Welfare Effects of Food Miles Labels

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Abstract

We assessed the consumer welfare effects of two generic food miles labels: carbon dioxide (CO_2) emission label and number of miles label. Using data from a choice experiment, our results generally suggest that a mandatory labeling policy for either type of label would have a positive welfare effect on both informed and uninformed consumers. However, a label informing consumers about the number of miles the food product has travelled provides greater positive welfare effects than a label informing consumers about the amount of CO_2 emission.

Keywords: welfare effect, generic food miles labelling programs, choice experiment, Italy.

1. Introduction

"Food miles" is a term coined in a 1994 Report (Paxton, 1994) by the Sustainable Agriculture Food and Environment (SAFE) Alliance to indicate the distance food travels from the time it was produced until it reaches the consumers. Several studies that have focused on food miles have estimated the environmental effect of the transportation of food products around the world (Smith et al., 2005; Pretty et al., 2005; Weber and Matthews, 2008), as well as the differences in environmental impact of domestic and imported food products (Pirog et al., 2001; Jones, 2002).

The issue about the environmental effects of food miles is however still under debate in the scientific literature. Many studies focused on food miles and on the effect of food transportation on the environment report mixed results and do not provide empirical evidence on whether domestic or imported food products generate a greater environmental impact. For example, Blanke and Burdick (2005) compared the energy cost of locally-grown and controlled atmosphere stored German apples versus apples imported from New Zealand. The authors calculated the 'primary energy requirement' in delivering apples from these two sources to German consumers. They conclude that the local apples were indeed more energy-efficient although the difference was relatively modest (i.e., 5893 MJ/tonne German apples vs. 7499 MJ/tonne for New Zealand apples). On the other hand, Carlsson (1997) performed an analysis of energy consumption of tomatoes in retail outlets in Sweden. He concluded that it was actually far better for the environment to purchase imported outdoor tomatoes from the Canary Islands during the winter than to purchase hothouse-grown local tomatoes. Despite the current debate on whether domestic or imported food product is more sustainable, the "food miles" concept can be used as a quality cue of a food product since it informs consumers about the environmental impact and the distance travelled by the food they eat. Basically, information about "food miles" could include information about the amount of carbon dioxide (CO_2) emitted during the transportation of the food products or the number of kilometers that the food travelled. Thus, the implementation of a food miles labeling system could provide information that can help consumers make informed purchasing and consumption decisions.

The distance that food travels might have important implications in terms of the social, economic, and environmental sustainability of the food system. For this reason, *food miles* is now becoming a concept of interest for both consumers and policy makers. From a consumer's point of view, the introduction of food miles labeling could reduce the asymmetry of information between consumers and producers as well as increase the utility of consuming products that carry such labels especially for consumers with higher sustainability/environmental concerns. For policy making, food miles labels can be used as an incentive to promote the sustainable production/consumption of food products in accordance with international trends.

The purpose of our study is to calculate the consumer welfare effects of a mandatory food miles labeling policy. With the implementation of a food miles labeling program, it is possible that unlabeled products will become unavailable and thus consumers will have to turn to labeled products or withdraw from the market. Calculating the welfare effects of food miles (FM) labels is important since this information can help policy makers make informed decisions on whether to develop and implement mandatory labeling policies related to food miles.

2. Background

In past studies, welfare effects estimation of food policies were carried out using consumer demand data and the application of different methods such as discrete choice method (Hu et al., 2005; Lusk et al., 2006), individual WTP method (Lusk et al., 2005; and Rousu et al., 2007), and the average WTP method[1] (Marette et al., 2008a, 2008b) or from a combination of them (Lusk and Marette, 2010).

In all of these applications, the authors evaluated the change in consumers' welfare associated with different policy instruments, related to the presence or the absence of particular information on the food product available in the market.

In the case of the discrete choice method, the parameters are obtained from a discrete choice model where the probability of purchase is conditional on price and other attributes of the food products of interest. Only a few studies, however, have attempted to calculate consumer welfare effects using this method. For example, Hu et al. (2005), analyzed consumers' preferences for prepackaged sliced bread with genetically-modified (GM) ingredients under two labeling policies: mandatory labeling and voluntary labeling. They focused on how the two different labeling schemes affect consumers' choices and on the possible welfare implications of these two labeling policies. Their findings suggest that the magnitude of consumers' welfare increased with the mandatory labeling policy and as more bread products were covered by the labeling policy. In particular, the magnitude (absolute value) of the loss in consumer welfare associated with the "GM attribute" was consistently larger than the absolute value of the welfare increases associated with the "non-GM" attribute.

Lusk et al. (2006), estimated the direct and indirect benefits of a ban on feeding subtherapeutic antibiotics in pork production among a sample of grocery shoppers in Oklahoma. Their results indicated that the welfare effects of a ban depend heavily on assumptions about consumers' current

[1] The difference between the individual WTP method and the average WTP method is that with the former, the allocation of each respondent along the distribution of the parameters is done by taking into account the additional information available on the alternative chosen, while with the later respondents are randomly assigned along the continuous distribution of the parameters. For details see Hensher, Greene and Rose (2003).

knowledge about antibiotic use in pork production and the extent to which consumers are currently able to purchase antibiotic-free pork.

Finally, Lusk and Marette (2010) estimated the welfare effects of food labels and bans on beef cloning and methylmercury in fish by combining discrete choice methods with other alternative willingness to pay (WTP) measures such as individual WTP and average WTP. They compared each value elicitation approach in terms of the consumer surplus changes that resulted from these two regulations related to beef cloning and methylmercury in fish. Their findings suggest that the while the sign of welfare measures was invariant across the three methods used, the magnitude of these welfare measures varied significantly across these methods.

We are not aware of any other study that has evaluated consumer welfare effects of food miles labeling.

3. Objectives

The aim of this study is twofold: (1) to test if the presence of two different food miles labels affects consumer choice, using a choice experiment (CE) approach, and (2) to calculate the welfare effects of mandatory labeling policy related to these two types of food miles information: CO2 emission (CO2) and number of miles (nmiles) travelled by the food product.

4. Data and Methodology

4.1 Data collection and survey instrument

The data used in this article are drawn from responses to a survey instrument administered to 200 consumers during spring 2009 in Naples, Italy. Adult food shoppers (at least 18 years old) were randomly selected in three different grocery stores. The questionnaire was administered face to face by trained interviewers who conducted the survey in grocery stores at different days of the week and different times of the day. The interviewers asked the randomly selected individuals two screening questions related to whether they were the main household food shopper and whether they consumed fresh tomato. If the response to both questions was yes, then the individual was interviewed for the choice experiment (CE). The questionnaire included the CE questions on fresh tomatoes and other questions regarding sustainable and organic consumption, purchase and consumption habits of fresh tomato, and socio-demographics characteristics. In the CE section of the survey, people were asked to answer a series of discrete choice questions regarding which of the two fresh tomato profiles (with a "none" option) they would buy when grocery shopping. In particular, in each fresh tomato profile option, two types of generic food miles labels were considered: one which would provide information about the distance and time the food traveled and one which would provide information on the amount of CO_2 emission from the transportation. The other attributes included in the CE design are price (with values 1.1, 2.1, 3.1, 4.1 EUR), type of tomato (cherry, plum and brief) and method of production (organic, conventional).

To determine which fresh tomato profiles to present to respondents, we used an orthogonal design for "main effects" to reduce the 72 ($4x2x3^2$) possible combinations of attributes and levels into 32 pair-wise comparisons of alternative fresh tomato scenarios, which were then randomly grouped into pairs and split into four different blocks of 8 choice sets, erasing one card from each block due to repetition of some combinations. Prior to the choice question, the choice experiment was explained to the participants including information about the fresh product attributes and their levels. We also told them to assume that the product profiles have identical environmental impact in terms of their production and transportation. Finally, given the hypothetical nature of our investigation and the possible presence of hypothetical bias related with this type of studies, we included, following Silva et al. (2009), a cheap talk in all questionnaires right before the choice questions to minimize possible hypothetical bias from the responses.

4.2 Data analysis

The choice questions were analyzed using the random utility framework. Thus, the final specification of the utility function is assumed to depend on the attributes and attribute levels considered in the choice questions. The utility that individual *i* obtains from alternative *j* at choice situation *t* is:

(1) $$U_{ijt} = \beta_0 * I + \beta_1 Price_{ijt} + \beta_2 Cherry_{ijt} + \beta_3 Plum_{ijt} + \beta_4 Method_{ijt} + \\ + \beta_5 Nmiles_{ijt} + \beta_6 CO_{2_{ijt}} + \varepsilon_{ijt}$$

Where I is a dummy variable taking the value of 1 for the no-choice (none) option and 0 otherwise, *price* is the price of one kilogram of fresh tomato, while the rest of the attributes enter the model as either an effect code (method) or dummy code (types of tomatoes and food miles attributes). In particular, the production method attribute is coded with a value of +1 if production method in option *j* is organic, and -1 if the production method in option *j* in choice situation *t* is conventional; whereas *cherry*, *plum*, *nmiles*, and *CO2* are coded as dummy variables that take the value of 1 if they are true for option *j* in choice situation *t* and 0 otherwise.

We analyzed the data using the Random Parameter Logit model (RPL) since it allows for possible heterogeneous preferences across consumers and does not assume that irrelevant alternatives are independent. As shown by Train (2003), the probability that an individual *i* chooses alternative *j*, is represented as:

(2) Prob {j is chosen} $= \dfrac{\exp(\beta` x_{ij})}{\sum_i \exp(\beta` x_{ij})}$

For the maximum likelihood estimation, the conditional probability of the sequence of choices made by each respondent is obtained according to the following expression (Train, 2003):

(3) $S_i(\beta_i) = \prod_t P_{ij(i,t)} \beta_i$

where *ij(i,t)* represents the alternative chosen by person *i* in choice occasion *t*. Because β_i is assumed to be a random parameter varying across respondents, the random logit probability can be derived by integrating the probability over all values of β

(4) $P_i(\theta) = \int S_i(\beta_i) f(\beta_i|\theta) d\beta_i$

Because equation (9) lacks a closed form solution, the parameters of the model are estimated by simulated maximum likelihood estimation technique following Train (2003). As in Revelt and Train (1998), we assume that the price coefficients are invariant across individuals and that the coefficients of the other attributes and levels of the attributes are random parameters with a normal distribution. For the estimation of the RPL model, 500 Halton draws rather than random draws are used since the former provides a more efficient simulation for this model.

The fact that random utility theory is based on the assumption that consumers derive utility from consumption of good according to their attributes permits a theoretically sound transformation of parameter estimates of each attribute into WTP measures for specific product quality characteristics.

4.3. Policy simulation

Using the results from our CE we attempt to estimate the effect that a mandatory food miles labeling policy would have on consumers' welfare. To accomplish this, one has to consider the corresponding changes that a food miles policy would enforce on consumers. When the change in situation is purely the introduction of a labeling policy, the actual attributes or qualities under consideration are exactly the same before and after the application of the policy (Hu et al., 2005). Thus, changes in attributes caused by the introduction of food miles labeling in the market are a reflection of changes in the amount of consumer information. According to Lusk (2010), the new product can be perceived by consumers as being of higher quality compared to what has traditionally been sold in the market (e.g., organic) or it can be perceived by consumers as being of lower quality than what has traditionally been sold (e.g., genetically modified, etc). From our CE estimates, we found that the two food miles labels we considered both have a positive impact on the utility function (i.e., with positive coefficients). Hence, we expect these food miles labels to provide consumer welfare benefits.

For a better understanding of the market dynamics, following Lusk and Marette (2010), we shall consider two extreme situations: one in which consumers are fully aware of the change in product quality introduced by the food miles labels due to the reduction in information asymmetry (i.e., this group will be called "informed consumers" hereafter) and one in which consumers notice no difference in product quality between labeled and unlabelled products (i.e., "uninformed consumers" group). In the first case, the demand curve shifts following consumers' change in preferences while in the latter case, the food miles labels are unnoticeable or non-sensible to the consumers; thus consumers simply move along the demand curve. For this reason, to fully characterize the welfare effect of the policy on consumers, one has to examine the (perceived) choices consumers are undertaking before and after the mandatory labeling scheme in the two aforementioned cases. Additionally, we assume that producers are characterized by perfectly elastic supply curves with production functions represented by constant returns to scale. This implies that producer marginal profits remain intact by the introduction of the policy as the extra cost is transferred directly to the consumers.

Before the new labeling policy is adopted, both informed and uninformed consumers have no other option but to buy the unlabelled product at a price P_1. However, after the implementation of the policy, consumers have now to choose between buying the food miles labeled tomatoes at a price $P_2>P_1$ and refraining from purchasing tomatoes. Nevertheless, informed consumers do realize the shift in quality while the only observable change for the uninformed consumers is the change in price. In other words, uninformed consumers think they are buying the same product as before (i.e., when it was unlabeled) with a non-sensible or even unnoticeable label that provides no contribution to their utility. According to Foster and Just (1989), this situation also encumbers the uninformed consumers with an additional cost known as the cost of ignorance. The cost of ignorance is the cost that is embodied to the uninformed consumers' choices due to the fact that their choice is based on limited or no information.

Formally, according to Lusk and Marette (2010) the per choice change in consumer surplus or "anticipated benefit" (Leggett, 2002) associated with the implementation of the food miles labeling policy for the uninformed consumers corresponds to the average area on the left of the demand curve between the price change and is given by:

$$(4)\ \Delta CS_{Uninformed} = \frac{[\ln(e^{\alpha_U+\beta P_2}+e^{\alpha_N})-\ln(e^{a_U+\beta P_1}+e^{\alpha_N})]}{(-\beta)}$$

Where a_U is the sum of the marginal utilities derived from all other than price attributes of the unlabeled product, β is the marginal utility of price, P_1 and P_2 are the prices before and after the implementation of the mandatory labeling policy, respectively, and α_N is a parameter that sets the utility level of the no-choice alternative. However, as mentioned before, mandatory food miles labeling would also introduce an extra cost to the uninformed consumers; the cost of ignorance. This cost should be subtracted from (4) when estimating the total welfare effect of the examined policy. The cost of ignorance is given by:

$$(5)\ CI_{Uninformed} = \left(\frac{e^{\alpha_U+\beta P_2}}{e^{\alpha_U+\beta P_2}+e^{\alpha_N}}\right)\frac{[\alpha_L-\alpha_U]}{\beta}$$

Where α_L is the same as a_U but for the labeled product. Note that since β is negative and $P_2>P_1$, $\Delta CS_{Uninformed}$ is expected to be also negative, thus appearing as an extra cost rather than benefit. The interpretation of this is that the uninformed consumers experience a welfare loss from mandatory FM labels, based on their incorrect beliefs about the quality of the product. On the other hand, taking also into account that $\alpha_L > \alpha_U$ (the marginal utility of both labels is positive, see table 2), (5) is also expected to be negative, thus being an actual benefit instead of a cost (since it is subtracted from (4)). In other words, the implementation of the policy would "force" uninformed consumers to make decisions closer to those they would have made, had they received more information. As a consequence, the relative magnitude of these two figures will determine whether the adoption of the policy would have a positive or negative impact on uninformed consumers' welfare.

For informed consumers, the notion is simpler and the welfare surplus change in every choice situation is given by:

$$(6)\ \Delta CS_{Informed} = \frac{[\ln(e^{\alpha_L+\beta P_2}+e^{\alpha_N})-\ln(e^{\alpha_U+\beta P_1}+e^{\alpha_N})]}{\beta}$$

Since we used the RPL model to estimate the parameters of our model, the welfare measures of (4), (5) and (6) could not be numerically calculated but could be estimated using a simulation approach. In our analysis, we use the Monte Carlo simulation method with 10,000 draws from a multivariate normal distribution.

In order to get the average per-choice welfare effect of the policy for all three types of fresh tomatoes included in the design, we consider a composite product (33.3% cherry and 33.3% plum and 33.3% brief) and the mean price of fresh tomatoes. The hypothetical nature of the product is not at all restrictive and enhances the usefulness of our results as they reflect the average welfare effect for the three types of fresh tomatoes. Accordingly, from this point on, the term “fresh tomato” will be used to refer to this composite product. In fact from table 2, one could notice that the parameters associated with the dummy variables for cherry and plum product attributes are only statistically significant at the 10% level.

We consider a situation where regardless of which food policy is being implemented, consumers have three choices: organic fresh tomato, conventional fresh tomato, and none of these. According to the Italian Institute of Services for the Agri-Food Market (ISMEA), in 2009 the average price of fresh tomato was 1.73 €/kilo. Therefore, we set the price of conventional fresh tomato at 1.16 €/kilo (1.73 - 33%) and the price of organic fresh tomato at 2.30 €/kilo (1.73+33%). We use these values to describe the prices before the implementation of the mandatory labeling (P_1).

Furthermore, we assume that the food miles labels will raise the production costs and hence the average price of tomato by 20%. As a result, the prices after the policy is adopted (P_2) are considered to be 20% higher than those before the implementation of the policy (P_1). To assess the sensitivity of our results to this assumption, we test all possible increments on P_1 from 1% to 100% to find the level of the price increase that would reverse the sign of the welfare effect.

5. Results

The RPL estimates are reported in table 2. Results suggest that the price effect is negative**,** indicating that increases on the price variable can decrease the associated utility level provided by the choice. The coefficient of constant β_0 is also negative which suggests that the utility that consumers derive from having nothing at all (alternative C) is lower than the utility from buying one of the designed alternatives (A or B). All the other product attributes considered in the utility function exhibited positive mean value. Thus, our respondents on average prefer organic fresh tomato. Both food miles information are also found to positively affect consumers’ choices. Results also show that respondents slightly prefer cherry and plum tomatoes over brief tomatoes. The standard deviations of all variable coefficients reported in the last column of table 2 are statistically significant at the 0.01 level, confirming the hypothesis of heterogeneity in the population in terms of consumers' preferences for type of tomato, production method, and food miles information.

The estimated welfare effects of a mandatory labeling policy, assuming a 20% increment on the initial price of fresh tomatoes are presented in tables 3 and 4. The results indicate that for both food miles labels (i.e., CO_2 emission and number of miles labels), a mandatory labeling policy would have a positive effect on both informed and uninformed consumers. However, the number of miles (*Nmiles*) label has a greater positive impact on consumers' welfare than the CO_2 label, which is expected considering that the Nmiles label added more to the utility of consumers, as indicated by the results of the RPL model.

As expected, at first, uninformed consumers experience a negative anticipated "benefit" from the policy scheme for both examined labels. However, this welfare loss is a result of their incorrect beliefs about the new product's quality since they have no understanding about the usefulness of that label in reducing the existing information asymmetry in the market. Once this welfare effect is calibrated to include the cost of ignorance (benefit in this case), it becomes positive and relatively high compared to the average price of the product considered. On the other hand, for informed consumers, the anticipated benefit is positive for both labels and greater than that of the uninformed consumers. Thus, a mandatory labeling scheme is preferable to the status quo (no labeling) in terms of consumers' welfare in both cases. For the CO_2 label, the welfare effect of a mandatory labeling scheme is 0.45 €/choice for uninformed consumers and 0.54 €/choice for the informed ones, while for the Nmiles label the effects are 0.68 €/choice and 0.79 €/choice for the uninformed and informed consumers, respectively.

Since the above results could be an artifact of the assumption that prices would be 20% higher after the policy is implemented, we simulate different situations where the hypothetical increment takes on values from 1% to 100%. Column 4 of tables 3 and 4 present the highest possible increment on the initial price for which the welfare effect remains positive. The robustness of our findings is confirmed since for CO2 labels, uninformed consumers could bear a 52% rise in price of fresh tomatoes and still have a welfare gain; for informed consumers the highest price for positive welfare effect would be 60% higher than the current price. On the other hand, for Nmiles label the corresponding percentages are 67% and 81% for uninformed and informed consumers, respectively. Hence, the positive welfare impact of the policy is relatively robust to different price increases as a result of the mandatory labeling policy.

6. Conclusions

In this study, we assessed the welfare effect of two generic food miles labeling programs. In particular, we attempted to estimate the effect that a mandatory labeling policy would have on consumers' welfare. To achieve our objective we considered two extreme market situations: one in which consumers are fully aware of the change in product quality introduced by food miles labels and one in which consumers notice no difference in product quality between labeled and unlabelled products. Using data from a choice experiment survey conducted in Italy, our results generally suggest that for both food miles labels, a mandatory labeling policy would have a positive effect on both informed and uninformed consumers. This positive welfare effect is relatively robust to different levels of price increases of the product after the implementation of the mandatory labeling policy. Specifically, our results indicate that the *Nmiles* label has a greater positive impact on consumers' welfare than the *CO2* label. This finding is expected since as indicated by the results of the RPL model, consumers get a higher utility from number of miles label than from CO_2 label.

No other known study has evaluated the consumer welfare effects of food miles labels. Our study fills this void. However, in order to evaluate the overall usefulness of the mandatory labeling policy, one should take into account the extra costs associated with the implementation of the labeling policy scheme. These costs could include those associated with monitoring procedures to make sure that the level of CO_2 emission or number of miles reported on the label is accurate and the cost of restructuring the supply chain to comply with the new standards. Therefore, the costs involved in the implementation of the mandatory labeling policy should be compared to the welfare benefits before any decision about the adoption of the labeling policy should be made. This comparison is beyond the scope of the current paper but would be a good topic for future research. Lastly, since our study is based on a choice experiment conducted in Italy, future research should use other types of WTP elicitation mechanisms as well as data collected in other geographic areas to test the robustness of our welfare estimates.

7. References

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8. Tables

Table 1. Socio-demographic characteristics of the sample. (N = 200)

Socio-demographic characteristic	% of total
Gender	
Male	36.5%
Female	**63.5%**
Age Group	
18-24	20.5%
25-40	28.5%
41-54	**26.0%**
55-64	15.5%
Over 64	9.5%
Marital status	
Single	36.5%
Married	**46.0%**
Widowed	4.5%
Other	6.5%
Educational level	
No formal education	16.0%
Up to High school degree (1-12 years)	**48.5%**
More than 12 years and less than 16 years	16.0%
Graduate from college (16 years)	18.5%
More than 16 years (PhD, Masters)	1.0%
Annual Income	
Euro 19,999 or less	37.5%
Euro 20,000 – 39,999	**36.0%**
Euro 40,000 – 59,000	18.0%
Euro 60,000 – 79,000	7.0%
Euro 80,000 – 99,000	0.5%
More than Euro 100,000	1.0%
Missing data	0

Table 2. RPL model estimates

Attribute	***Description***	***Mean***	***St.Dev***
No-buy	Dummy, 1 for 'none of the above' option, 0 otherwise	- 4.47***	1.81
Price	Price of the product	1.35***	0
CO2	Dummy, product bears a CO2 label	1.14***	1.89
Nmiles	Dummy, product bears a Nmiles label	1.50***	1.83
Organic	-1 for conventional production method , 1 for organic	1.52***	0.61
Cherry	Dummy, product is a cherry tomato	0.50*	1.99
Plum	Dummy, product is a plum tomato	0.36*	1.22

*** Values statistically significant at 1% level.

* Values statistically significant at 10% level.

Table 3. Welfare effect of a CO_2 mandatory labeling scheme

CO2 LABEL				
UNINFORMED CONSUMERS				
	Anticipated Benefit (€/choice)	***Cost of Ignorance (€/choice)***	***TOTAL welfare effect***	***Max. increment for positive wel. effect***
MEAN (SD)	-0.28 (0.07)	-0.73 (1.15)	0.45 (1.14)	***52%***
INFORMED CONSUMERS				
	Anticipated Benefit (€/choice)			***Max. Increment for positive wel. effect***
MEAN (SD)	0.54 (1.17)			***60%***

Table 4. Welfare effect of a Nmiles mandatory labeling scheme

NMILES LABEL				
UNINFORMED CONSUMERS				
	Anticipated Benefit (€/choice)	***Cost of Ignorance (€/choice)***	***TOTAL welfare effect***	***Max. increment for positive wel. effect***
MEAN (SD)	-0.28 (0.07)	-0.96 (1.22)	0.68 (1.21)	***67%***
INFORMED CONSUMERS				
	Anticipated Benefit (€/choice)	***Max. Increment for positive wel. effect***		***Max. Increment for positive wel. effect***
MEAN (SD)	0.79 (1.25)	***81%***		***81%***