Comparison of Consumer Food Waste Decisions in British and Thai Consumers: A Vignette Approach

ABSTRACT

This study uses an experimental vignette methodology to investigate and compare for the first-time consumer food waste decisions in the United Kingdom and Thailand. Specifically, we examine consumers' decisions to discard leftovers during meal scenarios featuring varying contextual and economic factors. Different consumer segments are identified and characterized, and the results suggest that consumers in the United Kingdom and Thailand are more likely to save leftovers when dining at home, when the meal cost is high, and when a whole meal is left over. These findings are discussed in providing recommendations to practitioners, and policymakers aiming to reduce food waste.

Keywords: Comparison; Consumer food waste decisions; Thailand; United Kingdom; Vignette methodology.

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 recognized as an environmental, economic, social, and food security issue by policymakers worldwide (European Parliament 2011; FAO 2019). Indeed, recent estimates indicate that around 30% of all the food produced in the world is lost or wasted by food operators and consumers (FAO 2019). Furthermore, FW is at the heart one of the United Nations' key Sustainable

Development Goals (SDGs), which aims, by 2030, to "*halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses*" (United Nations 2015). As a consequence, policymakers have recognized the need to take action, motivating politicians and managers to seek policy prescriptions capable of reducing FW (Landry and Smith 2019).

The economic motivation for policy intervention to reduce FW is based on market failure arguments, posing many societal challenges. Problems caused by FW include the cost of the wasted food itself, inefficiencies in the supply chain, upward pressure on prices, reduced profits (Roodhuyzen et al. 2017), and increases in greenhouse gas emissions (Heller and Keoleian 2015). FW is also associated with inefficiencies in energy use, livestock rearing, and crop cultivation (Eriksson and Spångberg 2017). Furthermore, increases in global food prices reduce food access to the poorest consumers, which in turn may reduce labor productivity and push wages down (HLPE 2014).

FW is generated at different stages along the food supply chain, including consumption (Gustavsson et al. 2011). Previous research indicates that in developed countries, the majority of FW occurs at the consumption stage (Aschemann-Witzel et al. 2015), while in developing countries it occurs mainly at 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 2020). Among the many ways consumers generate FW, FW generated during meals (e.g., discarded leftovers) is increasing rapidly both in developed countries (Gunders 2017) and developing countries (Xu et al. 2020). A key driver of the FW generated during meals is the level of economic development (Xu et al. 2020). As the level of economic development increases, FW generated during meals also increases (Dung et al. 2014). Populations in developing countries are growing rapidly and adopting food consumption trends typical of developed countries (e.g., increased eating out at fast food chains). This could cause consumption-stage FW in developing countries to more closely match levels typically observed only in developed countries (Xu et al. 2020).

Consumer research on FW decisions has increased rapidly in the last decade (Reynolds et al. 2019), but there is still room for further investigation (Lopez Barrera and Hertel 2020). First, research on FW is largely descriptive in nature and aimed mainly at understanding and describing consumers' behaviors, attitudes, and motivations (e.g., Porpino, Parente, and Wansink 2015; Stancu, Haugaard, and Lähteenmäki 2016). Still other research has explored the role of information provisions on consumer FW decisions (e.g. Wilson et al., 2017). Second, the majority of the research has been conducted in developed countries (e.g., Kavanaugh and Quinlan 2020; Ellison, Muth, and Golan 2019), while only a few studies have been conducted in developing countries (e.g., Qi, Lai, and Roe 2020; Min, Wang, and Yu 2020). Third, an increasing amount of research focuses on the estimation of FW (e.g., Bellemare et al., 2017; Yu and Jaenicke, 2020). Lastly, a growing body of literature focuses on the effectiveness of different food policies initiatives to reduce FW (e.g., Hamilton and Richards 2019).

The decision to save or waste food could be framed as an economic decision depending on consumers' incentives, preferences, habits, contextual factors, and resource constraints (Ellison and Lusk 2018). However, only in recent years have consumer FW decisions been considered the outcome of a trade-off between such factors as the direct cost of FW and the cost of the resources involved in mitigating FW. However, there are scant economic analyses providing theoretical frameworks or empirical evidence about the costs and benefits of potential FW mitigation measures. What findings do exist focus mainly on developed countries. There is a need for studies aimed at understanding how consumers in developing countries make FW decisions (Lusk and McCluskey 2018; Chaboud and Moustier 2020), given their rapid population and income growth and their poor understanding of FW at the consumption stage (Liu 2014). Currently, only a few studies have investigated consumer decisions about FW as economically motivated. Ellison & Lusk (2018) investigated consumer decisions about FW at the household level in the United States. Landry and Smith (2019) explored the demand for FW in response to changes in food prices and household resources, while Smith and Landry (2021) examined at-home FW in the context of inefficiencies in household food production. In addition, Xu et al. (2020) investigated the impact of consumers' preferences for variety and restaurants' dish portions in China.

Practically, the decision to waste or save leftovers could be framed as an economic outcome that depends on several contextual factors involved in maximizing utility. This research focuses on five key factors. First, the location where consumers have a meal might influence the decision to save or waste leftovers. Ellison & Lusk (2018) found that US consumers waste more food when dining out than when dining in. Second, the meal cost is an important factor influencing the decision to save or waste leftovers. Ellison & Lusk (2018) found that US consumers waste more leftovers when the meal cost is high. Third, the amount of leftovers is another important factor influencing the decision to waste food (Stancu, Haugaard, and

Lähteenmäki 2016). This may be because having enough leftovers for a full meal has greater economic value than having only half of a meal. There is great convenience in not needing to purchase and cook additional food to prepare a future meal. Fourth, the decision to waste or save leftovers may also have a social component (Aschemann-Witzel et al. 2015). FW may vary depending on whether people dine alone or with others. Moreover, another factor that may affect the decision to waste or save leftovers is whether consumers already have a meal plan for the following day. Having already planned the next meal will likely increase FW (Ellison and Lusk 2018; Pratesi, Secondi, and Principato 2015). However, there has been scant empirical investigation into economic factors influencing consumers' utility-maximizing decision to save or waste food. In particular, existing studies have yet to fully explore differences in FW decisions between high- and low-income countries with a focus on meal situations.

This study fills existing gaps in the literature by investigating and comparing consumers' FW decisions regarding leftovers from a fully prepared meal during different scenarios featuring varying contextual and economic factors. This investigation was accomplished through an online stated-preference survey, sampled from consumers in the United Kingdom and Thailand. Our contribution is threefold. First, we aim to determine how decisions about FW on the whole were affected by the following factors: whether consumers dine alone or with others, the location of the meal, the meal cost, the amount of leftovers, and whether there was a future meal plan. Second, we aim to understand how economic factors drive the decision to save or waste food. Finally, we compare consumers' FW decisions between a high-income country (i.e., the United Kingdom) and a low-income country (i.e., Thailand).

2. MATERIALS & METHODS

2.1 Experimental vignette methodology (EVM)

To investigate consumer FW decisions, we applied the experimental vignette methodology (EVM) (Alexander and Becker 1978; Hainmueller, Hangartner, and Yamamoto 2015). Similar to conjoint analysis, EVM is a type of stated-preference experiment. Participants are asked to evaluate (e.g., rank) multiple hypothetical descriptions of objects, such as product profiles, vignettes[1], or scenarios the varying attributes of which 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 applied EVM because the vignettes, though hypothetical in nature, give short and concrete descriptions of product profiles or scenarios containing the most important factors in participant decision making (Alexander and Becker 1978). The use of vignettes facilitates participant response by providing contexts for FW where it would otherwise be difficult to estimate the amount of FW.

This study uses a within-subject vignette design. Respondents are presented with multiple vignette scenarios and asked to rank each scenario based on the likelihood to save or waste their leftover meal.

2.2 Experimental design

[1] A vignette is defined as ‘‘*a short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics*’’ (Atzmüller & Steiner, 2010:128).

The data in this study are drawn from an online stated-preference survey conducted during the autumn of 2018 with 417 consumers from the United Kingdom and Thailand using the online platform Qualtrics (Provo, Utah, US). Consumers were randomly recruited by Qualtrics using sampling quotas requiring age and gender groupings to be equal between both countries for comparison purposes. Only consumers aged 18 and up who were citizens of the United Kingdom or Thailand were included in the study.

Five attributes were used to describe the different eating scenarios. These were presence, place, cost, amount, and plan (see Table 1). *Presence* defines whether the person dined alone or with others. *Place* defines the meal's location, whether at home or in a restaurant. *Cost* defines either of two price levels: 100 Baht/£6[2] or 500 Baht/£30[3]. *Amount* defines the extent of food left over after a meal, either a half meal or a full meal. *Plan* defines whether consumers have a meal plan or not for the following day.

Table 1. Attribute levels used in the study.

The selected attributes and their levels were then used to generate a 2^5 factorial design in balanced incomplete blocks. This resulted in the creation of 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.

[2] The lower cost has been calculated as lower price for an average meal in both Thailand and the United Kingdom. Baht is the currency for Thailand and £ (pound sterling) is the currency for the United Kingdom.
[3] The higher cost has been calculated as the higher price for an average meal in both Thailand and the United Kingdom.

Vignettes were randomized within each block of the eight scenarios. The experimental design was created using the software Minitab v. 17.0 (Minitab Inc.: State College, Pennsylvania, United States).

The basic vignette[4] shown to participants is provided below. Participants are 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’re full, but there is still food left on the table enough for a [half/whole meal] lunch tomorrow. You [don’t/already] have meals planned for lunch and dinner tomorrow”.*

After the ranking task, the survey included a series of questions about consumer FW decisions (adapted from Lally, Bartle, and Wardle 2011; Di Noia and Cullen 2015), and FW habits (adapted from Aschemann-Witzel et al. 2015; Pratesi, Secondi, and Principato 2015), rated from 1 (strongly disagree) to 7 (strongly agree). Furthermore, we collected a series of socio-demographic characteristics.

The questionnaire was designed in English and administered in English to the British participants. The questionnaire was translated into Thai for the Thai participants, then back-

[4] Adapted from Ellison and Lusk (2018).

translated into English to ensure quality and consistency in the translation. The complete English and Thai questionnaires are available in upon request. 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 in the study only participants who took more than one third of the median survey duration to complete the survey. Second, we omitted straightliners[5], as recommended by Qualtrics.

We investigated socio-demographic characteristics across the United Kingdom and Thailand (see Table B1 in Appendix B). The outcomes reveal that the hypotheses of equality of means between socio-demographics across treatments failed to be rejected at the 5% significance level for gender and age in our sample. However, we found significant differences between some socio-demographics. Specifically, Thai participants had larger families, higher education levels, and households with a greater number of people under age 18 compared to the British participants. In addition, the Thai participants tended to have been raised or currently live in urban areas, were more likely to be students or independent workers, and had more wealth than their British counterparts.

3. ECONOMETRIC ANALYSIS

We analyzed the data in three steps. We first analyzed the data for each country separately, using the Rank Ordered Mixed Logit (ROML) model (Boyd and Mellman 1980). This approach

[5] Participants who selected over and over the same answers in the rating questions.

assumes that ranking options are formally equivalent to being able to choose 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 is deemed equivalent to making seven discrete preference selections.

The ROML is a generalization of the Rank Order Logit (ROL) model (Beggs, Cardell, and Hausman 1981) in that it allows each respondent to have their own preferences in this case, marginal utilities, where a normal overall distribution of preferences is assumed. The ROML can be estimated classically using Maximum Likelihood (ML) estimation, provided 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 should there be high dimensional set of options to be ordered. The recovery of individual preferences, or marginal utilities, from the ROML can also be difficult using the ML approach. Accordingly, here 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 are then used to simulate the distributions of all parameters within the ROML, including the individual marginal utilities.

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

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

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, and for the results presented here it is assumed that β has a prior distribution that is normally distributed with mean 0 and an identity precision matrix. The diagonal elements of Ω have half-normal priors.

Since ROML assumes that the total utility derived by consumers from a scenario can be segregated into the marginal utilities given by the attributes of a scenario, the specification of the utility (U) function in our study can be 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 individual ($j=1...,J$) obtains utility U_{ij} for the i^{th} option (i.e., vignette) ($i=1...,8$). PRESENCE is a dummy variable representing whether participants dine alone or with others, taking the value of 0 if the consumer is dining “Alone” and 1 if dining “With others.” PLACE is a dummy variable representing the location of the meal, taking the 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 the value of 0 if the cost of the meal is lower (i.e., “100 Baht/£6”) and 1 if the cost is higher (i.e., “500 Baht/£30”). AMOUNT is a dummy variable representing the amount of food left after the meal, taking the value of 0 if the amount is “Half meal” and 1 if it is “Whole meal.” Finally, PLAN is a dummy variable representing whether consumers already have a plan for the following day, taking the value of 0 for “No plan” and 1 for “Plan.”

The results given for the ROML were estimated using Hamiltonian Markov Chain Monte Carlo (MCMC) methods (Neal 2011), as implemented by STAN software. The STAN code was provided by Jim Savage (Savage 2018).

The essential assumption of the ROML is that consumers have normally distributed preference parameters. As we shall see in the results section, there is evidence that this assumption does not hold for our data. Therefore, in the second step we also investigate consumer heterogeneity using the Latent Class Logit (LCL) model (Greene and Hensher 2003). The LCL model assumes that the overall population can be split into two or more groups by assuming constant model parameters within each group, capturing consumer heterogeneity 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 constituted of I_t alternatives, is 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 the likelihood, these choice probabilities have to be multiplied across the choice sets and finally combined across all individuals.

To estimate the LCL model we used the expectation–maximization (EM) algorithm, which allows for a 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, Texas, US). We then assigned consumers to groups based on the highest posterior probabilities.

Lastly, to characterize and describe the consumer groups based on consumer attributes, we used the Multinomial Logit (MNL) model because the groups have no natural ordering (Greene 2018). The general form of a MNL model is:

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

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 are row vectors of unknown parameters. The MNL model was estimated using the module *mlogit* run in Stata 16.1.

4. RESULTS

4.1 Estimation results from the rank ordered mixed logit (ROML) model

The parameter estimates of the main effects of participant citizenship (i.e., United Kingdom versus Thailand) using the ROML model are exhibited 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, which describe the value of the mean estimate divided by the standard error of that mean (Train 2009). While this is not strictly a Bayesian approach, it is similar to a classical t-value in terms of its size, conveying whether the mean has a posterior mass away from zero. Results show that participants from both countries have a higher probability to save the leftovers when (i) they dine at home, (ii) the meal cost is high, and (iii) they have enough leftovers for a whole meal. In addition, the British participants have a higher probability to save their leftovers when they did not have a meal plan for the following day, while the Thai participants have a higher probability to save the leftovers when dining alone.

Looking at the magnitudes, we note that it is the relative size of the parameters that matter here, rather than the absolute size. Readers are reminded that all variables were coded as either 0 or 1. The cost parameter therefore represents the impact of a £24 or 400 Baht increase in price for the United Kingdom and Thailand, respectively. Place and cost are the attributes that most affect the likelihood to save or waste food.

Table 2. Parameter estimates from the rank ordered mixed logit (ROML) model for the United Kingdom and Thailand.

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

We next compared the distributions (i.e., kernel density estimates) of the marginal utilities between participants from the United Kingdom and Thailand (see Figure 1). Here we can see that not only do the mean values for each of the marginal utilities differ, but also some of the marginal distributions are much more diffuse than others. This is particularly true for the attributes of place and cost. What is also evident here is that the normality assumption employed by the ROML does not seem wholly consistent with the data. In particular, cost for both countries describes a bimodal distribution, with the marginal utilities for a subgroup of respondents particularly sensitive to this attribute. Likewise, there is a subgroup of British respondents that is particularly likely to waste leftovers at a restaurant. This suggests a potential to segment consumers.

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

4.3 Estimation results from latent class logit (LCL) model.

In view of the multimodality of some of the attributes within the ROML model, we now investigate the possibility that there are distinct groups of consumers. To investigate such consumer heterogeneity, we used the LCL model for each country.

Regarding the United Kingdom, based on the BIC[6] parameter (Hong Il 2020), the optimal number of groups for the LCL model was three, as BIC was the lowest[7]. The results of the LCL model with the three-groups solution are reported in Table 3 including the regression coefficients for PRESENCE, PLACE, COST, AMOUNT and PLAN, as well as their corresponding standard errors (SEs) and significances (p-values). The LCL model identifies one larger and two smaller groups of consumers. Group 1 participants ("Home savers," *N*=51) most likely save leftovers when eating at home, quite likely save leftovers when the meal cost is higher, and quite likely

[6] Bayesian Information Criterion.
[7] However, differences in BIC among different groups number were negligible[7] (Raftery 1995).

save leftovers when there is no meal plan for the following day. Group 2 participants ("Multi-factor savers," *N*=118) quite likely save food when the meal cost is higher, when there is a full meal left, and when there is no meal plan for the following day. Finally, Group 3 participants ("Cost savers," *N*=39) most likely save food when the meal cost is higher, quite likely save food when there is a full meal left, and quite likely save food when there is no meal plan for the following day.

Table 3. Estimated regression coefficient from latent class logit (LCL) model for the United Kingdom.

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 others number of groups (i.e., 2-4) that have been estimated. However, given the negligible differences among the groups[8], and because some groups had a low number of participants, we choose the three-groups solution for a better comparison to the British groups. The results of the LCL model with the three-groups solution are reported in Table 4. The results show one larger and two smaller groups. Group 1 participants ("Cost savers," *N*=35) most likely save leftovers when the meal cost is high although there is noisy. Group 2 participants ("Unaffected savers," *N*=107) are not affected by any particular attributes when deciding to save leftovers. Finally, Group 3 participants ("Multi-factor savers," *N*=67) are affected by all the attributes when they decide to save leftovers. Specifically, consumers save leftovers when eating alone, at home, when the meal cost is high, when there are

[8] The BIC value is 4302.91 with two groups, 4275.23 for three groups, 4284.41 for four groups, 4272.69 for five groups. Raising it further to six groups results in numerical convergence problems.

leftovers for a whole meal, and quite likely save leftovers when there is no meal plan for the following day.

Table 4. Estimated regression coefficient from latent class logit (LCL) model for Thailand.

Note. SE: Standard error.

4.4 Consumer segment characterization

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

Table 5 presents the results of the MNL models for the United Kingdom and Thailand, including regression coefficients for the consumer attributes along with their corresponding standard errors (SEs) and significances (p-values). For the United Kingdom, the model fits the data well according to the likelihood ratio (LR) chi-square test while pseudo R-square measures indicate that the model explains 8.00% of the variance. The segment "Multi-factor savers" has been taken as the reference group. Only a few attributes affect the decision to save or waste food. Specifically, "Home savers" tend to be older and less likely than "Multi-factor savers" to throw away food that has passed its "best before" date. There are no significant differences in any of the investigated consumer attributes between "Cost savers" and "Multi-factor savers."

For Thailand, the model fits the data well according to the LR chi-square test, while pseudo R-square measures indicate that the model explains 12.00% of the variance. The segment "Unaffected savers" has been taken as the reference group. "Multi-factor savers" tend to be more educated and less likely to see that reducing FW is needed for diminishing hunger rates of global compared to “Unaffected savers.” They also tend more to dine with others who often have food left on their plates that is subsequently discarded. In contrast with “Unaffected savers,” “Cost savers” have higher incomes, tend not to see that reducing FW is needed for diminishing hunger rates of global hunger, think that it is not better to throw away food that has passed the “best before” date, hate to throw away food, and dine with others who have food left on their plates to be discarded after a meal.

Table 5. Multinomial Logit (MNL) models: latent class membership regressed on consumers’ attributes for the United Kingdom and Thailand.

5. DISCUSSION

This study has investigated FW decisions between British and Thai survey respondents. We find several revealing outcomes. First, consumers tend to save more leftovers when meal cost is higher, when dining at home, and when there are enough leftovers for a whole meal. We also find that these results are the same for British and Thai survey groups. Corroborating the findings of Ellison and Lusk (2018), the majority of differences relate to cost and time. Indeed, there is a monetary element, with a more expensive meal related to an increased probability of saving leftovers. Furthermore, when a meal is prepared at home, there is a time cost for that meal that people do not want to discount by throwing away leftovers. This may be because a meal prepared at home has a higher intrinsic value, given the time and effort spent on food shopping and preparation compared to restaurant dining. Another possible explanation is that restaurant portions may be too large, and consumers may not feel a sense of ownership or responsibility over the leftovers (Giorgi 2013), increasing the likelihood of FW. In addition, consumers can save time and money in situations where there are enough leftovers for a whole meal and when there are no meal plans for the following day.

Second, we find some telling differences between the two countries' results. British participants show a higher probability of saving leftovers when there are no meal plans for the following day, corroborating Ellison and Lusk (2018), while not having future meal plans did not affect the probability of saving leftovers among Thai participants. In addition, the social aspects of the dining context show a greater impact on FW decisions in the Thai participants than among the British participants. Specifically, we find Thai participants more likely to save leftovers when dining alone. This corroborates the findings by Xu et al. (2020) and Qian et al. (2021), but contrasts with Tsai, Chen, and Yang (2020). Moreover, for British participants, the meal cost and place of eating have similar importance as a driver of FW decisions, while for Thai participants the place of eating is of less importance.

Third, at the individual level, we find that British consumers are more likely decide to save leftovers based on a combination of several factors of similar importance, while for two smaller groups of consumers the decision to save leftovers is based strongly on two main factors, such as dining at home or high meal cost. By contrast, among Thai participants, we find 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 the 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

Recommendations for practitioners and policy implications follow from this study. Our results suggest that vendors might usefully encourage consumers to eat their entire meal at the restaurant or bring home and reuse the leftovers by providing discounts for a future meal. Restaurants should also be encouraged to provide suggestions to consumers via booklets or other media about how to better reuse leftovers. This could be done by providing suggestions on handling leftovers, such as combining leftover food with other dishes to create a whole meal. Restaurants can also encourage waiters to proactively offer doggy bags to preserve leftover food. Policymakers can promote and incentivize vendors to adopt these strategies, for example by giving recognition through a food waste certification for vendors who adopt such strategies. Vendors can then promote these conscientious practices to their clients using FW labeling which could also facilitate them the access to government funding. Restaurants can also provide menus with varying portion sizes, from which consumers can choose the portion size that best fits their need. This in turn can help reduce FW (Giorgi 2013). Governments can also support restaurants by providing food-preservation materials like doggy bags through a central resource, such as a website. Restaurants in Thailand might incentivize their waste-reduction efforts by specifically targeting consumers who dine with others rather than those who dine alone.

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 meal planning or to dine in larger or smaller groups. However, for many consumers, meal cost is an important driver in the decision to save or waste food, with cheap meals associated with a propensity to waste leftovers when dining out. This was evident in both Thai and British participants. Consequently, policymakers can focus their policies on food outlets serving cheap meals, such as fast-food restaurants.

Several longer-term policy recommendations can be identified. First, policymakers in the United Kingdom and Thailand need to promote educational campaigns aimed at reducing FW by better targeting educational efforts to the consumers most susceptible to high levels of FW. This should include British and Thai people who tend to eat out more frequently in cheap restaurants, and Thai people who eat alone. One possibility is to provide consumers with information about the long-term negative effects of FW on the economy, the environment, and food security. Second, policymakers should use social sanctions to incentivize people to internalize the external effects of FW. This might be achieved by restaurants adopting information campaigns similar to those used to discourage other antisocial activities, such as drunk driving. Furthermore, policymaking interventions in both the United Kingdom and Thailand should be more targeted to cheap restaurants. Thai policymakers should also focus on people who dine alone at restaurants.

Future studies are needed to verify and generalize the findings in both high- and low-income countries and across cultural contexts. Larger samples would naturally be beneficial, and future studies might also consider other contextual factors, particularly in Asian countries. Future research might investigate consumers' FW decisions in non-hypothetical eating situations by conducting field experiments in restaurants. In addition, future research should test the waste-reduction effectiveness of information campaigns surrounding the economic, social, and environmental consequences of FW.

To conclude, our findings reveal that among both British and Thai consumers, FW decisions are dependent on economic and other contextual factors and differ considerably within and across populations. Nonetheless, meal cost and dining location are key determinants of consumer FW decisions, and we argue that this provides an avenue for policy interventions in both high- and low-income countries.

TRASPARENT REPORTING

Pre-registration of the study is available at https://aspredicted.org/blind.php?x=n3e7rg.

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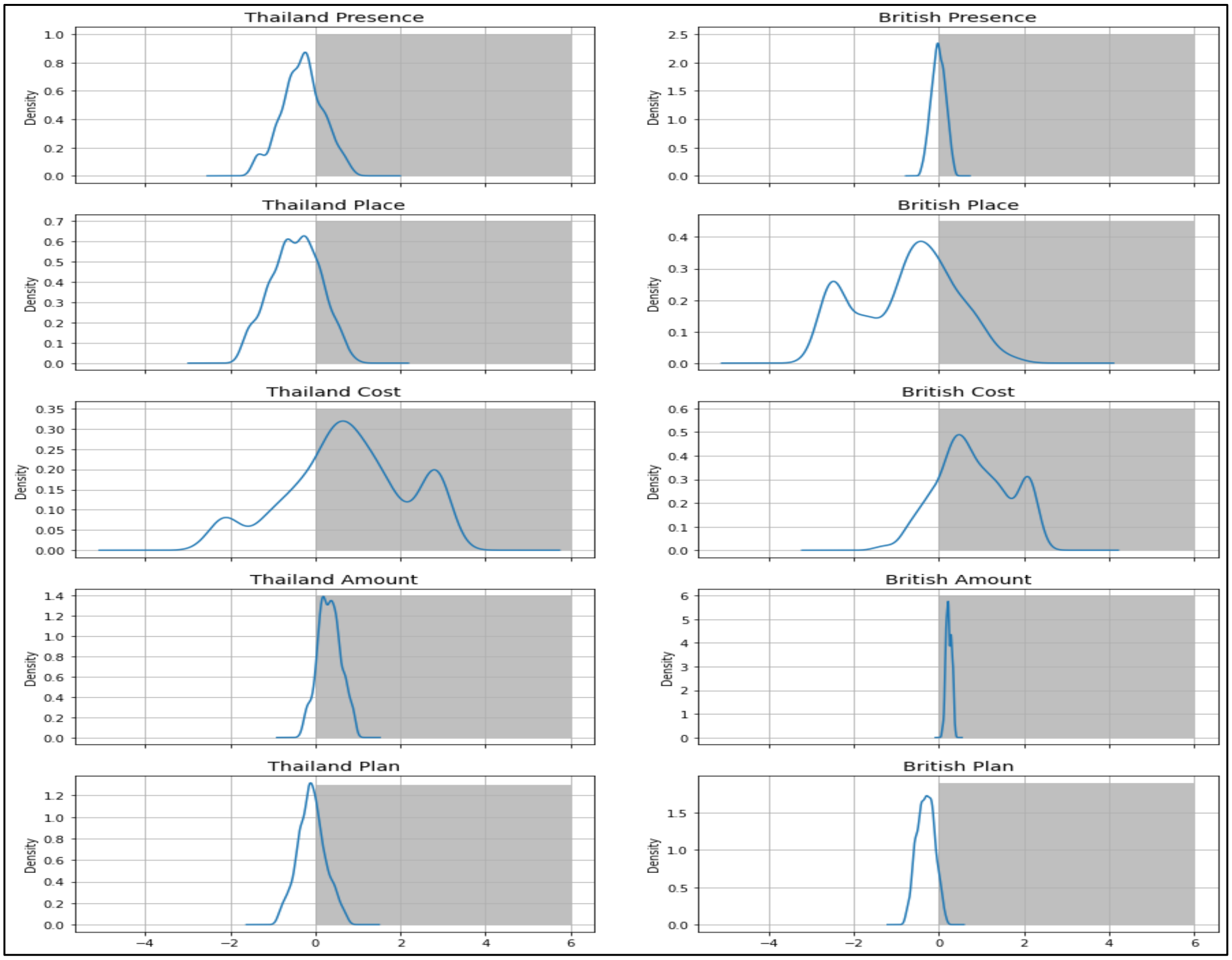

Figure 1. Distribution of marginal utilities across individuals from the United Kingdom and Thailand.

Table 2. Attribute levels used in the study.

ATTRIBUTE	LEVEL
Presence	Alone With others
Place	Home Restaurant
Cost	100 Baht/£6 500 Baht/£30
Amount	Half meal Full meal
Plan	No plan Plan

Table 2. Parameter estimates from the rank ordered mixed logit (ROML) model for the United Kingdom and Thailand.

ATTRIBUTE	UNITED KINGDOM (*N = 208*)				THAILAND (*N = 209*)			
	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

Note. SD: Standard deviation.

Table 3. Estimated regression coefficient from latent class logit (LCL) model for the United Kingdom.

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

Note. SE: Standard error.

Table 4. Estimated regression coefficient from latent class logit (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

Note. SE: Standard error.

Table 5. Multinomial Logit (MNL) models: latent class membership regressed on consumers' attributes for the United Kingdom and Thailand.

ATTRIBUTES	UNITED KINGDOM (*N = 208*)		THAILAND (*N = 209*)	
	Reference segment: *Multi-factor savers*	**Coefficient (SE)**	**Reference segment:** *Unaffected Savers*	**Coefficient (SE)**
Socio-demographics				
Gender		-0.32 (0.38)		-0.45 (0.37)
Age		0.39 (0.18)**		0.02 (0.19)
Household size		0.08 (0.15)		0.13 (0.12)
Education		0.05 (0.23)		0.60 (0.25)**
Childs		-0.50 (0.50)		-0.70 (0.39)
Income		0.15 (0.10)		-0.18 (0.07)
	Home savers		Multi-factor savers	
Food waste habits				
bbf_risk		-0.23 (0.12)*		-0.05 (0.13)
second_help		0.09 (0.15)		0.13 (0.17)
hunger_carer		-0.00 (0.16)		-0.68 (0.25)***
hate_binfood		-0.28 (0.21)		-0.03 (0.21)
i_waste		-0.07 (0.21)		-0.14 (0.21)
other_waste		-0.12 (0.14)		0.30 (0.13)**
Cons		0.01 (1.65)		0.53 (2.03)
Socio-demographics				
Gender		-0.48 (0.41)		0.52 (0.46)
Age	Cost savers	0.33 (0.21)	Cost savers	-0.17 (0.23)
Household size		-0.05 (0.17)		0.07 (0.14)
Education		0.25 (0.26)		-0.17 (0.26)
Childs		0.16 (0.51)		0.13 (0.48)

Income		0.02 (0.11)		0.14 (0.08)*
Food waste habits				
bbf_risk		0.02 (0.12)		-0.34 (0.15)**
second_help		0.19 (0.18)		0.12 (0.21)
hunger_carer		0.18 (0.20)		-0.92 (0.30)***
hate_binfood		0.13 (0.28)		0.52 (0.29)*
i_waste		0.02 (0.19)		0.20 (0.22)
other_waste		0.07 (0.15)		0.27 (0.16)*
cons		-5.53 (2.03)***		0.71 (2.37)
Log-likelihood of null model	-179.35		-175.53	
LR test chi-square (8)	31.32		47.03	
Prob > chi-square	0.14		0.00	
Pseudo R-square	0.08		0.12	

Note. ***, **, * significance respectively at 1%, 5%, 10% level.
Note. SE: Standard error.
Note. "*bbf_risk*": "In general, for food with a "Best Before" date, it is better to throw it away if the date has passed than to risk eating it".
Note. "*second_help": "*I would rather have a second helping than leave food on my plate".
Note. "*hunger_carer*": "As long as there are still hungry people in this world, food should not be thrown away".
Note. "*hate_binfood": "*I hate it when I need to throw food in the bin".
Note. "*i_waste": "*How often do you have food left on your plate to be discarded after a meal?"
Note. *"other_waste":* "In your opinion, how often do other people around you have food left on their plate to be discarded after a meal in general?"