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Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study

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The ecological footprint of food transport can be communicated using carbon dioxide emissions (CO_2 label) or by providing information about both the length of time and the mileage travelled (food miles label). We use stated choice data to estimate conventional unobserved taste heterogeneity models and extend them to a specification that also addresses attribute nonattendance. The implied posterior distributions of the marginal willingness to pay values are compared graphically and are used in validation regressions. We find strong bimodality of taste distribution as the emerging feature, with different groups of subjects having low and high valuations for these labels. The best fitting model shows that CO_2 and food miles valuations are much correlated. CO_2 valuations can be high even for those respondents expressing low valuations for food miles. However, the reverse is not true. Taken together, the results suggest that consumers tend to value the CO_2 label at least as much and sometimes more than the food miles label.

Key words: attribute nonattendance, choice experiment, latent class analysis, transport footprint, willingness to pay.

1. Introduction

In recent years, the expansion of international food trade has significantly increased the transportation of food products around the world with negative impacts on the environment. Transportation of food products and the highly publicised food contamination accidents (Onozaka and McFadden 2011) have prompted consumers to question the safety standards in the global food system, as well as their actual environmental and social sustainability (Zadek *et al*. 1998). Food transportation, especially by air and road, consumes large quantities of fossil fuel releasing greenhouse gases that contribute to global climate change. Food that is sourced by major retailers from global supply

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chains often travels for thousands of miles before consumption (Smith *et al.* 2005). This suggests that the environmental cost of food transport is inadequately internalised, thereby giving rise to market failures. The globalisation of food supply chains has exacerbated the problem. It has led to lower visibility to consumers of information on food origin and miles travelled, which may be used as proxies for the social and environmental impacts of food production and transportation.

This trend has prompted many consumers to expect food labelling to be informative about the environmental and social sustainability aspects related to the product. There is ample evidence suggesting that not only do consumers care about the physical properties of the food they eat (Briggeman and Lusk 2010), but also about other ethical issues such as how the food is produced, who benefits from their purchases (ie local versus distant producers), where it comes from and how its transportation impacts on the environment in terms of, for example, carbon dioxide emissions (CO_2) or on food freshness.

'Food miles' is a term coined in a 1994 report (Paxton 1994) by the Sustainable Agriculture Food and Environment (SAFE) Alliance, to signal the distance food travels from the place of production to that of consumption. Although there has generally been no public regulations related to food miles yet, recent labelling initiatives are emerging in several countries from the private sector (eg, Tesco, Marks & Spencer, Swiss supermarket Coop, Frito Lay). However, lower food miles do not necessarily guarantee either lower environmental degradation, fresher food or a small ecological footprint of the production system (Blanke and Burdick 2005; Weber and Matthews 2008).Therefore, the question surrounding the adequacy of food miles as a generic label indicator of sustainability, freshness and as a proxy for the economic stimulus to the local economy is still under debate, especially because the scientific evidence as to whether domestic or imported food products generate the strongest environmental impact is inconclusive (Lang and Heasman 2004; Pretty *et al.* 2005; Coley *et al.* 2009).

A few studies have focussed on consumers' attitudes towards the distance food travels (Seyfang 2006; Sirieix *et al.* 2008; Kemp *et al.* 2010) and on consumers' valuation for specific food labelling information related to food miles (Pirog 2004; Onozaka and McFadden 2011). However, if what consumers are mainly concerned about is the climate change contribution of transporting food from afar, related but potentially alternative labelling schemes should also be examined: that is, one providing the amount of greenhouse gas equivalent (CO_2-equivalent) emitted due to transportation, and the other giving the distance travelled. The key question investigated in this study is which of these two types of information is preferred by consumers in food labels, everything else equal – including the environmental impact of food production. No other known published study has investigated this question in the past. As displaying information on food labels comes at an often high opportunity cost for other information, it is important to assess how consumers value different types of information on labels.

More specifically, the purpose of our study is to assess consumers' valuation for two types of food miles or food transportation footprint labels: one providing information about distance that food travelled and time of transport (*NMILES*), and the other providing information only on the amount of CO_2 emitted in transportation only (CO_2), excluding emission from other stages of production. We use a stated choice experiment to investigate this issue. Initially, we use three different but commonly employed choice models. The three econometric specifications are of gradually increasing complexity and include the multinomial logit (MNL) – our baseline model, the random parameter logit (RPL), and the error component random parameter logit (RPL-EC) models. All these embed the conventional assumption of fully compensatory preference across all choice attributes. We then depart from this approach and consider partially compensatory models by using equality constrained latent class (ECLC) specifications. These allow us to account for a frequently adopted decision heuristic with potentially severe consequence on welfare estimation: attribute nonattendance (Hensher 2006; Campbell *et al.* 2008; Scarpa *et al.* 2009). Because standard attribute nonattendance models fail to account for preference heterogeneity, we also propose an extension that allows for both preference heterogeneity and attribute nonattendance. Finally, for the purpose of results validation, we run panel regressions on the individual-specific posterior marginal WTP estimates of sample respondents and present their distributional features.

2. Full and partially compensatory models of choice

In the conventional analysis choice experiment data, a random utility model is typically assumed. For the nth consumers', the utility of option j in choice situation t is defined as:

$$U_{njt} = \boldsymbol{\beta}_n' \mathrm{x}_{njt} + \varepsilon_{njt} \tag{1}$$

where $\mathbf{x}_{njt}$ is a vector of observed variables relating to alternative j and individual n; $\boldsymbol{\beta}_n$ is a vector of structural taste parameters; ε_{njt} is the independently and identically Gumbel distributed unobservable utility, assumed to be independent of $\boldsymbol{\beta}$ and $\mathbf{x}$.

We consider here a general specification of the RPL model, which allows for more flexibility (Revelt and Train 1998), including taste correlation. In a choice experiment, respondents provide a sequence of choice responses. Thus, a panel data approach is used to allow for the obvious correlation among individual preferences in a sequence of choice decisions (seven choice sets in our case). Consider a sequence of observed choices i by individual n, one for each choice task in the assigned sequence of T choice tasks, $i = (i_1, \ldots, i_T)$, conditional on $\boldsymbol{\beta}$ the probability that individual n makes this sequence of choices, is represented by the following joint probability:

$$L_{ni}(\boldsymbol{\beta}) = \prod_{t=1}^{T} \left[\frac{e^{\boldsymbol{\beta}_n' \mathbf{x}_{nit}}}{\sum_j e^{\boldsymbol{\beta}_n' \mathbf{x}_{njt}}} \right] \tag{2}$$

as the ε_{njt}'s in Eqn (1) are independent over utilities, choices and respondents. Consequently, the unconditional probability is the integral of this product over all values of $\boldsymbol{\beta}$ in the space of the distribution:

$$P_{ni} = \int \mathrm{L}_{ni}(\boldsymbol{\beta}_n) f(\boldsymbol{\beta}) d\beta. \tag{3}$$

The presence in all our choice sets of the no purchase alternative can cause systematic effects because it may be conjectured differently by different respondents. It is unlikely that the unobservable utility of this alternative is distributed with the same variance as the unobservable of utilities associated with alternatives involving a purchase. Scarpa *et al.* (2005a,b) suggest that because the no purchase option is actually experienced by the consumer and repeats itself in each choice task while the experimental options are hypothetical and change in each choice task, the utilities of the latter are likely to be more correlated between themselves than with the no purchase option. One way to capture this correlation in the estimation is to make experimental alternatives share an extra zero mean error component in the utility structure, which is missing in the utility of the no purchase alternative. To account for this form of heteroskedasticity in our study, we also estimated a panel random parameter logit with error component (RPL-EC).

The discussion above is about fully compensatory models, in the sense that all respondents are assumed to trade off and consider all attributes used in the description of the product. However, decision heuristic and preference structures are likely to give rise to decision processes best described by partially compensatory models. These models account for the fact that changes in certain dimensions may not be compensated for by changing any amount of other dimensions of the composite good. For example, some attributes are sometimes ignored by respondents due to the implementation of decision heuristics aimed at simplifying the cognitive effort of choice tasks or due to genuine indifference by respondents with regard to specific attributes or levels used in the experiment. So, our second set of models is estimated to infer what has been termed elsewhere in the literature as serial nonattendance to specific attributes (Scarpa *et al.* 2010). For such inference, we use ECLC models for panel data (Hess and Rose 2007; Scarpa *et al.* 2009; Campbell *et al.* 2011).

In our ECLC model, the unconditional probability of the observed panel of choices is a weighted average over the k classes with weight π_k:

$$P_{ni} = \sum_k \pi_k \prod_{t=1}^{T} \left[\frac{e^{\boldsymbol{\beta}_k' \mathbf{x}_{kit}}}{\sum_j e^{\boldsymbol{\beta}_k' \mathbf{x}_{kjt}}} \right]. \tag{4}$$

The population estimates of marginal willingness to pay (WTP) from latent class models are derived by weighting by the class membership probability π_k the marginal WTP of each class k obtained by the usual ratio between attribute coefficient and cost coefficient $\beta_{1,k}/\beta_{\$,k}$, or $\text{WTP}_1 = \Sigma_k \pi_k \beta_{1,k}/\beta_{\$,k}$.

2.1. Comparisons of posterior WTPs and validation

As a way to provide model evaluations beyond the usual fit statistics, we report a comparison of the derived posterior individual estimates of expected marginal WTPs for each attribute. These are obtained conditionally on the whole set of observed choices in the panel provided by each respondent (eg see Scarpa and Thiene 2005; Scarpa *et al*. 2005a,b), as originally recommended by von Haefen (2003). We present both comparisons of distributional features of these sample values via kernel smoothing across models and pairwise comparisons between *NMILES* and *CO2* labelling for the best models estimates.

The analysis of hypothetical choices is more persuasive when supported by a theoretical validity assessment (Bishop *et al.* 1995). One way to evaluate theoretical validity is to investigate whether the variation of posterior WTPs can be explained by socio-economic characteristics, especially income. The focus on the effect of socio-economic covariates on posterior WTP is warranted on two grounds. First, respondents with similar socio-economic covariates may have similar posterior WTP estimates for some attributes even when the socio-economic covariates *per-se* are uninformative for the membership probabilities in the model. This is so because firstly, the posterior estimates are conditioned on the entire pattern of observed choices and secondly because the WTP estimates are derived as ratios of coefficients, so that two different pairs of coefficients can give the same ratio and hence WTP estimate. We report panel OLS regression estimates of the determinants of posterior WTPs for all the main models.

3. Data

3.1. Experimental design/Study design and variables

The product of interest in our study is fresh tomato because it familiar to most and it is one of the most consumed vegetables across the United States. We described fresh tomatoes as a combination of price, food miles and production method. The hypothetical shopping scenarios were made more realistic by including as an attribute the type of fresh tomato, with levels being cherry, plum and beefsteak tomatoes. Four levels were used for price (\$1.1, \$2.1, \$3.1 and

\$4.1), and two for the production method (organic/conventional). Finally, assuming an identical environmental impact of the transportation of fresh tomatoes from the place of origin, we used three levels of information on transport footprint in the labels: (i) the distance and time travelled (*NMILES*); (ii) the amount of CO_2 emitted during transport (*CO2*); and (iii) no information at all (no information). We consider *CO2* and *NMILES* as mutually exclusive.

Information regarding attributes was given to respondents immediately before the choice experiment. Subjects were informed that fresh tomatoes differed only in terms of four attributes, while all other characteristics were identical across product profiles. With regard to transport footprint, respondents were told that tomatoes had the same origin and that their environmental impact in terms of distance travelled, and transport-related CO_2 emissions were identical across profiles. Hence, the observed choices should reflect exclusively how respondents value alternative types of transport footprint information.

Considering the number of attributes and levels, a full factorial design implies 72 possible combinations of attribute and levels ($4 \times 2 \times 3^2$). Established experimental design techniques (see Louviere *et al.* 2000) were used to obtain an orthogonal design arranged into 32 pairwise comparisons of fresh tomato choice tasks. Such tasks were first split into four orthogonal blocks of eight choice tasks each, which after elimination of duplicates, gave 4 blocks of seven choice tasks. Such elimination reduces the degree of orthogonality, but this does not prevent the design from achieving identification of coefficient estimates. This design was evaluated ex post in terms of D-error for the MNL model estimated from the data. We found our design to require 36 design replicate to ensure significance of all estimates. Given the 4 blocks, this implied 144 respondents. Our sample of 200 respondents far exceeds this need. The design we used seems to have adequately performed as the sample size compensated for the lack of efficiency.

To prevent systematic order effects, the order of choice tasks presented to respondents was randomised. Respondents were asked to select their favourite alternative between the three options listed in each choice task, which included two fresh tomato profiles and one ‘no-buy’ option. Prior to facing the choice tasks, respondents were given a cheap talk script to mitigate the hypothetical bias often observed in this type of studies (see Cummings and Taylor 1999; Lusk 2003; Silva *et al.* 2011) (available as supplementary material at AJARE online).

3.2. Data collection and sample characteristics

The study took place during spring 2009 in Patterson, New Jersey, which was selected due to the diversity of its population. Adults responsible for food shopping were randomly selected in three different grocery stores, and the survey was administrated face to face.

A total of 200 respondents completed the choice experiment surveys. Summary statistics for the characteristics of the full sample are presented in Table S1 available as supplementary data at AJARE online. Overall, the sample is comparable to the US Census data for Paterson city in terms of age, marital status, education and income.[1] However, our share of women is higher than in the census data because we targeted those in charge of household grocery shopping.

4. Estimation results

4.1. Utility Specification

All models presented in this study are estimated on 1400 choices, based on responses from 200 individuals, each performing 7 choice tasks. The final specification of the utility function includes an alternative-specific constant representing the 'no-buy' option choice (β_0) and the other attributes and attribute levels considered in the choice design. Thus, in all models the utility that individual n obtains from alternative j is

$$\begin{aligned} U_{njt} = {} & \beta_0 NO-BUY + \beta_1 PRICE_{njt} + \beta_2 CHERRY + \beta_3 PLUM \\ & + \beta_4 ORGANIC + \beta_5 NMILES + \beta_6 CO_2 + \epsilon_{njt} \end{aligned} \tag{5}$$

where j pertains to option A, B and C. *PRICE* is the price of 2.2 pounds of fresh tomato, while the rest of the attribute levels are dummy coded. In particular, *CHERRY, PLUM, ORGANIC, NMILES* and CO_2 are coded as dummy variables that take the value of 1 if they are present in option j and 0 otherwise. Dummy coding is necessary for the use of the attribute nonattendance restrictions that assign zero on the coefficient values. Posing this zero restriction on a binary effect-coded variable $\{-1, 1\}$ would not be equivalent to a zero weight in the utility function, but to a weight which is intermediate between absence and presence of the attribute. Dummy coding is less than ideal because of the potential confounding with the 'no-buy' alternative-specific constant, but in our case, this should be mitigated by the very low probability predicted for the no-buy option by all our models.

As mentioned, the RPL and RPL-EC models were estimated using a panel data structure and full correlation. The RPL-EC model included a normally distributed zero mean error component shared by the two purchase alternatives, which is correlated with the other random parameters.

[1] http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml

4.2. Estimates from fully compensatory models

Table 1 reports the coefficient estimates for the following fully compensatory models: MNL, RPL and RPL-EC with correlated random taste and error. Table S2 (available as supplementary data at AJARE online) reports the estimated correlations of the RPL-EC model, which emerges as the best fitting model out of the three models. We conclude that preference heterogeneity as well as extra variance of utility of the purchase alternative cannot be rejected.

As expected, the coefficient estimates for price β_1 is, in all models, negative and statistically significant at the 0.01 level. The coefficient on the no-buy constant shows that this alternative's utility (alternative C, the no-buy) is perceived on average to be lower than the utility from a purchase alternative (A or B).

The coefficient estimates of all other attributes are positive and different from zero at the 0.01 level. The highest utility increment occurs when information on the *ORGANIC* production method is present, followed by CO_2 label, *NMILES* label and *PLUM*. Thus, on average, respondents manifest highest marginal utility for organic production methods. The travel footprint information seems to be better appreciated when expressed in terms of *CO2* than when it is expressed in terms of food miles and length of time that the food travelled (*NMILES*). However, this is only suggested by the point estimates, while the interval estimates for the two overlap, as do the implied distributions of taste.

Table 1 MNL, RPL and RPL-EC model estimates

Parameters	MNL	RPL	RPL-EC
NO-BUY	−2.46*** (15.05)†	−2.89*** (13.99)	−3.02*** (12.04)
PRICE	−0.74*** (15.84)	0.92*** (13.97)	−0.95*** (13.15)
St. Dev. Of Err. Comp			1.18*** (4.34)
CO2			
Mean	0.67*** (6.37)	0.86*** (5.97)	0.91*** (5.31)
St.dev.		0.91*** (3.86)	1.43*** (5.00)
NMILES			
Mean	0.52*** (4.79)	0.79*** (4.91)	0.85*** (4.91)
St.dev.		1.11*** (5.12)	1.31*** (4.20)
ORGANIC			
Mean	0.69*** (7.79)	0.89*** (6.94)	0.99*** (6.62)
St.dev.		0.70*** (4.22)	1.13*** (5.70)
PLUM			
Mean	0.51*** (4.80)	0.59*** (4.15)	0.57 *** (4.08)
St.dev.		1.02*** (5.15)	0.86 *** (3.80)
CHERRY			
Mean	0.45*** (3.68)	0.54*** (3.18)	0.47*** (2.68)
St.dev.		1.02*** (4.28)	1.11*** (4.42)
N	1400	1400	1400
Log-lik.	−1093.46	−1064.85	−1052.81

Note: ***, **, *significance at 1, 5 and 10% level. †Number in parenthesis are \|t-stats\|.

Some information can also be derived by examining the implied correlation coefficient matrix derived from the Cholesky matrix[2] . Organic preferences are positively correlated more with preferences for plum shaped than cherry shaped tomatoes, and both preferences for *NMILES* and *CO2* labelling are somewhat positively correlated with preferences for *ORGANIC*. On the side of negative correlation, those who like *PLUM* shaped tomatoes tend not to like *CHERRY* shaped ones.

4.3. Estimates from partially compensatory ECLC models

Table 2 reports the estimates of the two ECLC models.

The first model is called LC1 + 2 ANA because it has a single preference class and two classes with some attribute nonattendance (classes 2 and 3) as well as one with full attendance (class 1). This model was selected for presentation as a result of a specification search carried out over all the possible combinations of classes, with restrictions of parameters to zero within the common constraint of a single set of preference parameters. According to this model, only 42 per cent of the sample, represented by class 1, produced a pattern of choices consistent with a fully compensatory set of preferences, while the remaining 58 per cent is chosen according to a noncompensatory decision process. This 58 per cent is further divided into two noncompensatory classes, each with a different form of attribute nonattendance, but the attended attributes have the same weight as in class 1. Class 2 (37 per cent) is the first noncompensatory class and shows zero coefficient values for transport footprint labels (*NMILES* and CO_2). Class 3 (21 per cent) is the second noncompensatory class, and it includes respondents whose choices are consistent with having ignored *NMILES* label and the *ORGANIC* mode of production. This model implies that transport information in the form of CO_2 is only ignored by 21 per cent of respondents, while *NMILES* is ignored by 58 per cent. This is a first sign of the higher importance of the CO_2 label in terms of commanding attention more frequently from consumers.

The second noncompensatory model selected for presentation is named LC2 + 3 ANA (eg 2 preference classes and 3 attribute nonattendance class), and it extends the attribute nonattendance model to account for preference heterogeneity. In this model, classes 1 and 2 share the same taste intensities and hence have the same preference structure in terms of relative intensity, but they differ in terms of attribute attendance. Attendance class 1 is fully compensatory, while attendance class 2 is noncompensatory as *NMILES* and *ORGANIC* are not attended to. Together attendance classes 1 and 2 make up 38 per cent of the sample and constitute preference class 1. Their preferences are different from those in attendance classes 3, 4 and 5, which together

[2] The Cholesky matrix from RPL + EC estimates is available as supplementary data at AJARE online (Table S3).

Table 2 Latent class models estimates

	LC1 + 2 ANA			LC2 + 3 ANA				
Preference	Class 1			Class 1		Class 2		
Attendance	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 4	Class 5
Class probabilities	0.42 (3.45)***	0.37 (3.83)**	0.21 (2.32)**	0.28 (3.35)***	0.10 (1.53)	0.37 (1.78)*	0.13 (2.02)**	0.12 (1.92)**
NO-BUY	−2.57 (14.43)***,†	−2.57 (14.43)***	−2.57 (14.43)***	−6.21 (5.86)***	−6.21 (5.86)***	−1.40 (4.79)***	−1.40 (4.79)***	−1.40 (4.79)***
PRICE	−0.79 (15.18)***	−0.79 (15.18)***	−0.79 (15.18)***	−2.11 (5.81)***	−2.11 (5.81)***	−0.39 (4.46)***	−0.39 (4.46)***	−0.39 (4.46)***
CO2	1.14 (3.69)***	0 (fixed)	1.14 (3.69)***	0.65 (1.99)**	0.65 (1.99)**	1.23 (2.50)**	0 (fixed)	1.23 (2.50)**
NMILES	1.55 (3.05)***	0 (fixed)	0 (fixed)	1.11 (1.89)*	0 (fixed)	1.14 (2.51)**	0 (fixed)	0 (fixed)
ORGANIC	0.98 (6.34)***	0.98 (6.34)***	0 (fixed)	1.03 (2.33)**	0 (fixed)	1.06 (4.32)***	1.06 (4.32)***	0 (fixed)
CHERRY	0.51 (3.79)***	0.51 (3.79)***	0.51 (3.79)***	0.68 (1.71)*	0.68 (1.71)*	0.43 (2.51)**	0.43 (2.51)**	0.43 (2.51)**
PLUM	0.52 (4.47)***	0.52 (4.47)***	0.52 (4.47)***	0.96 (2.46)**	0.96 (2.46)**	0.48 (3.13)***	0.48 (3.13)***	0.48 (3.13)***
N	1400			1400				
Log-lik.	−1086.82			−1059.92				

Note: ***, **, *significance at 1, 5 and 10% level. †Number in parenthesis are |t-stats|.

represent 62 per cent and all belong to preference class 2. Both preference groups have a fully compensatory class: these are attendance class 1 in the first preference group and attendance classes 1 and 3 in the second preference group. All other attendance classes display some form of systematic nonattendance. What is of interest is that now that with LC2 + 3 ANA, some taste variation is allowed for, the group displaying fully compensatory preferences has a 65 per cent share – a much higher share than the 42 per cent implied by model LC1 + 2 ANA. This seems to indicate that not accounting for at least some degree of preference variation is a crucial assumption in terms of consequences in prediction of noncompensatory behaviour.

Attendance classes 2 (10 per cent) and 5 (12 per cent) that display zero values for *NMILES* and *ORGANIC* in model with two preference classes (LC2 + 3 ANA) acquire the same share that is collected in the model with 1 preference class (LC1 + 2 ANA). So, this form of nonattendance is not affected much by the introduction of a second preference class. However, attendance class 4, in which both food miles labels are ignored, is greatly reduced. It is only 13 per cent in the model with two preference classes, down from the original 37 per cent in LC1 + 2 ANA, and it belongs entirely to the second set of preferences (ie classes 3, 4 and 5). The difference between the fraction of those ignoring CO_2 and *NMILES* is still predicted to be greatly in favour of the notion that CO_2 is much more frequently attended to (87 per cent of the sample) than the *NMILES* label (65 per cent of the sample).

Table 3 reports the information criteria that can be used to discuss the relative fit of the various models presented here while accounting for the proliferation in parameter estimates that the more complex models induce. The lower the information criterion value, the better is the fit. It is a well-known fact that using the BIC (AIC) tends to under-fit (over-fit) models, while the evidence provided by Dias (2006) shows that AIC3 (with 3 instead of 2 as weight for parameter penalisation) outperforms the other two, correcting for the over-fitting. However, the BIC assumes that one of the models is the true one, which is unlikely to be the case here, while the AIC is aimed at finding model in the considered set that best approximates the unknown data generating process (via minimising the expected estimated Kullback-Leibler divergence). We think that it is safe to rule out the MNL as a candidate as it does not account for a variety of features that are plausibly taking place in decision behaviour, such as the panel nature of the data and

Table 3 Comparison of information criteria

Model	Choices	Log-Lik	Parameters	BIC/N	AIC/N	AIC3/N
MNL	1400	−1093.46	7	1.598	1.572	1.577
RPL-correlation	1400	−1064.85	22	1.635	1.553	1.568
RPL-EC-correlation	1400	−1052.81	28	1.649	1.544	1.564
LC1 + 2 ANA	1400	−1086.82	9	1.599	1.565	1.572
LC2 + 3 ANA	1400	−1059.92	18	1.607	1.540	1.553

various sources of heterogeneity. Hence, we focus on the other specifications. The BIC favours the noncompensatory LC specifications, while the AIC and AIC3 favour the LC2 + 3 ANA over the competing second best, which is represented by the RPL-EC model. The combined evidence of ruling out the RPL and preferring the LC2 + 3 ANA suggests that this is indeed the best model.

Table 4 reports the estimated means of the marginal WTP from the best fitting noncompensatory models, LC2 + 3 ANA. As can be seen, this model predicts a class (preference class 2, with membership probability of 62 per cent) with high marginal WTPs for travel footprint labels, especially for CO_2 labelling (USD3.13, versus USD2.90 for *NMILES*). But these values are conditional on having a WTP > 0, and the predicted probability of this event are higher for CO_2 than *NMILES* in preference class 2 (0.49 versus 0.37). This difference persists in preference class 1, in which *CO2* has 10 per cent more of the predicted probability of WTP > 0 than *NMILES* (0.38 versus 0.28), although the mean WTP for *NMILES* is slightly higher (USD0.53) than that for CO_2 (USD0.31).

The *ORGANIC* production attribute in this model is predicted to command a similar WTP amount as much of the other attributes in preference class 1 (USD 0.49), although it is much higher in class 2 (USD2.69) and closer to travel footprint information than to the amount expressed for the shape of the tomato. Preference class 1 implies a WTP of 18 cents more for *CHERRY* (USD0.45) tomatoes than *PLUM* tomatoes (USD 0.32) against the baseline of beefsteak tomatoes. Preference class 2 shows higher WTP for *PLUM* tomatoes (USD1.22 compared to USD1.08). However, these differences are insignificant in either class.

4.4. Distribution of posterior marginal WTP estimates across models

We visualise the predicted distributions of marginal WTP for attributes across the sample. Figure 1 reports the kernel smoothing of the empirical

Table 4 WTP estimates from best noncompensatory model

Class probabilities	LC2 + 3 ANA			
	0.38		0.62	
	Preference Class 1	Pr WTP > 0	Preference Class 2	Pr WTP > 0
CO_2	0.31 (0.14)	0.38	3.13 (1.62)	0.49
NMILES	0.53 (0.28)	0.28	2.90 (1.40)	0.37
ORGANIC	0.49 (0.19)	0.28	2.69 (0.96)	0.50
CHERRY	0.45 (0.17)	0.38	1.08 (0.44)	0.62
PLUM	0.32 (0.19)	0.38	1.22 (0.44)	0.62

Number in parenthesis are standard errors.

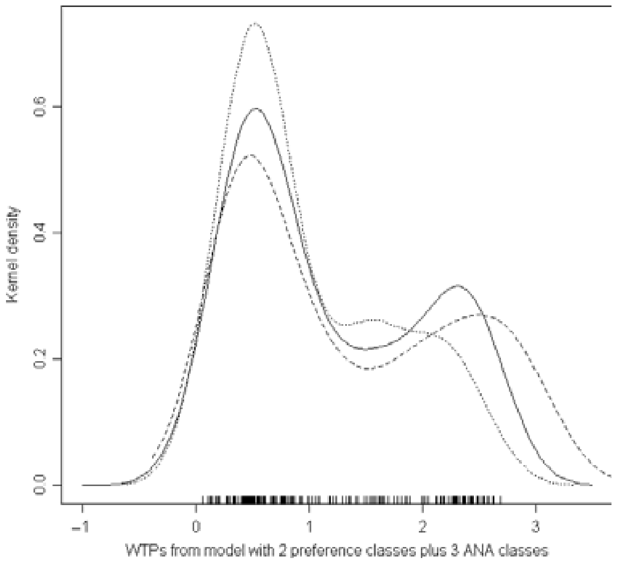

Figure 1 Kernel densities of posterior marginal WTPs. Lines: Continuous ORGANIC, Dashed CO_2, dotted for NMILES.

densities of the implied individual-specific marginal WTP for the three attributes, as predicted by model LC2 + 3 ANA. Kernel smoothing is a way to describe a distribution by means of local averages, and it is a function available in many software packages. Here, we used R and the 'sm' package by Bowman and Azzalini (1997). From this illustration, we can see how similar the empirical WTP densities for *ORGANIC* and CO_2 are, while the density for *NMILES* is higher around zero and lower around higher WTP values. This model predicts that most respondents in the sample have low values for *NMILES* information type and that the remaining fraction of respondents exhibit only moderately high values. This suggests that, on average, more value is attached to CO_2 labelling than to *NMILES* labelling.

Figure 2 reports the scatter plot of individual marginal WTP estimates for *NMILES* and *CO2* from the LC2 + 3 ANA model. Interestingly, it shows that while a certain number of respondents have a higher valuation for CO_2 labels and low valuations for *NMILES*, the opposite is never true. It is as if having a certain valuation for CO_2 is a precondition for having at least as high a WTP for *NMILES*. For consumers who show sensitivity to CO_2 information as describers of travel footprint, it would seem that it does not matter for how long and from how far food travels, as long as information about CO_2 emissions is provided in the label.

4.5. Validity analysis via panel regression

To explore the determinants of inferred individual posterior marginal WTPs, we conducted a validity regression (see Table 5). As each respondent in the

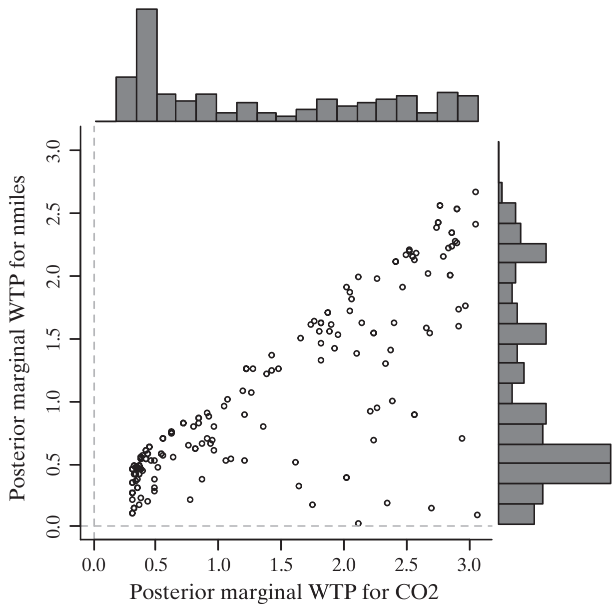

Figure 2 *X-Y* scatter plots with associated histograms of posterior marginal WTPs.

Table 5 Least squares panel regressions totest coefficient differences

Coefficient label	Estimate (*t*-value)
$\delta(NMILES\text{ -}CO_2)$	−0.313 (5.90)
$\delta(NMILES\text{-}ORGANIC)$	−0.18 (3.18)
$\delta(ORGANIC\text{ - }CO_2)$	0.13 (2.39)
αCO_2	1.49 (6.45)
$\alpha NMILES$	0.17 (5.18)
$\alpha ORGANIC$	1.35 (5.96)
Woman	−0.21 (1.84)
Young person	−0.02 (0.08)
Mid-age person	−0.19 (0.98)
Low education	0.21 (1.52)
Mid-education	1.14 (1.06)
Low income	−0.28 (2.14)
Mid-income	0.13 (1.05)
Buys organic	0.02 (0.20)
N	600
Regression Mean	1.17
Regression St. deviation	0.84
R^2	0.08

choice experiment reveals her marginal WTP for the attributes, the estimates referring to the same respondent are correlated. A three-period panel regression is run on the 600 WTP estimates, one period for each of the three attributes (CO_2, *ORGANIC* and *NMILES*) and for each of the 200 respondents. The sign, magnitude and significance of the estimates can help validate the variation of estimated WTPs from hypothetical choices.

We also wanted to run a regression that tests the hypotheses of difference between individual-specific WTP estimates for *NMILES, ORGANIC* and CO_2 attributes. A convenient way to do this is by using a difference parameter panel regression to test the equality constraint across the intercepts for each WTP. For example, let the generic population regression for WTP_{gi} be $WTP_{gi} = \alpha_{\text{WTP-org}} + \alpha_{\text{WTP-CO}_2} + \Sigma_w \beta_w z_{wti} + \varepsilon_{ti}$, where $\alpha_{\text{WTP-org}}$ and $\alpha_{\text{WTP-CO2}}$ are the three WTP-specific constants only two of which are identifiable (g = WTP-org, WTP-CO2, WTP-NMILES), β_w are the w coefficients for the w socio-economic covariates, and ε_{ti} is a regression error. Three equivalent types of such regressions can be run depending on the selection of the pairs of WTP-specific constants. We are interested in testing if, conditional on the variation explained by the socio-economic covariates z, there is a residual difference in the mean of the individual-specific WTPs. We formulate this in terms of a hypothesis testing the differences between WTP-specific constants. For example, in one pair, the null hypothesis of equality is $\alpha_{\text{WTP-org}} = \alpha_{\text{WTP-CO}_2}$, while the alternative H_a: $\alpha_{\text{WTP-CO}_2} \neq \alpha_{\text{WTP-org}}$. The artificial difference parameter δ for WTP-org and WTP-CO_2 is set up as follows: $\alpha_{\text{WTP-CO2}} - \alpha_{\text{WTP-org}} = \delta_{\text{WTP-CO}_2,\text{WTP-org}}$, and the difference regression will be $WTP_t = \alpha_{NMILES} + \alpha_{CO_2} + \delta_{\text{WTP-CO}_2,\text{WTP-org}} + \Sigma_w \beta_w z_{wt} + \varepsilon_t$, null hypothesis is that $\delta_{\text{WTP-CO2, WTP-org}}$ is equal to 0. A significant δ will reject the null, supporting the hypothesis of difference. Three such difference regressions can be run for $\delta_{\text{WTP-NMILES, WTP-CO}_2}$, $\delta_{\text{WTP-CO}_2,\text{ WTP-org}}$ and $\delta_{\text{WTP-NMILES, WTP-org}}$. The tests for the WTPs from the LC2 + 3 ANA model are reported in Table 5. The low R-squared is not uncommon in cross-sectional data analysis. The tests always reject the null hypothesis of equality, with a P-value of 0.0168 for the equality between WTP of CO_2 and *ORGANIC* and 0.0015 for the equality of *NMILES* and *ORGANIC*. Most importantly, for our investigation between *NMILES* and CO_2, the test strongly rejects the null of this type of equality with a P-value smaller than 0.0001. We conclude that at the respondent level, after accounting for differences in socio-economic covariates, the estimated marginal WTPs are different from each other, even though at the population level, the estimated utility coefficients showed no significant difference. Such is the power of identification by conditioning on the sequence of choices in the panel.

As for the socio-economic covariates, we find that having a low income has a negative and significant effect in the regression explaining posterior marginal WTP estimates from model LC2 + 3 ANA, as predicted by economic theory. We take this as a validity result. Interestingly, this was not so in similar regressions run on estimates from RPL-EC and LC1. The results also indicate that being a woman respondent has a negative and significant effect of 21 cents, indicating that women tend to have lower marginal valuation than men for these attributes. None of the other socio-economic covariates is significant.

5. Conclusions

Using a choice experiment, we investigate consumer preference for two generic transport footprint information labels, the first provides information in terms of the amount of CO_2 emission (*CO_2*), and the second provides information on the distance and time the food travelled (*NMILES*). Our study differs from the previous literature in that we do not focus on local foods versus nonlocal foods to test the effect of food miles labels. Instead, we assess consumers' valuation for two types of labelling information on food transport. This enables us to measure preferences towards these two types of labels.

We find evidence of preference heterogeneity, but also of attribute processing heterogeneity and noncompensatory choice processes. We extend the modelling approach based on ECLCs to simultaneously account for both attribute nonattendance and preference variation. Our approach allowed us to tease out different implications of heterogeneity of preference. Our results based on the best model suggest that WTP for CO_2 can be high even for respondents with low valuations of *NMILES*, but not vice versa. Interestingly, results also indicate that the majority of respondents with high valuations for CO_2 also have a proportionally high valuation for *NMILES*. Formal tests of equality of individual-specific WTP estimates across production and transportation attributes are all rejected by the panel data regression analysis, suggesting that even after accounting for standard socio-economic factors, differences remain. Income affects predicted WTP significantly and so does being a woman.

Our results generally suggest that it would be better for producers to use the *CO_2* label rather than the *NMILES* label as consumers tend to value the *CO_2* label at least as much and sometimes more than the *NMILES* label. Also, they tend to pay more frequent attention to *CO_2* label. Hence, consumers may be more interested in the concept of food miles if it is expressed in terms of energy and ecological costs of transporting food. This novel finding is consistent with growing consumers' concerns over climate change and the several private initiatives on carbon labelling schemes adopted voluntarily by private companies in different countries such as the United States and Europe (eg, Wal-Mart, Tesco, Casino, etc).

Our finding can have important implications for consumers as well as for both organic and local producers. From the consumers' point of view, the introduction of food miles labels will allow them to make more informed purchasing and consumption decisions based on the information about the environmental footprint of the food they eat. Producers could use transport footprint information as a tool to differentiate their low transport footprint food products not only when selling these products directly to consumers but also when approaching retailers to carry their products in the retail stores. Importantly, while a low footprint is not necessarily synonymous with local or short distance travelled, our results suggest that producers of low carbon footprint local foods could further differentiate their products by using food miles labels such as the CO_2 label examined in this study.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Sample percentages of socio-demographic characteristics, (N = 200).

Table S2. Correlation Matrix from RPL-EC model.

Table S3. Cholesky Matrix from RPL + EC estimates.