A HOLISTIC APPROACH TO THE ENVIRONMENTAL EVALUATION OF FOOD WASTE PREVENTION

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Appendix (D) Literature review: the rebound effect

The rebound effect has been originally defined by energy economists as the increase in the supply of energy services due to behavioural and systemic responses to improvements in technological efficiency causing a decrease in the effective price of energy services (Khazzoom 1980; Brookes 1990; Greening et al. 2000). Although none of food waste prevention studies addresses rebound effects related to food waste prevention, there is a few studies that have looked to this issue in a similar context.

Alfredsson (2004) explores the quantitative direct and indirect impacts on energy consumptions and carbon dioxide emissions if households in Sweden were to adopt “greener” consumption patterns addressing three categories of consumption: travel, housing, and food. Analyzing a sample of 1104 Swedish households, the study shows that switching to a “greener diet”, consisting more food intake from lower down the food chain (e.g. vegetables and fruits) and to a lesser extent from higher up the food chain (e.g. diary products, fish and meat (Alfredsson, 2004, p.516), reduces energy consumption by 5% and CO2 emissions by 13% compared to “current diet”. Nevertheless, total analysis shows that CO2 emissions increases by 2% (i.e. backfire) as money saved will be spent on energy-intense categories. (Lenzen and Dey, 2002) have also looked at the consequences of changing of switching to a “greener diet” in Australia. With 30% reduction in total food expenditure and considering the rebound effect, the net effect is backfire for energy consumption by 4-7% although CO_2 emissions reductions by 18-20%. But they also show huge variation of rebound effect 45-50%.

The impact of the rebound effect due to savings made by purchasing less food and thus reducing food waste has been also examined by Druckman et al. (2011). The study looks at the redound effect associated with reducing food purchased by one third by eliminating food waste. It estimated that the rebound effect will reduce environmental benefits by 52%. This considerable rebound effect emphasizes the importance of including it in the modeling process of FW prevention activities (Bernstad and Cánovas, 2015). However, the estimation here is highly uncertain due to the high level of aggregation of expenditure categories (i.e. 12 categories) and the use of a UK average household despite the variation of the rebound effect estimates among numerous income groups with different demographic characteristics (Chitnis et al., 2014)

In addition to methodological differences in modelling the rebound effect as discussed above, the modelling process has a few considerations.

The first consideration is the method applied to calculate the rebound effect. The rebound effect has been approached in the literature using a variety of quantitative methods, among which those based on econometrics are widespread due to their robustness and flexible data requirements (Sorrell 2007). Within these, three approaches are the most popular: those based on marginal shifts in income groups (Alfredsson 2004; Thiesen et al. 2008), expenditure elasticities or Engel curves (Murray 2009; Chitnis et al. 2012) and demand systems (Mizobuchi 2008; Brännlund et al. 2007). Among these, the latter stands out due to the capacity to capture both the income and the substitution effects from changes in real income (Chitnis and Sorrell 2015). In the context of environmental assessment, some authors speak of the 'environmental rebound effect' (ERE) (Goedkoop et al. 1999; Font Vivanco et al. 2016), which focuses on the lifecycle environmental consequences of overall demand changes as a result of behavioural and systemic responses to technical efficiency improvements in products that liberate or bound consumption and production factors. The ERE offers a number of advantages in the context of environmental assessment, such as the representation of the rebound effect as multiple environmental indicators and the increased technology detail (Font Vivanco and van der Voet 2014).

The second consideration stems from a conclusion made by WRAP that 50% of freed effective income is re-spent on buying higher quality products. In other words, households pay higher prices for the same functional unit. This conclusion is contrary to Druckman et al. (2011) who assume re-spend is not allowed on the same category when modelling the rebound effect. For the purpose of this study, the authors agree on WRAP's approach and therefore include the re-allocation of expenditure savings in purchasing food products, as shown in scenario 2 of modelling the sensitivity analysis, see Appendix E.

However, considering a monetary-based model, this scenario would overestimate the increase in GHG emissions with increasing prices due to the linearity of the model: paying higher prices per functional unit increases GHG emissions in the same way as buying more conventional products (Vringer and Blok, 1996; Girod and de Haan, 2010). This 'unrealistic' concept has led (Hertwich, 2005) to propose a household consumption model based on a functional unit and adopt price (money paid per functional unit) as a measure of quality. It reduces the magnitude of overestimation in modeling the rebound effect, and allows integration between household consumption and LCA process-based data. This economic-value-based FU model was also recommended as a better method to quantify environmental impacts for a given expenditure(van der Werf and Salou, 2015). For the purpose of this study, we assume a constant physical functional unit. In other words, additional money will be spent to quality-oriented products having the same nutritional and compositional value as conventional food products.

The last consideration is the variation of environmental impacts of conventional and quality-oriented products. There is abundant literature that show significant variations among studies that make it difficult to draw a conclusive picture on the environmental impacts of conventional and quality oriented food products (Tuomisto et al., 2012; Meier et al., 2015). For example, reviewing bottom-up LCA studies looking at agricultural food products, Literature is abundant with studies in favour of organic farming: corn and soy (Pelletier et al., 2008), rice (Blengini and Busto, 2009), wheat and wheat-based products (Braschkat et al., 2003; Meisterling et al., 2009). On the other hand, there are various studies conclude that organic farming has a higher environmental burden: apple orchard (Alaphilippe et al., 2013), pear (Liu et al., 2010), beans (Abeliotis et al., 2013). Inconsistency in results of environmental impacts of normal and quality-oriented meat, dairy and poultry products are also reported (Thiesen et al., 2008; van der Werf and Salou, 2015). These considerable variations and inconsistencies could be attributed to various reasons: lower yields in organic farming, the selection of the functional unit of the study, the general drawbacks of LCA modeling discussed before, and the quality of data and the specific-system processes used in these studies. Variations of environmental impacts of different categories of food products were also reported in a top-down study by (Girod and de Haan, 2010). Based on a household consumption model based on functional units, Girod’s work shows that purchasing more expensive food products give you overall reduction of 8% but when you look at all sub-categories, variation varies ranges between -48% and 20%.

To sum up, modelling the rebound effect requires the consideration of all factors discussed above, in particular the impact of upgrading to purchase quality oriented products. For the purpose of this study, Freed Effective Income (FEI) will be allocated by calculating the marginal budget shares (MBS) for each consumption category i. The MBS are derived using a linear specification of an Almost Ideal Demand System (AIDS), a demand system model developed by (Deaton and Muellbauer, 1980) with properties that makes it more advantageous to competing models (Deaton and Muellbauer, 1980; Chitnis and Sorrell, 2015). In addition to that, we introduce different scenarios to address the uncertainty in modeling the rebound effect and include the variation in GHG emissions between conventional and quality-oriented products. Appendix xx depicts scenarios considered in this study.

Appendix (E) Modelling of the rebound effect: the study scenarios

This study considers five scenarios addressing uncertainty related to the modelling of the rebound effect. Figure (E.1) depicts these scenarios.

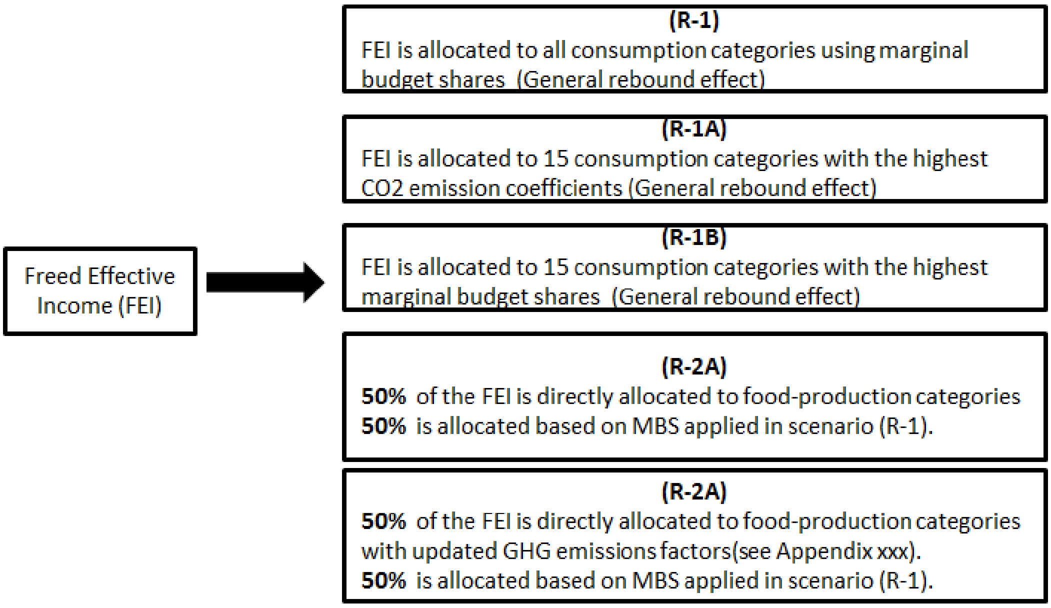

Figure E.1 Sensitivity analysis scenarios considered in modelling the rebound effect.

[1] Behaviour-as-usual (R-1):

A reference scenario that assumes the re-spend occurs in line with elasticity of expenditure calculated using the methodology discussed in section 2.3. Freed Effective Income (FEI), listed in appendix xx, is used to distribute savings made due to food waste prevention activities on each consumption category.

[2] Major spending scenario: GHG based (R-1A):

This sub-scenario was introduced to investigate the level of variation when changes in MBS occur. Using the top 25 major consumption categories accountable of nearly 90% of expenditure, this scenario allocates the re-spend to the top 15 consumption categories in terms of CO_2. The distribution was allocated among these categories based on weight of each category as calculated in the original model (section 2.3). Table xx shows the RE coefficient used in this scenario

[3] Major spending scenario: expenditure based (R-1B)

Similar to the approach used in scenario R-1A, this sub-scenario allocates effective savings into the top 15 consumption categories in terms of monetary expenditure. Appendix I allocations factors used for both sub-scenarios, R-1A and R-1B.

[4] Up-trade scenario: Exiobase GHG intensities (R-2A)

This scenario is based on a finding by WRAP that 50 % of savings due to food waste prevention activities will be re-spent on purchasing quality oriented food products. The remaining 50% would follow the same pattern of spending in scenario R-1. This scenario assumes that GHG emissions factors are the same for both conventional and quality-oriented products.

[5] Up-trade scenario: updated GHG intensities (R-2B)

This scenario investigates the variation in GHG intensities as a result of purchasing quality oriented products. Conversion factors, listed in table E.2, are used to update GHG emissions factors of food product categories in Exiobase database.

Data on conventional vs organic impacts were collected from a recent review Meier et al. (2015). In January 2016, this database was supplemented by Web of Science searches for missing product categories. Specifically, we did web searches for: LIFE CYCLE ASSESSMENT or LCA and ORGANIC and BEVERAGE, COTTON, and RICE. We assumed there was no difference in the environmental impact of the conventional and up-traded versions of “Fish and other fishing products”, “Fish products”, and “White Spirit & SBP”. Dairy impacts were assumed to be the same as for milk, because the largest contributor to the environmental profile of dairy products is the raw milk production at dairy farms (Djekic et al, 2014). “Animal products not elsewhere classified” were calculated from studies of egg production. Other definitions are listed in the table.

Table E.2 lists average GHG emission factors used to update Exiobase database. A detailed list of data and background information are available in Appendix. Increases reported coefficients in Table (E.1) could be attributed to various factors such as size and shape of fruits and vegetables, cut of meat, range and ingredients used, packaging materials used and provenance.

Table (E.1) Average variation coefficients of Exiobase GHG emission factors. A detailed list of coefficients is presented in Appendix G.

No.	Products	Change (%) Positive = conventional better; negative = organic better	Comment
1	Paddy rice	7.44	
2	Wheat	6.36	
3	Cereal grains nec	-23.42	
4	Vegetables, fruit, nuts	9.84	
5	Oil seeds	-23.8	
6	Sugar cane, sugar beet	-38.37	
7	Plant-based fibers	-58.33	
8	Crops nec	-2.45	
9	Cattle	18.39	Mean of "Products of meat cattle"
10	Pigs	27.36	Mean of "Products of meat pigs"
11	Poultry	20.66	Mean of "Products of meat poultry"
12	Meat animals nec	22.41	Mean of "Products of meat cattle, pigs, and poultry"
13	Animal products nec	22.73	Eggs
14	Raw milk	0.5	
15	Fish and other fishing products; services incidental of fishing	0	Assumption: no difference between conventional and traded up good
16	Products of meat cattle	18.39	
17	Products of meat pigs	27.36	
18	Products of meat poultry	20.66	
19	Meat products nec	22.41	
20	Products of Vegetable oils and fats	-23.8	Mean of "Oil seeds"
21	Dairy products	0.5	Mean of "Raw milk"
22	Processed rice	7.44	Mean of "Paddy rice"
23	Sugar	-38.37	Mean of "Sugar cane, sugar beet"
24	Food products nec	2.75	Mean of all food products
25	Beverages	1.32	
26	Fish products	0	Assumption: no difference between conventional and traded up good
27	White Spirit & SBP	0	Assumption: no difference between conventional and traded up good