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Article

Consumer food waste decisions in British and Thai consumers: A vignette approach

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Abstract

This study uses an experimental vignette methodology to investigate and compare, for the first time, consumer food waste (FW) decisions in the UK and Thailand. Specifically, we examine consumers' decisions to discard leftovers during meal scenarios affected by varying economic and contextual factors. Different consumer segments are identified and characterised, and our results suggest that consumers in the UK and Thailand are more likely to save leftovers when dining at home, when meals are expensive, and when a whole meal is left over. We discuss these findings and provide recommendations for practitioners and policymakers aiming to reduce FW.

Keywords: Consumer decisions, Food waste, Thailand, United Kingdom, Vignette methodology

JEL codes: Q18, C5

1. Introduction

Food waste (FW) is food generally intended for human consumption that is discarded or left to spoil along the food supply chain or by consumers (HLPE 2014). FW is increasingly recognised as an environmental, economic, social, and food security issue by policymakers worldwide (FAO 2019; Zurek, Hebinck, and Selomane 2021). Indeed, recent estimates indicate that around 30 per cent of all the food produced in the world is lost or wasted by food operators and consumers (FAO 2019). Furthermore, FW is central among the United Nations' Sustainable Development Goals (SDGs), which aim—by 2030—to 'halve per capita global FW at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses' (Clark and Wu 2016). Consequently, policymakers have recognised the need to take action, motivating politicians and managers to seek policies that can reduce FW (Landry and Smith 2019).

Policy interventions to reduce FW are economically motivated by market failure. This is because the optimisation of the consumer's FW decisions does not necessarily lead to less FW. Indeed, the consumer decision to waste food may not always be a 'mistake' or due to a lack of information, but rather results from legitimate economic incentives and trade-offs

(Daniel 2016; Lusk and Ellison 2020). Thus, if foods were thrown away as a result of a consumer maximisation decision, policy interventions are needed to fill this market failure. This poses many societal challenges. FW problems include the cost of the wasted food itself, supply chain inefficiencies, upward price pressure, and reduced profits (Roodhuyzen et al. 2017). Furthermore, FW increases greenhouse gas (GHG) emissions (Heller and Keoleian 2015). For example, the US Environmental Protection Agency (EPA) estimated that each year, FW represents 170 million metric tonnes of carbon dioxide in GHG emissions,[1] equal to the annual CO_2 emissions of forty-two coal-fired power plants (EPA 2021). FW is also associated with inefficiencies in energy use, livestock rearing, and crop cultivation (Eriksson and Spångberg 2017). FW also increases global food prices by reducing the poorest consumers' food access; in turn, this inaccessibility may reduce labour productivity and suppress wages (HLPE 2014).

FW is generated during different stages of the food supply chain, including consumption (Gustavsson et al. 2011). Previous research indicates that, in developed countries, the majority of FW occurs during the consumption stage (Aschemann-Witzel et al. 2015). Meanwhile, in developing countries, it occurs mainly during the production stage (FAO 2011). However, recent estimates indicate that the global calorie waste at the consumption stage will double by 2050, especially in Asia (Lopez Barrera and Hertel 2021). Among the many ways consumers generate FW, FW generated during meals (e.g. discarded leftovers) is increasing rapidly in both developed (Gunders 2017) and developing countries (Xu et al. 2020). Since a key driver of the FW generated during meals is economic development levels (Xu et al. 2020), as these levels rise, the FW generated during meals also increases (Dung et al. 2014). Developing countries' populations are growing rapidly and adopting food consumption trends typical of developed countries (e.g. increased dining at fast-food chains). This trend could increase consumption-stage FW in developing countries significantly, more closely matching the levels typically observed only in developed countries (Xu et al. 2020).

Despite the growing research on consumer FW behaviour (e.g. Aschemann-Witzel et al. 2015; Porpino, Parente, and Wansink 2015; Schanes, Dobernig, and Gözet 2018; Yu and Jaenicke 2020), the phenomenon's causes and solutions remain unclear (Lusk and Ellison 2017), although more recent reviews have provided new important insights. For example, Boulet, Hoek, and Raven (2021) proposed a new and multi-level framework including both household and consumer FW behaviour to better and more realistically investigate people's FW behaviour. Dhir et al. (2020) critically analysed the state-of-the-art of FW both in food services and hospitality by providing some inferences for practitioners, and proposing a framework that brings together the findings to inform future empirical research in the area. Principato et al. (2021) conducted a systematic review on household FW and provided a new theoretical framework called 'The Household Wasteful Behaviour Framework' aimed at better explaining consumer FW behaviour at household level. Vizzoto, Testa, and Iraldo (2021) found that there is a shortage of solutions to curb leftovers and serving waste, and that academia and food practitioners are misaligned with the key strategies in reducing FW.

In addition, much of the research on consumer FW conceptualises this problem as an inefficiency or a mistake, rather than an economic phenomenon that arises from incentives, preferences, and constraints (Lusk and Ellison 2017). Indeed, practically, consumers face time and other resource constraints, which imply that—in many cases—saving all the leftovers from a meal is not worthwhile. Therefore, the decision to save or waste food could be framed as an economic decision that depends on consumers' incentives, preferences, habits, contextual factors, and resource constraints (Ellison and Lusk 2018). However, the few examples of economic research that provide theoretical frameworks or empirical evidence about the costs and benefits of potential FW mitigation measures have focussed mainly on developed countries. For example, Ellison and Lusk (2018) used a stated-preference methodology to investigate consumer behaviour surrounding the decision to save or waste leftovers in the USA. These researchers found that consumer decisions to discard food vary based on some contextual factors, such as meal costs, leftover amounts, and future meal plans. Landry and Smith (2019) explored American consumer behaviour about FW in response to changes in food prices, and they found that the decision to waste food depends on prices. Smith and Landry (2021) examined US at-home FW in the context of inefficiencies in household food production, finding that such inefficiencies depend on socio-demographics, joint meal preparation, distance travelled to food stores, and food shopping frequencies. Additionally, Xu et al. (2020) investigated the impact of people's preferences for variety and restaurant dish portions in China, finding that greater food variety reduces plate waste while larger portion sizes increase plate waste. Therefore, more studies aimed at explaining how consumers in developing countries make FW decisions are needed (Lusk and McCluskey 2018; Chaboud and Moustier 2020), given these countries' rapid population and income growth, as well as the poor understanding of FW during the consumption stage (Liu 2014). Specifically, to the best of our knowledge, there is a lack of studies that explore consumer FW decisions framed as an economic phenomenon, especially in developing countries. Furthermore, previous studies have yet to fully explore differences in FW decisions between developed and developing countries while focussing on meal situations that can inform food vendors and policymakers hoping to reduce FW.

The current study fills gaps in the literature by investigating and comparing consumers' FW decisions in the UK and Thailand regarding leftovers from a fully prepared meal across different eating scenarios using an online, stated-preference survey, particularly adopting the experimental vignette methodology (EVM). The studied eating scenarios feature five economic and contextual factors, particularly whether the person is dining at home or at a restaurant, the meal's cost, the amount of food left over after the meal, whether the person dines alone or with others, and whether consumers have a meal plan or not for the following day.

We sampled consumers from the UK and Thailand for three main reasons. First, these countries have different cultures. For example, the UK is considered an individualistic country, while Thailand is considered a collectivistic country (Hofstede Insights 2022), and these differences could affect consumers' FW behaviour. Second, we chose the UK because it is among the developed countries with the highest per-capita FW (Vanham et al. 2015) and one of the first countries to establish a FW reduction programme—the so-called Waste & Resources Action Programme (WRAP) (WRAP 2000), created in 2000. Third, we chose Thailand because it is among the developing countries with the fastest-growing economies (OECD 2021) and it is increasingly adopting Western food behaviour lifestyles (Neo 2020), with a rising number of people dining out and largely contributing to FW generation (Sawasdee, Rodboonsong, and Joemsittiprasert 2020). Moreover, in the last two decades, Thailand's consumer FW generation has greatly increased, for example, per capita FW generation in Bangkok raised from 0.36 kg/day in 2003 to 0.61 k/day in 2018 (Bunditsakulchai and Liu 2021).

Our manuscript has several main contributions. First, we aim to determine how decisions about FW are affected by economic, social, and contextual factors, such as meal location, meal cost, leftover amount, whether consumers dine alone or with others, and whether they have a meal plan in place for the next day, which has received limited research attention so far. Second, we aim to explain how these economic, social, and contextual factors drive decisions to save or waste food in specific contexts, although this is hypothetical, which may help address the lack of empirical economic studies on consumer FW behaviour. Third, we compare consumers' FW decisions between a developed country (the UK) and a developing country (Thailand) to provide more information on how to design and implement FW policies in different countries. Fourth, we identified and characterised several consumer segments to provide more information on how to design and implement FW policies for specific segments. Fifth, compared to the research from Ellison and Lusk (2018), we included a social aspect of eating (i.e. eating alone or with others) and investigated a developing country (i.e. Thailand), which expands the current knowledge of consumer FW behaviour. Finally, we used the EVM, which is increasingly used in social studies and fits well with studies on consumer FW decisions.

1.1. Consumer FW literature review

An increasing number of studies have investigated consumer FW behaviour in both developed and developing countries (see, e.g. Oelofse and Nahman 2012; Chalak et al. 2016; Jagau and Vyrastekova 2017; Abdelradi 2018; Cronjé, Van der Merwe, and Müller 2018; Baig, Gorski, and Neff 2019; Drabik, de Gorter, and Reynolds 2019; Fami et al. 2019; Annunziata et al. 2020; Bilska, Tomaszewska, and Kołożyn-Krajewska 2020; Katt and Meixner 2020; Nabi, Karunasena, and Pearson 2021; Abu Hatab et al. 2022; Heng and House 2022). Most of the literature on consumer FW behaviour is descriptive, aimed at understanding and describing their behaviours, habits, attitudes, and motivations. To illustrate, previous research shows that consumer FW behaviour is affected by several main elements. First, some authors found that consumer socio-demographic characteristics, such as household size (Mallinson, Russell, and Barker 2016), age, education, employment status, and presence of old members in the family (Wang et al. 2016), influence consumer FW behaviour. Second, consumer perceived behavioural control (PBC)[2] for food shopping, planning routines (Stancu, Haugaard, and Lähteenmäki 2016), consumers' cooking abilities (e.g. skills to plan accurately and cook creatively) and opportunities (e.g. at-home equipment and store supply) (van Geffen et al. 2020), and meal planning habits (Talwar et al. 2021) affect consumer FW behaviour. Third, several authors also found that situational factors (Sebbane and Costa 2018), social norms (Sirieix, Lála, and Kocmanová 2017), and the presence of other people when eating (Hamerman, Rudell, and Martins 2018) shape consumer FW behaviour. Fourth, previous literature identified different types of consumers who are more wasteful than others, including casual consumers (i.e. those who buy and waste significant amounts of food) and kitchen evaders (i.e. those who dislike food shopping and cooking, but prefer convenience, take-away food, and eating out) (Mallinson, Russell, and Barker 2016). Fifth, consumer FW decisions also depend on food products characteristics, including packaging formats, prices (Mallinson, Russell, and Barker 2016), and sensory aspects (Teng, Wang, and Chuang 2022). Sixth, some authors found that consumer FW decisions are shaped by the regulatory, normative, and cultural–cognitive systems (Diekmann and Germelmann 2021). Seventh, consumer previous farming experience, environmental protection consciousness, and reasons for dining out significantly influence the leftover packing consumer behaviour (Wang et al. 2016). Eighth, literature shows that consumer sensitivity, as well as health, safety, and ethical concerns, affect consumer FW behaviour (Teng, Wang, and Chuang 2022). Ninth, consumers who perceive that taking away leftovers helps to reduce FW and save cooking time have a more favourable attitude toward taking away leftovers (Talwar et al. 2021).

This manuscript investigates people's likelihood to save/waste leftover food in different eating scenarios feature five economic, social, and contextual factors. First, the location where consumers have a meal might influence their decision to save or waste leftovers. Ellison and Lusk (2018) found that consumers waste more food when dining out than when dining in. Thus, we expect that people who eat at home are more likely to save leftovers. Second, meal costs are an important factor influencing the decision to save or waste leftovers. Ellison and Lusk (2018) found that consumers waste less/save more leftovers when meals are expensive. Thus, we expect that people who eat more expensive meals are more likely to save leftovers. Third, the amount of leftovers is another important factor influencing the decision to waste food. Indeed, Stancu, Haugaard, and Lähteenmäki (2016) found that the amount of leftovers is one of the most important contributors to FW, perhaps because sufficient leftovers for a full meal offer greater economic value than half a meal's worth of leftovers due to the convenience of not needing to purchase and cook additional food for the meal. Thus, we expect that with a larger amount of leftover, people are more likely to save food. Fourth, the decision to waste or save leftovers may also involve a social component: Aschemann-Witzel et al. (2015) found that household type, family stage, individual behaviours, and perceptions affect consumers' FW behaviour. Specifically, Hamerman, Rudell, and Martins (2018) found that people's willingness to save/waste food depends on whether they are eating with others or not, and by the type of people. Specifically, when consumers eat with other people that they want to impress, they tend to save less food because it is considered more embarrassing, while when they dine with people with whom they feel more comfortable (e.g. family, friends, etc.), they tend to save more leftovers. Therefore, since we hypothesise that consumers more frequently eat with people with whom they feel more comfortable, we expect that dining with other people will reduce FW. Fifth, another factor that may affect the decision to waste or save leftovers is whether consumers already have a meal plan in place for the following day. Having already planned one's next meal likely increases FW, as Ellison and Lusk (2018), as well as Pratesi, Secondi, and Principato (2015), have found. Thus, we expect that people who have already planned their next meal will likely increase their FW.

2. Materials and methods

2.1. EVM

To investigate consumer FW decisions, we applied the EVM (Alexander and Becker 1978; Hainmueller, Hangartner, and Yamamoto 2015). Similar to conjoint analysis, EVM is a type of stated-preference method. Participants are asked to evaluate (e.g. rank) multiple hypothetical descriptions of objects, such as product profiles, vignettes,[3] or scenarios whose varying attributes are presumed to be important determinants of consumer decision-making (Alexander and Becker 1978). EVM enables the researcher to identify the relative importance of each attribute of participant decision-making in a predetermined context created by the researcher (Hainmueller, Hangartner, and Yamamoto 2015). We used EVM because vignettes, although hypothetical in nature, provide short and concrete descriptions of product profiles or scenarios that contain the most important factors in participant decision-making (Alexander and Becker 1978). A main advantage of EVM is that it is a suitable approach in cases where survey questions are difficult or too vague for the respondents to answer. In these situations, the EVM can help to overcome these limitations by providing a more concrete scenario that accounts for the most likely decision criteria, holds these criteria constant across respondents, and allows for standardisation (Ellison and Lusk 2018). Due to these benefits, EVM is increasingly used in consumer behavioural studies (see, e.g. Hartmann et al. 2018; Tonkin et al. 2019; Kellershohn, Walley, and Vriesekoop 2021), and in particular regarding consumer FW behaviour (Ellison and Lusk 2018; Fesenfeld, Rudolph, and Bernauer 2022). Specifically, the use of EVM in FW studies facilitates the participant responses by providing FW behaviour with concrete contexts in which estimating FW amounts would otherwise be difficult (Ellison and Lusk 2018).

This study used a within-subject vignette design. Respondents were presented with multiple vignette scenarios and asked to rank each scenario based on their likelihood of saving or wasting their meal leftovers.

2.2. Experimental design

This study's data were collected from an online stated-preference survey conducted during the autumn of 2018 with a sample of 417 consumers from the UK ($N = 208$) and Thailand ($N = 209$) via the online platform Qualtrics (Provo, UT, USA). Consumers were recruited

Table 1. Attribute levels used in the study.

Attribute	level
Presence	Alone With others
Place	Home Restaurant
Cost	฿100/£6 ฿500/£30
Amount	Half meal Full meal
Plan	No plan Plan

through Qualtrics using sampling quotas that required equal age and gender groupings across both countries for comparison purposes. Only consumers aged eighteen and older who were citizens of the UK or Thailand were included in the study.

Five attributes were used to describe the different meal scenarios: *presence*, *place*, *cost*, *amount*, and *plan* (see Table 1). These attributes are the same used by Ellison and Lusk (2018), except for the attribute *presence*. *Presence* defines whether the diner ate alone or with others. *Place* defines the meal's location, whether at home or at a restaurant. *Cost* defines either of two price levels of the meal: (a) ฿100 or £6[4] or (b) ฿500 or £30.[5] *Amount* defines the amount of food leftover after a meal, either a half-meal or a full meal. *Plan* defines whether consumers have a meal plan in place for the following day or not.

The selected attributes and their levels were then used to generate a 2^5-factorial design in balanced incomplete blocks. This process created thirty-two vignettes that were then divided into four blocks of eight scenarios each in order to prevent participant fatigue (see Table A1 in Appendix A). Each block of vignettes was administrated to fifty participants per country. Vignettes were randomised within each block of eight scenarios. The study's experimental design was created using the Minitab v. 17.0 software (Minitab Inc.: State College, PA, USA).

The basic vignette[6] shown to participants is provided below. Participants were asked to rank each randomly presented vignette from 1 (*most likely to save the leftovers*) to 8 (*most likely to throw away the leftovers*). Participants were able to rank the vignettes and review their previous choices. The attributes that were experimentally varied across vignettes are shown in brackets.

> Imagine you have just finished eating dinner [alone/with others] [at home/out at a restaurant]. The meal costs about [฿100 (£6)/฿500 (£30)] per person. You are full, but there is still food left on the table, enough for a [half-/whole-meal] lunch tomorrow. You [do not/already] have meals planned for lunch and dinner tomorrow.

After the ranking task, we collected a series of sociodemographic characteristics (e.g. gender, age, etc.). The questionnaire was designed in English and administered in English for British participants. The questionnaire was translated into Thai for Thai participants and then back-translated into English to ensure quality and consistency. The complete English and Thai questionnaires are available in Appendix B. Informed consent was obtained from all participants, and the study was approved by a university ethics committee.

2.3. Data

We took two steps to ensure the best possible data quality. First, we included only study participants who took more than one-third of the median survey completion duration to complete the survey. Second, we omitted twenty straightliners[7] (ten in the UK and ten in Thailand) who provided at least in four out of seven rating questions—that have at least three items—the same answer.

We investigated sociodemographic characteristics across the UK and Thailand (see Table C1 in Appendix C). The results revealed that our hypotheses about equality of means between sociodemographic groups across countries failed to be rejected at the 5 per cent significance level for gender and age in our sample. However, we found significant differences between some sociodemographic groups. Specifically, Thai participants had larger families, higher education levels, and households with more people under 18 years old compared to British participants. Additionally, Thai participants tended to have been raised or to currently live in urban areas, were more likely to be students or independent workers, and had more wealth than their UK counterparts.

3. Econometric analysis

We analysed the data in three steps. First, we analysed the data for each country separately using the rank-ordered mixed logit (ROML) model (Boyd and Mellman 1980). This approach assumes that ranking options are formally equivalent to the choice of the most preferred option from a set of options, then the second-most preferred option, and so on until the least preferred option is identified. Thus, ranking eight scenarios from *most likely* to *least likely* to save food was deemed equivalent to making seven discrete preference selections.

The ROML is a generalisation of the rank-ordered logit (ROL) model (Beggs, Cardell, and Hausman 1981) in that it allows each respondent to express their own preferences—in this case, marginal utilities, for which a normal overall distribution of preferences was assumed. The ROML can be estimated classically using maximum likelihood (ML) estimation, provided that the likelihood function can be accurately simulated and has a unique maximum. However, while the ML approach is straightforward for the ROL model, it can often fail to converge for the ROML model if a high-dimensional set of options ordered. The recovery of individual preferences, or marginal utilities, from the ROML can also be difficult using the ML approach. Accordingly, we used the Bayesian approach, which multiplies the full data likelihood by prior distributions for the parameters governing the distribution of the latent marginal utilities. Monte Carlo Markov chain (MCMC) methods were then used to simulate the distributions of all parameters within the ROML, including the individual marginal utilities.

Formally, we assumed that the j^{th} person ($j = 1\ldots, J$) obtains utility U_{ij} for the i^{th} option (i.e. vignette) ($i = 1\ldots, 8$):

$$U_{ij} = \beta_j X_{ij} + \varepsilon_{ij}, \tag{1}$$

where ε_{ij} is the unobserved random error (independent across i and j), which is assumed to be extreme-value (Gumbel) distributed, X_{ij} is a column vector of observed attributes, and β_j is a row vector of unobserved latent marginal utilities, such that it has (i) a mean vector β with precision matrix (inverse covariance matrix) Ω, which is assumed to be diagonal, or (ii) a mean vector that is a linear function of covariates $z_j\ \beta$ with precision matrix (inverse covariance matrix) Ω, which is assumed to be diagonal. The prior distributions must be specified for β and Ω; for our results, we assumed that β had a prior distribution normally distributed with a mean of 0 and an identity precision matrix. The diagonal elements of Ω have half-normal priors.

Since ROML assumes that the total utility that consumers derive from a scenario can be segregated into the marginal utilities given by the scenario's attributes, the specification of the utility (U) function in our study was defined as

$$U_{ij} = \beta_{1j}PRESENCE_{ij} + \beta_{2j}PLACE_{ij} + \beta_{3j}COST_{ij} + \beta_{4j}AMOUNT_{ij} + \beta_{5j}PLAN_{ij} + \varepsilon_{ij}, \tag{2}$$

where j individually ($j = 1\ldots, J$) obtains utility U_{ij} for the i^{th} option (i.e. vignette) ($i = 1\ldots,$ 8). *PRESENCE* is a dummy variable representing whether participants dine alone or with others, taking a value of 0 if the consumer is dining 'alone' and 1 if they are dining 'with others'. *PLACE* is a dummy variable representing the location of the meal, taking a value of 0 if the location is 'home' and 1 if it is 'restaurant'. *COST* is a dummy variable representing the cost of the meal, taking a value of 0 if the cost of the meal is lower (i.e. ฿100 or £6) and 1 if the cost is higher (i.e. ฿500 or £30). *AMOUNT* is a dummy variable representing the amount of food left after the meal, taking a value of 0 if the amount is a 'half-meal' and 1 if it is a 'whole meal'. Finally, *PLAN* is a dummy variable representing whether consumers already have a meal plan in place for the following day, taking the value of 0 for 'no plan' and 1 for 'plan'.

The results obtained for the ROML were estimated using Hamiltonian Markov chain Monte Carlo (MCMC) methods (Neal 2011) via STAN software. The STAN code was provided by Jim Savage (Savage 2018).

The ROML's essential assumption is that consumers have normally distributed preference parameters. As the results section below shows, evidence suggests that this assumption does not hold for our data. Therefore, in the second step of our analysis, we also investigated consumer heterogeneity using the latent class logit (LCL) model (Greene and Hensher 2003). The LCL model assumes that an overall population can be split into two or more groups by assuming constant model parameters within each group, capturing consumer heterogeneity, and assuming a mixing distribution for the groups (Greene and Hensher 2003). The choice probability that an individual of a class or group s chooses alternative i from a particular set comprised of I_t alternatives was expressed as

$$P_{i/s}\frac{\exp(\boldsymbol{\beta}'_s\mathbf{x}_{it})}{\sum_{j=1}^{I_t}\exp(\boldsymbol{\beta}'_s\mathbf{x}_{jt})}, \tag{3}$$

where $s = 1, \ldots S$ represents the number of classes, β's is the fixed (constant) parameter vector associated with class s and X_{ijt} is a vector of attributes associated with each vignette. To establish likelihood, these choice probabilities must be multiplied across the choice sets and, finally, combined across all individuals.

To estimate the LCL model, we used the expectation–maximisation (EM) algorithm, which allows for good numerical stability and good performance in terms of runtime (Bhat 1997; Train 2008). The LCL model was estimated using the modules *lclogit2*, *lclogitml2*, and *lclogitpr2* (Hong Il 2020) on Stata 16.1 software (StataCorp LP: College Station, TX, USA). We then assigned consumers to groups based on the highest posterior probabilities.

Finally, to characterise and describe the consumer groups based on consumer attributes, different approaches can be used, such as, for example, bivariate analysis (Gracia and Gómez 2020) We used the multinomial logit (MNL) model because the groups had no natural ordering (Greene 2018). This approach is largely used (Honkanen, Olsen, and Myrland 2004; Yeh, Hartmann, and Langen 2020). The general form of the MNL model is

$$P_{ji} = P(Y_i = j) = \frac{e_j^{\beta'}X_i}{\sum_{j=1}^{J} e_j^{\beta'}X_i}, \tag{4}$$

where i indicates the participants, J indicates the number of groups, P_{ji} is the predicted probability of participant i to be in the j^{th} segment, X_i is a row vector of explanatory variables describing the participant, and β_j is a row vector of unknown parameters. The MNL model was estimated using the module *mlogit* run in Stata 16.1.

Table 2. Parameter estimates from the ROML model for the UK and Thailand.

	UK (n = 208)				Thailand (n = 209)			
Attribute	Coefficient	SeM	SD	Pseudo t-value	Coefficient	SeM	SD	Pseudo t-value
Presence	–0.01	0.07	0.16	–0.20	–0.31	0.09	0.49	–3.50
Place	–0.78	0.13	1.15	–6.01	–0.46	0.09	0.57	–4.95
Cost	0.81	0.11	0.85	7.34	0.75	0.14	1.41	5.43
Amount	0.23	0.07	0.06	3.58	0.33	0.08	0.27	4.29
Plan	–0.31	0.07	0.20	–4.37	–0.09	0.08	0.32	–1.14

4. Results

4.1. Estimation results from the ROML model

The parameter estimates of the main effects of participant citizenship (i.e. the UK versus Thailand) using the ROML model are presented in Table 2. Table 2 includes the regression coefficients for *presence*, *place*, *cost*, *amount*, and *plan*, as well as the corresponding standard deviations (SDs). Pseudo t-values are also presented, describing the value of the mean estimate divided by the standard error (SE) of that mean (Train 2009). While this approach was not strictly Bayesian, it was similar to a classical t-value in terms of its size, conveying whether the mean had a posterior mass away from zero. Our results show that participants from both countries were more likely to save leftovers when (i) they dine at home, (ii) the meal is expensive, and (iii) they have enough leftovers for a whole meal. Additionally, British participants were more likely to save their leftovers when they did not have a meal plan for the following day, while Thai participants were more likely to save leftovers when dining alone.

After examining the magnitudes, we noted that the relative size of the parameters mattered more in our context than the absolute size, given that all variables were coded as either 0 or 1. The cost parameter, therefore, represents the impact of a £24 or ฿400 price increase for the UK and Thailand, respectively. The *place* and *cost* attributes most affect the likelihood to save or waste food.

4.2. Distribution of marginal utilities across individuals for the UK and Thailand

Next, we compared the distributions (i.e. kernel density estimates) of the marginal utilities between participants from the UK and Thailand (see Fig. 1). We found not only that the mean values of each marginal utility differed but also that some of the marginal distributions were much more diffuse than others—particularly the *place* and *cost* attributes. Another evident finding was that the normality assumption employed by the ROML did not seem wholly consistent with the data. In particular, *cost* for both countries described a bimodal distribution, with the marginal utilities for a subgroup of respondents particularly sensitive to this attribute. Likewise, a subgroup of UK respondents was particularly likely to waste leftovers at a restaurant. This finding suggests a potential to segment consumers.

4.3. Estimation results from the LCL model

In view of the multimodality of some attributes within the ROML model, we then investigated the possibility of distinct consumer groups in our sample. To investigate such consumer heterogeneity, we used the LCL model for each country.

Regarding the UK, based on the Bayesian information criterion (BIC) parameter (Hong Il 2020), the optimal number of groups for the LCL model was three, as BIC was the lowest.[8] The results of the LCL model with the three-group solution are reported in Tables 3 (unconditional probabilities) and 4, including the regression coefficients for *PRESENCE*,

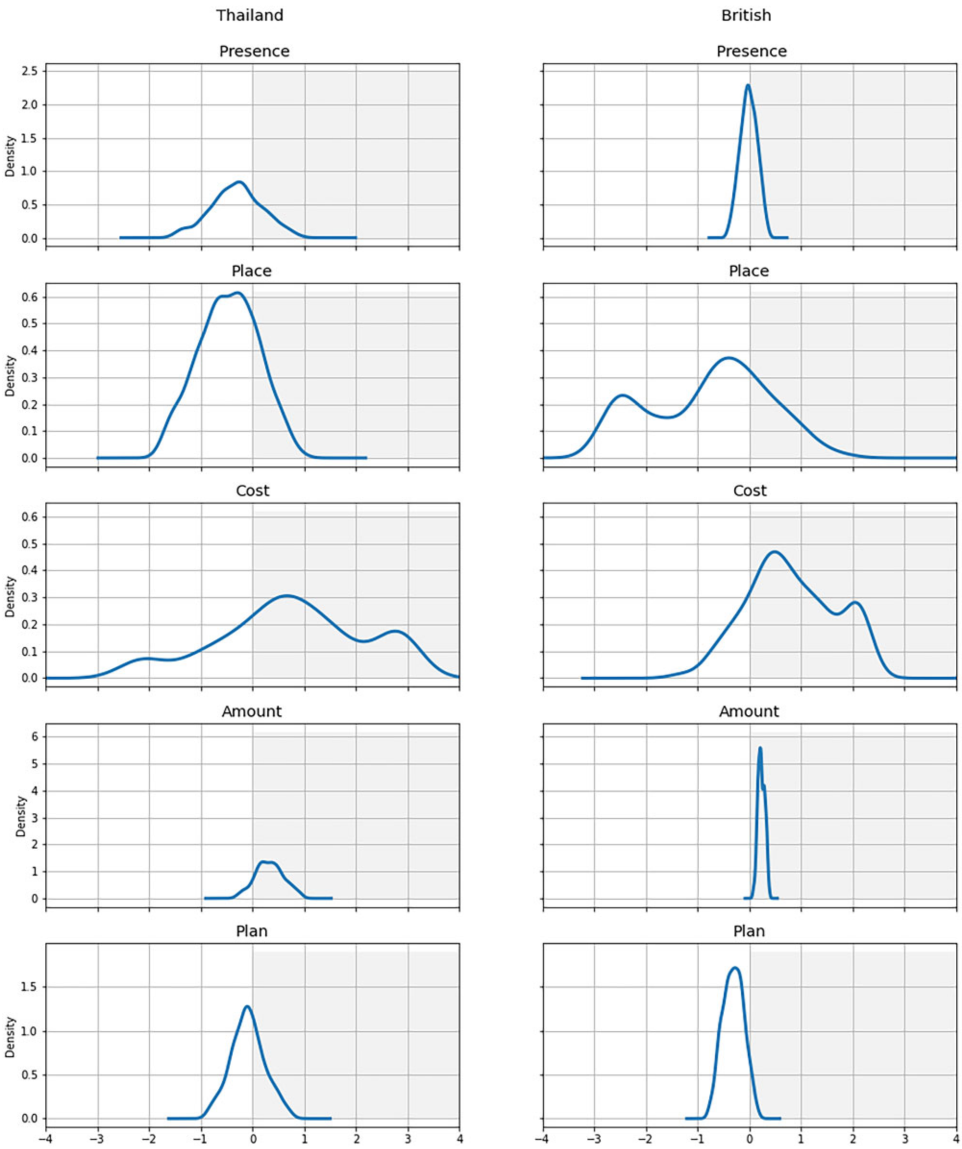

Figure 1. Distribution of marginal utilities across individuals from Thailand and the UK.

Table 3. Estimated unconditional probabilities from the LCL model for the UK.

Group	Unconditional probability (%)
1	24.33
2	58.15
3	17.52

Table 4. Estimated regression coefficient from the LCL model for the UK.

Attribute	Group 1 '*home savers*' (N = 51)			Group 2 '*multi-factor savers*' (N = 118)			Group 3 '*cost savers*' (N = 39)		
	Coefficient	SE	*P*-value	Coefficient	SE	*P*-value	Coefficient	SE	*P*-value
Presence	−0.22	0.16	0.18	0.06	0.08	0.42	0.01	0.18	0.94
Place	−3.64	0.45	0.00	0.01	0.09	0.96	−0.31	0.17	0.08
Cost	0.64	0.16	0.00	0.19	0.09	0.04	3.96	0.72	0.00
Amount	0.06	0.14	0.68	0.18	0.08	0.02	0.62	0.19	0.00
Plan	−0.50	0.14	0.00	−0.19	0.08	0.02	−0.44	0.19	0.02

Table 5. Estimated unconditional probabilities from the LCL model for Thailand.

Group	Unconditional probability (%)
1	14.94
2	51.80
3	33.26

PLACE, *COST*, *AMOUNT*, and *PLAN*, as well as their corresponding SEs and significances (*P*-values). The LCL model identifies one larger and two smaller groups of consumers. Group 1 participants ('home savers', 24.33 per cent, $n = 51$) most likely save leftovers when eating at home, quite likely save leftovers when the meal cost is higher, and quite likely save leftovers when they have no meal plan in place for the following day. For participants in Group 2 ('multi-factor savers', 58.15 per cent, $n = 118$), the decision to save food is driven by three attributes with a similar importance. Specifically, they likely save food when the meal cost is higher, when a full meal is left, and when they have no meal plan in place for the following day. Finally, for Group 3 participants ('cost savers', 17.52 per cent, $n = 39$), the decision to save leftovers is mainly driven by meal cost (i.e. consumers most likely save food when the meal cost is higher), and less driven by the amount of leftovers and meal plan. More specifically, consumers likely save food when a full meal is left and quite likely save food when they have no meal plan in place for the following day.

Concerning Thailand, based on the BIC parameter, the optimal number of groups for the LCL model was five because BIC was slightly lower than the other groups' numbers (i.e. two to four) that were estimated. However, given the negligible differences among the groups[9] and some groups' low number of participants, we chose a three-group solution for a better comparison with the UK groups. The results of the LCL model with the three-group solution are reported in Tables 5 (unconditional probabilities) and 6. These results show one larger and two smaller groups. Group 1 participants ('cost savers', 14.94 per cent, $n = 35$) most likely save leftovers when the meal cost is high, although some statistical noise was observed concerning this finding. Group 2 participants ('unaffected savers', 51.80 per cent, $n = 107$) are not affected by any particular attributes when deciding to save leftovers. Finally, Group 3 participants ('multi-factor savers', 33.26 per cent, $n = 67$) are affected by all the studied attributes when deciding whether to save leftovers. Specifically, consumers save leftovers when eating alone, when at home, when the meal cost is high, and when they have leftovers for a whole meal, and they are quite likely to save leftovers when they have no meal plan in place for the following day.

4.4. Consumer segment characterisation

Finally, we characterised respondents' consumer segments in terms of consumer socio-demographics. For each studied country, we applied an MNL model, taking each participant's latent class membership based on the highest posterior probabilities as the dependent variable. Individual consumer socio-demographics were taken as independent variables.

Table 7 presents the results of the MNL models for the UK and Thailand, including regression coefficients for the consumer socio-demographics, along with their corresponding SEs and significances (*P*-values). For the UK, the model fit the data well, according to the likelihood ratio (LR) chi-square test, while pseudo-*R*-squared measures indicated that the model explained 4.27 per cent of the variance. The 'multi-factor savers' segment was taken as the reference group. We found that 'home savers' tend to be older than 'multi-factor savers'. No significant differences in any of the investigated consumer attributes were observed between 'cost savers' and 'multi-factor savers'.

Table 6. Estimated regression coefficient from the LCL model for Thailand.

Attribute	Group 1 '*cost savers*' ($N = 35$)			Group 2 '*unaffected savers*' ($N = 107$)			Group 3 '*multi-factor savers*' ($N = 67$)		
	Coefficient	SE	*P*-value	Coefficient	SE	*P*-value	Coefficient	SE	*P*-value
Presence	0.12	0.19	0.50	0.03	0.10	0.77	–0.96	0.25	0.00
Place	0.12	0.19	0.54	–0.09	0.12	0.44	–1.06	0.21	0.00
Cost	6.63	7.44	0.37	–0.22	0.14	0.13	1.12	0.26	0.00
Amount	0.11	0.17	0.50	0.06	0.09	0.54	0.73	0.19	0.00
Plan	–0.23	0.17	0.19	0.12	0.10	0.24	–0.38	0.17	0.02

The high magnitude of SE means that the measurement of the coefficient is less precise, thus the interpretation should be treated with cautious.

Table 7. MNL models: latent class membership regressed on consumers' socio-demographics for the UK and Thailand.

	UK ($n = 208$)		Thailand ($n = 209$)	
Attributes	**Reference segment:** ***multi-factor savers***	**Coefficient (SE)**	**Reference segment:** ***unaffected savers***	**Coefficient (SE)**
Socio-demographics				
Gender	Home savers	0.28 (0.36)	Multi-factor savers	0.05 (0.41)
Age		0.44 (0.17)**		0.01 (0.21)
Household size		0.09 (0.15)		0.11 (0.14)
Education		0.13 (0.22)		0.15 (0.24)
Childs		–0.57 (0.46)		0.11 (0.45)
Income		0.12 (0.09)		0.11 (0.73)
Socio-demographics				
Gender	Cost savers	–0.49 (0.40)	Cost savers	–0.63 (0.35)*
Age		0.29 (0.19)		0.04 (0.18)
Household size		–0.06 (0.17)		0.14 (0.11)
Education		0.30 (0.24)		0.50 (0.23)**
Childs		0.37 (0.50)		–0.73 (0.38)**
Income		–0.01 (0.11)		–0.03 (0.06)
Log-likelihood of null model	–186.68		–188.41	
LR test chi-square (12)	16.66		21.26	
Prob > chi-square	0.16		0.05	
Pseudo R-squared	0.04		0.05	

Note: *, ** significance at 10 per cent, 5 per cent level, respectively.

For Thailand, the model fit the data well, according to the LR chi-square test, while pseudo-*R*-squared measures indicated that the model explained 5.34 per cent of the variance. The ‘unaffected savers’ segment was taken as the reference group. In contrast with ‘unaffected savers’, ‘cost savers’ tend to be more educated and have fewer children.

5. Discussion

This study has investigated FW decisions among UK and Thailand survey respondents using the EVM approach. We employed an economic perspective by considering that consumer FW decisions can be the outcome of practical economic reasons. This is because practically, people’s decision to save/waste food face time (e.g. time to prepare and cook meals, etc.) and resource constraints (i.e. budget/income, etc.), which imply that in many situations saving all the leftovers from a meal is not worthwhile, which in turn increase FW. Thus, according to Lusk and Ellison (2017, 2018), the decision to waste leftovers could be framed as an economic decision that depends on several economic aspects. Given the lack of studies that employ the economic perspective (see, e.g. Ellison and Lusk 2018) on consumer FW decisions, our results provide useful insights on better understanding consumer FW behaviour.

We obtained several revealing results. First, consumers tend to save more leftovers when their meal is more expensive, when dining at home, and when they have enough leftovers for a whole meal. We also found that these results were the same for our UK and Thailand survey groups. Specifically, we found that a more expensive meal increases a consumer’s probability of saving leftovers, showing the importance of cost. This finding is corroborated by Ellison and Lusk (2018), who found that American consumers waste less food when their meals are more expensive. Furthermore, when a meal is prepared at home, a time cost is accrued for that meal that people do not want to discount by throwing away leftovers. Again, this finding is corroborated by Ellison and Lusk (2018), who found that consumers waste less food when eating at home, and by Evans (2011) and Ananda et al. (2021), who have shown that less frequent dining-out behaviour is associated with lower FW. This finding may be due to a home-prepared meal having a higher intrinsic value given the time and effort spent on food shopping, preparation, and cooking compared to restaurant dining. Another possible explanation is that FW increases when dining out because bringing leftovers home is sometimes practically inconvenient (Nikolaus, Nickols-Richardson, and Ellison 2018). Additionally, restaurant portions may be too large, and consumers may not feel a sense of ownership or responsibility for their restaurant leftovers (Giorgi 2013; Nikolaus, Nickols-Richardson, and Ellison 2018), increasing the likelihood of FW. Moreover, we found that consumers tend to save more leftovers when they have enough leftovers for a whole meal. Again, this finding is corroborated by Ellison and Lusk (2018), who found that consumers waste less food when they have enough leftovers for a whole meal. This finding can be explained by the convenience and time savings of not having to purchase raw materials, prepare and cook a new meal at home, and spend money to dine out.

Second, according to Stancu, Haugaard, and Lähteenmäki’s (2016) and Stuart’s (2009) findings regarding Danish and Romanian consumers, we found that the drivers that affect FW are similar across different countries. However, we found two exceptions between our two studied countries’ results: British participants showed a higher probability of saving leftovers when they had no meal plans in place for the following day, corroborating Ellison and Lusk’s (2018) results, while the lack of a future meal plan did not affect Thai participants’ probability of saving leftovers. In addition, the social aspects of the dining context showed a greater impact on FW decisions among Thai participants than British participants. Specifically, we found that Thai participants are more likely to save leftovers when dining alone. This finding corroborates the findings of Xu et al. (2020) and Qian et al. (2021) in China, as well as the findings of Broshuis (2021) in the Netherlands, but it contrasts with the findings of Tsai, Chen, and Yang (2020) in China and Nikolaus, Nickols-Richardson, and Ellison (2018) in the USA. Tsai, Chen, and Yang (2020) and Nikolaus, Nickols-Richardson, and Ellison (2018) found that sharing food with others likely reduces FW. However, both the social aspects of the dining context (i.e. saving leftovers and sharing food with others) have different effects since they refer to different phases in the consumption process. While eating and sharing food with other people may diminish the amount of leftovers, after the meal is finished, keeping the leftovers rather than wasting may occur more readily when a person is eating alone. These effects can occur simultaneously and do not rule each other out. Moreover, for British participants, we found that meal cost and dining location are similarly important drivers of FW decisions, while for Thai participants, dining location is less important.

Third, at the individual level, we found that UK consumers are more likely to decide to save leftovers based on a combination of several similarly important factors, while for two smaller groups of consumers, the decision to save leftovers is strongly based on two main factors: dining at home and high meal costs. By contrast, among Thai participants, we found that the decision to save food is only marginally determined by the attributes considered in our study, while two smaller groups saved more leftovers when their decision was strongly based on one main factor, such as when the meal cost was higher for one group. The other group was influenced by all the attributes investigated in this study.

6. Policy implications and conclusions

Based on this study, we offer recommendations for practitioners and policy implications. Our results suggest that vendors might usefully encourage consumers to eat their entire meals at restaurants or to bring home and reuse their leftovers by providing discounts for future meals. Restaurants should also be encouraged to provide suggestions to consumers about how to better reuse leftovers via booklets or other media. These suggestions could address how to handle leftovers, such as by combining leftover food with other dishes to create a whole meal.

Policymakers probably have limited short-term influence over some of the factors examined in this study. For example, policymakers are unlikely to easily induce people to increase their meal planning or to dine in larger or smaller groups. However, for many consumers, meal cost is an important driver of the decision to save or waste food, and cheap meals are associated with a propensity to waste leftovers when dining out. This association was evident among both Thai and British participants in our study. Consequently, policymakers could focus their FW reduction policies on food outlets that serve cheap meals, such as fast-food restaurants. Thai policymakers should also focus this strategy on people who dine alone at restaurants.

Future studies are needed to verify and generalise our findings in both high- and low-income countries and across cultural contexts. Larger samples would be beneficial to investigate, and future studies could also consider other contextual factors, particularly in Asian countries. Future research could also investigate consumers' FW decisions in empirical eating situations by conducting field experiments in restaurants. Additionally, future research should test the waste reduction effectiveness of information campaigns concerning FW's economic, social, and environmental consequences.

This study has several limitations. First, the rank-order approach used to analyse the data does not provide any information as to whether leftovers would or would not be saved for specific meals. A higher or lower ranking of a scenario does not by itself imply that leftovers would or would not be wasted, but only the likelihood. Second, our experimental design is similar, except for one attribute, to the one used by Ellison and Lusk (2018), which may limit the value of the study. Third, the sample size was rather small compared to many other studies that adopted online survey methodologies, and the results of online surveys are less representative because they consider only online residents and lack of data of no-citizens.

To conclude, our findings reveal that both British and Thai consumers' FW decisions depend on economic and other contextual factors, which shows that consumer FW decisions can also be framed as an economic phenomenon that depends on people's incentives, preferences, and constraints. Meal costs and dining locations are key determinants of consumers' FW decisions, and we have argued that they provide an avenue for policy interventions aimed at reducing FW in both developed and developing countries.

Supplementary material

Supplementary data are available at *Q Open* online.

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Data availability

The data and codes underlying this manuscript will be shared by the authors upon request.

Transparency reporting

This study's pre-registration information is available at https://aspredicted.org/blind.php?x=n3e7rg.

End Notes

1 This total excludes landfill emissions.
2 *Perceived behaviour control* refers to consumers' perceptions of their ability to perform a given behaviour.
3 A *vignette* is defined as 'a short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics' (Atzmüller and Steiner 2010: 128).
4 The lower cost was calculated as the lower price for an average meal in both Thailand and the UK. Baht (฿) is the currency of Thailand, and pounds sterling (£) is the currency of the UK.
5 The higher cost was calculated as the higher price for an average meal in both Thailand and the UK.
6 Adapted from Ellison and Lusk (2018).
7 *Straightliners* are participants who select the same numbered response to rating questions repeatedly.
8 However, BIC differences among different groups were negligible in number (Raftery 1995).
9 The BIC values were 4,302.91 for two groups, 4,275.23 for three groups, 4,284.41 for four groups, and 4,272.69 for five groups. Raising the BIC value further to six groups resulted in numerical convergence problems.

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