The data base which I have developed builds on previous work in this area (Hall et al. 2009a; Hiç et al. 2016; M. Verma et al. 2020) and represents another step in the direction of having a global, internationally comparable data set on food waste. However, more cross-validation of this approach with independent estimates (and ideally observations) of food waste is required.

In closing, there are some significant limitations to the analysis in the current chapter. First and foremost is the simplicity and level of aggregation of the model. SIMPLE does not attempt to capture all of the complexity present in the global food economy (see Appendix D). The model also operates at a high level of aggregation, thereby abstracting from country-specific details that may be especially relevant from a policy perspective. The regional results are indicative of possible future outcomes at the country level but are no substitute for careful national analysis to inform country-level policies. Secondly, the long run relationship which I estimate between the share of food availability that is wasted and per capita income needs a more complete theoretical underpinning. Such a theory should also help to explain the wide variation in the share of food waste at a given income level. Also, there is a need for more detailed analysis of what types of food that are being wasted. Due to data limitations, I have been silent on this matter, simply working with a caloric aggregate. Commodity-specific food waste estimates would naturally lead to the use of a more detailed commodity market model of the global food system.

Finally, while I shed light on the potential benefits of curbing future trajectories of food waste focusing on limiting the expected increase in food waste in emerging economies, I do not analyze the potential costs related to efforts required to prevent food waste. Policy initiatives to prevent food waste encompass a wide range of instruments -- from economic incentives (fees, taxes, and subsidies) to regulatory approaches (such as laws and standards, and/or mandatory management plans), to education/information campaigns, to solutions at retailors level (packaging, date-labelling, etc.). For an extensive literature review of these alternatives see (Schanes, Dobernig,

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and Gözet 2018). Some of these policy instruments have been found to be successful in reducing food waste. Some examples are the use of economic incentives as weight-based fee systems in some developed countries; the use of regulatory approaches as the National Pact against Food Waste in France; and the education campaigns such as the "Love Food Hate Waste" lead by WRAP in the UK. However, most of these policies have been implemented in the context of developed economies. It may prove more challenging to implement these policies in the low-to middle income countries that are likely to account for most of the growth in food waste over the next three decades. Addressing the effectiveness and cost-benefit analyses of such instruments in the context of emerging economies is beyond the scope of this study. However, given the prominence of these economies in the projections of food waste, this is an important area for future research.

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# CHAPTER 3. EXCESS CALORIE AVAILABILITY AND ADULT BMI: A COHORT ANALYSIS OF PATTERNS AND TRENDS FOR 156 COUNTRIES FROM 1890 TO 2015

**Motivation and rationale:** Current trends in adult obesity threaten global health. Although changes in diets, lifestyles, and food environments have been implicated in the rise in BMIs in most countries, the specific role of excess calorie availability (ECA) and the cohort mechanisms that underlie patterns and trends in BMI are poorly understood. I examine these relationships for 156 countries over the past century using an age-, sex-, and cohort-specific approach to measure the association between increases in food energy supply and changes in body mass index (BMI) across countries and time. I find positive and significant associations between ECA and adult body mass index for both males and females, and between ECA during early childhood and BMI at adulthood for males. I also find a strengthening of these correlations over successive generations. Evidence of underlying cohort mechanisms suggest a positive correlation between changes in the food environment and trends in subsequent BMI. These cohort mechanisms are boosted by age effects, leading individuals in each successive cohort to reach unhealthy BMI levels at younger ages. Individuals in more recent cohorts are overweight or obese earlier and for larger proportions of their lifespan than those in earlier cohorts. This pattern is consistent across countries and appears to be driven, in part, by availability of calories in excess of underlying requirements. Findings from this chapter provide novel insights into the role of ECA and potential unintended health consequences of agricultural and trade policies directed at increasing calorie supplies.

## 3.1 Introduction

Previous studies have underscored the importance of secular changes or “period effects” in driving these patterns. These include changes in diets (Popkin, 1994, 2001), food environments (Kennedy & Fanzo, 2018; Miljkovic et al., 2015; Popkin et al., 2020; Swinburn et al., 2011), urbanization (Popkin, 1999), and changes in work environments (Popkin, 2001; Popkin et al., 2020). Previous studies also highlight the importance of the increase in the available food supply in driving trends and patterns of global diets (Drewnowski and Popkin 2009). The association between obesity and diets has been explored across countries and time, with specific attention on the role of macronutrients (Hall, 2018), ultra-processed foods (Monteiro et al., 2018;

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Popkin & Reardon, 2018), and fats and sweeteners (Drewnowski and Popkin 2009). However, the specific role of calorie availability, which has increased markedly over the past few decades, remains unclear.

Available evidence suggests being overweight or obese at some point in early stages of life (e.g., childhood or adolescence) is significantly correlated with overweight, obesity, and related health outcomes in later life (Guo et al., 2000; Guo et al., 2002; Maner et al., 2017; Olsen et al., 2006; Simmonds et al., 2016; Singh et al., 2008; Stokes & Preston, 2016). Birth cohort effects have been found to shape Body mass index BMI patterns at the country level; noteworthy examples include the United States (Reither, Hauser, and Yang 2009; Rosenquist et al. 2015), Denmark (Olsen et al. 2006), and France (Diouf et al. 2010). The possible role of underlying cohort-related mechanisms in explaining observed trends remains unclear, and findings to date are mostly derived from cross-sectional data or based on analyses of single cohorts, with some notable exceptions (Miljkovic et al., 2015).

The nexus between overweight/obesity and non-communicable diseases suggests that the observed historical growth and patterns in adult BMI represent an important ‘canary in the coal mine’ for developing a better understanding of the drivers shaping BMI in current cohorts as potential future trends and momentum in adult obesity and related health outcomes. The objective of this chapter is to investigate factors correlated with observed patterns and trends in BMI over time and across countries. I focus on the long-term relationship between changes in different aspects of excess energy availability. A better understanding of this relationship is particularly important for countries currently at an early stage in the nutrition transition (Drewnowski and Popkin 2009; Schmidhuber and Shetty 2005). Using a repeated cross-sections of country-level data I construct a pseudo-panel (Deaton 1985) that allows us to track age- and sex-specific cohorts through time. Country-specific cohorts matched by age of birth move through different life stages together and are thereby affected by the same historical and social events at the same ages. This allows to estimate how changes in calorie availability in excess of calorie requirements—what I refer to as excess calorie availability (ECA)—correlate with adult BMI for specific cohorts at particular ages, whilst controlling for unobserved mechanisms operating at the level of individual countries.

The remainder of this chapter is organized as follows. Section 3.2 introduces the materials and methods and the econometric approach employed in the study. Section 3.3 presents the

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empirical results. Section 3.4 discusses the outcomes of the study in the context of potential limitations. Finally, section 3.5 concludes and draws potential policy implications.

## 3.2 Materials and Methods

### 3.2.1 Conceptual Framework and the Fixed Effects Regression Model

I develop a model to estimate the main drivers of observed patterns and trends in adult body mass index (BMI). I frame the investigation in terms of energy balance, which is a fundamental principle of nutrition related to energy conservation. This principle expresses that changes in body weight are associated with an imbalance between the intake of energy content of food eaten and the energy required by the body to maintain life, adjust to temperature changes in the environment, and perform physical work (Hall et al. 2012; Spiegelman and Flier 2001). The energy balance framework provides a reference point to examine changes in body weight (ΔBW). Energy balance can be expressed as the difference between Energy Intake (EI) and Energy Expenditure (EE):

$$\Delta BW_{i,j,t} = EI_{i,j,t} - EE_{i,j.t} \tag{3.1}$$

In equation (3.1) all terms are expressed as energy per unit of time (i.e., kcal/cap/day). EI represents energy from food and fluids consumed. Even for a healthy individual who has no difficulty absorbing nutrients, not all energy intake is absorbed. Net absorption is determined by the amount of metabolizable energy in the food and its digestibility. This varies among individuals and also depends on the specific food items eaten and on how those are cooked. EE includes energy expended during biological processes, any physical activity performed, heat lost due to thermoregulation (radiant, conductive, and convective), and latent heat losses due to evaporation. The rate of energy expenditure (REE) accounts for most energy expended – roughly two-thirds (Hall et al. 2012). Hence, a usual approximation for the total EE comes from adjusting the basal metabolic rate (BMR) by different ratios of physical activity level (PAL). The calculations are for adult males and females aged 20 years or older. Details on the estimates for EE used in the calculations are reported in the Appendix B, sub-section *Data on average energy requirements for adults used in Chapter 3 and Chapter 4.*

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BMI is defined as the ratio of body weight to height:

$$\mathrm{BMI} = \frac{\mathrm{W}}{\mathrm{H}^2} \tag{3.2}$$

In equation (3.2) W is the individual's weight (in kgs) and H is the individual's height (in meters). Since adult stature is fixed, changes in BMI are a direct consequence of changes in W. Given the global scope of the study, I simplify the framework by assuming that most energy intake translates into absorption and that features that influence or alter absorption, for example changes in diet composition or food preparation and processing, are captured through changes in the food environment (FENV). Accordingly, I model BMI empirically as a function of three groups of variables:

$$\mathrm{BMI}_{i,j,t} = \theta_0 + \alpha_{i,j,t}\mathrm{EI}_{i,j,t} + \beta_{i,j.t}\mathrm{EE}_{i,j.t} + \gamma_{i,j.t}\mathrm{FENV}_{i,j,t} + \mu_{i,j,t} \tag{3.3}$$

In equation (3.3) where subscript *i* represents sex, *j* represents country, and *t* represents year. The composite error term consists of unobservable country effects ($c_{I,j}$ ); unobservable time effects ($\delta_{I,t}$) and unobservable country-time effects ($\epsilon_{I,j,t}$):

$$\mu_{i,j,t} = c_{i,j} + \delta_{i,t} + \epsilon_{i,j,t} \tag{3.4}$$

Based on this setup, I use fixed effects Least Squares Dummy Variable regressions models to measure the magnitude and statistical significance of the correlation between changes in adult BMI of country-specific cohorts matched by age of birth with variables of interest. I introduce country-fixed effects to avoid omitted variable bias when measuring changes within cohorts across time. In regression models utilizing panel data sets, the error term corresponding to a particular observation is typically considered to consist of three components: one that is specific to the individual unit, one that is specific to time, and one that is both time- and individual-specific. In the fixed effects model the quantities observed in the explanatory variables are treated as non-random. This allows us to control for unobservable heterogeneity, when such heterogeneity is constant over time and correlated with the independent variables. The constant is then removed from the model through first differencing, which eliminates the components of equation (3.3) that are invariant over time. These country-specific fixed effects are those unobserved historical and institutional factors that are relevant to the country's food system and likely to be correlated with explanatory variables (such as calorie availability) included in the regressions.

### 3.2.2 Data and Empirical Estimation

We rely on publicly available data assembled from several different sources. Data on average daily supply of calories (ADSC) and for the estimations of the average dietary energy requirement (ADER) for adults and infants were obtained from the Food Balance Sheets (FBS) reported by the Food and Agriculture Organization of the United Nations (FAO) and FAO documents and reports.

***Data on Body Mass Index***

In the absence of long-run global panel data sets of adult BMI obtained at the country levels, I use NCD-RisC's data to develop a pseudo-panel from repeated cross-sectional data (Deaton, 1985). To build a pseudo-panel, I begin by grouping BMI data by birth year. I then track each cohort across time. For example, the US male cohort born in 1955 and aged 20-24 in 1975 becomes the US male cohort aged 25-29 in 1980, the male cohort aged 30-24 in 1985, etc. (**Figure 3.1**).

| country | year | BMI (f) | BMI (m) | agegroup | Year of birth |
|---|---|---|---|---|---|
| United States | 1975 | 23.4 | 23.9 | 20-24 | 1955 |
| United States | 1980 | 24.1 | 24.9 | 25-29 | 1955 |
| United States | 1985 | 25.0 | 25.9 | 30-34 | 1955 |
| United States | 1990 | 26.2 | 26.8 | 35-39 | 1955 |
| United States | 1995 | 27.5 | 27.8 | 40-44 | 1955 |
| United States | 2000 | 28.8 | 28.7 | 45-49 | 1955 |
| United States | 2005 | 29.8 | 29.4 | 50-54 | 1955 |
| United States | 2010 | 30.5 | 29.9 | 55-59 | 1955 |
| United States | 2015 | 30.9 | 30.0 | 60-64 | 1955 |
| United Kingdom | 1975 | 22.5 | 22.4 | 20-24 | 1955 |
| United Kingdom | 1980 | 23.1 | 23.6 | 25-29 | 1955 |
| United Kingdom | 1985 | 23.9 | 24.7 | 30-34 | 1955 |

**Figure 3.1. Generating a pseudo-panel data set using repeated cross-sectional data on BMI**.
Data is obtained from NCD Risk Factor Collaboration (NCD-RisC). The figure highlights changes in BMI of adult females after being matched by year of birth.

To track BMI changes for each cohort I match the datapoints by year of birth. For example, to track the 1955 US male cohort, I first calculate the average BMI for a male between 20 and 24 years of age in 1975. Subsequent datapoints for the cohort are calculated as the average BMI observed in each subsequent five-year band. This process yields a pseudo-panel dataset from repeated cross-sectional data for the period between 1975 and 2015 (Deaton 1985).The final dataset allows us to track changes in BMI corresponding to 21 sex- and country-specific cohorts spaced at five-year intervals, born over the period 1890 to 1995. Data cover 156 countries which together represented 95% of the global population in 2015. **Figure B.1** illustrates changes in adult male BMIs for four male cohorts in three countries.

***Data on Calorie Availability***

The FBS constitute the most extensive global database on countries' food systems. The average daily supply of calories (ADSC) in the FBS is an indicator of food availability at the consumer level obtained as a result of an accounting process in each country. These data are reported on an annual basis starting in 1961. For each food item, the domestic supply (quantity) consists of domestic production, net imports (imports minus exports), adjustments for intermediate usages (e.g., feed, seed, etc.), and adjustments for variations in stocks and losses through the different stages of the supply chain. The quantity of food obtained through this accounting process (in gms) is then used to calculate country-level calorie availability by converting the edible parts of each food item into kilocalories. Dividing the latter result by 365 (days in the year) and the country's total population in that year, FAO reports the ADSC for a year in terms of calories per capita per day (kcal/cap/day).

The FBS underwent some changes in methodology for data reported after 2013. I downloaded food balance data from the website of the FAO (http://faostat3.fao.org/home/E); data and methodology updated December 2017). By matching calorie availability to BMI, I am able to examine the long-term correlations between BMI and the supply of calories for the cohorts at particular points in time. For example, in 1975 I observe at age 75 the cohorts born in 1900, at age 70 those born in 1905, at age 65 those born in 1910, and so on.

The average dietary energy requirement (ADER) is defined as the calorie intake (kcal/cap/day) required to provide energy balance in a given individual of a healthy weight for their sex, age and activity levels. The ADER for adults, used in Models 3.1 and 3.2 (presented later in this section), is calculated based on the country-specific average height and weight, adjusted by physical activity levels (PAL). I compiled ADER values under different scenarios of PAL, sedentary or light activity lifestyle, active or moderately active lifestyle, and vigorous or vigorously active lifestyle with PAL adjustment factors equal to 1.55, 1.76, and 2.25 respectively (FAO/WHO/UNU 1985).

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Data for age-, sex-, and country-specific BMI, by year, come from the NCD Risk Factor Collaboration (NCD-RisC) database (http://ncdrisc.org/index.html). This database has been widely used in studies of long-run trends in human anthropometric (NCD Risk Factor Collaboration (NCD-RisC) 2016a; 2016b; NCD Risk Factor Collaboration (NCD-RisC) 2019) and related health outcomes (NCD Risk Factor Collaboration (NCD-RisC) – Africa Working Group et al. 2017; Nowbar et al. 2019). The database provides a range of variables of interest for the analysis of risk factors for non-communicable diseases. Data are compiled from more than 2,545 population-based surveys administered in 193 countries. Data collection began in 1957, and risk factor levels have been measured for nearly 130 million participants. The NCD-RisC provides data on sex-specific BMIs for adults more than 20 years old by country, by year, and by five-year age-groups for the period between 1890 and 2015 **Figure 3.1**.

I define, compute, and track over time and across countries excess calorie availability (ECA) as the difference between the ADSC and ADER, i.e., $ECA = ADSC - ADER$, where both measures evolve over time. I construct the pseudo-panel dataset from repeated cross-sections (Deaton, 1985), spaced at five-year intervals. The dataset allows us to track changes in BMIs and their correlations with the ECA for 21 country-specific age-sex cohorts born between 1890 and 1995 and observed between 1975 and 2015. The dataset covers 156 countries which together represented 95% of the global population in 2015.

***Estimations of Average Energy Requirements for Children Used in Model 3.3***

In Model 3.3 (presented later in this section), I use for children an energy requirement concept analogous to that used for adults in Model 3.2. The average dietary energy requirement (ADER) for a child is also defined as the calorie intake (kcal/cap/day) required to provide energy balance in a given individual of a healthy weight for their sex, age and activity level. However, the assessment of energy expenditure in children raises complications. Few studies with direct measures of energy requirements in this age group appear in the literature, and published work has often suffered from technical shortcomings (Ferro-Luzzi and Durnin 1981). Therefore, information for children in this age group is scarce, making it necessary to indirectly estimate child energy requirements from data on dietary intake (FAO/WHO/UNU 1985). Energy requirements depend on the age and weight (**Table 3.1**).

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**Table 3.1. Prediction of energy requirements for children aged 12-60 months.**

| Age | Median weight (kg) | Energy requirements (kcal/day) |
|---|---|---|
| 1-2 | 11.0 | 1150 |
| 2-3 | 13.5 | 1350 |
| 3-5 | 16.5 | 1550 |

*Note: Data from FAO/WHO/UNU (9) based on methodology provided by the National Center for Health Statistics (15). Note that sexes are not differentiated for children up to 5 years; median weight represents the average for boys and girls at the mid-point of the age range with adjustments for activity levels and energy expenditure.*

Similar to the Models 3.1 and 3.2, subtracts the imputed value of energy requirements for children from the ADSC reported in FAO's FBS. In this case I focus on early childhood (ages 12-60 months) of each cohort to analyze the potential correlation of the ECA with the BMI level at the age of adulthood (20 years). I do not consider the ECA during the first year of each cohort (0 to 12 months) since at this stage a child's food intake largely depends on breastfeeding. For example, if the cohort was born in 1975, I consider the years 1976, 1977, 1978, and 1979 as "early childhood" for this model. I use the imputed ECA during those years to calculate the average ECA during early childhood by sex (i), country (j), and cohort (c) $(\mathrm{ECA5}_{\mathrm{I,j,t-15}})$. I then test the correlation of the $\mathrm{ECA5}_{\mathrm{I,j,t-15}}$ with body mass index at the age of reaching adulthood $\mathrm{BMI20}_{\mathrm{I,j,t}}$ (1995 for this particular example)

In the empirical estimation, I introduce country-fixed effects to avoid omitted variable bias when measuring changes within cohorts across time (Wooldridge 2010). I estimate the regression models using Least Squares Dummy Variable (LSDV) methods. The regressions to test the correlation between ECA and adult BMI Model 3.1 and Model 3.2:

**Model 3.1.** $\mathrm{BMI}_{\mathrm{i,j,t}} = \theta_0 + \beta_{\mathrm{i,j.t}}\mathrm{Age}_{\mathrm{i,j.t}} + \gamma_{\mathrm{i,j.t}}\mathrm{Cohort}_{\mathrm{i,j,t}} + \mathrm{C}_{\mathrm{i,j}} + \epsilon_{\mathrm{i,j,t}}$ (3.5)

**Model 3.2.** $\mathrm{BMI}_{\mathrm{i,j,t}} = \theta_0 + \alpha_{\mathrm{i,j,t}}\mathrm{ECA}_{\mathrm{i,j,t}} + \beta_{\mathrm{i,j.t}}\mathrm{Age}_{\mathrm{i,j.t}} + \gamma_{\mathrm{i,j.t}}\mathrm{Cohort}_{\mathrm{i,j,t}} + \mathrm{C}_{\mathrm{i,j}} + \epsilon_{\mathrm{i,j,t}}$ (3.6)

I also test for the existence of correlation between ECA during early childhood and BMI at the time of adulthood in Model 3.3 by estimating fixed effects regressions of the form:

**Model 3.3.** $\mathrm{BMI20}_{\mathrm{i,j,t}} = \theta_0 + \alpha_{\mathrm{i,j,t}}\mathrm{ECA5}_{\mathrm{i,j,t-15}} + \gamma_{\mathrm{i,j.t}}\mathrm{Cohort}_{\mathrm{i,j,t}} + \mathrm{C}_{\mathrm{i,j}} + \mu_{\mathrm{i,j}} + \epsilon_{\mathrm{i,j,t}}$
(3.7)

In these models, subscript i corresponds to males and females, j indexes countries, and t corresponds to year; C represents country fixed effects that embody relevant but unobserved historical and institutional features of a country that are highly likely to be correlated with explanatory variables in the models; and ϵ represents an error term. In Models 3.1 and 3.2, BMI is the age- and sex-specific body mass index (BMI). Age represents a vector of variables controlling age-related unobservable effects, Cohort is the year of birth, and ECA represents excess calorie availability in year t. In Model 3.3, BMI20 is the sex-specific BMI at age 20 and ECA5 is the average excess calorie availability during early childhood (12-60 months) of each cohort. Similar to the construction of ECA, ECA5 is calculated as the difference between the ADSC and ADER for children between 12-60 months. I do not consider the effects of ECA during the first year of life since food intake at that age is heavily influenced by breastfeeding practices.

## 3.3 Results

**Table 3.2** summarizes the overall findings. I find positive correlations between adult BMI and both contemporaneous ECA and ECA during early childhood (ECA5) under all model specifications. ECA has a positive and significant correlation with BMI in adults, for both males and females. I also find positive cohort effects resulting in successively stronger correlations between ECA and adult BMI over generations. These cohort mechanisms are boosted by positive and statistically significant age effects. Additionally, I find a positive correlation between ECA5 and BMI at the age of adulthood (20 years), although this relationship is statistically significant only in the case of males.

**Table 3.2. Summary of regression results for different model specifications.**

| **Variables** | **Model 3.1** | | **Model 3.2** | | **Model 3.3** | |
|---|---|---|---|---|---|---|
| | male | female | male | female | male | female |
| **Age** | +** | +** | +** | +** | n/a | n/a |
| **Cohort** | +** | +** | +** | +** | +** | +** |
| **ECA** | n/a | n/a | +** | +** | n/a | n/a |
| **ECA5** | n/a | n/a | n/a | n/a | +** | + |

*Note: Full regression results are presented in*

***Table C.1**. All regressions include country fixed effects. ** indicates the estimated coefficient is significantly different from zero at the 5% test level; + indicates a positive correlation between the explained and the explanatory variable; n/a indicates the variable is not included in the model.*

### 3.3.1 Calorie Effects

Over previous decades, increases in total factor productivity (TFP) in agriculture combined with increases in international food trade have increased the total supply of calories in virtually every country in the world (FAO 2017a). Total calorie supply is projected to continue increasing to 2050 (Uris Lantz C. Baldos and Hertel 2014a). Over the past five decades, average *per capita* calorie availability also has risen in every country (**Figure 3.2**). While a substantial portion of calories may result in "plate waste" at the consumer level (Barrera and Hertel 2020), evidence points to a sustained energy imbalance that is correlated with long run BMI outcomes (Fallah-Fini et al. 2019).

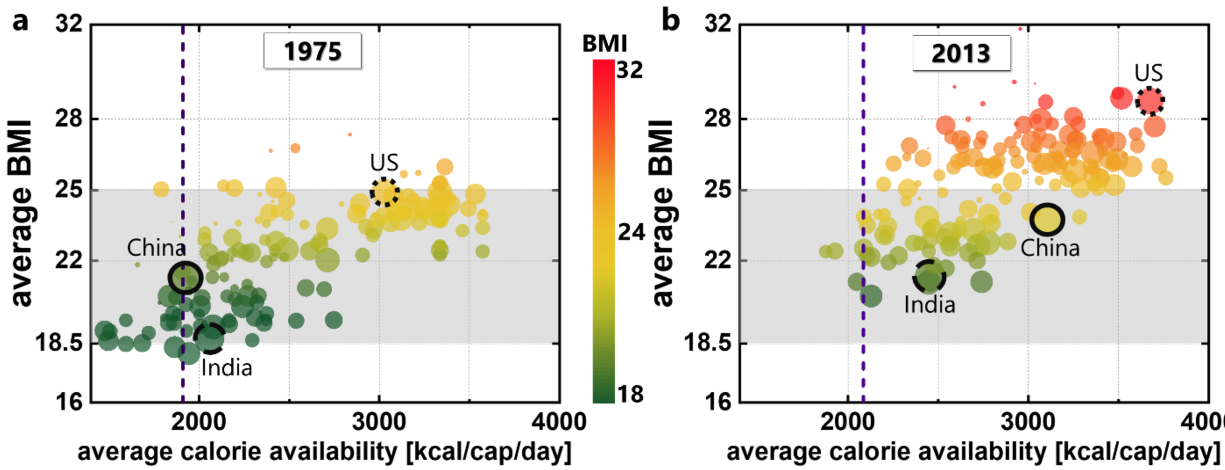


**Figure 3.2. Average daily supply of calories (kcal/cap/day) and average BMI in 1975 and 2013 across 156 countries.**

Average BMI is the population-weighted average composite of adult males and females. The gray shaded areas in the figures correspond to healthy BMI ranges. Dashed lines represent the global average daily energy requirement (kcal/cap/day) in reference years. Circle sizes are proportional to countries' populations, using log-transformation weighting.

In recent decades, average global per capita calorie availability has increased more than 32%. According to the FAO's Food Balance Sheets (FBS; http://faostat3.fao.org/home/E), in the early 1960s average per capita calorie availability (2196 kcal/cap/day) was similar to average per capita energy requirements. Since the mid-20th century, the calorie gap has risen sharply at a global level (**Figure A.1**), with calorie availability exceeding calorie requirements by more than 800 kcal/cap/day in 2015 (**Figure A.1**). Although average calorie requirements have increased in recent decades in most countries, largely due to increases in body weight and changes in the age composition of populations (Barrera and Hertel 2020; Fallah-Fini et al. 2019; Hiç et al. 2016), the

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rate of increase in calorie availability has outstripped this increase in requirements. Accordingly, in Model 3.2 I find a positive and significant correlation between ECA and BMI for both males and females (**Table B.2** and **Table B.4**). This correlation is greater in magnitude for females than males; it also becomes larger in magnitude at older ages for both males and females (**Table B.2**). The econometric model 3.2 in this chapter is developed to isolate the role of ECA as an historical driver of adult BMI. Therefore, the differences, for men and women, on the ECA parameters may reflect underlying gender gaps. Changes in number of pregnancies and breastfeeding prevalence in recent decades might play a role in the gender differences regarding the ECA role as a historical driver of adult BMI (Dewey 2004; Lutter and Morrow 2013; Vaz et al. 2021; Neves et al. 2021).What emerges as a stylized pattern across most countries is that more recent cohorts reach adulthood with a higher BMI than previous cohorts (**Figure 3.3**), a result that is consistent with spending earlier stages of life in an environment that facilitates weight gain (Swinburn et al., 2011).

Model 3.3 further tests this correlation and reveals a positive correlation between ECA5 and BMI at age 20, although this relationship is statistically significant only in the case of males (**Table B.3**). The differences in the role of excess calorie availability in early childhood and BMI at adulthood in girls vs. boys may be explained by cultural and behavioral attitudes. Previous evidence suggests that unequal resource distribution within households is affected by certain family characteristics (Chen, Huq, and D'Souza 1981; Harris-Fry et al. 2017; Brown, Calvi, and Penglase 2018). Women, children, and the elderly are more likely than men of facing poverty even in households with per-capita expenditure above the poverty threshold (Brown, Calvi, and Penglase 2018). Furthermore, girls more often receive less food than boys, previous studies in developing countries have shown that intake ratios of calories and protein were 1.16 and 1.14 times higher in boys compared to girls, respectively (Chen, Huq, and D'Souza 1981; Harris-Fry et al. 2017). Our findings here are an step forward on evidencing potential gender gaps in the energy intake at early childhood, that might cascade in undesirable nutritional and health outcomes for women at the age of reaching adulthood (De Pee, Taren, and Bloem 2017). Moreover, while here I provide evidence on the fact that energy imbalance is implicated, other mechanisms — including behavioral and environmental influences — may also correlate with observed trends in BMI (Rutter 2011).

### 3.3.2 Temporal Effects

I examine BMI as an outcome of individuals' interactions with time-varying phenomena and environmental influences that are particular to each country (**Figure 3.3**). The linear dependency of age, period, and cohort dimensions with time presents a potential identification problem (Yang and Land 2013). Resolution is typically achieved through the introduction of one or more variables that underlie at least one of the three temporal dimensions. **Figure 3.3** illustrates the need to control for country-specific eccentricities in the models used in this chapter. I find that most countries present similar age and cohort patterns for changes in adult BMI for females (**Figure 3.3**) and males (**Figure B.1**) but at different BMI levels. Countries differ in many respects with regard to food regulations, diets and food culture, relative prices of food with respect to non-food items, the cost of a healthy diet (Bai et al., 2020; Miljkovic & Nganje, 2008), and infrastructure that may affect food systems and nutritional outcomes (Badiane and Shively 1998; Shively 2017). These differences may imply time-invariant country-specific mechanisms correlated with observed trends and patterns in adults' BMIs (**Figure B.2**). To control for unobservable country-specific mechanisms affecting BMI, I use country fixed effects when estimating Models 3.1, 3.2, and 3.3. Results are presented in the Appendix B (**Figure B.2**, **Figure B.3**, and **Figure B.4**).

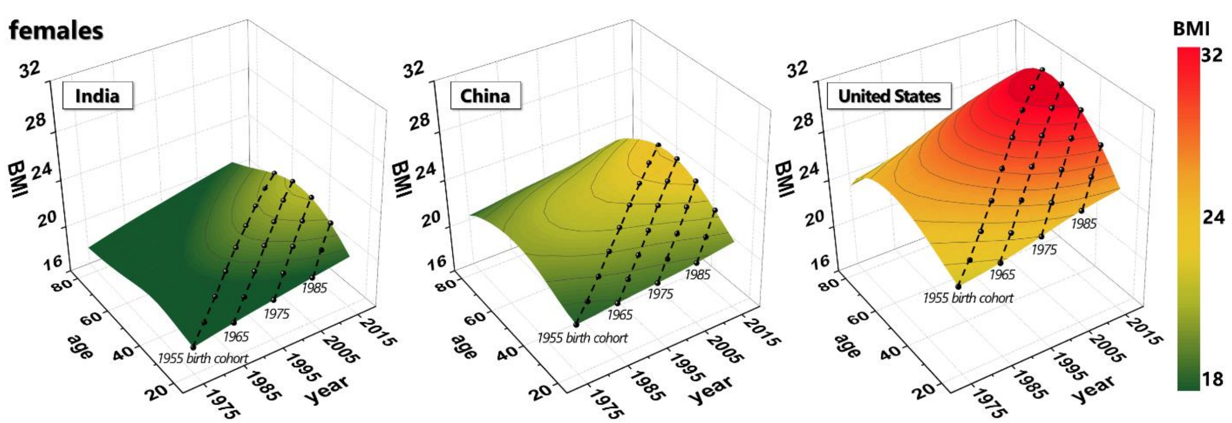


**Figure 3.3. BMI trajectories for adult females in three countries.**
Changes in BMI for cohorts matched by age of birth are illustrated by dashed lines. India (low income), China (middle income), and the US (high income) present similar age and cohort patterns but at different BMI levels.

### 3.3.3 Cohort Effects

Age, period, and cohort effects carry distinct substantive meanings for the observed changes in BMI. Period effects reflect the accumulation of historical events and environmental factors that

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can affect the phenomena under study. Changes in food environments, technologies, urbanization, and incomes help drive increases in calorie consumption (Malik, Willett, and Hu 2013; Popkin 2001; 1994). Simultaneously, changes in daily activity and work requirements during recent decades have tended to reduce energy needs (Popkin 2001; Popkin, Corvalan, and Grummer-Strawn 2020a) contributing to the increase in energy imbalances (Hall et al. 2011; Thomas et al. 2011). I find that this energy imbalance is correlated with the rapid increase in BMI across countries (Model 3.2). While ECA and BMI have both increased in virtually every country and region in the world in recent decades (**Figure 3.2**), they have not increased at the same or uniform rates. This raises the possibility that largely ignored cohort-related mechanisms also might contribute to observed trends in BMI (**Figure 3.2**).

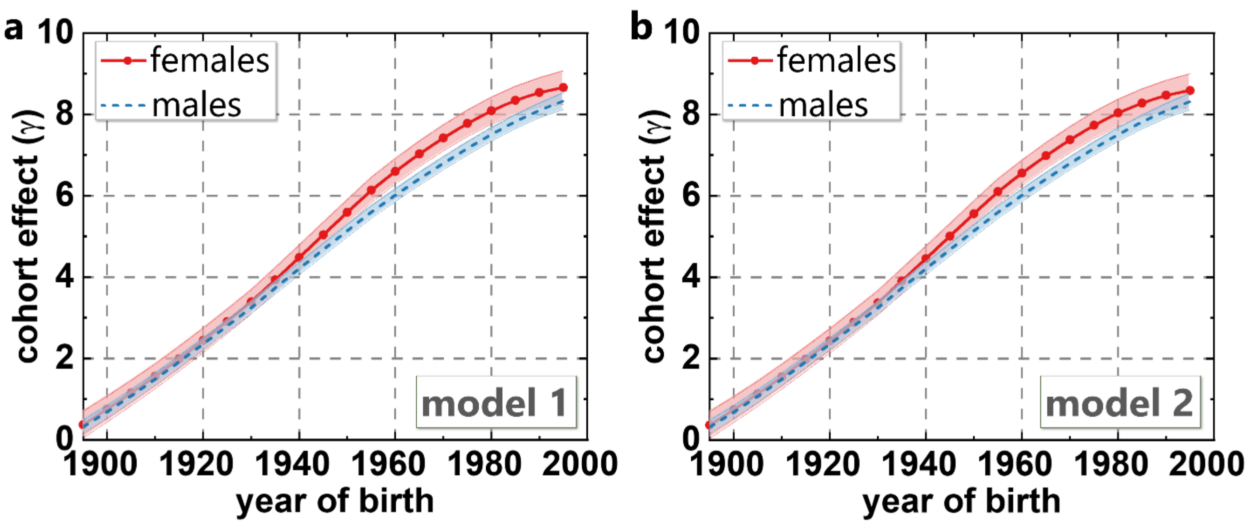


**Figure 3.4 Observed global average cohort effects on BMI under two model specifications.**
The vertical axis measures the total increase in global average BMI for each of the 21 successive birth-year cohorts, with the BMI for those born in 1890 serving as the base (e.g. in Panel a, corresponding to Model 3.1, a female belonging to the cohort born in 1980 presents an average BMI that is 8.0 points higher than a female born in 1890, while a male presents a BMI that is 7.5 points higher than his 1890 cohort). Shaded areas in Panel a (Model 3.1) and Panel b (Model 3.2) represent 99% confidence intervals for the estimated cohort-specific parameters.

Cohort effects are defined as changes across groups of people who experience an initial event (such as birth or marriage) in the same year or years (Yang and Land 2013). Here I develop a cohort analysis where BMI is a function of cohort membership, age, and ECA. Members of a birth cohort move through different life stages together and are affected by the same historical and social events at the same stages of their life. There is evidence to suggest observed increases in BMI might be a consequence of recent birth cohorts spending larger shares of their life in environments more favorable to weight gain (Allman-Farinelli et al., 2008; Reither et al., 2009;

Swinburn et al., 2011). Here I provide evidence for cohort mechanisms driving BMI over time and across countries. Models 3.1 and 3.2 (**Figure 3.4**) control for country- (**Figure B.2** and **Figure B.3**) and age-specific mechanisms (**Figure 3.5**) and therefore provide evidence on the independent presence of cohort mechanisms as a factor underlying current trends in adult BMIs. More recent male and female cohorts present higher BMIs compared with earlier cohorts. ECA appears to play a significant role in driving increases in BMI. Furthermore, this effect intensifies when energy imbalances occur at earlier stages in life (Model 3.3). I find that male cohorts with larger ECA during early childhood reached adulthood with greater BMIs (**Table B.3**). For both males and females, I also find a positive fixed effect on BMI from one cohort to the next during most of the 20th century (**Table B.2**). I find a marked increase in the cohort effects for individuals born between 1940 and 1990, a period that coincided with rapid increases in energy imbalances in most countries. This pattern is consistent with previous evidence (Swinburn et al. 2011).

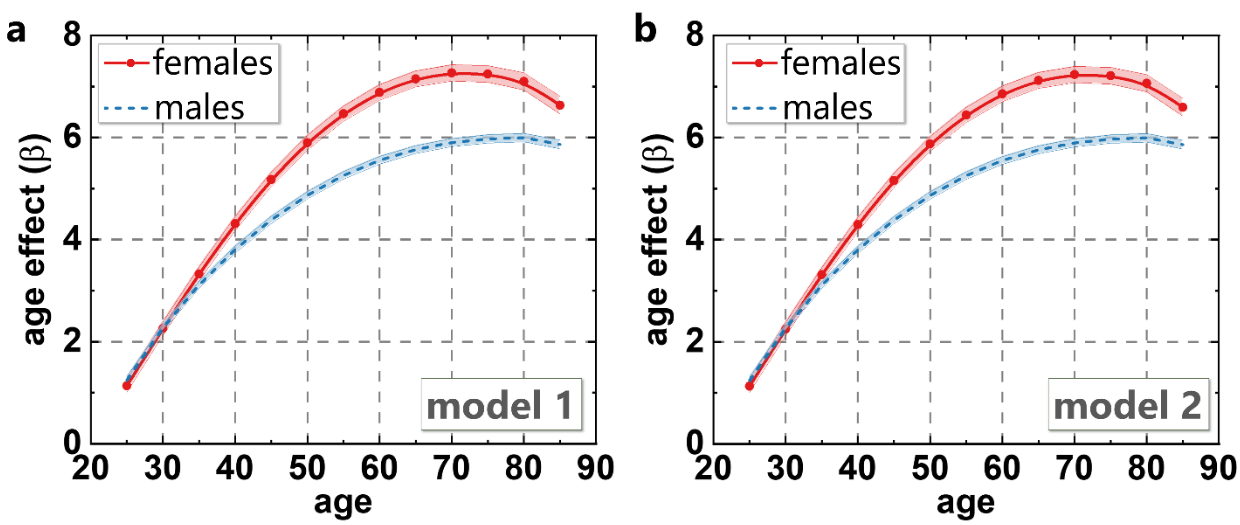


**Figure 3.5. Observed age effects on BMI under two model specifications.**
The vertical axis measures the increment in global average BMI associated with each adult age group, with BMI at age 20 serving as the base (e.g., in Panel a, corresponding to Model 3.1, a female that is 60 years old presents an average BMI 6.8 points higher than a female that is 20 years old, while a male that is 60 years old presents a BMI that is 5.5 points higher than his 20-year-old cohort). The shaded areas in Panel a (Model 3.1) and Panel b (Model 3.2) represent 99% confidence intervals for the estimated age specific parameters.

### 3.3.4 Age Effects

Age effects reveal changes in energy requirements and intake due to variations associated with different chronological age groups. They thereby provide evidence for biological or physiological changes and changes in lifestyle due to shifts in in social roles or status (Hadgraft et al., 2015). As people age, they tend to gain BMI as a result of changes in lifestyle and metabolism. A lower energy requirement due to a decrease in physical activity, combined with an increase in energy intake due to changes in social status (Feng, Li, and Smith 2020; Hayes et al. 2015; Lean et al. 2013; Tanamas et al. 2014) and changes in basal metabolic rates (National Research Council (US) 1989; Piers et al., 1998) may explain a portion of observed age effects. While the general trends are similar for both males and females, the age effect appears to play a stronger role in females, especially after age 30, likely due to childbirth and changes in lifestyle (Weng et al. 2004). Positive and increasing age effects as individuals grow older reinforce the importance of the cohort mechanisms. With each cohort reaching adulthood at a higher BMI than the previous cohort, the age effect works synergistically with the cohort effect. This process leads individuals to reach unhealthy BMI levels at younger ages and to remain overweight and/or obese for larger proportions of their adult life. I also observe a downturn in BMI at advanced ages, which likely reflects attrition bias arising from the deaths at younger ages of individuals with higher BMIs (Preston, Vierboom, and Stokes 2018; Stenholm et al. 2017; Narayan et al. 2007).

## 3.4 Discussion and Limitations

The global prevalence of obesity among adults is rising in virtually every country across the globe. I find a significant positive correlation between observed trends in adult BMI and ECA across countries, even after controlling for country-specific effects. Cohort mechanisms underlie BMI for both males and females. Each cohort reaches adulthood with a higher BMI than the previous cohort, and this cohort effect is particularly large for those born between 1940 and 1990, a period that coincided with the emergence of per capita energy imbalances in many countries. Results also provide evidence of a positive correlation between ECA during early childhood and BMI at the age of adulthood for males. This highlights the importance of food environments characterized by an abundance in calories during early stages of life on subsequent overweight and obesity outcomes in adulthood. I also find that the cohort mechanisms are boosted by age effects. I observe significant and positive age effects for both males and females, with each cohort reaching adulthood at higher baseline BMI than the previous cohort. As a result, across generations, the age effect leads individuals to become overweight and/or obese at younger ages. The combination of age and cohort effects presents a serious social challenge given the health and economic implications associated with overweight and obesity. Each cohort's time of exposure to risk has grown larger over time, which could be expected to have implications for increases in related mortality, morbidity, disability-adjusted life years (DALYs), and health care costs.

Findings should be interpreted in the context of several limitations in the data and analysis. First, the ECA imputations are based on data for calorie availability, not calorie intake. Country-level estimates for calorie *intake* are not available, and FAO Food Balance Sheet data are not without criticism (Hall et al. 2009b; Svedberg 1999a). FAO's methodology tends to underestimate calorie availability in emerging economies, particularly in rural areas where unreported subsistence production represents an important share of the food intake (Hawkesworth et al. 2010). Second, although recent revisions to FAO's methodology mitigates some of those acknowledged inaccuracies (FAO 2019a), for the purposes of the analyses in this chapter the database still carries the limitation that an important but unknown proportion of calories available ends up uneaten (Barrera and Hertel 2020). Third, while the results from this chapter highlight the underlying long-run correlation between ECA and adult BMI, the approach taken in this chapter cannot uncover the importance of other diet-related factors, such as the role of macronutrient composition (e.g. fat, carbohydrates, etc.), that likely play a role in weight maintenance (Paeratakul et al. 1998; Prewitt et al. 1991). Finally, although it is true that the NCD-RisC's data sets are widely used, they contain potent measurement errors, especially for early cohorts. For some of the variables in the dataset (e.g., height) measurements began in the 1980s. Hence, the earlier birth cohorts are based on either measurements of very old persons or on interpolation from countries for which some early data are available.

The results from this chapter have implications for future projections of BMI and related outcomes. I find evidence that ECA during early childhood is correlated with BMI at the age of reaching adulthood. Long-run per capita calorie availability is projected to continue increasing in coming decades in most countries, particularly in emerging economies. As a result, cohorts born now and in the near future are likely to reach adulthood in an environment characterized by a super-abundance of calories. In addition, our findings here offer further evidencing of potential gender gaps in the energy intake at early childhood, that might cascade into undesirable nutritional and health outcomes at the age of reaching adulthood (De Pee, Taren, and Bloem 2017). The differences in the role of excess calorie availability in early childhood and BMI at reaching adulthood in girls vs. boys are consistent with previous evidence in these matters (Chen, Huq, and D'Souza 1981; Harris-Fry et al. 2017; Brown, Calvi, and Penglase 2018).

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One caveat is that the current global spread of SARS-CoV-2 introduces considerable uncertainty into projections of future trends in food availability, as the pandemic is creating a number of social and economic disruptions that may measurably affect nutritional outcomes; these include trade restrictions, food supply disruptions, lower incomes, and potentially higher food prices. A slowdown in economic growth and rising unemployment are aggravating food insecurity, particularly in vulnerable groups, in virtually all of the world's economies. Early estimations project that rates of wasting and stunting may rise if food supply disruptions intensify and food prices remain high (Roberton et al. 2020; Headey et al. 2020). On the other hand, extended and repeated lockdown cycles with lengthy periods of confinement might shift diets toward unhealthy foods and reduce physical work and exercise in already-overweight populations. Addressing the complexities introduced by the global pandemic on BMI trajectories is beyond the scope of this study. However, given the magnitude of current disruptions within food supply chains, modification to lifestyles, and potential changes in mortality and morbidity rates, this is an important area for future investigation. Moreover, the models 3.1, 3.2, and 3.3, present the country fixed effects that aim to embody relevant but unobserved historical and institutional features of a region that are likely to be correlated with explanatory variables. That means a variety of phenomena might be captured within those fixed effects (from cultural, to policy, to behavioral differences, etc.). This is the reason I refrain from further commenting on those results. However, a deeper examination of regional differences (e.g., different gender effects across regions) might be an important area for future research.

## 3.5 Conclusions

This analysis has focused on measuring the role of excess calories availability (ECA) as a historical driver of overweight and obesity globally. I detect a pronounced ECA effect that is boosted by age effects, increasing the number of years that individuals are exposed to risks related to overweight and obesity. Incorporating a multidimensional consideration of time into the analysis of long-run BMI trajectories illustrates underlying mechanisms driving current trends. These results provide a number of policy-relevant insights. First, the findings highlight how some standard agricultural and trade policies oriented toward reducing hunger by increasing calorie supplies might have unintended consequences for undesirable overweight, obesity, and health-related outcomes (Law 2019). In light of current trends in food supply, these findings are of particular importance for developing countries already dealing with the complexities of a rising malnutrition double burden. Second, as the world continues to push toward increasing the supply of food to alleviate hunger among those still facing food insecurity, there is a simultaneous need to underscore and address, through policy and education, the importance of nutrition and diet quality, including the production, promotion and availability of affordable healthy diets, to avoid intensification of the already worrisome trends in adult BMI. Third, these findings highlight potential gender gaps in the within-household distribution of food that might cascade into undesirable nutritional and health outcomes in women during their adulthood. From a political perspective, these results imply a new argument in line with the fact that reducing the gender gap would boost global food and nutrition security.

# CHAPTER 4. CONFRONTING THE DOUBLE BURDEN OF MALNUTRITION YIELDS HEALTH AND ENVIRONMENTAL BENEFITS.

**Motivation and rationale:** Prevalence rates of overweight and obesity are increasing across the globe. In this chapter, I present a novel framework that extends the UN-FAO's methodology for assessing undernutrition to also encompass excessive calorie consumption and its association with the evolution of adult Body Mass Indexes (BMI). By incorporating these relationships into a global partial equilibrium model of the food sector (SIMPLE), I develop future trajectories of age-, sex-, and cohort-specific adult BMI across major world regions over the next three decades. This allows for an examination of the dynamics of the double burden of malnutrition between 2015 and 2050. I find that the excessive consumption of calories will play a key role in driving rising BMI levels, particularly in emerging economies. As a consequence of reaching higher levels of BMI at younger ages, future cohorts will increase their exposure to the health risks attributable to overweight and obesity, including coronary heart disease (CHD), stroke, site-specific cancers, and type 2 diabetes (T2DM) I use this framework to shed light on the health, food, and environmental security impacts of changing food consumption behavior. A key finding is that environmental benefits of shifting consumption patterns are dominated by food waste reductions as opposed to changes in dietary composition.

## 4.1 Introduction

In this chapter analyze the trade-offs and synergies posed by the dynamics of the malnutrition double burden towards the mid-21st century. While the global prevalence of undernutrition is expected to decline in coming decades (Uris Lantz C. Baldos and Hertel 2014b), the prevalence of overweight and obesity are expected to rise (FAO 2017b; Popkin, Corvalan, and Grummer-Strawn 2020b). Trends and patterns in BMI can be examined from different temporal perspectives (Reither, Hauser, and Yang 2009; Yang and Land 2013). Previous authors have examined: (i) age effects (Feng, Li, and Smith 2020; Hadgraft et al. 2015; Hayes et al. 2015; Lean et al. 2013; Tanamas et al. 2014), (ii) period effects, that refer to events which occur at a particular point in time uniformly influencing all age groups and cohorts (Kennedy and Fanzo 2018b; Miljkovic et al. 2015; Popkin 1994; 2001; Popkin, Corvalan, and Grummer-Strawn 2020b), and

(iii) cohort effects of BMI (Diouf et al. 2010; Olsen et al. 2006; Reither, Hauser, and Yang 2009; Rosenquist et al. 2015).

I advance the current state of knowledge by presenting a novel framework for analysis of age-cohort and gender-specific changes in BMI in a way that extends the Food and Agriculture Organization's Prevalence of Undernourishment (PoU) methodology to consider excessive calorie consumption (Wanner et al. 2014a). Previous studies have also explored the human health and environmental co-benefits of moving from current levels of food purchasing to healthier dietary intake (Springmann et al. 2016b; Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, and Carlson 2018) However, they have failed to disentangle key differences between current food purchases and food consumption under a healthy diet. Much of the literature has just looked at total calories from the Food and Agriculture Organization's (FAO) Food Balance Sheets (FBS) and concluded that reducing them to a healthy level would greatly benefit the environment. However, the FBS calories have included food waste at consumers' level. Although recently some adjustments have been made the inaccuracy persists (FAO 2019a). Therefore, the excessive consumption of food in current diets, understood as the gap between current food consumption levels (equated to food availability from FAO's FBS) and healthy dietary intake levels, includes both food waste and excessive intake.

Additionally, since shifting towards healthier diets usually implies not only the reduction in food consumption, but also shifting towards more plant-based diets, there is also a third contributor--the composition of these calories—that must also be considered. I extend the existing literature on this topic by disaggregating, for the first time, these three elements of the linkage from food purchasing behavior and the environment: changes in the composition of food consumption to achieve a more balanced diet, reductions in overall food intake, and reductions in food waste (Section 4.5). I examine the relative contribution of each subcomponent to environmental sustainability, revealing that the food waste component of what has been dubbed in the literature 'dietary changes' represents the largest contributor to the environmental benefits of shifting food purchases to a more sustainable level.

I explore how the incidence of overweight and obesity would be affected by current trends in agricultural productivity, population, and income, as well as the complexities introduced by the changing diets. I then incorporate this novel framework into a global, partial equilibrium model of the agriculture sector, the Simplified International Model of Crop Prices, Land Use and the

Environment (SIMPLE) ( Hertel and Baldos 2016c). This approach offers several analytical advantages over prior work. Firstly, it allows for an historical validation of the novel methodology to see how well it reproduces observed historical patterns on overweight and obesity. By looking back, before looking forward with the SIMPLE model (Baldos & Hertel, 2013), the novel methodology allows the construction of more credible baseline projections of adult BMI towards 2050. Secondly, it allows us to assess the main factors driving projected increases in adult BMI, including income growth and changes in diets and food waste and the demand side, and technological change through increasing food availability on the supply side. Thirdly, it allows us to simulate several alternative future scenarios to examine the implications of changing diets for health and environmental outcomes as well as prices and food security. The findings from this chapter shed light on some of the critical challenges of the agriculture-environment-health trilemma posed by the rising malnutrition double burden.

## 4.2 The Impact of Excessive Consumption of Calories on Adult BMI

Since the mid-20th century, the calorie gap between average availability and daily requirements has risen sharply across the world (**Figure 4.1**). Indeed, these nutrition transitions, have tipped the balance between energy intake and energy expenditure, leading to widespread increases in rates of overweight and obesity. The double burden of malnutrition, characterized by high national rates of undernutrition with the simultaneous rise in obesity, continues to increase in low- and middle-income countries. These trends present a serious threat to global health. In this context, there is a need to better understand the potential trade-offs of policies aiming to reduce hunger and their unintended consequences for overweight and obesity prevalence.

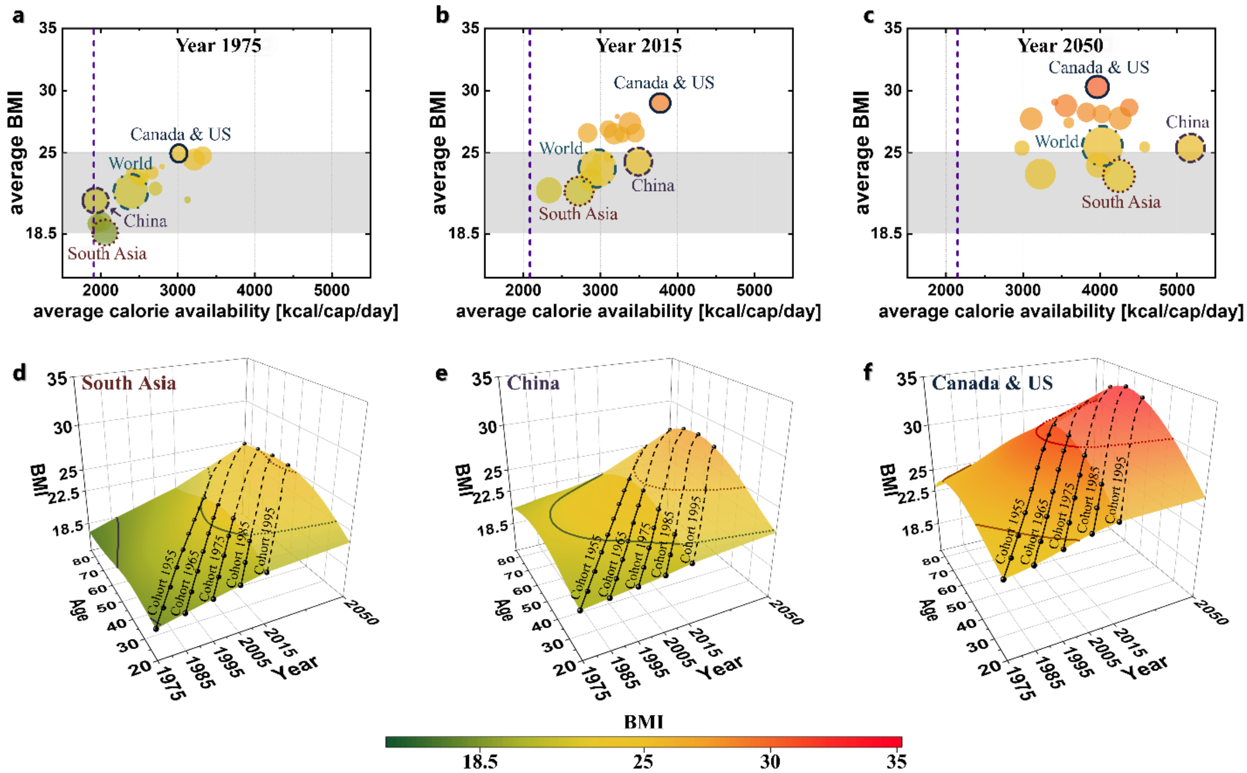


**Figure 4.1. The excessive calorie availability and adult BMI.**

The top three panels present the average daily supply of calories (kcal/cap/day) and average BMI in 1975 (**a**), 2015 (**b**), and projected towards 2050 (**c**) across regions. Average BMI is the population-weighted average composite of adult women and men. The gray shaded areas in the figures correspond to healthy BMI ranges. Dashed vertical lines represent the global average daily energy requirement (kcal/cap/day) in reference years. Circle sizes in **a-c** are proportional to countries' populations. Panels **d-f** illustrate how BMI evolves across cohorts and over time at different income levels, for adult women in three regions (See Appendix C for the remaining regions, **Figure C. 6** for BMI in adult women and **Figure C. 7** for men). Observed changes in BMI for cohorts matched by age of birth are illustrated in the solid lines, while projections towards 2050 are given by the dashed lines. The isoquants in these panels represent different BMI levels: 18.5 (purple), 22.5 (green), 25 (brown), 30 (red). South Asia (**d**) (a low-income region), China (**e**) (middle-income), and Canada & US (**f**) (high-income), present similar age and cohort patterns but at different BMI levels. These lower panels were constructed by aggregating results from a fixed-effect, country/panel statistical model into 15 regions (Appendix C) and making projections to 2050 (Appendix D).

While it is projected that this gap will almost double by 2050 (**Figure 4.1c**) there is also a positive correlation between excessive calorie consumption and adult BMI that has been strengthening with each successive generation over the past century (Appendix C, Section Empirical estimation of BMI and ADEC relationship in the long run). Consequently, more recent cohorts reach higher BMI levels at younger ages and therefore experience longer durations of obesity over their lifetimes. This pattern emerges consistently across regions (**Figure 4.1 d-f**) and appears to be correlated with changes in the food environment faced by each new cohort. This is a serious concern, since higher BMI levels re associated with a series of non-communicable diseases (Afshin et al. 2019; Scherer and Hill 2016) and loss of years disease-free years (Nyberg et al. 2018).

The SIMPLE model's nutritional module mirrors the FAO's methodology for the Prevalence of Undernourishment (Uris Lantz C. Baldos and Hertel 2014b). The FAO's PoU is used as the official indicator to monitor progress towards the United Nations Sustainable Development Goal 2.1 target[4]. This indicator estimates caloric content of food commodities, shifts the FAO distribution of those calories among the population across time based on incomes and prices, and utilizes an average minimum caloric requirement to produce an estimate of the share of the population that does not meet the minimum threshold of calories required for a healthy life (Cafiero et al. 2014). For this work, I extend the FAO methodology by incorporating into the analysis the concept of excessive calorie consumption (**Figure 4.2**), which includes both, the excessive calorie intake and the imputed food waste (Barrera and Hertel 2020).

### 4.2.1 FAO PoU's Extension: Excessive Acquisition of Calories and the Malnutrition Double Burden

The Food and Agriculture Organization's (FAO) prevalence of undernourishment indicator (PoU) monitors the proportion of people suffering from hunger. Estimates of the number of undernourished (NoU) are calculated by multiplying the PoU by the size of the reference population. The PoU is defined as the probability that a randomly selected individual from the reference population is found to consume less than his/her calorie requirement for an active and healthy life. It is calculated as follows (green area in **Figure 4.2a**):

$$PoU = \int_0^{MDER} f(x)\, dx \qquad (4.1)$$

In equation (4.1) f(x) is the probability density function of per capita calorie consumption. The country-specific parameters involved in the estimation are: The mean level of dietary energy consumption (DEC) annually updated based on FAO food balance sheets; a threshold Minimum Dietary Energy Requirement (MDER) also annually update based on demographics (age, sex, PAL) using UN population data; the coefficient of variation (CV) as a parameter accounting for inequality in food consumption updated when information from National Household Surveys

[4] *Sustainable Development Goal 2.1: "By the year 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round".*

(NHS) is available ; and a skewness (SK) parameter accounting for asymmetry in the distribution, also updated when NHS data is available. In its standard version and in recent refinements, the methodology assumes a lognormal density function for the caloric distribution among the population of reference (Wanner et al. 2014b).

Before proceeding to the next step, it is important to acknowledge that the FAO's PoU methodology for estimating undernourishment suffers from several limitations, which need to be considered when analyzing the results presented in this chapter (See Appendix C for details on these limitations). A key set of limitations are related to the fact that the indictor provides information on a very specific aspect of food insecurity overlooking relevant aspects about the affordability and accessibility of food (Cafiero et al. 2014; Headey et al. 2020; Roberton et al. 2020) as well as regarding the distribution and severity of undernourishment (Cafiero et al. 2014). Another group of limitations, that are more directly related and are more relevant to the results and extension presented in this chapter, are the ones regarding the choice of the probabilistic model and minimum requirements to represent the representative individual's dietary intake. Some of these criticism arise from the misinterpretation of the indicator and its methodology (Wanner et al. 2014b; Naiken 2021; Cafiero 2014). However, FAO's recent refinements have acknowledged and mitigated some of these limitations by improving the estimates of the relevant parameters and exploring more flexible functional forms (Cafiero 2014; Naiken 2021) to represent the probabilistic distribution of calories. Consistently with most recent advances in FAO's methodology it is possible to simultaneously estimate the prevalence of undernourishment and over-consumption based on information of the average and the distribution of daily average energy requirements as presented in this chapter.

Here I extend this approach to look at the high levels of caloric availability – excess acquisition– to focus on prevalence of overweight and obesity and food waste (**Figure 4.2a**):

$$PoO = \int_{ADER}^{\infty} f(x)\, dx \qquad (4.2)$$

In equation (4.2) f(x) is the probability density function of per capita calorie consumption. Similarly, to the PoU's the proposed estimation for the population overconsumption (PoO) is defined as the probability that a randomly selected individual from the reference population is found to consume (purchase) more calories than his/her Average Dietary Energy Requirement (ADER) which is defined as the calorie intake (kcal/cap/day) required to provide energy balance in a given individual of a healthy weight for their sex, age, and activity levels. The PoO is calculated as follows, I start by defining a maximum threshold, in this case the ADER which is calculated based on country specific energy requirements, constructed from country-specific basal metabolic rate (BMR) and physical activity level (PAL) using country-specific demographics (age and sex). Also, similarly to the PoU methodology, the number of people over consuming calories (NoO) is calculated by multiplying the PoO by the size of the reference population.

I use then split the over-consumption of calories into excessive intake of calories and food waste based on previous estimations of the share of calories purchased in excess that end up uneaten (**Figure 4.2b**) (Barrera and Hertel 2020). This second step enables to differentiate whether the excessive acquisition of calories is indeed intake or end up uneaten by the average consumer. This is a very important distinction since consumer behavior with respect to those are responsive to complete different sets of policies. Moreover, previous studies have emphasized that the potential environmental benefits of reducing from current food consumption levels towards healthier and more sustainable diets. However, while the excessive intake of calories influences health through affecting body weight, the excessive purchasing of food that ends up uneaten does not affect body weight.

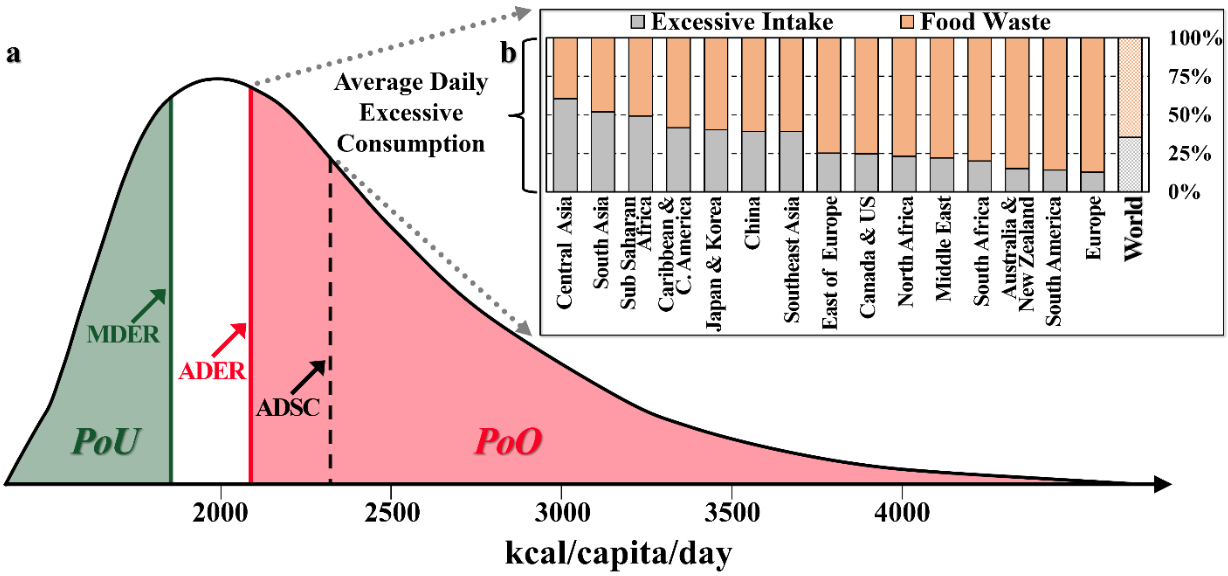


**Figure 4.2. Extension of the FAO's Prevalence of Undernourishment methodology.**
The solid black curve in panel **a** represents the probability distribution of habitual (i.e., annual average) daily energy consumption (purchases) and is based on country-specific parameters and therefore vary by region (Section 4.2.1). The dashed vertical line represent the Average Daily Supply of Calories (ADSC) obtained from the FAO's Food Balance Sheets (**a**). (acquisition) of an individual in the population (**a**). At the lower end of the calorie distribution, the solid green vertical line represents the Minimum Dietary Energy Requirements (MDER), which is the calorie intake (kcal/cap/day) compatible with good health and normal physical activity for an average individual; the green shaded area represents the Prevalence of Undernourishment (PoU) --the share of population that does not meet the MDER (**a**). The solid vertical red line represents the Average Dietary Energy Requirement (ADER) which is defined as the calorie intake (kcal/cap/day) required to provide energy balance in a given individual of a healthy weight for their sex, age, and activity levels; the solid red area represents the Prevalence of Overconsumption (PoU) --the share of the population with excessive consumption of calories (**a**). Panel **b** represents the split of average daily excessive consumption (ADEC) of calories (ADEC=ADSC-ADER) into the imputed calorie intake (gray share of the bars) and imputed share of food waste (orange share of the bars) using estimates from previous studies (Barrera and Hertel 2020).

This novel extension of the PoU methodology allows us to simultaneously analyze both ends of the caloric distribution, thereby producing estimates of the double burden of malnutrition which is now a dominant concern in countries at earlier stages of the nutrition transition (Popkin, Corvalan, and Grummer-Strawn 2020b). Indeed, the coexistence of undernutrition and overweight/obesity constitutes an unprecedented challenge to global health. Effectively responding to this requires a better understanding of the dynamics of the underlying phenomena (Popkin et al., 2020; Webb & Block, 2012). Moreover, reducing excess acquisition of calories is critical for improving resource efficiency towards sustainable food systems (FAO 2018a). Here I split the excessive acquisition of calories (**Figure 4.2**) into excessive intake and food waste. Food waste is assumed to increase with income after the average dietary energy requirements are satiated (Barrera and Hertel 2020).

Incorporating this extended nutritional module into a partial equilibrium framework (Thomas W. Hertel and Baldos 2016c), is possible to analyze likely future scenarios based on shared socio-economic pathway (SSP) projections for the global economy. After building a baseline scenario, I examine several counterfactual scenarios involving changes in consumer behavior to shed light on the associated linkages, trade-offs, and synergies, focusing specifically on overweight and obesity, as well as undernutrition. Further, it is possible to analyze the potential for multiple dividends (environmental and health co-benefits) of curbing future trajectories of over consumption of food products.

### 4.2.2 Empirical estimation of BMI and ADEC relationship in the long run

***A regions FE model for men and women BMI***

In Chapter 2 I define, compute, and track over time and across countries excess calorie availability (ECA) as the difference between the average daily supply of calories (ADSC) and average dietary energy requirements (ADER), i.e., ECA=ADSC-ADER, where both measures evolve over time. Here we follow a similar strategy but adapting and framing the analysis into a global partial equilibrium framework, therefore we equate the supply of calories (from FAO's FBS) to the demand (average daily demand of calories). As a result, we define the average daily excessive consumption of calories (ADEC) such as ADEC=ECA=ADSC-ADER. Similarly, to what is done in Chapter 2, in this chapter I construct a pseudo-panel dataset from repeated cross-sections (Deaton 1985), spaced at five-year intervals (See Appendix C for details on regional aggregation of data used in Chapter 2).

In the empirical estimation, we introduce regional, age, and cohort fixed effects to avoid omitted variable bias when measuring changes within cohorts across time (Wooldridge 2010). We estimate the regression models using Least Squares Dummy Variable (LSDV) methods. The regression to test the correlation between ADEC and adult BMI are described in Model 4.1:

**Model 4.1.** $\mathrm{BMI}_{i,j,t} = \theta_0 + \alpha_{i,j,t}\mathrm{ADEC}_{i,j,t} + \beta_{i,j.t}\mathrm{Age}_{i,j.t} + \gamma_{i,j.t}\mathrm{Cohort}_{i,j,t} + \mathrm{R}_{i,j} + \epsilon_{i,j,t}$

In this model, subscript i corresponds to males and females, j indexes countries, and t corresponds to year; *R* represents region-specific fixed effects that embody relevant but unobserved historical and institutional features of a region that are highly likely to be correlated with explanatory variables in the models; and $\epsilon$ represents an error term. In this model, BMI is the age- and sex-specific body mass index (BMI). Age represents a vector of variables controlling age-related unobservable effects, Cohort is the year of birth, and ADEC represents the average daily excess of consumption of calories. Results from these regressions are presented in

**Table C.1** and **Figure C.1**.

## 4.3 Model Validation, Uncertainties, and Baseline Projections Towards 2050

Following Baldos and Hertel (2014) and Lopez Barrera and Hertel (2020) who used the SIMPLE framework to examine the evolution of undernourishment and food waste respectively, I start our analysis by evaluating how well the model projects changes in adult BMI over an historical period: 2005–2015.

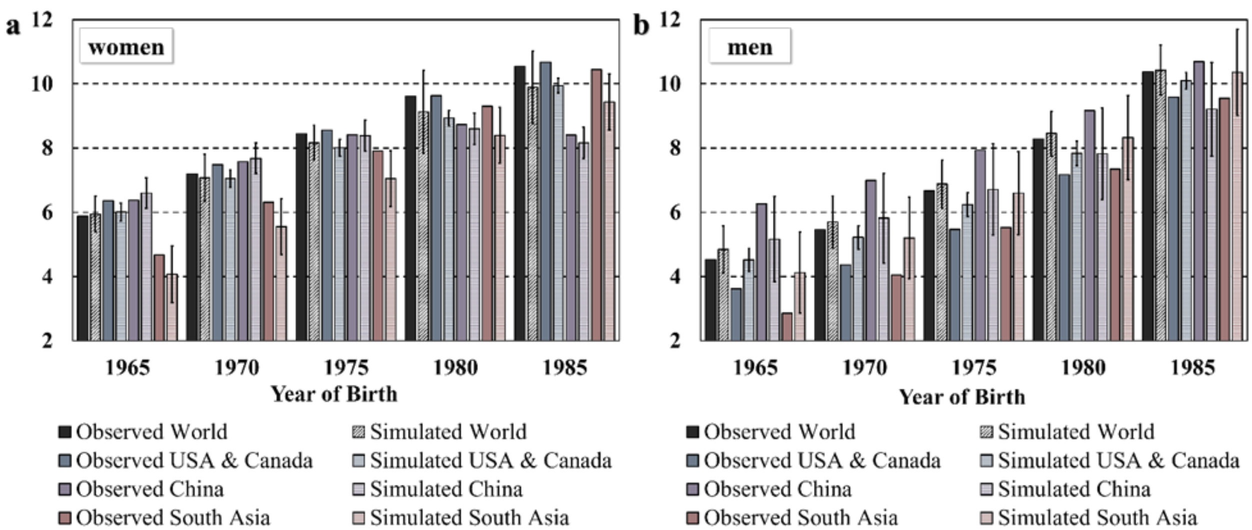


**Figure 4.3. Historical validation of the BMI module in SIMPLE for the period 2005 to 2015.**
Solid (pattern) colored bars represent observed (projected) percentage changes in adult BMI for cohorts matched by the birth year (x-axis) for women (**a**) and men (**b**). The error bars represent 95% confidence intervals in the projected values. Consistently with previous studies (Barrera and Hertel 2020; Uris Lantz C. Baldos and Hertel 2014c; Uris Lantz C Baldos and Hertel 2013; McCalla and Revoredo 2001b), the model does a fair job globally and the projections lose precision with higher levels of resolution. The uncertainties are heterogeneous across regions, those already in the later stages of the nutritional transition (higher ADEC levels and BMI levels) (as in the US and Canada) present lower uncertainties as BMI is expected to have relatively smaller changes in adult BMI. On the other hand, regions that are in earlier stages of the nutritional transition - a lower ADEC and BMI level - (such as South Asia), present greater uncertainties.

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Often studies that use economic models to project future outcomes are not validated against history, yet this is a critical step. Additionally, this historical assessment provides valuable inputs for examining future changes. The model's historical projections in (**Figure 4.3**) perform best at the global level; projections are less accurate at the regional level, but still capture the broad trends. This is consistent with previous studies attempting to validate global agricultural models (Uris Lantz C. Baldos and Hertel 2014b; Barrera and Hertel 2020; McCalla and Revoredo 2001c). Also consistent with previous literature, there is considerable regional variation in the model uncertainties. The framework used in this study allows for systematic investigation of the impacts of variations in the key inputs on driving the results simulation results (Appendix D). In the case of the results on BMI projections, the systematic sensitivity analysis was driven by incorporating variations on the age- cohort- and region-specific as well as the sex-specific ADEC parameters (model 4.1). Specifically, in this analysis, the Gaussian quadrature approach to systematic sensitivity analysis draws parameters from the previously estimated distributions and produces 95% confidence intervals for the model results. regression results for the aforementioned parameters I find that, regions already at higher levels of excessive calorie availability and BMI (such as the US) present lower uncertainties. On the other hand, regions at earlier stages in the nutrition transition, such as South Asia, present larger uncertainties.

Following model validation, I turn to business-as-usual (BAU) projections of adult BMI from 2015 to 2050. The SIMPLE model is projected forward with exogenous shocks to population, per capita incomes, total factor productivity (TFP) growth in agriculture, and biofuel consumption. Growth rates for population and income were derived from the Shared Socioeconomic Pathways (Fricko et al. 2017). The baseline follows the BAU Shared Socioeconomic Pathway (SSP2) which is widely used to evaluate climate change and environmental outcomes. This provides a natural starting point from which to explore integrated solutions for achieving societal objectives to reduce pressure on environmental resources (Fricko et al. 2017). Projected TFP growth rates are based on the historical estimates from (Ludena et al. 2007b) and (Fuglie 2012). Future growth in global biofuel consumption is from the (International Energy Agency 2019). All of these inputs are reported in the Appendix D.

The projections of PoO to 2050 (**Figure 4.4**) rely on the incorporation of the FAO PoU's extension (Section 4.2.1) – albeit with the regionally calibrated parameters – into the SIMPLE model which produces estimates of total caloric availability (acquisition) (Uris Lantz C. Baldos and Hertel 2014c). Following projected increases in global average per-capita availability of calories, the share of population over consuming calories is projected to increase in virtually every region and at the global level. Additionally, those that regions that are already at latter stages in the nutrition transition --projected to have relatively lower growth in ADSC-- are the ones that are projected to have relatively lower growth in PoO (i.e., Canda & US and Europe). In the other hand, those regions that are at earlier stages in the nutrition transition --projected to have relatively larger growth in ADSC-- are the ones that are projected to have relatively lower growth in PoO (i.e., South Asia and Sub Saharan Africa). When this is combined with the projected growth in population, the millions of adults overconsuming calories are projected to more than double towards 2050 and regions already dealing with malnutrition, such as South Asia, double burden are projected to dominate excessive acquisition of calories towards 2050.

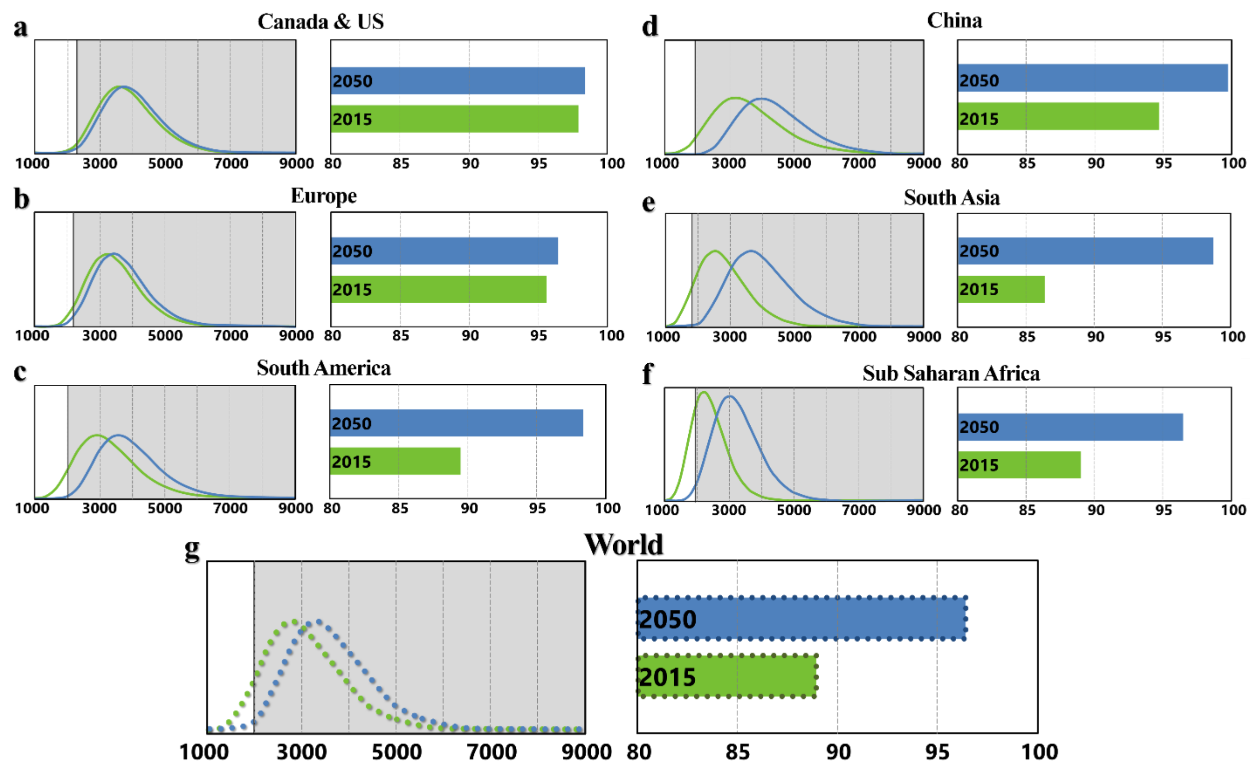


**Figure 4.4 Baseline projections of the PoO towards 2050.**

The green and blue curves in panel **a-g** represent the probability distribution of habitual (i.e., annual average) daily energy consumption (purchasing) (Section 4.2.1) projected to 2015 and 2050 respectively. Gray shaded areas delimit the region were purchasing of calories are greater than the average daily energy requirements (ADER). The green and blue bars represent the Prevalence of Overconsumption (over-acquisition) of calories projected to 2015 and 2050 respectively. Regions are ordered across the income spectrum (from higher to lower income according to World Bank 2019 classification) through panels **a** to **f**. Panel **g** presents projected results at the global level.

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The average daily excessive consumption of calories (ADEC=ADSC-ADER) is projected to increase around 58% women and 60% in men at the global level. Consistently with the findings on the PoO projections, the projected growth in ADEC is especially large in regions such us South Asia and China, where the ADEC is project to growth around 98% (105%) and 82% (84%) respectively, in adult women (men). As described in the Section 4.2.2, we rely on the incorporation of the Model 4.1 into a global partial equilibrium of the food sector (SIMPLE) for projecting average adult BMI (**Figure C.3)** and age-specific adult BMI **(Figure 4.5 a-c** and **Figure C. 8**) towards 2050, for both, men and women.

## 4.4 Health implications of adult BMI in 2050

Under the SSP2 baseline, increases in average calorie availability would lead to a dramatic increase in the percentage of people overconsuming calories. While wealthier regions such as USA and Europe are not expected to experience large changes, middle- and low-income regions will experience dramatic increases in the over acquisition and consumption of calories. This is the case for regions that already struggling with a growing malnutrition double burden such as South America and South Asia (**Figure 4.4**).

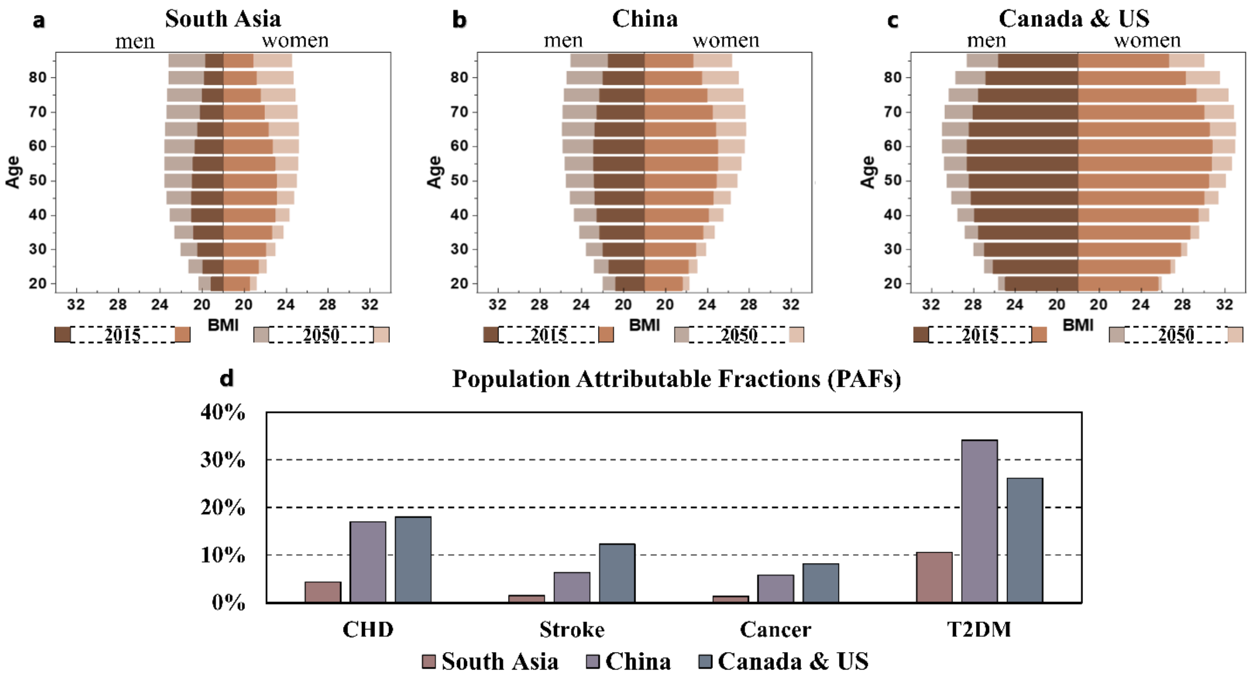


**Figure 4.5. Projections of the age-specific average adult BMI and PAFs.**

Panels **a**, **b** and **c**, present population pyramids for the age-specific average BMI in adult men (left-side) and women (right-side of each pyramid). Observed average adult BMIs in 2015 are represented in darker colors and projected average adult BMIs in 2050 are represented in lighter colors for the South Asia, China, and Canada &US regions (See Appendix C, **Figure C. 8** for the remaining regions used in the study). The bar chart at the bottom (d) reports population attributable fractions (PAF), representing the potential reduction in population diseases attributable to overweight and obesity, coronary heart disease (CHD), Stroke, some types of cancer, and Type 2 Diabetes (T2DM), if the average adult BMI levels did not increase as projected by 2050.

Based on the underlying relationships between the excessive calorie availability and adult BMI I project expected changes in adult BMI towards 2050 (**Figure 4.5**). Average adult BMI is projected to increase in virtually every region and for every age range, for both, men and women. Regions at earlier stages on the nutrition transition such as South Asia (**Figure 4.5a**) are expected to experience the larger increases. This will increase not only the average obesity, but also by reaching higher levels of BMI at younger ages, individuals will increase the number of years that they are exposed to the health risks related to overweight and obesity. Moreover, the projected increases in BMI will also be accompanied by dramatic increases in related diseases (Berrington de Gonzalez et al. 2010; Prospective Studies Collaboration 2009).

### 4.4.1 The Disease Burden Attributable to Weight-Related Risk Factors: Population Attributable Fractions (PAFs).

The projected growth in average adult BMI (**Figure C.3**) will boost already worrisome trends in adult obesity. Additionally, also by reaching higher levels of BMI at younger ages (**Figure 4.5a-c** and **Figure C. 8**) individuals will increase the number of years that they are exposed to the health risks related to overweight and obesity. I estimate the disease burden attributable to weight-related risk factors by calculating population attributable fractions (PAFs). The PAFs represent the proportions of disease cases that would be avoided when the risk exposure is changed from a baseline situation to a counterfactual situation and are calculated using the following general formula:

$$PAF = \frac{\int RR(x)P(x)dx - \int RR(x)P'(x)d(x)}{\int RR(x)P(x)dx} \tag{4.3}$$

In equation (4.3) *RR (x)* is the relative risk of disease for risk factor level x, *P(x)*is the number of people in the population with risk factor level x in the baseline scenario, and *P'(x)* is the number of people in the population with the risk factor level x in the counterfactual scenario. I assume that changes in relative risks follow a dose-response relationship (Lim et al. 2012) and that PAFs combine multiplicatively (Lim et al. 2012; Murray et al. 2012). Therefore, it can be shown that $PAF_{TOT} = 1 - \pi_i(1 - PAF_i)$ where the i's denote independent risk factors.

I rely on publicly available data from different sources to parameterize the comparative risk analysis. I use two large-pooled analyses of prospective cohort studies (Berrington de Gonzalez et al. 2010; Prospective Studies Collaboration 2009) to infer the parameters describing disease attributable to weight-related relative risks. I adopted the relative risk parameters linking weight-related disease factors and BMKI from previous studies, focusing in 4 categories: coronary heart disease (CHD), stroke, type-2 diabetes mellitus (T2DM) (Prospective Studies Collaboration 2009), and some type of cancers (Berrington de Gonzalez et al. 2010). The weight-related relative risk parameters were aggregated to the BMI categories used in this study and normalized to a risk-neutral normal weight category consistent with the epidemiological evidence (Berrington de Gonzalez et al. 2010; Prospective Studies Collaboration 2009). For the purposes of the analyses on this chapter, the PAFs a based on a comparison of the relative risk exposures caused by the average adult BMI levels projected towards 2050 with the counterfactual hypothesis of BMI levels fixed at 2015 levels (**Figure 4.5d** and **Figure C. 8**). Therefore, PAFs in this study represent the proportion of disease cases that would be avoided if average adult BMI, for adult men and women, did not increase as expected towards 2050.

I find that the PAFs attributable to projected changes in adult BMI are substantial for many major non-communicable diseases related to overweight and obesity (Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson, et al. 2018), likely impacting mortality paths towards 2050 (Preston, Vierboom, and Stokes 2018). This expected increase in major disease burdens will further stress national health care systems (Springmann et al. 2016a). These results will also be associated with many economic and health costs (Springmann et al. 2016a), which is particularly relevant in developing countries, characterized by weak institutions with highly differentiated access to good quality health systems (Leatherman et al. 2010).

The PAF results reported in **Figure 4.5d** provide very important insights. However, attributable mortalities are just a portion of the implications of the rapid growth in adult BMI on disease burden. These results should be complemented with the analysis of morbidity implications. One of the main findings on chapters 3 and 4 is that more recent cohorts are reaching (and are projected to reach) adulthood with higher BMIs and become overweight and obese at younger ages. Increasing the years of exposure to the risks attributable to wight-related diseases will cascade in significant growths in future morbidity for future cohorts. Future analysis needs to incorporate the examination of the Disability-adjusted life years (DALYs). The DALY analysis may provide important insights health benefits and cost-effectiveness. One "DALY" can be thought of as one lost year of "healthy" life and are calculated for a disease or health condition are calculated as the sum of the years of life lost (YLL) due to premature death in the population, and the years lost due to disability (YLD) for people living with a disease or its consequences.

## 4.5 Multiple Dividends from Altering Future Food Purchasing Patterns

There is an increasing awareness of the role that food consumption choices can play in simultaneously addressing human health and climate change challenges (Willett et al. 2019). Following ongoing transitions in food consumptions patterns (Bodirsky et al. 2020; Masters et al. 2016), the global daily per-capita food availability and consumption of animal products increased have significantly increased in recent decades. Consequently, the population of cattle, sheep and goats supplying livestock products for human consumption have increased by 1.4-fold and that of pigs and poultry by 1.6 and 3.7-fold, respectively, with attendant increases in direct and indirect GHG emissions (IPCC 2017). Animal agriculture now accounts for 8–10.8% of global greenhouse gas (GHG) emissions under the IPCC framework and the contribution of livestock rises to 18% of global emissions on the basis of lifecycle analysis (O'Mara 2011). Consumption of these products is predicted to grow as middle and lower income regions continue to develop; livestock consumption generally increases as incomes rise (FAO 2018b).

Previous studies have examined how the consumption of healthy and sustainable diets presents major opportunities to reduce environmental pressure (Bodirsky et al. 2020; Springmann et al. 2016a; Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson, et al. 2018). Moreover, previous studies also highlight the importance of the increase in food availability in driving trends and patterns of global diets (Drewnowski and Popkin 2009). The association between obesity and diets has been explored across countries and time, with specific attention on the role of macronutrients (Hall, 2018), ultra-processed foods (Monteiro et al., 2018; Popkin & Reardon, 2018), and fats and sweeteners (Drewnowski and Popkin 2009). Here I use the novel framework to examine the potential multiple dividends, including health and environmental co-benefits, as well reductions in undernutrition, of shifting towards healthier and more sustainable consumption levels.

I expand the previous literature by examining the specific role of changes in dietary composition, reduction in food intake and food waste on natural resource use, crop production and environmental outcomes. **Figure 4.6** presents projected deviations from the 2050 baseline in average adult BMI, for both men and women (percentage of 2050 values). As consequence of shifting towards dietary intake levels that follow the healthy dietary guidelines (HDG), I observe reductions in projected BMI, for both men and women. (Results are similar when shifting towards Flexitarian Diets. (See Appendix C: **Figure C.3**, **Figure C.4**, and **Figure C.5** for results on flexitarian diets pathway). Men's BMIs are more sensitive than women's BMIs to changes in diets. Also, those regions at earlier stages of the nutrition transition such as Central Asia, China, and South America present larger decreases in BMI with respect to the baseline scenario in 2050 (**Figure 4.6**).

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### 4.5.1 Specification of the Counterfactual Scenarios

***The Healthy Dietary Guidelines (HDG) and the Flexitarian (FLX) Diets Scenarios***

I adapt the counterfactual scenarios in previous studies (Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, and Carlson 2018) regarding shifting towards healthier and more sustainable diets. The counterfactual diet scenarios analyzed in this chapter include diets aligned with global dietary guidelines (HDG), and more plant-based flexitarian diets (FLX) that are reflective of present evidence on healthy eating. The HGD scenario is based on global guidelines on healthy eating issued by WHO/FAO Expert Consultations on diet, nutrition (WHO 2003) and human energy requirements (FAO/WHO 2001) and the FLX is a more ambitious dietary change that implies larger levels of substitution of animal source proteins for vegetable source proteins. I start by comparing the BAU projections on food consumption from Springmann et al.'s with the ones in this study obtained with SIMPLE, under the SSP2 scenarios. I do so by aggregating across food groups from Springmann et al. into "crop" and "livestock" categories. I find that baseline projections from both studies are very similar, and global averages of per capita consumption of crops and livestock are around 1130 grams and 412-425 grams, respectively.

In Springmann et al. authors develop two different counterfactual scenarios regarding shifting towards healthier and more sustainable diets. One in which average consumers follow the Healthy Dietary Guidelines (HDG) and another one in which the average consumers follow a flexitarian style diet (FLX). In both scenarios, regional diets maintain their character of preferred foods but are restricted to an intake of 2100-2300 kcal per person per day, with specified grams per person per day servings of food categories such as red meat, dairy, fruits and vegetables, and staple crops. The flexitarian diet pathway is a more ambitious dietary change projection, in the sense that it implies a larger restriction in the consumption of livestock products and a boost in the nut and legume intake.

To calculate the necessary shocks to simulate Springmann et al.'s two dietary change scenarios, regional per capita food consumption in grams is obtained from the QCONS_GRAM variable. Because this information is separated into "crops," "livestock," and "processed food" categories, the food groups in Springmann et al. are aggregated for comparison. Thus, wheat, rice, maize, legumes, vegetables, nut & seeds, et cetera are summed for "crops," while "livestock" included such categories as beef, poultry, and eggs. For the healthy diets' scenario, this corresponds to 1093.6 g of crops and 369 grams of livestock products per person per day, while the flexitarian diet consists of 1110.3 grams of crops and 240.6 grams of livestock products. To translate these values into shocks, the percentage change necessary in per capita consumption to meet the scenario values was calculated.

In order to better understand the dynamics of the malnutrition double burden, I restrict the exogenous changes in food consumption to those regions that are already at latter stages in the nutrition transition (Bodirsky et al. 2020). This allows us to project endogenous changes in caloric undernutrition in those regions that host most of the current and projected hunger individuals. So doing, I observe the potential multiple dividends (i.e., health and environmental benefits) derived from the shift towards healthier dietary intake levels in those regions that project higher levels on adult BMI. **Table 4.1** lists the shocks in food consumption with respect to the baseline case, for the HDG and the FLX diets scenarios.

**Table 4.1. Shocks on per capita consumption in grams by type of food (i.e., crops, livestock, and processed food) in SIMPLE**

| | **HDG** | | | **FLX** | | |
|---|---|---|---|---|---|---|
| | Crops | Livestock | Proc_Food | Crops | Livestock | Proc_Food |
| **East of Europe** | -15.9 | -46.2 | -35.3 | -14.6 | -64.9 | -22.0 |
| **South America** | 12.0 | -39.2 | -60.5 | 13.7 | -60.3 | -45.8 |
| **Aust& N. Zealand** | 10.3 | -52.7 | -31.5 | 12.0 | -69.1 | -18.4 |
| **Europe** | -3.8 | -42.4 | -49.5 | -2.3 | -62.4 | -33.1 |
| **South Africa** | 31.3 | 16.1 | -140.1 | 33.3 | -24.3 | -123.9 |
| **Canada & US** | -3.7 | -54.1 | -48.9 | -2.3 | -70.1 | -41.7 |
| **China** | -37.2 | -3.4 | -40.8 | -36.2 | -37.0 | 77.0 |
| **Japan and Korea** | 11.5 | 6.3 | -77.6 | 13.2 | -30.7 | -58.3 |
| **Central Asia** | -14.2 | -35.7 | 6.6 | -12.9 | -58.1 | 33.8 |

*Note: Shocks on per capita consumption in grams by type of food (i.e., crops, livestock, and processed food) in SIMPLE. These shocks imply exogenous shifts for the average consumer, to move from the projected baseline diets towards 2050 to more healthy and sustainable intake levels. I develop the counterfactual diets scenarios following healthy dietary guidelines scenario (HDG) and the flexitarian (FLX) diets scenario from Springmann et al. 2018.*

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***Extending the Counterfactual Scenarios: Splitting the Excessive Consumption Between Excessive Intake and Food Waste***

Much of the previous literature has just looked at total calories from the FAO's FBS and concluded that reducing them to a healthy level would greatly benefit the environment. However, the FBS calories have included food waste at consumers' level– although recently some adjustments have been made the inaccuracy persists (FAO 2019a). Therefore, the excessive consumption of food in current diets, understood as the gap between current food consumption levels (equated to FAO FBS's) and healthy dietary intake levels, really includes both food waste and excessive intake. Additionally, since shifting towards healthier diets usually imply not only the reduction in food consumption, but also shifting towards more plant-based diets, there is also a third contributor – the composition of these calories. Here, I decompose, for the first time, these three elements (composition of diets, excessive intake, and food waste) of the linkage from food purchasing behavior and the environment to analyze their relative contribution to environmental sustainability. In order to decompose the relative environmental benefits of each of the subcomponents, I design a 3-steps complementary experiments to decompose the overall environmental benefits of shifting towards healthier diets, in both HDG and FLX, dietary scenarios described in the previous sub-section.

I start by isolating the relative contribution of the changes in the composition of diets (i.e., shifting towards more plant-based food consumption bundle) when shifting towards HDG and FLX diets. I do so by imposing shifts in food consumption that imply the necessary changes in dietary composition in the HDG and FLX (i.e., relatively more calories from direct crop consumption and less from livestock) but maintaining the overall calories purchased as in the BAU towards 2050 scenario. This first step allows us to isolate the environmental benefits of changes in dietary composition by comparing the GHG emission and resource use resulting from this scenario with the ones resulting from the BAU. In the second step, in addition to the changes in the dietary composition, I impose a restrictions in food purchasing mimicking reductions in consumers' food waste based on imputed values of uneaten calories art consumers' level from previous studies (Barrera and Hertel 2020). The second step allows us to isolate the environmental benefits of reducing food waste by comparing the by comparing the GHG emission and resource use resulting from this scenario with the ones resulting of changes in dietary composition (results from step 1). In the third step of these complementary experiments, I isolate the environmental benefits of reductions in excessive intake of food by comparing the resulting GHG emissions and result use from the HDG and FLX diets scenarios (**Table 4.1**) with the ones resulting from the second step (food reduction + change in dietary composition) in these complementary experiments. **Table 4.2** lists the shocks in food consumption with respect to the baseline case, for the steps 1 and 2, that complements the HDG and the FLX diets scenarios.

**Table 4.2. Shocks on per capita consumption in grams by type of food (i.e., crops, livestock, and processed food) in SIMPLE.**

| | Step 1 | | | Step 2 | | |
|---|---|---|---|---|---|---|
| **HDG** | Crops | Livestock | Proc_Food | Crops | Livestock | Proc_Food |
| **East of Europe** | 53.8 | -1.6 | 18.3 | 7.7 | -31.1 | -17.2 |
| **South America** | 102.7 | 10.1 | -28.5 | 41.9 | -22.9 | -49.9 |
| **Aust. & N. Zealand** | 61.3 | -30.8 | 0.2 | 16.1 | -50.2 | -27.9 |
| **Europe** | 46.5 | -12.2 | -23.1 | 5.5 | -36.8 | -44.6 |
| **South Africa** | 89.2 | 67.3 | -157.8 | 43.8 | 27.2 | -144.0 |
| **Canada & US** | 62.3 | -22.6 | -13.8 | 8.8 | -48.2 | -42.2 |
| **China** | 37.0 | 110.8 | 29.2 | -4.1 | 47.5 | -9.6 |
| **Japan and Korea** | 40.4 | 33.9 | -71.7 | 15.4 | 10.0 | -76.8 |
| **Central Asia** | 62.4 | 21.7 | 101.8 | 16.2 | -12.9 | 44.3 |
| **FLX** | Crops | Livestock | Proc_Food | Crops | Livestock | Proc_Food |
| **East of Europe** | 57.8 | -35.2 | 44.2 | 10.5 | -54.6 | 0.9 |
| **South America** | 107.1 | -27.8 | -1.3 | 45.0 | -49.4 | -30.9 |
| **Aust & N. Zealand** | 66.1 | -54.2 | 21.0 | 19.6 | -67.0 | -12.9 |
| **Europe** | 50.5 | -42.1 | 3.0 | 8.3 | -58.3 | -25.8 |
| **South Africa** | 93.6 | 10.0 | -134.6 | 47.1 | -16.4 | -126.3 |
| **Canada & US** | 68.5 | -48.4 | 0.5 | 12.9 | -65.4 | -32.6 |
| **China** | 37.5 | 35.9 | 281.8 | -3.7 | -4.9 | 167.3 |
| **Japan and Korea** | 40.9 | -13.7 | -48.1 | 15.7 | -29.1 | -57.4 |
| **Central Asia** | 64.0 | -21.1 | 151.8 | 17.3 | -43.5 | 80.1 |

*Note: These shocks imply exogenous shifts for the average consumer, to move from the projected baseline diets towards healthier diets. Columns corresponding to Step 1 present shocks in per capita consumption that implies shifts in dietary composition that follows healthier diets (i.e., HDG and FLX) but respect the overall calorie consumption levels from BAU scenario. Columns corresponding to Step 2 to shocks that imply reductions on consumers food waste* (Barrera and Hertel 2020) *accompanying the changes in dietary composition necessary to achieve healthier diets (i.e., HDG and FLX).*

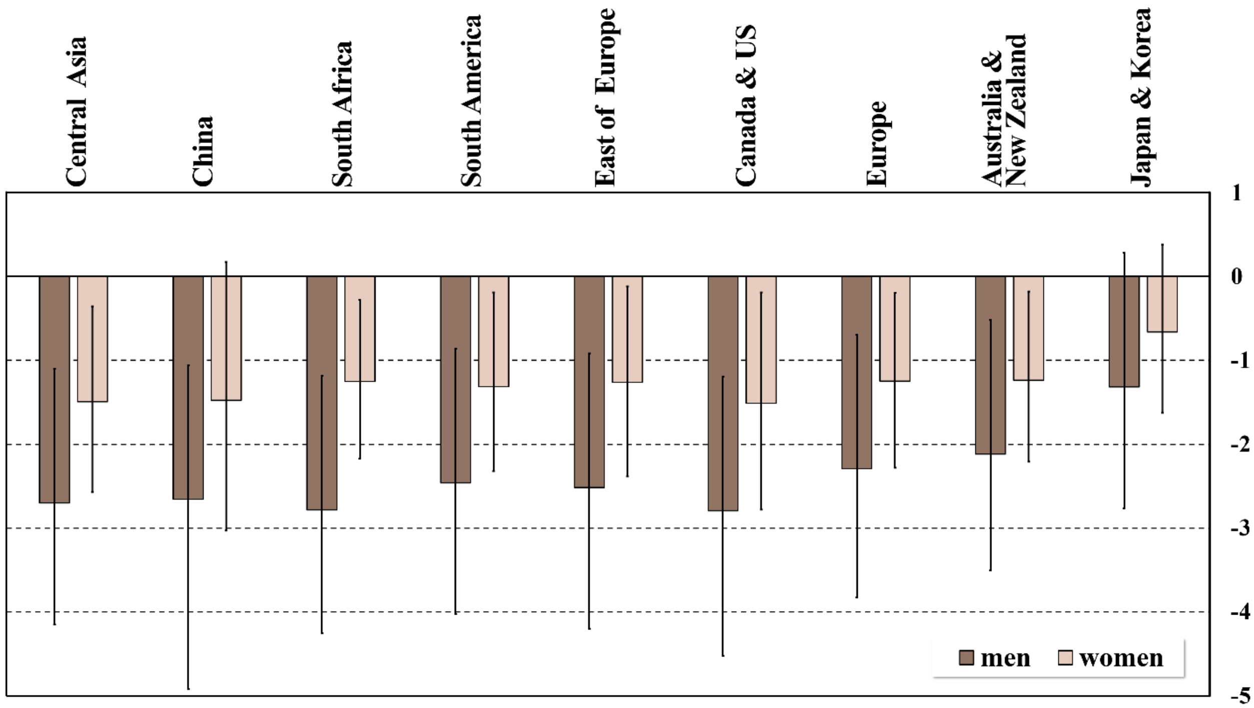


**Figure 4.6. Projected changes in BMI for men and women.**
The bars represent the projected percentage changes with respect to the 2050 baseline case caused by shifting towards diets following intake recommended in the healthy dietary guidelines (HDG) in those regions (See Appendix C: **Figure C.3**, **Figure C.4**, and **Figure C.5** for results on flexitarian diets pathway). Omitted regions are not subjected to the diet changes. Error bars represent 95% confidence intervals.

Shifting towards healthier consumption levels in more developed regions would imply a reduction in the overall caloric intake with consequent reductions in adult BMI with respect to the baseline projections towards 2050 (**Figure 4.6**). As was explored in the previous section, and also highlighted in previous research, there are several health benefits that ae associated with these results (**Figure 4.5d**) (Afshin et al. 2019). In addition, and consistently with findings in chapter 3, the results on reductions of adults BMI are larger on men than in women. These differences imply that the women might be less sensitive to the reduction on energy intake, that is consistent with previous studies on gender gaps on the distribution of food within households (Harris-Fry et al. 2017; Brown, Calvi, and Penglase 2018) and also consistent with current gender gaps on dietary intake levels (Afshin et al. 2019).

Several studies have explored the potential environmental benefits of shifting towards healthier diets (Springmann et al. 2016a), the role of reducing food waste (Barrera and Hertel 2020), as well as the contribution of cutting livestock consumption, in diminishing stress on natural resource use (Bajželj et al. 2014; Hedenus, Wirsenius, and Johansson 2014; Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson, et al. 2018). With a global decrease in food demand, as a result of the shift in diets, crop prices are lower than in the baseline scenario leading to a consequent reduction in the incentive to increase crop production (**Figure 4.7**), thereby reducing rates of cropland conversion as well as growth in the use of fertilizers and other yield-increasing inputs in all regions under both the flexitarian and the healthy dietary guidelines scenarios.

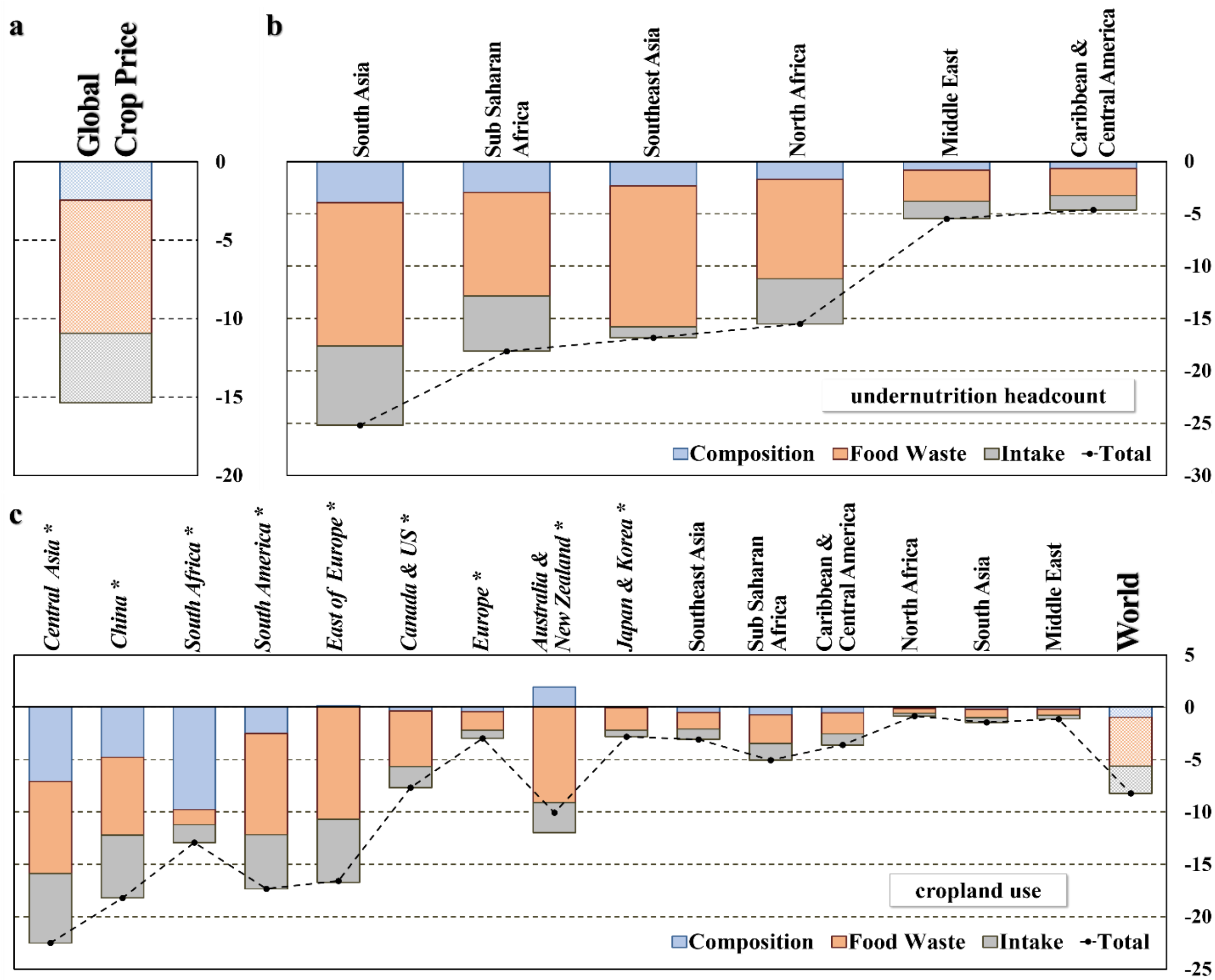


**Figure 4.7. Shifting towards healthy dietary intake levels reduce caloric undernutrition and land use.** Bars represent percentage changes in 2050 baseline outcomes caused by shifting towards diets following healthy dietary guidelines (HDG) in the regions in italic and marked with asterisk starting with Central Asia and ending with Japan and Korea. Regions exogenously shifted to the HDG are in italic and marked with an asterisk, consumption patterns in the remaining regions are endogenous. Panel **a** represents the percentage change in global crop price, panel **b** represents reductions in undernutrition headcounts in those regions where diets are endogenously determined as a function of prices, and panel **c** represents changes in cropland use. Colored segments of each bar decompose the total change into three different components of the shift from current consumption levels: the change within the food basket composition (i.e., the HDG scenario implies reductions in livestock consumption with respect to the baseline case), reductions in food intake, and reductions in food waste (Barrera and Hertel 2020). (**Figure C.4** presents results on flexitarian diets pathway).

Shifting towards healthier consumption patterns in more developed regions increases the affordability of staple foods, leading to reductions in undernutrition outcomes in key developing regions including South and Southeast Asia, Sub Saharan, and North Africa. Under this scenario, I project a reduction of 16 million people experiencing caloric undernourishment in those low-income regions.

Within the regions that are exogenously shifted towards HDG, those that are at earlier stages of the nutrition transition such as South America and Central Asia (Drewnowski and Popkin 2009; Malik, Willett, and Hu 2013) and/or that present higher levels of food waste such as China (Barrera and Hertel 2020), are the ones that present larger reductions in cropland use. In the reference case scenario, these regions are the ones that project the largest increases in cropland expansion due to growing regional and global demand for food. Consequently, the shift towards healthier diets has a bigger impact on these regions. Additionally, here I extend the existing literature by providing a breakout of the relative contributions within the shifts to in healthier consumption patterns (i.e., changes in the composition of the food basket, reductions in food intake, and reductions in food waste). Changes in diet composition (i.e., relative reduction in livestock consumption) plays a mild role in the observed environmental benefits as well as in food affordability. A considerable share of reductions global crop price and cropland use is derived from declines in food intake; however, most of the conservation in natural resource use in food production, as well as benefits from increased food affordability are driven by reductions in food waste.

When considering the implications for greenhouse gas emissions, results are heterogenous across regions (**Figure 4.8**). Global greenhouse gas emissions related to crop production are predicted to decrease by about 18% compared to the 2050 baseline, while global livestock related emissions would decrease by more than 30%. This stronger impact is due to the expected shifts towards greater consumption of animal source proteins in the baseline projections. Therefore, in the context of a shift towards healthier consumption patterns, the relative contribution of changes in diet composition (less livestock) plays a large role in the greenhouse emissions reduction. This finding is consistent with previous studies (Bodirsky et al. 2020; Pelletier and Tyedmers 2010; Springmann, Clark, Mason-D'Croz, Wiebe, Bodirsky, Lassaletta, de Vries, Vermeulen, Herrero, Carlson, et al. 2018; Tilman and Clark 2014). Moreover, a better understanding of global inequality is essential for developing effective policies that seek to ensure global sustainability (Motesharrei et al. 2016). While most of the malnourished live in lower income regions, they are responsible for a small share of the global GHG emissions. This results highlight that not only global resource use should be reduced, but also the international inequalities of production and supply need to be addressed and incorporated into the debate, which is consistent with previous research findings (Duro, Schaffartzik, and Krausmann 2018; United Nations 2015).

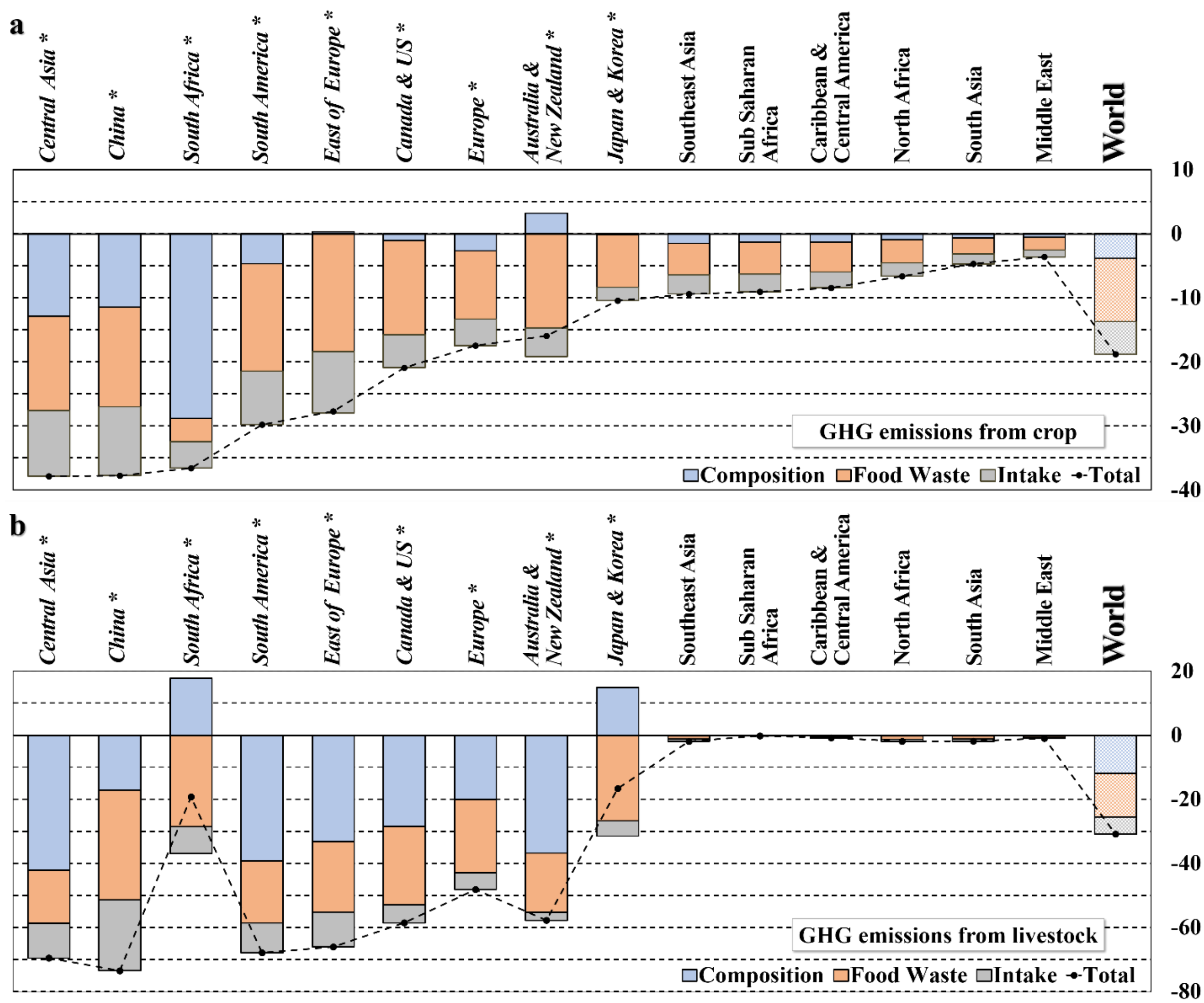


**Figure 4.8. Shifting towards healthy dietary intake levels reduce Green House Emissions.** Bars represent percentage changes with respect to the 2050 baseline case, caused by shifting towards diets following healthy dietary guidelines (HDG) in the regions in italic and marked with an asterisk. Results represent the breakout between three different components within the shifts in diets: the change within the food basket composition (i.e., the HDG scenario implies reductions in livestock consumption with respect to the baseline case), reductions in food intake, and reductions in food waste (Barrera and Hertel 2020). (**Figure C.5** presents results on flexitarian diets pathway).

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## 4.6 Discussion and Implications

I find a positive correlation between the excessive calorie availability and adult BMI – a link that is strengthening over successive generations. As a result, more recent generations present higher BMIs and are at risk of becoming overweight and obese earlier, and for larger proportions of their lifespan. Following projected increases in excessive calorie availability. Adult BMIs are projected to increase towards 2050 in virtually every country and region, which will imply worsening an already worrisome trends on non-communicable diseases attributable to overweight and obesity. This presents an extra challenge for developing countries, were weak institutions and limited access to health care systems are already challenging policy makers.

By providing a novel framework that enables the simultaneous examination of both ends of the distribution of caloric purchases within populations, I am able to uncover additional synergies and trade-offs between food policies oriented toward reducing hunger by increasing food supply, on the one hand, and overweight, obesity and health related outcomes, on the other. As the world continues to push toward increasing the supply of food to alleviate hunger there is a simultaneous need to address the importance of nutrition and diet quality, including the production, promotion, and availability of affordable healthy diets. Moreover, I provide evidence of potential multiple dividends of policies promoting healthier diets through behavioral affecting consumers' purchasing patterns. Shifting towards healthier and more sustainable food consumption levels, could synergistically address multiple health and environmental burdens.

Furthermore, I extend the previous literature by examining the relative contribution of the different subcomponents of shifting towards healthier and more sustainable consumption levels. By examining changes in food waste within the same framework as reductions in overall caloric intake and changes in dietary composition, I am able to assess its relative contribution to reducing the pressure on natural resources. While shifting towards healthier diets may have desirable health implications for overweight and obesity health related outcomes, much of the environmental benefits, in particular reductions in land use and crop related GHG emissions, are derived from the reductions in food purchasing (reductions in food waste and food intake) rather than changes in dietary composition in diets itself. A synergistic combination of measures will be needed to sufficiently mitigate the projected increase in environmental pressures, while also avoiding unintended consequences on already worrisome trends in malnutrition double burden, as the global food economy advances towards mid-century.

# CHAPTER 5. DISCUSSION AND CONCLUSIONS

This dissertation combines three essays that examines how future patterns of global food consumption will affect human health, and how the agricultural changes needed to support the ongoing global nutrition transition will affect the environment. Specifically, the dissertation focuses on the quantitative linkages among the waste and the excessive intake of food and its influences on human health and environmental sustainability. Outcomes from these studies may provide insights on tradeoffs and synergies among the excessive consumption of food --understood as the gap between current and healthy food consumption levels--, the environmental sustainability, and attributable weight-related diseases to current trends on adult BMI. The essays on this dissertation highlight potential unintended health consequences of agricultural and trade policies directed at increasing calorie supplies. In addition, results shed light on the potential multiple dividends of food waste and anti-obesity policies.

In the Chapter 2, the work focusses on better understanding consumer's food waste providing evidence on how the global pattern of food waste is evolving rapidly. The projected result is that under current trends, and in the absence of policy interventions or significant behavioral changes, the global calories wasted at consumers level will nearly double by 2050. This chapter extends the current state of knowledge in this area by exploring consumers' food waste through the income spectrum across countries and time. I find that per capita uneaten calories at the consumers level have leveled off in rich countries; however, this category is growing rapidly in middle income countries, and it is these countries that will drive future global changes. By the estimates in this chapter, China already dominates global food waste, but in the next three decades, it will be joined by South Asia and other lower income regions where rapid growth in food waste due to rising incomes, diversifying diets, and growing population could have a dramatic impact on the global total.

By modeling the evolution of food waste with per capita incomes, I am able to explore a richer set of (more realistic) scenarios than in previous studies in this area which have typically abstracted from future growth in food waste. Here I consider two cases wherein the share of food waste in food availability is frozen. Undertaking such a policy in 2020 would have a strong impact on global resource use and food security – particularly if accompanied by greater trade integration. However, if such measures are delayed until 2030, and if trade frictions lead to greater market segmentation, then this food waste mitigation pathway will likely have far more modest food and environmental security benefits. More generally, the interaction between food waste reduction measures and trade policies is a novel contribution of this chapter. Trade policies which increase agricultural market integration have the potential to amplify the benefits of food waste reductions for food security (by facilitating the accessibility to food in the most vulnerable regions) and for reduce pressure on natural resources.

Additionally, Chapter 2 also highlights the importance of developing new measurement methods for food waste that can be rapidly deployed across the globe. Measurement is the foundation of international action and there is a need for approaches which can be readily implemented with existing data sources and incorporated into quantitative models to explore impacts and consequences of mitigation measures. The data base which I have developed builds work represents a new step in the direction of having a global, internationally comparable data set on food waste. However, more cross-validation of this approach with independent estimates (and ideally observations) of food waste is required.

In the Chapter 3 of this dissertation, the analysis focuses on measuring the role of excess calories availability (ECA) as a historical driver of overweight and obesity globally. In the analyses realized for this chapter I detect a pronounced ECA effect that is boosted by age effects, increasing the number of years that individuals are exposed to risks related to overweight and obesity. This chapter extends the current state of the knowledge in this area by incorporating a multidimensional consideration of time into the analysis of long-run BMI trajectories that helps to illustrate underlying mechanisms driving current trends. I find a significant positive correlation between observed trends in adult BMI and ECA across countries, even after controlling for country-specific effects. Cohort mechanisms underlie BMI for both males and females. Each cohort reaches adulthood with a higher BMI than the previous cohort, and this cohort effect is particularly large for those born between 1940 and 1990, a period that coincided with the emergence of per capita energy imbalances in many countries. The analyses realized for this chapter also provide evidence of a positive correlation between ECA during early childhood and BMI at the age of adulthood for males. This result highlights the importance of food environments characterized by an abundance in calories during early stages of life on subsequent overweight and obesity outcomes in adulthood, which may have implications for future projections of BMI and health-related outcomes. Moreover, I also find that the cohort mechanisms are boosted by age effects. I observe significant and positive

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age effects for both males and females, with each cohort reaching adulthood at higher baseline BMI than the previous cohort. As a result, across generations, the age effect leads individuals to become overweight and/or obese at younger ages. The combination of age and cohort effects presents a serious social challenge given the health and economic implications associated with overweight and obesity. Each cohort's time of exposure to risk has grown larger over time, which could be expected to have implications for increases in related mortality, morbidity, disability-adjusted life years (DALYs), and health care costs.

The results from Chapter 3 provide a number of policy-relevant insights. The findings highlight how some standard agricultural and trade policies oriented toward reducing hunger by increasing calorie supplies might have unintended consequences for undesirable overweight, obesity, and health-related outcomes. In light of current trends in food supply, these findings are of particular importance for developing countries already dealing with the complexities of a rising malnutrition double burden. More generally, as the world continues to push toward increasing the supply of food to alleviate hunger among those still facing food insecurity, there is a simultaneous need to underscore and address, through policy and education, the importance of nutrition and diet quality, including the production, promotion, and availability of affordable healthy diets, to avoid intensification of the already worrisome trends in adult BMI. Finally, findings in this chapter offer additional evidence of potential gender gaps in the energy intake at early childhood. Consistent with previous literature on within-household inequalities on food distribution. results from this chapter evidence gender gaps in energy intake that might cascade in undesirable nutritional and health outcomes for women at the age of reaching adulthood.

In the Chapter 4, the analysis focuses on better understanding of the dynamics of the rising malnutrition double burden. By providing a novel framework (extending the widely used FAO's PoU methodology) that enables the simultaneous examination of both ends of the distribution of caloric purchases within populations, I am able to uncover additional synergies and trade-offs between food policies oriented toward reducing hunger by increasing food supply, on the one hand, and overweight, obesity and health related outcomes, on the other. In this chapter, I provide evidence of potential multiple dividends of policies promoting healthier diets through behavioral affecting consumers' purchasing patterns. Shifting towards healthier and more sustainable food consumption levels, could synergistically address multiple health and environmental burdens. I extend the previous literature in this area by examining the relative contribution of the different subcomponents of shifting towards healthier and more sustainable consumption levels. By examining changes in food waste within the same framework as reductions in overall caloric intake and changes in dietary composition, I am able to assess its relative contribution to reducing the pressure on natural resources. While shifting towards healthier diets may have desirable health implications for overweight and obesity health related outcomes, much of the environmental benefits, in particular reductions in land use and crop related GHG emissions, are derived from the reductions in food purchasing (reductions in food waste and food intake) rather than changes in dietary composition in diets itself. Results highlight that a synergistic combination of measures will be needed to sufficiently mitigate the projected increase in environmental pressures, while also avoiding unintended consequences on already worrisome trends in malnutrition double burden, as the global food economy advances towards mid-century. Moreover, a better understanding of global inequality is essential for developing effective policies that seek to ensure global sustainability. While most of the malnourished live in lower income regions those are responsible for a small share of the global GHG emissions. The results in this chapter highlight that not only global resource use must be reduced, but also the international inequalities of production and supply need to be addressed and incorporated into the debate.

The three essays Ph.D. dissertation advance the current state of knowledge in the literature exploring the trade-offs and synergies arising out of the competing demands on the planet's finite resources (such as water, land, clean air, biodiversity etc.), as well as potential pathways for sustainable development in the coming decades. Specifically, the outcomes from this dissertation provide several policy-relevant insights on the challenges related to the excessive consumption of food (understood as the gap between current food consumption levels), the environmental sustainability, and attributable weight-related diseases to current trends on adult BMI. From highlighting potential unintended health consequences of agricultural and trade policies directed at increasing calorie supplies, to shedding light on the potential multiple dividends (i.e., boost in food security, improve in health outcomes due to weight-attributable diseases, and save of resource use in food production) of food waste and anti-obesity policies.

# APPENDIX A. CHAPTER 2

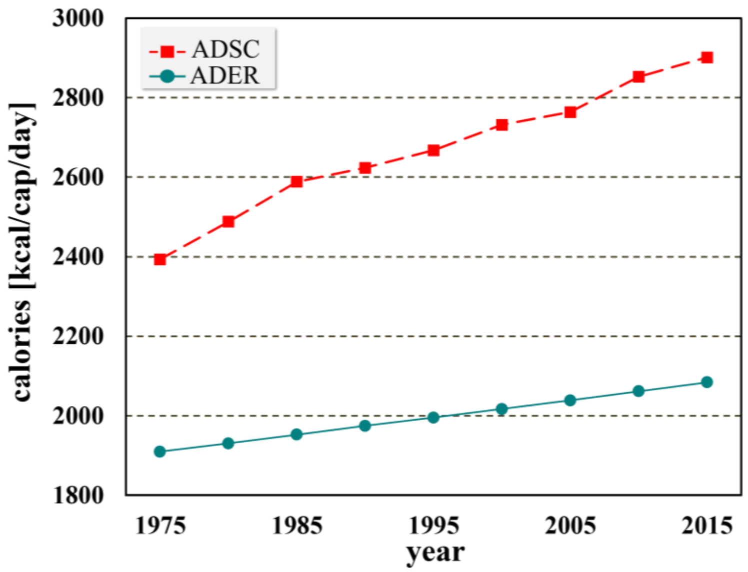


**Figure A.1. Global excess calorie availability (ECA) in kcal/cap/day, 1975-2015. ECA= ADSC-ADER.**
The figure illustrates the growing of the excess calorie availability (ECA), understood as the gap between average daily supply of calories (ADSC) and average daily energy requirements (ADER).

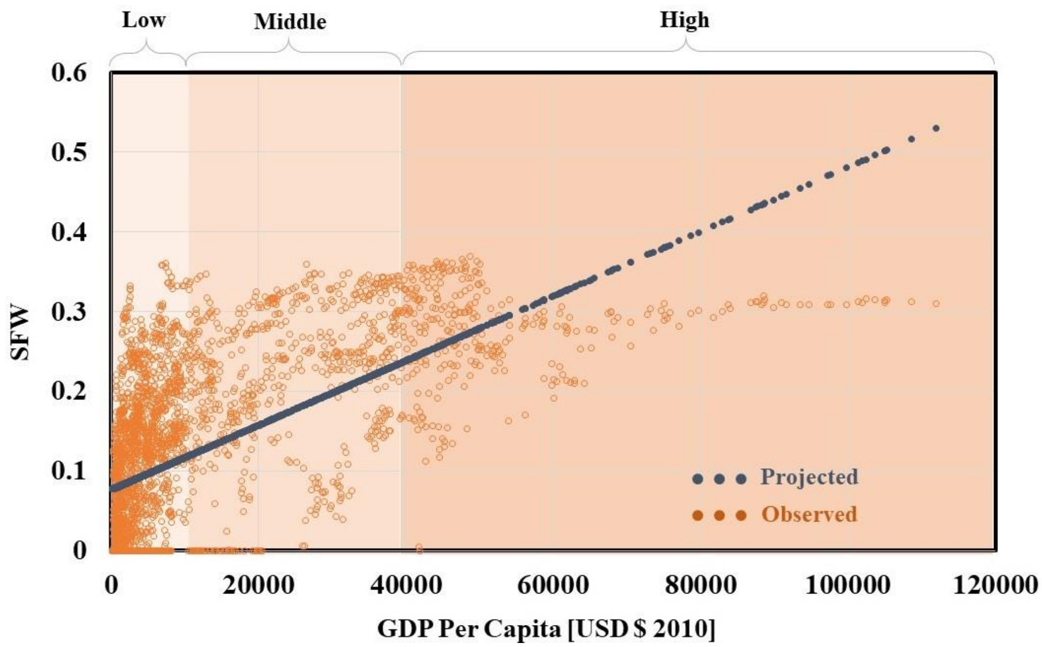


**Figure A.2. The linear approximation to model the Share of Food Waste (SFW).**
The observed data points of Share of Food Waste (SFW) data across the income spectrum and the SFW projections obtained through the linear function estimation.

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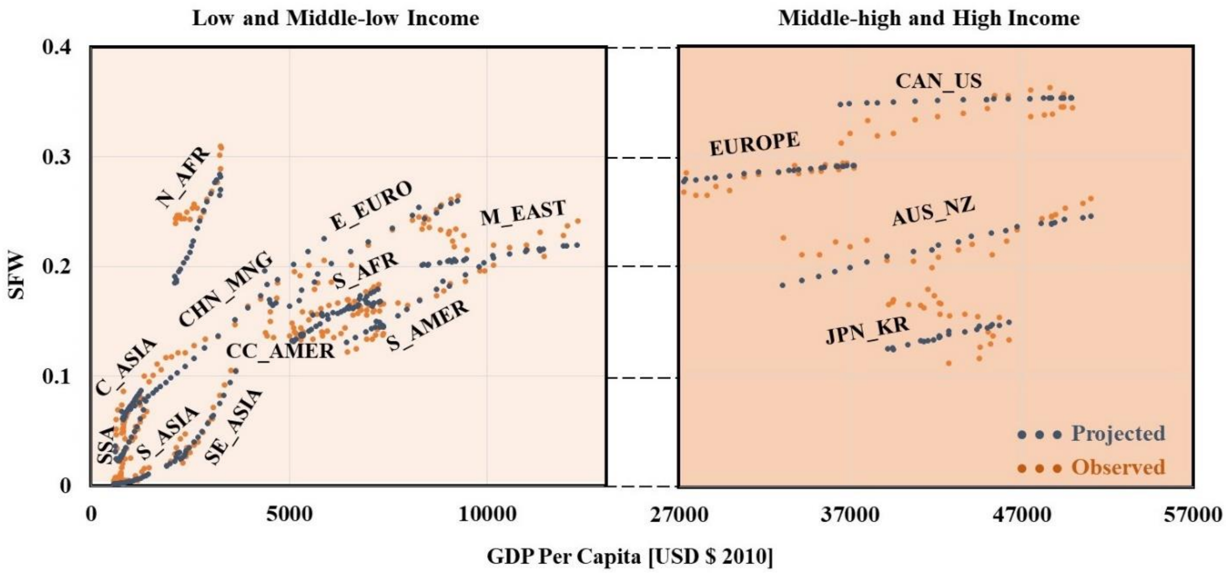


**Figure A.3. The logistic function projections and the observed levels of SFW**

The logistic function projections and the observed levels of SFW collapsing the data points through weighted population averages15 regions we obtain 22 annual data points (SFW & income for 1992-2013) for each region. This compiled version of the **Figure 2.4** collapsed into two panels allows to observe the response of food waste through the income spectrum.

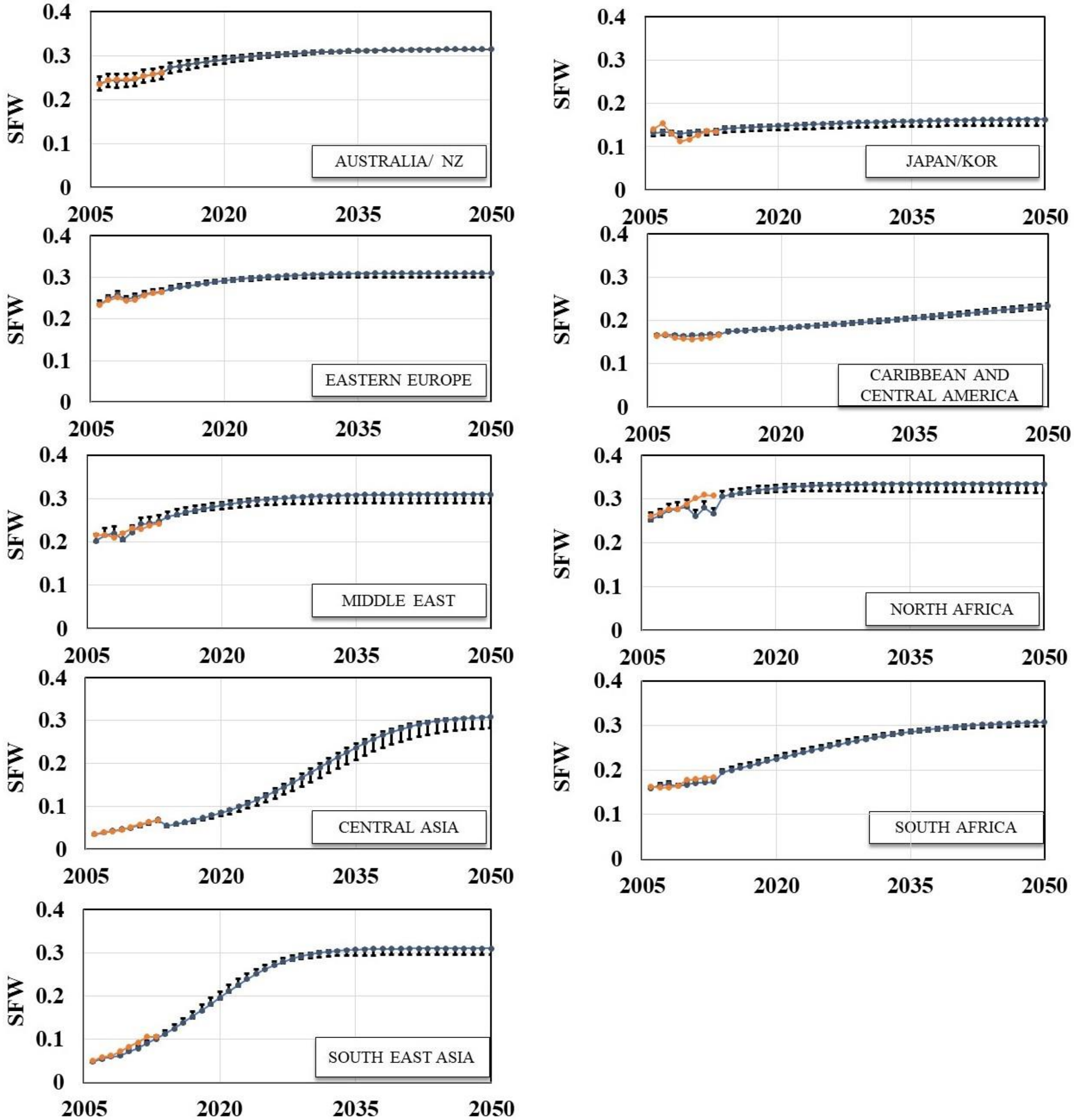


**Figure A.4. SFW observed between 2006-2013 and projected towards 2050.**
Regions are ordered from high to low-income level (according to World Bank 2018 classification of countries by income).

# APPENDIX B. CHAPTER 3

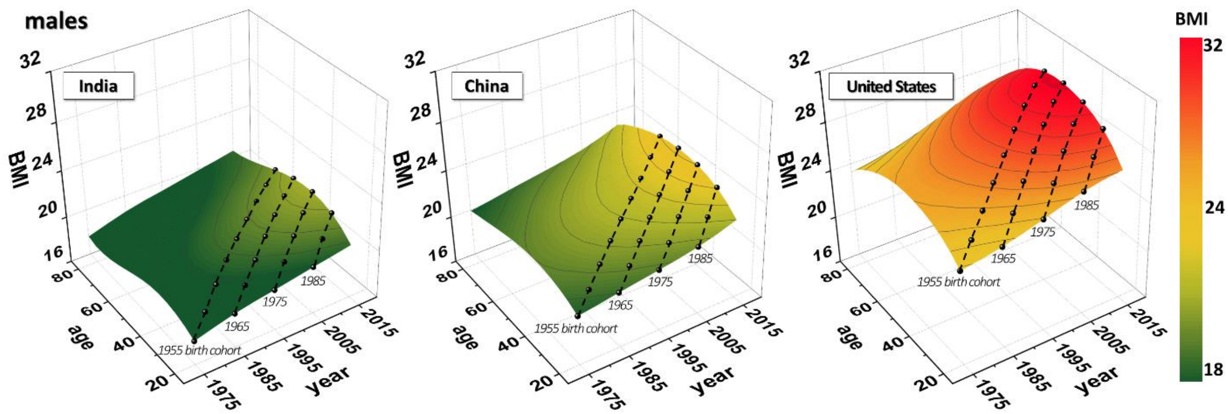


**Figure B.1. BMI trajectories for adult males in three countries.**
Changes in BMI for cohorts matched by age of birth are illustrated in the dashed lines. India (low income), China (middle income), and the US (high income) present similar age and cohort patterns but at different BMI levels.

### *Data on average energy requirements for adults used in Chapter 3 and Chapter 4*

The average dietary energy requirement (ADER) is defined as the calorie intake (kcal/cap/day) required to provide energy balance in a given individual of a healthy weight for their sex, age and activity levels. The ADER for adults, used in Models 3.1 and 3.2 (Chapter 3) and Model 4.1 (Chapter 4), is calculated based on the country-specific average height and weight, adjusted by physical activity levels (PAL). We begin by estimating the basal metabolic rate (BMR) for individuals of a given age, sex, height and weight. The NCD-RisC provides country-level data on sex-specific average height for adults more than 20 years old by country and by year of birth for the period between 1895 and 1995.

I downloaded the yearly reported estimates of the average adult height in each country from the *Our World in Data* web page (https://ourworldindata.org/human-height). By matching the data on the age- and sex-specific average BMI with the data on average height we calculated average weight at country level, by year and by age group. We then used the data on average height and weight to obtain estimations of the sex-specific basal metabolic rate (BMR) for each age group (**Table B.1**). In practice the BMR measure is approximately equal to the energy expenditure in kilocalories (kcal) of individuals during sleep. Therefore, the estimate obtained through this method is considered a valid approximation to the true BMR. **Table B.1** provides the equations used to compute the estimates of BMR for individuals of a given sex and weight (FAO/WHO/UNU, 1985; Schofield, 1985).

**Table B.1. Equations for the prediction of basal metabolic rate in adults**

| | Age range | Estimated BMR in kcal/day |
|---|---|---|
| **Male** | 18-30 | 15.4W - 27H + 717 |
| | 30-60 | 11.3W + 16H + 901 |
| | > 60 | 8.8W + 1 128H - 1 071 |
| **Female** | 18-30 | 13.3W + 334H + 35 |
| | 30-60 | 8.7W - 25H + 865 |
| | > 60 | 9.2W + 637H – 302 |

*Note: Data from FAO/WHO/UNU (9). Basal metabolic rate (BMR) data is computed from age and sex-specific data on height and weight form NCD Risk Factor Collaboration (NCD-RisC). The BMR is approximately equal to the energy expenditure (kcal) of individuals during sleep. Parameters in* ***Table B.1*** *are used to obtain precise estimates of BMR for individuals of a given age, sex, height and weight (FAO/WHO/UNU, 1985; Schofield, 1985).*

The total energy required for an individual to maintain a healthy life will vary with occupation, time spent working, and an individual's body size. Adjusting the age- and sex-specific BMR values for PALs we obtain estimates of the need-adjusted ADER (FAO/WHO, 2001; FAO/WHO/UNU, 1985). We compiled ADER values under different scenarios of PAL, sedentary or light activity lifestyle, active or moderately active lifestyle, and vigorous or vigorously active lifestyle with PAL adjustment factors equal to 1.55, 1.76, and 2.25 respectively (FAO/WHO/UNU, 1985). We use these different scenarios of PAL to test the sensitivity of the correlation between ECA and BMI to assumptions about energy needs (**Table B.4**). Finally, the ECA for adults used in Model 3.2 (Chapter 3) and Model 3.1 (Chapter 4), measured in kilocalories per capita and per day, is the difference between average daily supply of calories (ADSC) and the average daily energy requirements (ADER). We acknowledge that the FAO/WHO/UNU (1985) procedures may overestimate daily energy requirements, particularly in individuals with sedentary or light PAL (Alfonzo-Gonzalez et al., 2004). However, we believe this value provides an upper bound on adult ADER. Additionally, we acknowledge that the FBS is not free from criticism (Svedberg 1999a) and likely underestimates calorie availability, particularly in rural economies where unreported subsistence production represents an important share of the households' food consumption (Hawkesworth et al. 2010). However, the FBS is the most extensive global database on countries' food systems, and I believe the ADSC provides a reasonable lower bound on average calorie availability. The result is that, by using an upper benchmark for the ADER and a lower

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benchmark for the ADSC, I consequently obtain a conservative lower bound for the estimate of ECA by sex (i), country (j) , and year (t), ($\mathrm{ECA}_{\mathrm{I,j,t}} = \mathrm{ADSC}_{\mathrm{I,j,t}} - \mathrm{ADER}_{\mathrm{I,j,t}}$).

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**Table B.2. Results for LSDV regressions on Model 3.1 and Model 3.2 for adult females and males**

| Variable | | Model 3.1 | | Model 3.2 | |
|---|---|---|---|---|---|
| | | females | males | females | males |
| ECA | | n/a | n/a | 0.0003486 (0.0000)*** | 0.0002036 (0.000)*** |
| Age group | 25 | 1.1372 (0.0000)*** | 1.2445 (0.0000)*** | 1.1327 (0.0000)*** | 1.2434 (0.0000)*** |
| | 30 | 2.2583 (0.0000)*** | 2.2700 (0.0000)*** | 2.2498 (0.0000)*** | 2.2681 (0.0000)*** |
| | 35 | 3.3285 (0.0000)*** | 3.1111 (0.0000)*** | 3.3158 (0.0000)*** | 3.1084 (0.0000)*** |
| | 40 | 4.3127 (0.0000)*** | 3.8037 (0.0000)*** | 4.2970 (0.0000)*** | 3.8008 (0.0000)*** |
| | 45 | 5.1769 (0.0000)*** | 4.3844 (0.0000)*** | 5.1589 (0.0000)*** | 4.3817 (0.0000)*** |
| | 50 | 5.8963 (0.0000)*** | 4.8679 (0.0000)*** | 5.8756 (0.0000)*** | 4.8651 (0.0000)*** |
| | 55 | 6.4664 (0.0000)*** | 5.2569 (0.0000)*** | 6.4427 (0.0000)*** | 5.2539 (0.0000)*** |
| | 60 | 6.8832 (0.0000)*** | 5.5531 (0.0000)*** | 6.8561 (0.0000)*** | 5.5496 (0.0000)*** |
| | 65 | 7.1489 (0.0000)*** | 5.7635 (0.0000)*** | 7.1190 (0.0000)*** | 5.7599 (0.0000)*** |
| | 70 | 7.2657 (0.0000)*** | 5.8985 (0.0000)*** | 7.2339 (0.0000)*** | 5.8954 (0.0000)*** |
| | 75 | 7.2450 (0.0000)*** | 5.9722 (0.0000)*** | 7.2112 (0.0000)*** | 5.9694 (0.0000)*** |
| | 80 | 7.0995 (0.0000)*** | 5.9975 (0.0000)*** | 7.0634 (0.0000)*** | 5.9950 (0.0000)*** |
| | 85 | 6.6336 (0.0000)*** | 5.8640 (0.0000)*** | 6.5948 (0.0000)*** | 5.8614 (0.0000)*** |
| Year of birth | 1895 | 0.3710 (0.0040)** | 0.3191 (0.0000)*** | 0.3646 (0.0000)*** | 0.3167 (0.0000)*** |
| | 1900 | 0.7551 (0.0000)*** | 0.6865 (0.0000)*** | 0.7433 (0.0000)*** | 0.6824 (0.0000)*** |
| | 1905 | 1.1509 (0.0000)*** | 1.0797 (0.0000)*** | 1.1353 (0.0000)*** | 1.0748 (0.0000)*** |
| | 1910 | 1.5614 (0.0000)*** | 1.4902 (0.0000)*** | 1.5511 (0.0000)*** | 1.4899 (0.0000)*** |
| | 1915 | 1.9924 (0.0000)*** | 1.9162 (0.0000)*** | 1.9839 (0.0000)*** | 1.9184 (0.0000)*** |
| | 1920 | 2.4433 (0.0000)*** | 2.3548 (0.0000)*** | 2.4293 (0.0000)*** | 2.3554 (0.0000)*** |
| | 1925 | 2.9102 (0.0000)*** | 2.7999 (0.0000)*** | 2.8928 (0.0000)*** | 2.8000 (0.0000)*** |
| | 1930 | 3.3892 (0.0000)*** | 3.2461 (0.0000)*** | 3.3676 (0.0000)*** | 3.2454 (0.0000)*** |

| Variable | | Model 3.1 | | Model 3.2 | |
|---|---|---|---|---|---|
| | | females | males | females | males |
| Year of birth | 1935 | 3.9291<br>(0.0000)*** | 3.7334<br>(0.0000)*** | 3.9050<br>(0.0000)*** | 3.7327<br>(0.0000)*** |
| | 1940 | 4.4814<br>(0.0000)*** | 4.2096<br>(0.0000)*** | 4.4547<br>(0.0000)*** | 4.2089<br>(0.0000)*** |
| | 1945 | 5.0388<br>(0.0000)*** | 4.6782<br>(0.0000)*** | 5.0092<br>(0.0000)*** | 4.6774<br>(0.0000)*** |
| | 1950 | 5.5931<br>(0.0000)*** | 5.1400<br>(0.0000)*** | 5.5605<br>(0.0000)*** | 5.1389<br>(0.0000)*** |
| | 1955 | 6.1382<br>(0.0000)*** | 5.5966<br>(0.0000)*** | 6.1022<br>(0.0000)*** | 5.5952<br>(0.0000)*** |
| | 1960 | 6.5993<br>(0.0000)*** | 6.0135<br>(0.0000)*** | 6.5603<br>(0.0000)*** | 6.0118<br>(0.0000)*** |
| | 1965 | 7.0282<br>(0.0000)*** | 6.4143<br>(0.0000)*** | 6.9873<br>(0.0000)*** | 6.4130<br>(0.0000)*** |
| | 1970 | 7.4227<br>(0.0000)*** | 6.7978<br>(0.0000)*** | 7.3809<br>(0.0000)*** | 6.7975<br>(0.0000)*** |
| | 1975 | 7.7792<br>(0.0000)*** | 7.1631<br>(0.0000)*** | 7.7372<br>(0.0000)*** | 7.1643<br>(0.0000)*** |
| | 1980 | 8.0912<br>(0.0000)*** | 7.5075<br>(0.0000)*** | 8.0395<br>(0.0000)*** | 7.5046<br>(0.0000)*** |
| | 1985 | 8.3478<br>(0.0000)*** | 7.8233<br>(0.0000)*** | 8.2836<br>(0.0000)*** | 7.8147<br>(0.0000)*** |
| | 1990 | 8.5398<br>(0.0000)*** | 8.0990<br>(0.0000)*** | 8.4744<br>(0.0000)*** | 8.0914<br>(0.0000)*** |
| | 1995 | 8.6607<br>(0.0000)*** | 8.3273<br>(0.0000)*** | 8.5875<br>(0.0000)*** | 8.3167<br>(0.0000)*** |
| Constant | | 17.1760<br>(0.0000)*** | 18.3768<br>(0.0000)*** | 16.7938<br>(0.0000)*** | 18.1742<br>(0.0000)*** |
| R-squared | | 0.8426 | 0.9474 | 0.8432 | 0.9476 |
| No. of Observations | | 19656 | 19656 | 19656 | 19656 |

*Note: All regressions include country fixed effects. *** Significantly different from zero at the 1% level, ** Significantly different from zero at the 5% level, P-values within parentheses. Values for the "Year of birth" variables represent changes with respect to 1890 (omitted). For the ECA imputation we assumed light physical activity levels*

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**Table B.3. Results for LSDV regressions on Model 3.3 for females and males at the age of reaching adulthood (20 years old)**

| **Variable** | | **Model 3.3** | |
|---|---|---|---|
| | | females | males |
| ECA5 | | 0.00004<br>0.5780 | 0.000186<br>(0.0040)** |
| Year of birth | 1985 | 0.2639<br>(0.0000)*** | 0.3051<br>(0.0000)*** |
| | 1990 | 0.5029<br>(0.0000)*** | 0.5919<br>(0.0000)*** |
| | 1995 | 0.7304<br>(0.0000)*** | 0.8562<br>(0.0000)*** |
| Constant | | 25.1188<br>(0.0000)*** | 25.5653<br>(0.0000)*** |
| R-squared | | 0.9928 | 0.9945 |
| No. of Observations | | 544 | 544 |

*Note: All regressions include country fixed effects. *** Significantly different from zero at the 1% level, ** Significantly different from zero at the 5% level, P-values within parentheses. Values for the "Year of birth" variables represent changes with respect to 1890 (omitted).*

**Table B.4. Sensitivity of ECA and BMI correlation under different scenarios of PAL**

| PAL | **Variable** | **Model 3.2** | |
|---|---|---|---|
| | | females | males |
| Light | ECA | 0.000348<br>(0.0000)*** | 0.000203<br>(0.0000)*** |
| Moderate | ECA | 0.000318<br>(0.0000)*** | 0.000194<br>(0.0000)*** |
| Vigorous | ECA | 0.000247<br>(0.0000)*** | 0.000171<br>(0.0000)*** |

*Note: All regressions include country fixed effects.*** Significantly different from zero at the 1% level.*

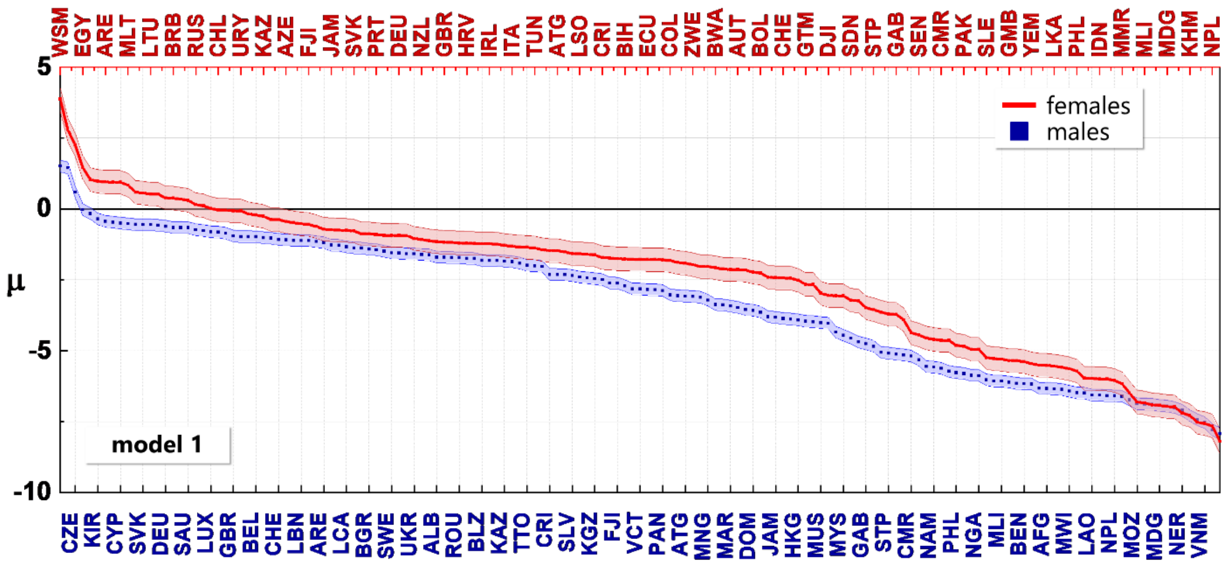


**Figure B.2. Country-specific fixed effects in BMI derived from Model 3.1.**

Moving from left to right, the countries are listed from largest to smallest fixed effect with respect to the US (omitted). For females (the solid red line), country labels appear at the top (in red); for males (blue-dotted line) labels appear at the bottom (in blue). The shaded areas represent 99% confidence bands for the estimated coefficients.

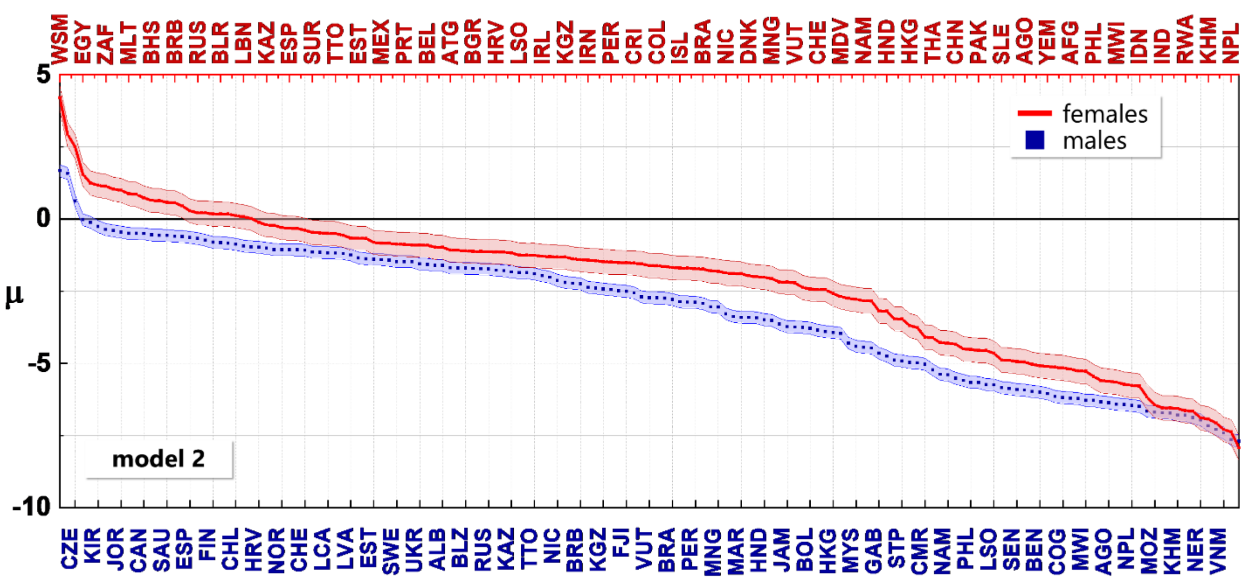


**Figure B.3. Country-specific fixed effects in BMI derived from Model 3.2.**

Moving from left to right, the countries are listed from largest to smallest fixed effect with respect to the US (omitted). For females (the solid red line), country labels appear at the top (in red); for males (blue-dotted line) labels appear at the bottom (in blue). The shaded areas represent 99% confidence bands for the estimated coefficients.

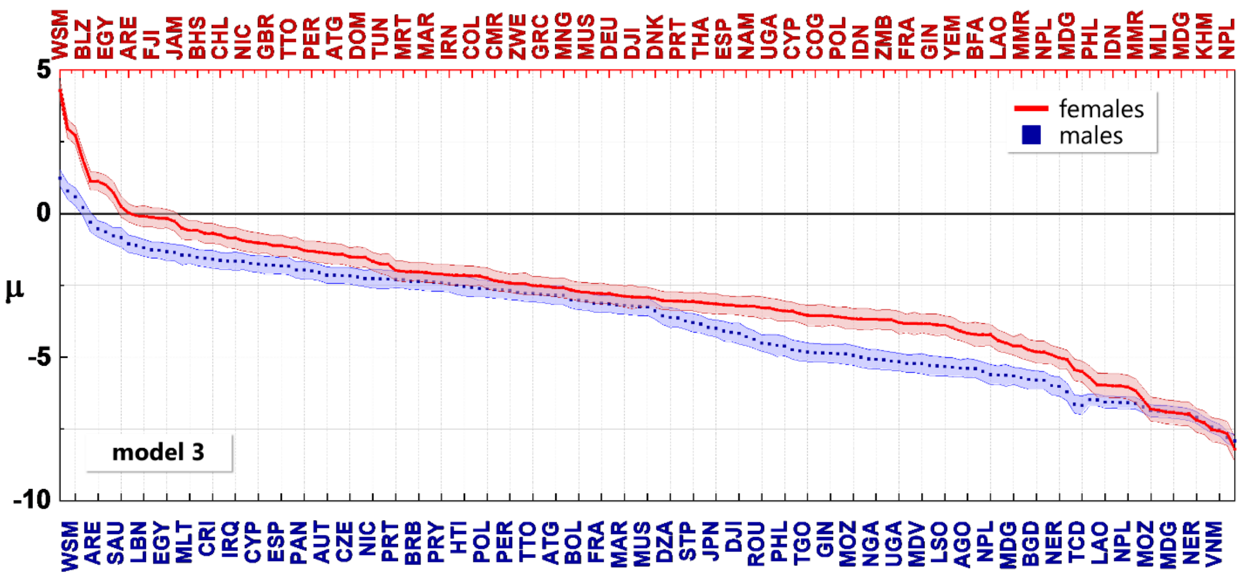


**Figure B.4. Country-specific fixed effects in BMI derived from Model 3.3.**

Moving from left to right, the countries are listed from largest to smallest fixed effect with respect to the US (omitted). For females (the solid red line), country labels appear at the top (in red); for males (blue-dotted line) labels appear at the bottom (in blue). The shaded areas represent 99% confidence bands for the estimated coefficients.

# APPENDIX C. CHAPTER 4

### *Limitations on the FAO's PoU methodology and the proposed extension*

It is important to acknowledge that the FAO's PoU methodology for estimating undernourishment suffers from several limitations, which need to be considered when analyzing the results presented in chapter 4. A key set of limitations are related to the scope and capability of the indicator to capture food insecurity. It is stated that the indicator focuses and captures only the yearly average per capita deficit in dietary caloric consumption which is a very specific aspect of the food insecurity (Cafiero et al. 2014). Another important limitation is that the PoU indicator does not capture within-year fluctuations in the acquisition of calories. As it was observed during disruptions throughout the food supply chain due to the pandemic outbreak in recent months, within-year fluctuations on food consumption play an important role in food security (Cafiero et al. 2014). Fluctuations in the accessibility and affordability of food can result in lower quality diets and/or short periods of lack of access to an adequate level of calorie consumption (Headey et al. 2020; Roberton et al. 2020). Moreover, the methodology does not allow for any biases that may exist in intra-household distribution of foods (Cafiero et al. 2014). An additional significant limitation is that it does not provide information on the degree of severity of the food insecurity conditions experienced by a population. The FAO's PoU only computes the share of the undernourished in a population but does not information report about the composition of undernourishment within that part of the population which might be valuable for policy makers.

Another group of limitations and criticism to the FAO's PoU methodology, that are more directly related and are more relevant to the results and extension presented in this chapter, are the ones regarding the choice of the probabilistic model to represent the distribution of dietary intake across the population. It is argued that some of this criticism arises from the misinterpretation of the probability distribution as the empirical distribution of the actual food consumption in the population (i.e.: the distribution that could be obtained through a food consumption census of the population) (Wanner et al. 2014b; Naiken 2021; Cafiero 2014). However, the correct interpretation of the distribution is as the level of dietary energy consumption that would be observed on a randomly selected individual in the population (Cafiero 2014; Naiken 2021). It follows that the PoU attempts to report the probability that a random selected individual from a given population would be found to be undernourished. In addition to this, the variability on the individual's energy requirements implies an extra challenge on choosing the appropriate "minimum" caloric threshold (Svedberg 2002; Cafiero 2014; Naiken 2021). This is also relevant when considering the extension proposed in this chapter to compute the share of population that overconsumes calories (Cafiero 2014; Naiken 2021). Following most recent advances in FAO's methodology it is possible to simultaneously estimate the prevalence of undernourishment and over consumption based on information the average and the distribution of daily average energy requirements (Naiken 2021). In this chapter, consistently with FAO's PoU recent advances (Cafiero 2014; Wanner et al. 2014b; Naiken 2021), I impute the lower caloric threshold in order to minimize the risk of overestimate the prevalence of undernourishment (i.e., choosing the minimum of the range of dietary energy requirement indicated by nutritionists as compatible with good health and normal physical activity for that group) (FAO/WHO 2001; Cafiero 2014). Similarly, I chose an upper bound, the average daily energy requirement—ADER--, that avoids the over estimation of the overconsumption of calories (i.e., choosing the upper bound of the range of ADER indicated by nutritionists as compatible with good health and normal physical activity for that group) (Naiken 2021).

Finally, there are certain limitations related to the choice of the functional form to represent the probabilistic distribution of calorie consumption of a representative individual in a given region. Historically, due to data restrictions, FAO's has reported the PoU under the assumption a lognormal distribution (Cafiero 2014; Wanner et al. 2014b). While this representation convenient for the purposes of analysis, is has limited flexibility, especially in capturing the skewness of the distribution (Wanner et al. 2014b). Hence, some reservation may be legitimate on the historical report as well as on future projections, especially for regions where the mean of the distribution present large growth in recent decades and/or is projected to considerably increase in the incoming decades. Future refinements on the approach presented in this chapter may include more flexible functional forms (e.g., three-parameter Skew-Normal, Skew-Log Normal, or the four-parameter Skew –T models) as viable alternatives to the previous lognormal (Wanner et al. 2014b).

***A pseudo-panel data set on average daily excessive consumption of calories***

In Chapter 2, I define, compute, and track over time and across countries excess calorie availability (ECA) as the difference between the average daily supply of calories (ADSC) and average dietary energy requirements (ADER), i.e., $ECA = ADSC - ADER$, where both measures evolve over time. Here we follow a similar strategy but adapting and framing the analysis into a global partial equilibrium framework, therefore we equate the supply of calories (from FAO's FBS) to the demand (average daily demand of calories). As a result, we define the average daily excessive consumption of calories (ADEC) as follows:

$$ADEC = ECA = ADSC - ADER.$$

Similarly to Chapter 2, we construct the pseudo-panel dataset from repeated cross-sections (Deaton 1985), spaced at five-year intervals. The dataset allows us to track changes in BMIs and their correlations with the ADEC for 21 country-specific age-sex cohorts born between 1890 and 1995 and observed between 1975 and 2015. The dataset covers 156 countries which together represented 95% of the global population in 2015. In anticipation to the projections to the economic projections to be undertaken using the framework of a partial equilibrium framework, we aggregate countries into 15 major geographic regions. This allows us to capture the long-run underlying systematic relationship between the ADEC and adult BMI while also dealing with potential eccentricities of individual countries and potential reporting errors to the FAO. This particular aggregation into 15 regions has the additional advantage of matching with the global model Simplified International Model of Crop Prices, Land Use and the Environment (SIMPLE) (Uris Lantz C Baldos and Hertel 2013) that we use in the economic projections towards 2050.

The underlying assumption on the long-run relationship between ADEC and adult BMI is that the changes in ADEC carry on information on the intertemporal effects of the excessive intake of calories on the observed changes in adult body weight. This assumption is consistent with the principle of the energy balance equation. However, authors recognize potential limitations on this approach when working with an average individual as reference and with a high level of aggregation. Firstly, even in healthy individuals (with no difficulty to absorbing nutrients) not all energy intake from food ends up absorbed in their bodies. In fact, the absorption is determined by the amount of metabolizable energy in the food and its digestibility. This varies among individuals and also depends on the specific food items eaten and on how those are cooked, implying that when working at an aggregated level and for the average individual, we might lose information on individual specifics. Secondly, the EE includes energy expended during biological processes, any physical activity performed, heat lost due to thermoregulation (radiant, conductive, and convective), and latent heat losses due to evaporation. The rate of energy expenditure (REE) accounts for most energy expended – roughly two-thirds (Hall et al. 2012). Hence, we follow the usual approximation for the total EE that is adjusting the basal metabolic rate (BMR) by different ratios of physical activity level (PAL). However, as in the case of the EI, variations at the individual level on EE during the different biological processes might be lost when working with an average individual as reference and a highly aggregated level.

Moreover, it should be noticed that the FAO reports are not free of criticism (Hall et al. 2009b; Svedberg 1999a). One recurrent criticism is that FBS likely underestimate food availability at consumers level in developing countries. This particularly important in rural based economies, where unreported subsistence production represents a substantial share of the households' consumption bundle (Hawkesworth et al. 2010). Another recurrent criticism is that one of the components of the FBS (often stocks) frequently take an outstanding unbalanced amount cause by inheriting all the statistical errors (including measurement errors, inaccuracies due to imprecise metrics on food losses within the different stages of supply chain, and on food waste at consumers level). Attending to these concerns, the FBS underwent some changes in methodology for data reported after 2017. The revised methodology reported by FAO mitigates some of those inaccuracies (FAO 2019a) by improving the estimates of the specific modules through the supply chain (e.g., stocks, food, feed, loss, etc.). Additionally, in the new methodology, imputations for the FBS components not reported by countries are generated by dedicated modules. The new approach implies a balancing mechanism to proportionally distribute the imbalances out among all the components (FAO 2019a). Furthermore, the revisited methodology incorporates a food loss module. This novel module reports essential information on food losses occurring across the different stages if the food supply chain up to and excluding the retail level. However, the availability of food at consumers level under the previous and also under the revisited methodology cannot be equated to food intake since the food waste imputations at the consumer level is still under review (FAO 2019a). This study is consistent with the latter, since equate the ADSC to the consumption of calories understood as the purchasing of calories; ergo the over-consumption of calories carries on information not only regarding the excessive intake of food but also regarding the calories that end up uneaten at the consumers' level (Barrera and Hertel 2020).

**Table C.1 Results for LSDV regressions on Model 4.1 for adult women and men.**

| Variable | | women | | men | |
|---|---|---|---|---|---|
| | | coefficient | p_value | coefficient | p-value |
| **ADEC** | | 0.0002158* | 0.055 | 0.0003725*** | 0.000 |
| **Age group** | 25 | 1.102923*** | 0.000 | 1.195964*** | 0.000 |
| | 30 | 2.198653*** | 0.000 | 2.182427*** | 0.000 |
| | 35 | 3.249096*** | 0.000 | 2.992504*** | 0.000 |
| | 40 | 4.216125*** | 0.000 | 3.660322*** | 0.000 |
| | 45 | 5.062172*** | 0.000 | 4.220509*** | 0.000 |
| | 50 | 5.759925*** | 0.000 | 4.686155*** | 0.000 |
| | 55 | 6.302513*** | 0.000 | 5.0587*** | 0.000 |
| | 60 | 6.684201*** | 0.000 | 5.338898*** | 0.000 |
| | 65 | 6.908474*** | 0.000 | 5.533227*** | 0.000 |
| | 70 | 6.981457*** | 0.000 | 5.649988*** | 0.000 |
| | 75 | 6.918327*** | 0.000 | 5.700924*** | 0.000 |
| | 80 | 6.734975*** | 0.000 | 5.696918*** | 0.000 |
| | 85 | 6.240975*** | 0.000 | 5.521108*** | 0.000 |
| **Year of birth** | 1895 | 0.3308762 | 0.264 | 0.2753695* | 0.063 |
| | 1900 | 0.6829636** | 0.016 | 0.6058509*** | 0.000 |
| | 1905 | 1.050823*** | 0.000 | 0.9673373*** | 0.000 |
| | 1910 | 1.434808*** | 0.000 | 1.35364*** | 0.000 |
| | 1915 | 1.83895*** | 0.000 | 1.755655*** | 0.000 |
| | 1920 | 2.260583*** | 0.000 | 2.168493*** | 0.000 |
| | 1925 | 2.697693*** | 0.000 | 2.587819*** | 0.000 |
| | 1930 | 3.146643*** | 0.000 | 3.009341*** | 0.000 |
| | 1935 | 3.652658*** | 0.000 | 3.46876*** | 0.000 |
| | 1940 | 4.171914*** | 0.000 | 3.918437*** | 0.000 |
| | 1945 | 4.69702*** | 0.000 | 4.361493*** | 0.000 |
| | 1950 | 5.220159*** | 0.000 | 4.798399*** | 0.000 |
| | 1955 | 5.735278*** | 0.000 | 5.230721*** | 0.000 |
| | 1960 | 6.168471*** | 0.000 | 5.620699*** | 0.000 |
| | 1965 | 6.575035*** | 0.000 | 6.000606*** | 0.000 |
| | 1970 | 6.951683*** | 0.000 | 6.368141*** | 0.000 |
| | 1975 | 7.293686*** | 0.000 | 6.720973*** | 0.000 |
| | 1980 | 7.590093*** | 0.000 | 7.049327*** | 0.000 |
| | 1985 | 7.832624*** | 0.000 | 7.349038*** | 0.000 |
| | 1990 | 8.014414*** | 0.000 | 7.612211*** | 0.000 |
| | 1995 | 8.127946*** | 0.000 | 7.83018*** | 0.000 |
| **Constant** | | 17.27239*** | 0.000 | 18.41231*** | 0.000 |
| **R-squared** | | 0.9041 | | 0.9672 | |
| **Observations** | | 1,890 | | 1,890 | |

*Note: All regressions include country fixed effects. *** Significantly different from zero at the 1% level, ** Significantly different from zero at the 5% level, * Significantly different from zero at the 10% level P-values within parentheses. Values for the "Year of birth" variables represent changes with respect to 1890 (omitted). For the ADEC imputation we assumed moderate physical activity levels.*

**Table C.2. Sensitivity of ECA and BMI correlation under different scenarios of PAL.**

| | | Model 4.1 | |
|---|---|---|---|
| PAL | **Variable** | women | men |
| Light | ADEC | 0.0002419<br>(0.032)** | 0.0003787<br>(0.001)*** |
| Moderate | ADEC | 0.0002158<br>(0.055)* | 0.0003725<br>(0.000)*** |
| Vigorous | ADEC | 0.0001551<br>(0.168)*** | 0.0003578<br>(0.000)*** |

*Note: All regressions include country fixed effects. *** Significantly different from zero at the 1% level, ** Significantly different from zero at the 5% level, * Significantly different from zero at the 10% level P-values within parentheses.*

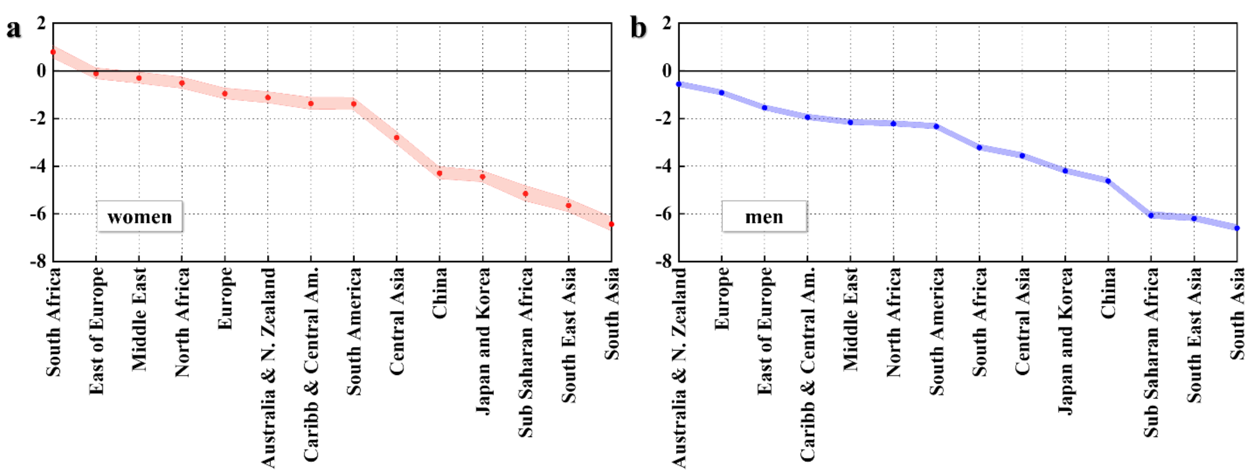


**Figure C.1. Region-specific fixed effects in BMI derived from Model 4.1.**
Moving from left to right, the countries are listed from largest to smallest fixed effect with respect to the US (omitted). For women (red dots, panel **a**) and for men (blue dots, panel **b**) region labels appear at the bottom. The shaded areas represent 95% confidence bands for the estimated coefficients.

### *Baseline projections of average adults BMI*

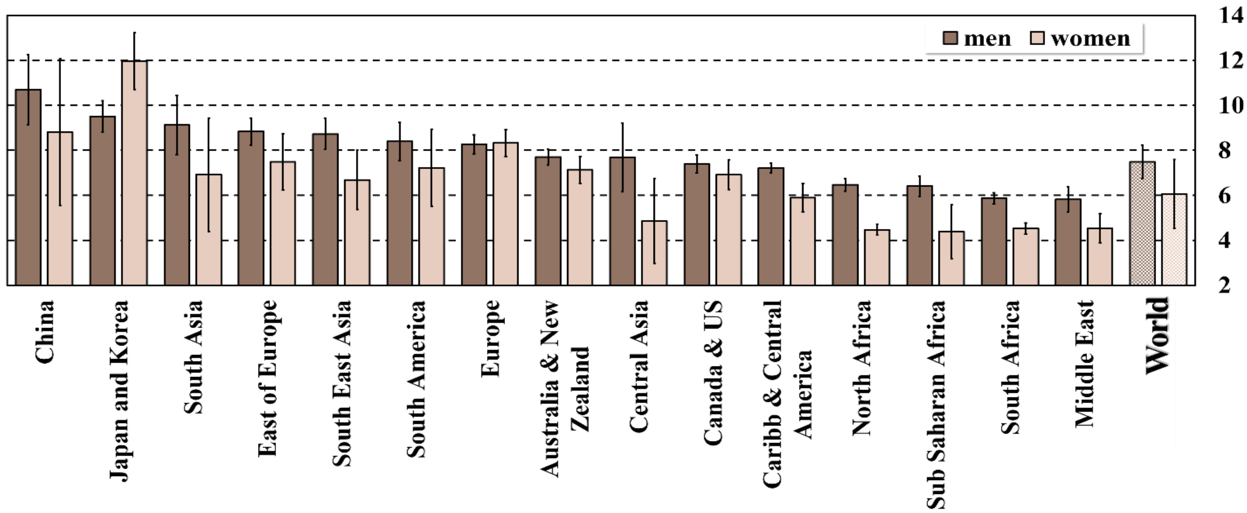


**Figure C.2. Baseline projections of average adult BMI towards 2050.**
The bars represent the percentage change in average BMI projected from 2015 to 2050 in the baseline scenario, for both, adult men and women. Error bars represent 95% confidence intervals.

### *Flexitarian Diets results*

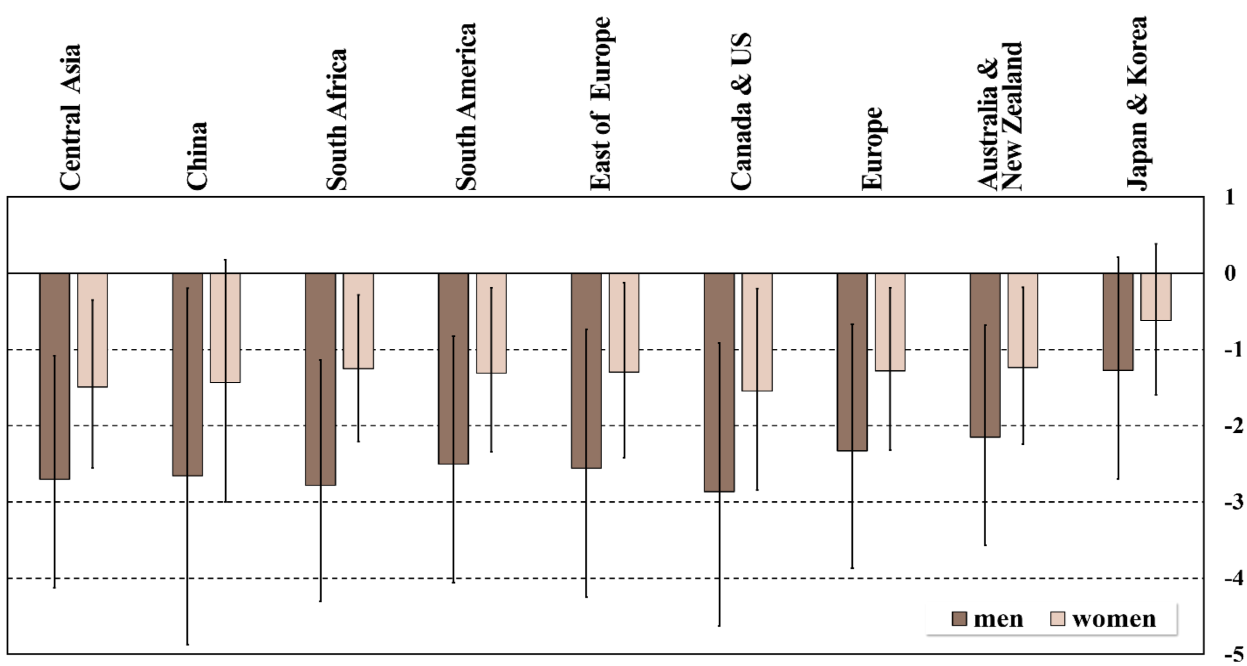


**Figure C.3. Projected changes in BMI for men and women.**
The bars represent the projected percentage changes with respect to the 2050 baseline case caused by shifting towards diets following intake recommended in the flexitarian diets pathway (FLX) in those regions. Omitted regions are not subjected to the diet changes. Error bars represent 95% confidence intervals.

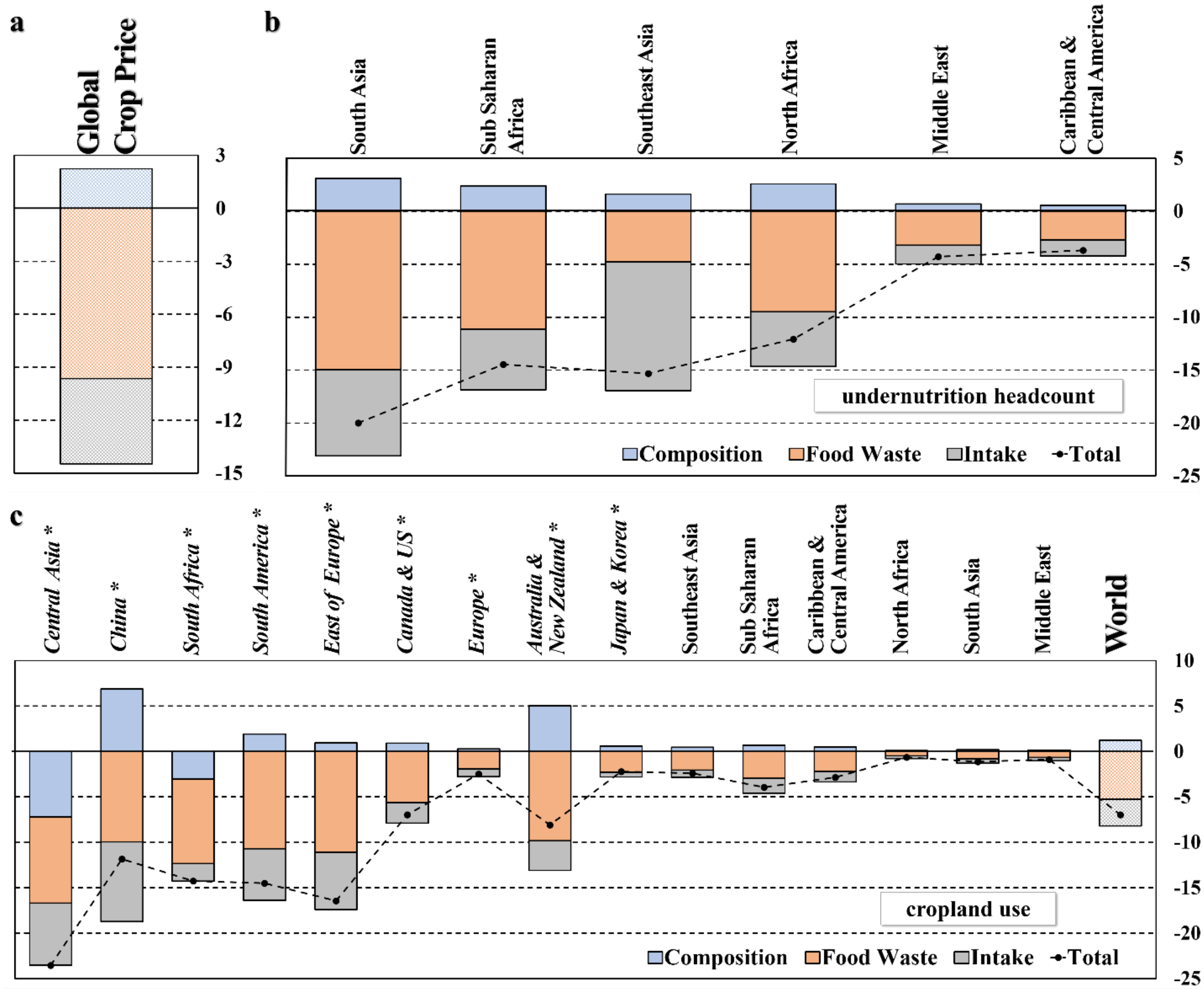


**Figure C.4. Shifting towards healthy dietary intake levels reduce caloric undernutrition and land use.** Bars represent percentage changes in 2050 baseline outcomes caused by shifting towards diets following flexitarian diets pathway (FLX) in the regions in italic and marked with asterisk starting with Central Asia and ending with Japan and Korea. Regions exogenously shifted to the FLX are in italic and marked with an asterisk, consumption patterns in the remaining regions are endogenous. Panel **a** represents the percentage change in global crop price, panel **b** represents reductions in undernutrition headcounts in those regions where diets are endogenously determined as a function of prices, and panel **c** represents changes in cropland use. Colored segments of each bar decompose the total change into three different components of the shift from current consumption levels: the change within the food basket composition (i.e., the FLX scenario implies reductions in livestock consumption with respect to the baseline case), reductions in food intake, and reductions in food waste (Barrera and Hertel 2020).

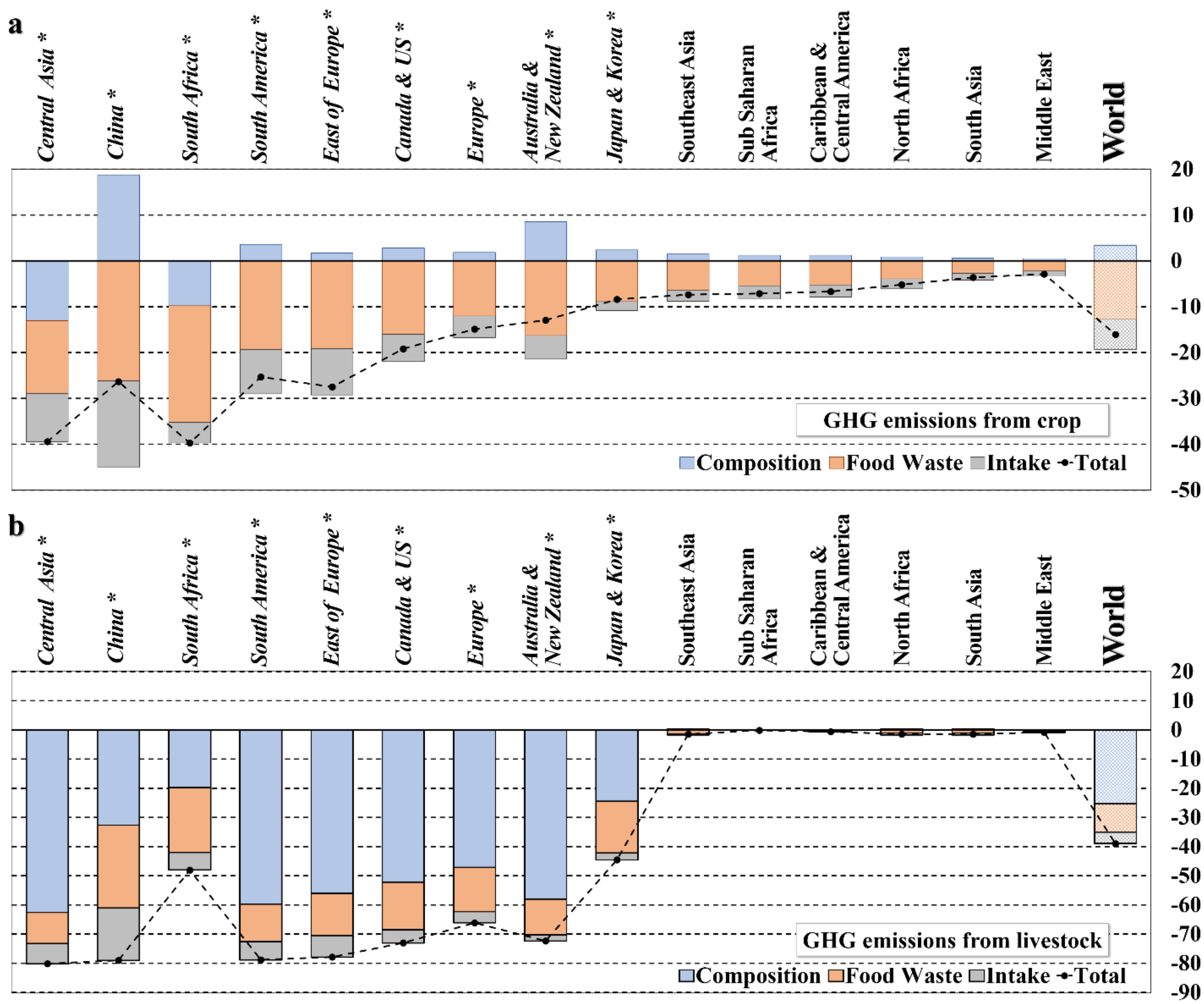


**Figure C.5. Shifting towards healthy dietary intake levels reduce Green House Emissions.**

Bars represent percentage changes with respect to the 2050 baseline case, caused by shifting towards diets following flexitarian diets pathway (FLX) in the regions in italic and marked with an asterisk. Results represent the breakout between three different components within the shifts in diets: the change within the food basket composition (i.e., the FLX scenario implies reductions in livestock consumption with respect to the baseline case), reductions in food intake, and reductions in food waste (Barrera and Hertel 2020).

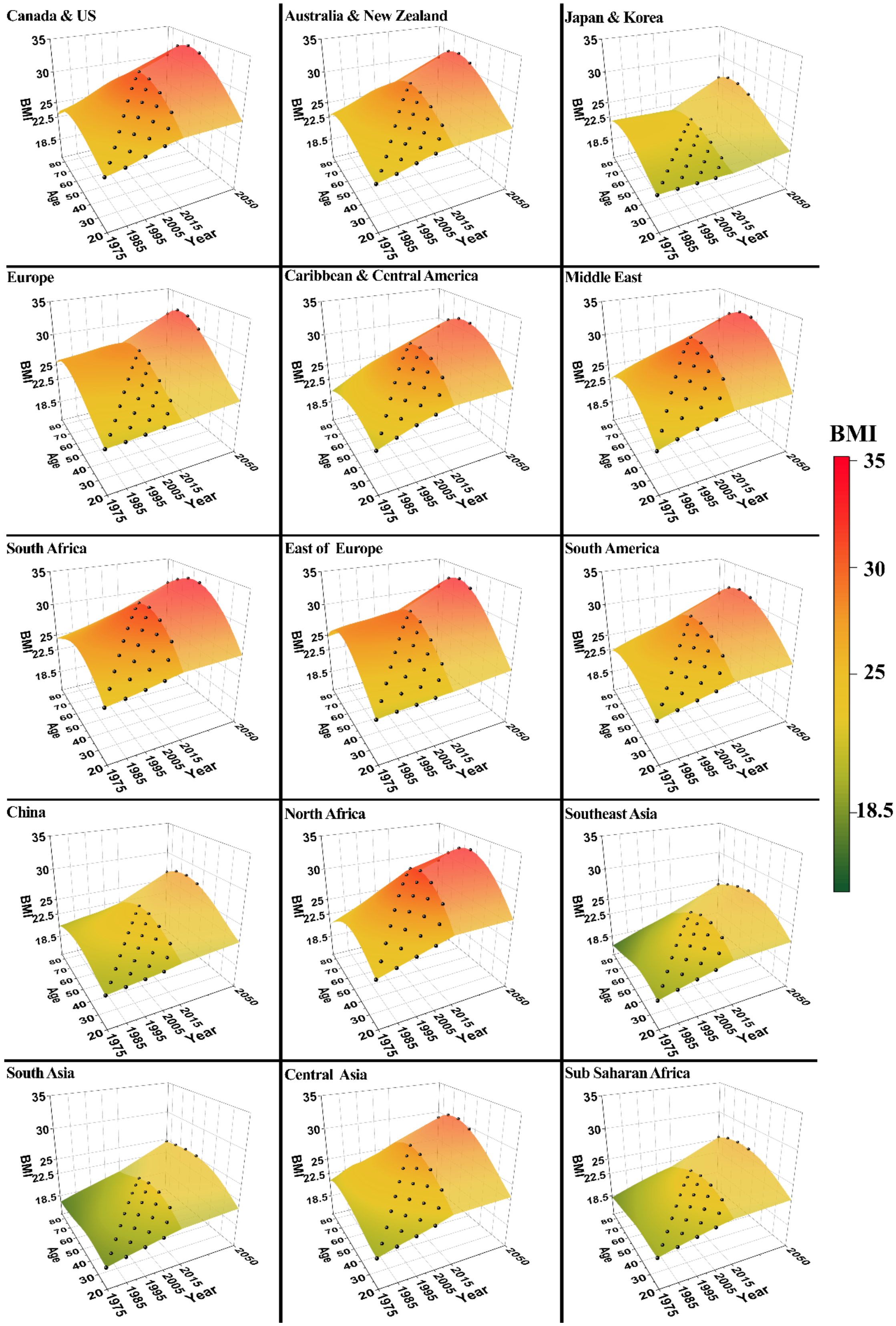


**Figure C. 6. BMI across cohorts and over time at different income levels for adult women.**

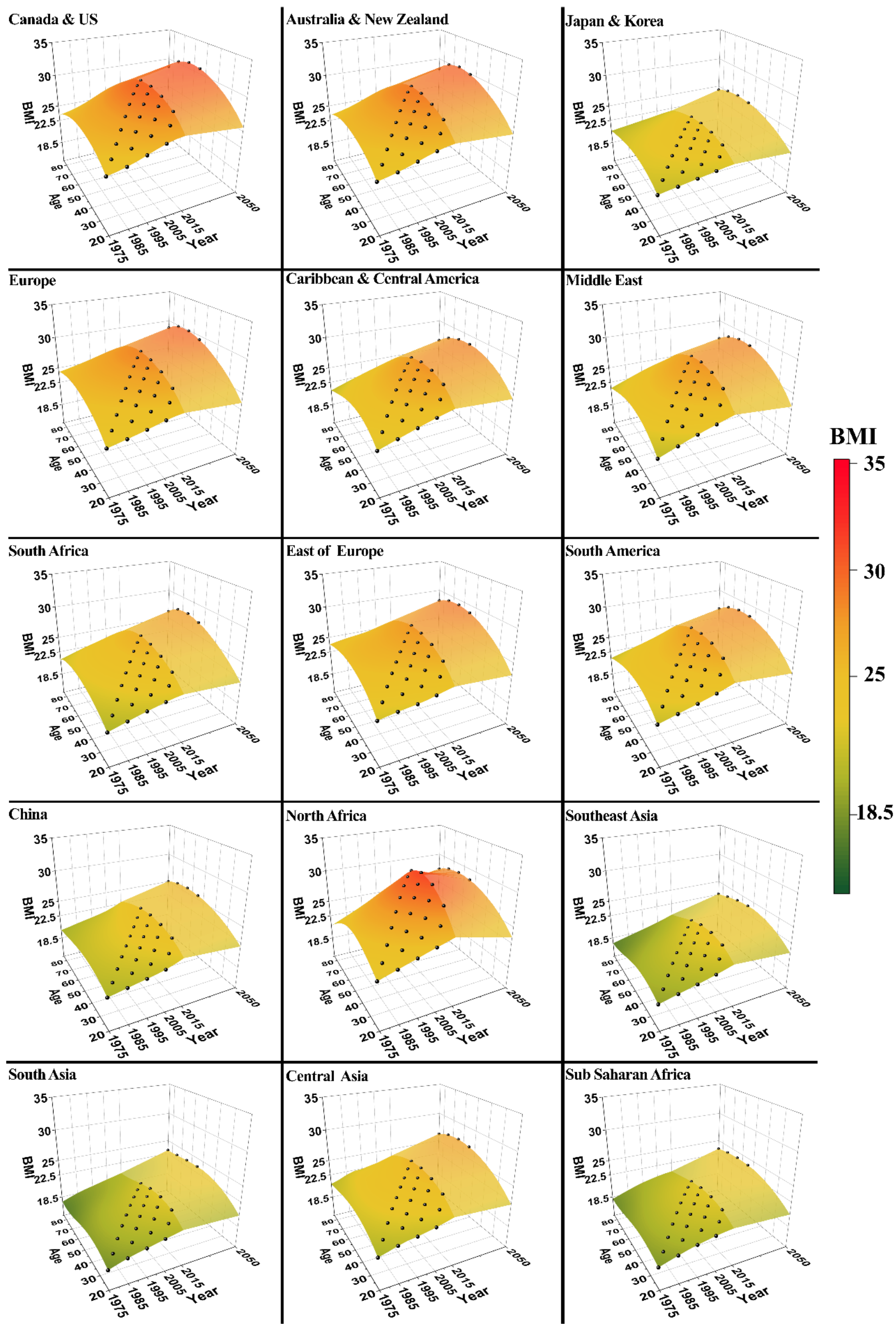


**Figure C. 7. BMI across cohorts and over time at different income levels for adult men.**

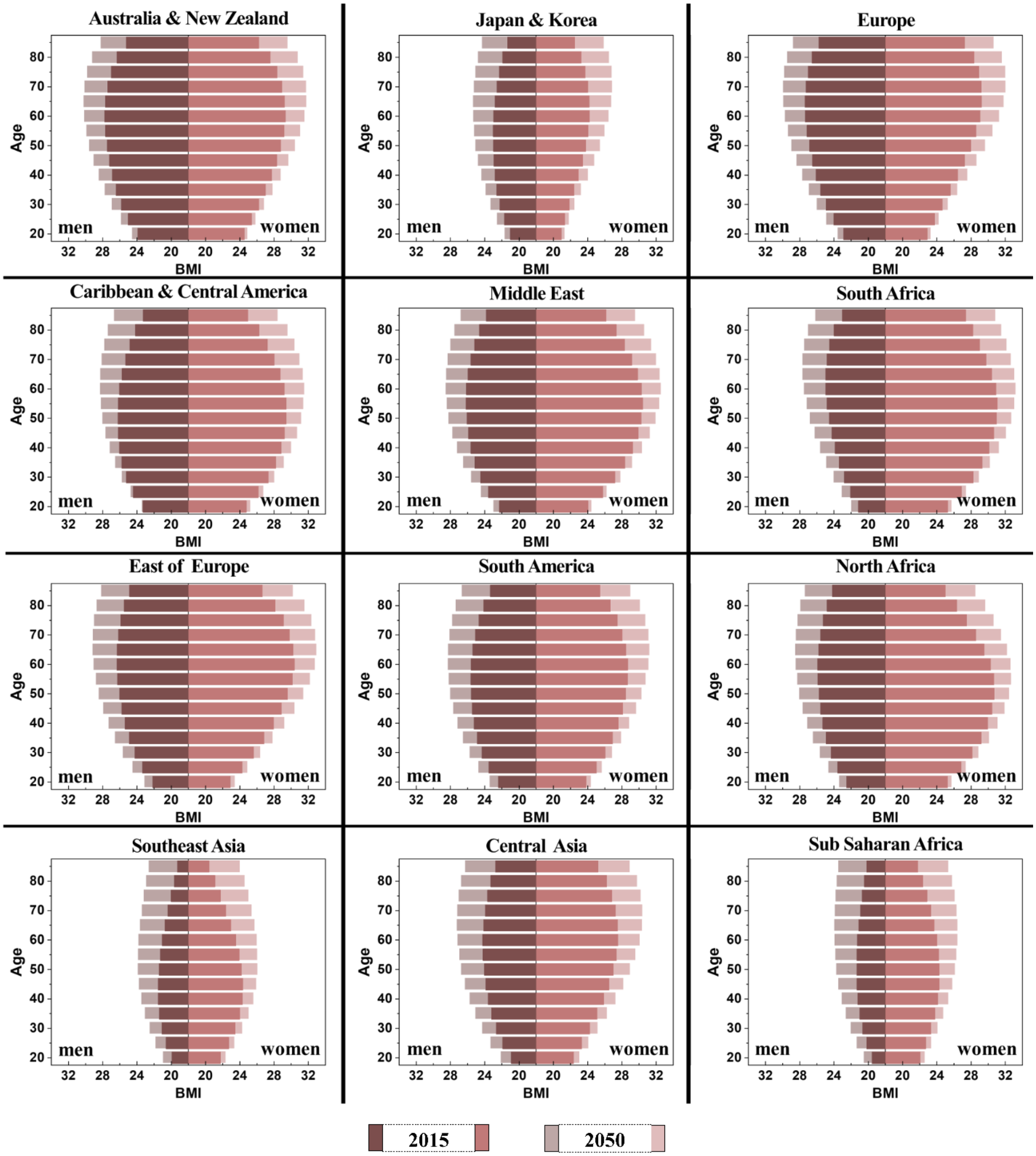


**Figure C. 8. Projections of the age-specific average adult BMI.**

## APPENDIX D. THE SIMPLE MODEL

### *Overview of the SIMPLE model*

In the Simplified International Model of Crop Prices, Land Use and the Environment (SIMPLE) (Thomas W. Hertel and Baldos 2016c), per capita consumer demands for three food types: crops, livestock and processed foods are log-linear functions of price and income, with these food demand elasticities varying as a function of per capita income in each region. Based on international cross-section estimates by (Muhammad et al. 2011), the absolute values of the income and price elasticities for all food types fall as incomes grow. Regional food demand is obtained by multiplying per capita demand by regional population.

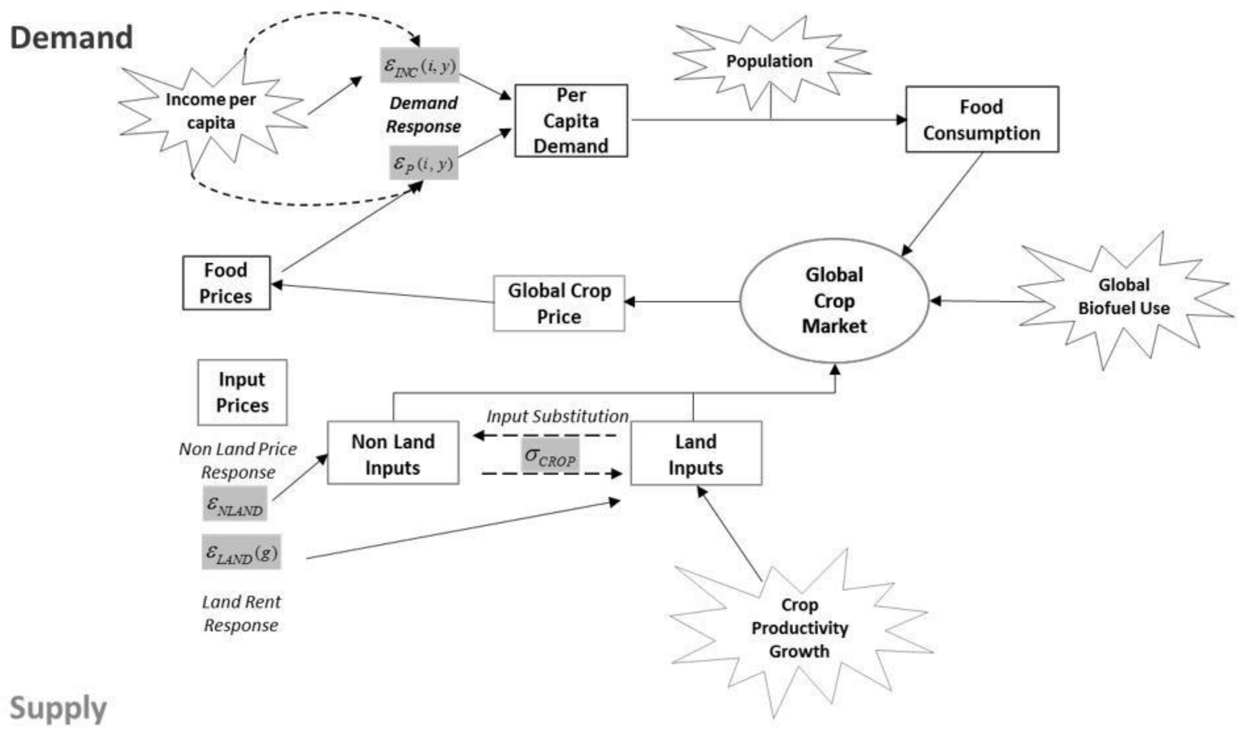


**Figure D.1. Graphical description of the SIMPLE model.**
SIMPLE is a global partial equilibrium model of the food sector. In this model, the per capita consumer demands for three food types: crops, livestock and processed foods are log-linear functions of price and income, and regional food demand is obtained by multiplying per capita demand by regional population. Global crop production is specified for each of the 15 model regions represented in the model as a constant elasticity of substitution function of land and non-land inputs, each with different yields and potentially differing rates of technological progress.

Since livestock and processed foods are valued-added products, these are produced within the consuming region using crop and non-crop inputs and therefore have region- specific prices. A substantial share of crop demands in the model is *derived demands*, obtained from the consumer demands for value-added food products. This is important since technological change and factor substitution in the livestock and processed food industries can lead to varying intensities of crop use in these food products. The global demand for crops is the summation of final demands and derived demands summed over all regions. The global demand for crop feedstocks in biofuels is exogenously specified and serves as an addition to global crop demand.

Global crop production is specified for each of the 15 model regions as a constant elasticity of substitution function of land and non-land inputs, each with different yields and potentially differing rates of technological progress. Cropland supply elasticities, which vary by region, are based on the estimates of Gurgel et al. (2007) and (Ahmed et al. (2009). Non-land factor supplies to agriculture are also less than perfectly elastic supply, but are more price responsive than land supply, based on the estimates offered by OECD (2001). Equilibrium in SIMPLE is attained when global crop supply equals global demand where the equilibrating variable is the global price of crops.

***Description of database and growth rate assumptions***

*SIMPLE database:* We construct separate base data for the years 2001 and 2006. Data from external sources include income, population, consumption expenditures and crop production and their sources are as follows. Information on GDP in constant 2000 USD and population are obtained from the World Development Indicators (2011) and from the World Population Prospects (2013), respectively. Data on cropland cover and production, utilization and prices of crops are derived from FAOSTAT (2011). We further converted the crop quantities into corn- equivalent quantities using weights constructed from world crop prices and the world price of corn. We then combined the data above with additional information on industry cost and sales shares in order to construct the rest of the database. The amount of crop feedstock used by the global biofuel sector is constructed using the sales shares by the global crop sector taken from GTAPBIO V.6 (Taheripour et al. 2007).Shares constructed from the crop utilization data were then used to split the remaining corn-equivalent crop quantities across 15 geographic regions and across different uses (i.e. food, feed and raw materials for processed food).

We then calculated the global crop price from the value and corn-equivalent quantity data of crop production. Using the global price and the allocated corn-equivalent crop quantities, we then derived the value of crop input use in the livestock and processed food industries. Under the assumption of zero profits, we calculated the total value of land and non-land input costs in the regional crop sectors using GTAP v.6 cost shares as our guide. We again used GTAP v.6 cost shares and the value of crop input usage in the livestock and process food industries to impute the value of non-crop inputs used in these sectors. Under the assumption of zero profits, we then derive consumer expenditures and price indices for livestock and processed food commodities. Land rents and crop yields for each geographic region were derived using the value of land inputs, corn-equivalent crop production and cropland areas.

*Key growth rates in the baseline scenarios:* We start by simulating the model over the historical period 2005 to 2015 (10-years) and then projecting towards 2050. For this experiment, we implement shocks in population, per capita incomes, total factor productivity (TFP) growth, and biofuel consumption. We then compare the simulated changes for the period 2005 to 2015 with the actual changes from our data base on average adult BMI for men and women. Growth rates for population and income were derived from the Shared Socioeconomic Pathway 2 (Fricko et al. 2017). TFP growth were based on the historical estimates (Ludena et al. 2007a) and by (Fuglie 2012). The growth in global biofuel consumption from the "Current policies" scenario published in the World Energy Outlook (International Energy Agency 2019). These forecasts are based on the results of a detailed world energy model given exogenous growths in GDP and population as well as assumptions on future energy prices and technology. We also calculate the growth in global biofuel consumption from the "Current policies" scenario published in the World Energy Outlook (International Energy Agency 2019). These forecasts are based on the results of a detailed world energy model given exogenous growths in GDP and population as well as assumptions on future energy prices and technology. TFP growth rates for the crop and the livestock sectors are based on the projections from (Ludena et al. 2007a) which are generated under the assumption of gradual convergence in productivity across regions. Growth rates of each driver for the period 2005 to 2015 (2050) are listed in Table D1.

**Table D.1. Assumed growth rates of exogenous variables (in % per annum rates)**

| Region | Population Annual rate | Per Capita Income Annual rate | Biofuels | TFP Annual rate |
|---|---|---|---|---|
| Eastern Europe | -0.35 | 3.23 | | 1.45 |
| North Africa | 1.06 | 3.25 | | 1.35 |
| Sub Saharan Africa | 2.46 | 4.43 | | 0.69 |
| South America | 0.78 | 2.85 | | 1.44 |
| Australia/New Zealand | 0.88 | 1.39 | | 0.89 |
| European Union | 0.03 | 1.23 | | 1.03 |
| South Asia | 0.99 | 5.70 | | 0.84 |
| Central America | 0.98 | 2.37 | | 1.43 |
| Southern Africa | 0.45 | 3.24 | | 1.25 |
| Southeast Asia | 0.80 | 4.26 | | 1.40 |
| Canada/US | 0.64 | 1.10 | | 1.28 |
| China | -0.13 | 5.77 | | 1.75 |
| Middle East | 1.46 | 1.89 | | 1.10 |
| Japan/Korea | -0.39 | 1.74 | | 1.40 |
| Central Asia | 1.18 | 4.72 | | 1.45 |
| World | | | 6.96 | |

*Note: From left to right – Population and per capita Income growths from SSP2* (Fricko et al. 2017). *The increase in demand for biofuels from* (International Energy Agency 2019) *. Future TFP growth rates from Ludena et al. (2007) using* (Fuglie 2012) *as regional scalars.*

### *Model implementation and systematic examination of uncertainties within the model*

We implement SIMPLE and the double burden of malnutrition module using the GEMPACK program (Harrison and Pearson 1996) which has many useful features for purposes of analysis (http://www.monash.edu.au/policy/gempack.htm). One of these is the subtotals feature developed by Harrison, Horridge, and Pearson (2000). The authors note that estimating the contribution of exogenous shocks in general equilibrium models will depend on the assumed path from one equilibrium point to another. They propose a numerical integration technique that exactly partitions the impacts of different exogenous shocks on endogenous variables of interest under the assumption that the assumed path is a straight line. This tool is critical in our analysis of the relative contribution of each key driver of global food security.

Results of simulations often hinge critically on values of key exogenous inputs (parameters and/or shocks applied to exogenous variables) (DeVuyst and Preckel 1997). GEMPACK is equipped with practical methods for systematic investigation of the impacts of variations in these key inputs conducting for any model solved using GEMPACK (Pearson and Arndt 2000; DeVuyst and Preckel 1997). In this process instead of projecting the endogenous variables within the model from a baseline to a projected period by solely "shocking" the key exogeneous variables and/or modifying parameters by their mean expected changes, the "shocks" on key exogenous inputs are drawn from a pool of potential expected changes, usually a triangular approximation for a normal distribution around the media of their respective expected changes. As a result, the procedure reports estimations of the mean and standard deviation for any endogenous variable in the model, resulting in a projection of future distributions of endogenous variables rather than just an average expected projection.

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