# How much does your environment matter?
# Estimating demand with consumption externalities

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Motivation and identification

# 1  Motivation

The planned research investigates the consumption of products with environmental labels. These labels – the EU-wide Eco-label, the Blaue Engel in Germany or the Nordic Swan in the Scandinavian countries – are supposed to influence consumers' brand choices by providing information about the environmental impacts of products. They are one of the proposed policy tools that try to reduce industrial pollution in a market friendly way through enabling consumers to pay for a cleaner environment. The usefulness of labels depends on how exactly demand is formed in final product markets. To have a significant effect, labelled goods should be able to reach high market shares in their respective markets. However, as the economic theorist argues, an individual purchase of such goods has nearly zero impact on environmental conditions, and consumers who are aware of this should not care about the consumption of such labelled goods. In fact, only coordinated behavior (when a sizeable fraction of consumers buy the product) would have a real environmental impact. This is the classic case of an (environmental) externality, and in such situations economic agents usually fail to coordinate their behavior in a strictly deregulated market setting. Nevertheless, there might be flaws in this intuition, as it was demonstrated by Bjørner, Hansen and Russell (2004). Based on Danish data these authors provide evidence that labels raise the willingness to pay by 13-18% percent of the retail price.

In order to understand why people are buying such products one has to take a more thorough look at what these labels signal to consumers. They provide information about the environmental quality of a product, and the resulting pollution abatement is a public good. Through buying products with environmental labels consumers contribute to this public good. Experimental economics (for example Fehr, Fischbacher and Gächter, 2001) provides plenty of evidence that behavior in the presence of public goods is shaped by conditional cooperation and – though to a lesser extent – unconditional cooperation. The

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first one in this context means that consumers are willing to pay extra for environmentally friendly products if they can expect their fellow consumers to buy such products too. The second one implies that there will be consumers who will value environmental quality so much that they are willing to buy labelled products even if nobody else buys them. Moreover, purchasing labelled products facilitates 'environmentally friendly' consumption, which might be an important factor for the self-respect of individuals in case environmental friendliness is a norm prevailing in their social reference group. In this case, the effect of environmental labels on consumer choice can be understood analogous to the complementarity of advertisement as discussed by Becker and Stigler (1977).

This aspect suggests that consumer choice is influenced by the decisions and opinion of other consumers. Therefore, demand estimation for such products has to incorporate the effect of fellow consumers' behavior on individual decision-making. This is not purely an exercise in making demand estimation more sophisticated. The presence or absence of the effect of other consumers is crucial information for policy-makers and firms. If other consumers' behavior matters, then there is a kind of herding effect and labelled goods can be expected to gain significant market share as time passes, and therefore can be expected to have a real environmental impact. If on the other hand demand for such goods is driven by the fraction of consumers who buy such goods unconditionally, then – unless consumer preferences change profoundly – one cannot expect these goods to dominate the respective markets and to achieve a significant environmental impact, since the fraction of such people is usually very low in the population.

In what follows I will show how demand externalities might be incorporated into consumer choice, outline the identification strategy and discuss the data requirements. It is important to point out that the proposed analysis can be extended to other markets where theoretical literature points out the importance of demand externalities as for example in the case of computer software.

## 2 Modelling consumer choice

As it was argued in the introduction the public good nature of environmental quality could lead to conditional cooperation among consumers which can be formulated as follows:

$$V_{ij} = \mathbf{x}'_j \boldsymbol{\beta}_i + \gamma_j + \alpha_j \left[ E_i(\sum_{j=1}^{J} L_j D_j) \right] L_j + \delta_j L_j + u_{ij}, \tag{1}$$

where the indices represent individuals: $i = 1, ...N$ and brands: $j = 1, ...J$. $V_{ij}$ is the indirect utility of individual $i$ choosing brand $j$, $\mathbf{x}_j$ is a vector of product characteristics, $L_j$ is a dummy for environmental labels and $u_{ij}$ is an *iid* disturbance. Greek letters are

the parameters of interest and $\beta_i$ denote individual specific taste parameters in the style of Ackerberg, Benkard, Berry and Pakes (2005). $E(\sum_{j=1}^{J} L_j D_j)$ is the expected market share of labeled products which is the measure of contribution of other consumers. The formulation $\alpha_j E(\sum_{j=1}^{J} L_j D_j) L_j$ expresses that individuals prefer to buy labelled products but this preference depends on the expected market share of these goods. In the introduction I argued that conditional cooperation might be an important determinant of behavior in the context of public goods because it matters for the individual what other people do. Market share is just the sum of choices for labelled alternatives, therefore it captures exactly this effect. Moreover, following the previous notation (1) translates to a probabilistic choice model of the following structure:

$$D_{ij} = F\left(\mathbf{x}_j'\boldsymbol{\beta}_i + \gamma_j + \alpha_j \left[E_i(\sum_{j=1}^{J} L_j D_j)\right] L_j + \delta_j L_j\right), \tag{2}$$

where $F$ is a probability density function and its exact form will depend on the assumptions one is willing to make about the disturbance $u_{ij}$. This framework implies that market share of labelled products is the same as the expected probability of purchasing labelled products. In what follows I will treat individual expectations as consistent with this choice model that is individual expectations are assumed to be formed based on (2) too.

The indirect utility function (1) was not derived from some fundamental theory about how individuals influence each other's decision and this might urge some readers to point to the 'ad hoc' way preferences are treated. To address such concerns let me present the following example, that illustrates why the somewhat loose connection between the verbal arguments in the introduction and the specification of the indirect utility function may suffice in case one seeks to estimate this model using revealed preference data.

Assume that conformity is the only reason for the consumption externality. Using the notation above such a model would formulate the consumption externality effect $(S)$ as follows:

$$S(L_j, E_i(\sum_{j=1}^{J} L_j D_j)) = -\mu_j \left[L_j - E_i(\sum_{j=1}^{J} L_j D_j)\right]^2, \tag{3}$$

that is if consumers perfectly conform to expectations about aggregate consumption of labeled goods then ceteris paribus their utility does not decrease. This represents a pure conformity effect analyzed for example by Brock and Durlauf (2001). Rearranging (3) yields:

$$S(L_j, E_i(\sum_{j=1}^{J} L_j D_j)) = -\mu_j L_j^2 + \mu_j 2\left[E_i(\sum_{j=1}^{J} L_j D_j)\right] L_j - \mu_j \left[E_i(\sum_{j=1}^{J} L_j D_j)\right]^2. \tag{4}$$

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The third part of this expression is a constant times an alternative specific coefficient, just like $\gamma_j$ in (1). Moreover taking into account that $L_j^2 = L_j$ (4) is the specification as (1) with the restrictions:

$$H_0 : \frac{\gamma_j}{\left[E_i(\sum_{j=1}^J L_j D_j)\right]^2} = \delta_j = -\frac{\alpha_j}{2},.$$

(5)

These and other restrictions can be tested, while they also provide some insight about the flexibility of the suggested specification of the consumption externality in (1).

# 3 Identification

The main difference between (2) and a usual demand specification is the presence of the term $\alpha_j E(\sum_{j=1}^J L_j D_j) L_j$. As it was discussed, this term captures the intuition that individuals are more likely to buy labeled goods when others buy it too. To identify such effects one needs to observe individuals under circumstances when a lot of people buy labeled products and under circumstances when only a few people buy labeled products. Consumer panel data with individual purchase decisions as the unit of observation provide such information. Figure 1. presents the structure of such data in a simplified way: a label was introduced in period 3 and purchases of labelled products are marked with black boxes. There are three levels of aggregation in such data: individual, group and market level.
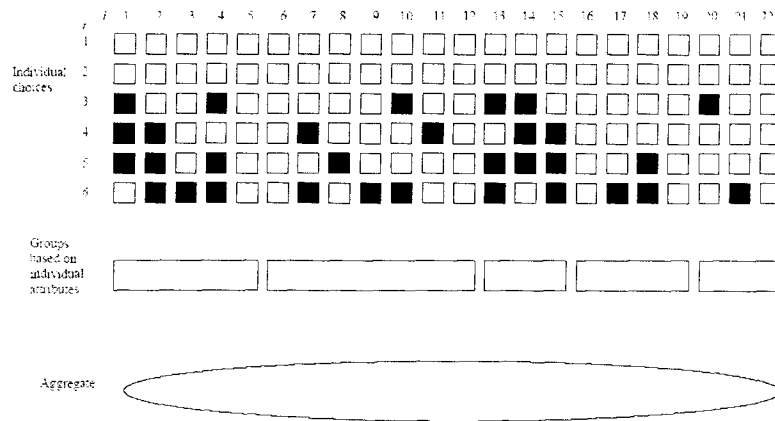


Figure 1: Panel structure

Given that there is enough time variance in the market share of labeled products (2) can be estimated assuming that each point in time represents a repetition of this

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coordination game. Therefore the task is to spell out the identification assumptions and estimation methods of a static discrete game.

There are two strands in the econometric literature that provide the identification conditions and estimation methods. One is the social interaction literature that developed econometric techniques for similar problems, although with a focus on geographically separate groups. Brock and Durlauf (2003) provide identification conditions for multinomial choice models in such settings. The cases they study compares groups of *different* people with varying group level behavior. In these cases the thought experiment is the following: "controlling for all other effects, how would the behavior if individual $i$ in group $g$ change if she would be rather member of group $h$". Recently, with the advent of empirical industrial organization, a different kind of literature emerged, focusing on the estimation of different types of games. Bajari, Hong, Krainer and Nekipelov (BHKN, 2006) provide identification conditions and estimation methods for static discrete games where the idea is that one can observe the *same* individuals in subsequent plays of the same game. To clarify the basic issues of identification, I will present the core problems pointed out in Manski (1993) and then show what kind of identification conditions were listed by Brock and Durlauf (2003) and BHKN (2006).

## 3.1 Manski and the identification problem

To focus discussion I will explore the identification problems on a data structure simpler than that illustrated by Figure 1. In this and the following subsection it will be assumed that the researcher can observe data for only one period, in the form presented by Figure 2.
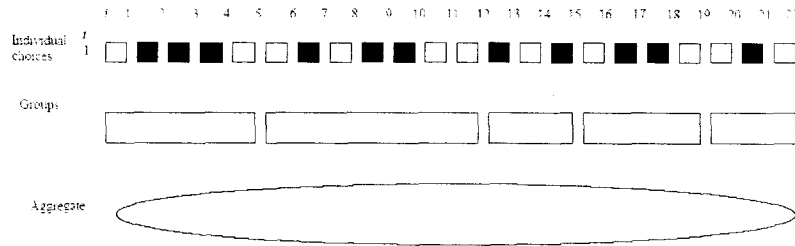


Figure 2: Cross-sectional structure

The basic issues concerning identification of social interactions was demonstrated by Manski on a simple **linear model**:

$$y_{ig} = \alpha + \theta E(y_{ig}|\mathbf{x}_g) + \mathbf{z}_{ig}'\beta + \mathbf{x}_g'\gamma + E(\mathbf{z}_{ig}|\mathbf{x}_g)'\delta + u_{ig}, \tag{6}$$

where the indexes represent individuals: $i = 1, ... N_g$, say students and groups: $g = 1, ..., G$, say schools that is there are $N = N_1 + N_2 + ... + N_G$ individuals in the whole sample. The variable $y_{ig}$ represents a scalar outcome, $\mathbf{x}_g$ group specific attributes and $\mathbf{z}_{ig}$ individual specific attributes. This model incorporates three effects:

1. Endogenous effects that are based on observed or expected behavior within the reference group $(\alpha E(y_{ig}|\mathbf{x}_g))$.

2. Contextual effects that capture the influence of different means individual attributes across groups $(E(\mathbf{z}_{ig}|\mathbf{x}_g)'\boldsymbol{\delta})$.

3. Correlational effects, due to unobserved common shocks, self-selection, or common institutional environment faced by the group $(\mathbf{x}_g'\boldsymbol{\gamma})$.

The identification problem can be demonstrated by three steps. First the **mean regression** of (6) is:

$$E(y_{ig}|\mathbf{x}_g, \mathbf{z_{ig}}) = \alpha + \theta E(y_{ig}|\mathbf{x}_g) + \mathbf{z}_{ig}'\boldsymbol{\beta} + \mathbf{x}_g'\boldsymbol{\gamma} + E(\mathbf{z}_{ig}|\mathbf{x}_g)'\boldsymbol{\delta}. \tag{7}$$

Second, integrating out $\mathbf{z}_{ig}$ from the mean regression and assuming $1 \neq \theta$ leads to the **aggregate equilibrium** equation:

$$E(y_{ig}|\mathbf{x}_g) = \frac{\alpha}{1-\theta} + E(\mathbf{z}_{ig}|\mathbf{x}_g)'\frac{\boldsymbol{\beta}}{1-\theta} + \mathbf{x}_g'\frac{\boldsymbol{\gamma}}{1-\theta} + E(\mathbf{z}_{ig}|\mathbf{x}_g)'\frac{\boldsymbol{\delta}}{1-\theta}. \tag{8}$$

Finally, plugging this expectation, which is nothing else than the endogenous effect, back to equation (7) yields:

$$y_{ig} = \frac{\alpha}{1-\theta} + E(\mathbf{z}_{ig}|\mathbf{x}_g)'\frac{\theta\boldsymbol{\beta}+\boldsymbol{\delta}}{1-\theta} + \mathbf{x}_g'\frac{\boldsymbol{\gamma}}{1-\theta} + \mathbf{z}_{ig}'\boldsymbol{\beta} + u_{ig} \tag{9}$$

(9) shows the basic problem: only $\boldsymbol{\beta}$ is identified, and even this is true only if $\theta \neq 1$ and if $[\mathbf{1}, E(\mathbf{z}_{ig}|\mathbf{x}_g), \mathbf{x}_g, \mathbf{z}_{ig}]$ are linearly independent (Manski, Proposition 1.). Clearly, one of the main assumption that leads to non-identification is linearity. There is another important point to make, however. If there are plausible exclusion restrictions that allow to partition $\mathbf{z}_{ig}$ in two subvectors $\mathbf{z}_{ig}^0$ and $\mathbf{z}_{ig}^1$ so that contextual effects are only due to $\mathbf{z}_{ig}^0$:

$$y_{ig} = \alpha + \theta E(y_{ig}|\mathbf{x}_g) + \mathbf{z}_{ig}'\boldsymbol{\beta} + \mathbf{x}_g'\boldsymbol{\gamma} + E(\mathbf{z}_{ig}^0|\mathbf{x}_g)'\boldsymbol{\delta} + u_{ig}. \tag{10}$$

In this case the aggregate equilibrium is

$$E(y_{ig}|\mathbf{x}_g) = \frac{\alpha}{1-\theta} + E(\mathbf{z}_{ig}|\mathbf{x}_g)'\frac{\boldsymbol{\beta}}{1-\theta} + \mathbf{x}_g'\frac{\boldsymbol{\gamma}}{1-\theta} + E(\mathbf{z}_{ig}^0|\mathbf{x}_g)'\frac{\boldsymbol{\delta}}{1-\theta}. \tag{11}$$

and (9) becomes:

$$y_{ig} = \frac{\alpha}{1-\theta} + E(\mathbf{z}_{ig}^0|\mathbf{x}_g)' \frac{\theta\beta+\delta}{1-\theta} + E(\mathbf{z}_{ig}^1|x_g)' \frac{\theta\beta}{1-\theta} + \mathbf{x}_\mathbf{g}' \frac{\gamma}{1-\theta} + \mathbf{z}_{\mathbf{ig}}'\beta + u_{ig}. \qquad (12)$$

In this case, because of the term $E(\mathbf{z}_{ig}^1|x_g)' \frac{\theta\beta}{1-\theta}$, not only $\beta$-s are identified but also $\theta$ and through it all the other parameters, provided that $\theta \neq 1$ and if $[\mathbf{1}, E(\mathbf{z}_{ig}|\mathbf{x}_g), \mathbf{x}_g, \mathbf{z}_{ig}]$ are linearly independent. Therefore the intergroup variation in $E(\mathbf{z}_{ig}^1|x_g)$ identifies social interactions in this case. Nevertheless, as (11) shows social interactions in a linear model can always be expressed as a function of observable variables. This is so because the linear model implies a linear expectation structure as summarized my the mean regression (7).

## 3.2 Identification and non-linearity

The proposed modelling framework for consumer choice implies a non-linear structure because it describes conditional choice probabilities. Non-linearity will be a powerful in identifying the social interaction effect, because expectations will be nonlinear in such models. To see the main identification requirements let me discuss the example of a conditional logit model analyzed by Brock and Durlauf (2003) with **expected indirect utility function**:

$$V_{ig}(y_{ig} = j) = \alpha_j + \theta E_i(\overline{y}_{gj}|\mathbf{x}_g) + \mathbf{z}_{ig}'\boldsymbol{\beta}_j + \mathbf{x}_g'\boldsymbol{\gamma}_j$$

and **choice probabilities**:

$$P(y_{ig} = j|\mathbf{z}_{ig}, \mathbf{x}_g) = \Lambda\left[\alpha_j + \theta E_i(\overline{y}_{gj}|\mathbf{x}_g) + \mathbf{z}_{ig}'\boldsymbol{\beta}_j + \mathbf{x}_g'\boldsymbol{\gamma}_j\right]. \qquad (13)$$

where the notation is the same as above and additionally the subscript $j = 1, ..., J$ denotes the alternatives, $\Lambda$ stands for the logit specification and $\overline{y}_{gj} = \frac{\sum_{i=1}^{N_g} I(y_{ig}=j)}{N_g}$ is the percentage of individuals in group $g$ who choose $j$ or the average choice of $j$ in group $g$, where $I(y_{ig} = j)$ is an indicator function taking the value of 1 if the argument is true. This model features both endogenous and correlated effects. In such models $E_i(\overline{y}_{gj}|\mathbf{x}_g)$ will denote expected choice probabilities of product $j$ within group $g$. Moreover Brock and Durlauf (2003) assume uniform expectations within groups which implies:

$$E_i(\overline{y}_{gj}|\mathbf{x}_g) = E(\overline{y}_{gj}|\mathbf{x}_g) = P^e(y_{ig} = j|\mathbf{x}_g) = P^e(y_{kg} = j|\mathbf{x}_g) \quad i, k = 1, ..., N_g. \qquad (14)$$

The **aggregate equilibrium** requires the expected probability of choosing alternative $j$ in group $g$ to equal the objective predicted probability implied by the choice model for

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the same choice and group:

$$P^e(y_{ig} = j|\mathbf{x}_g) = P(y_{ig} = j|\mathbf{x}_g) = \int \Lambda \left[\alpha_j + \theta P(y_{ig} = j|\mathbf{x}_g) + \mathbf{z}'_{ig}\boldsymbol{\beta}_j + \mathbf{x}'_g\boldsymbol{\gamma}_j\right] dP\left(\mathbf{z}_{ig}|\mathbf{x}_g\right).$$
(15)

This is a fixed point mapping which always has at least one equilibrium as pointed out by Manski (1993). Furthermore, one can see that the group level choice probabilities are conditional on the whole distribution of $\mathbf{z}_{ig}$-s. Finally, because of non-linearity individual choice probabilities will remain a function of group level choice probabilities. Brock and Durlauf (2003) establish the following identification conditions for such models:

1. $\mathbf{z}_{ig}$ and $\mathbf{x}_g$ are linearly independent in the population. (identification of $\gamma$)

2. $\mathbf{x}_g$ is full rank.

3. no linear combination of the elements of $\mathbf{z}_{ig}$ and $\mathbf{x}_g$ is constant. (identification of $\gamma$)

4. $\forall \; l \; \exists \; g$ such that $\mathbf{z}_{ig}|\mathbf{x}_g$ is full rank. (identification of $\boldsymbol{\beta}$)

5. non-of the elements of $\mathbf{x}_g$ possesses bounded support. (identification of $\gamma$)

6. $P(y_g = j)$ is not constant across groups $g$.(identification of $\gamma$ and $\beta$). If $P(y_g = j)$ is correctly modelled it will never be linearly dependent of $\mathbf{x}'_g\gamma_j$, because the cdf is a non-linear relationship.

7. $u_{ig}$ are iid disturbances, $E(u_{ig}|\mathbf{z}_{ig},\mathbf{x}_g) = 0$, which basically means that there are no correlational effects.

Although Brock and Durlauf (2003) do not discuss matters of estimation Manski (1993) mentions that such models are usually estimated by a two step procedure:

1. Estimate probability implied by endogenous effect non-parametrically,

2. Then maximize quasi-likelihood.

## 3.3   Identification and exclusion restrictions

BHKN (2006) offer a more general framework, where identification is spelled out not only for specifications where expected choices of a group influence individual choices but to any arbitrary influence of other agents' behavior. They discuss how the underlying utility function in discrete games can be identified and also suggest a two stage procedure for estimation.

Although their approach is similar to the literature discussed above there are some important differences. First of all BHKN (2006) have a panel data framework in mind, like

the one illustrated by Figure 1, when they build their model with repeated observations on the same individuals through time, instead of observations on individuals living in different cities, lets say. Second, they do not separate the three effects during the analysis as discussed above, although in the model they estimate there are both contextual and endogenous effects present.

From the game theoretic perspective economic agents use all the information available about all players to make equilibrium decisions. The key idea of BHKN (2006) is that in a non-linear framework, whatever the interactions among individual decisions, identification is possible as long as the deterministic part of the individual utility depends only on a subset of the information available in a given period. Their argument proceeds as follows. For individual $i$ a choice model relates probabilities of outcomes (choices) given observable information to underlying value functions given the same observable information through a decision model. BHKN (2006) formulate this as

$$(\sigma_i(0|s),...,\sigma_i(J|s)) = \Gamma_i(\Pi_i(1,s),...,\Pi_i(J,s)),$$

where $\sigma_i(j|s)$-s are individual $i$'s choice probabilities of alternative $j$ given the information $s$, $\Pi_i(j,s)$-s are the value functions and $\Gamma_i$ is the mapping from choice specific value functions to choice probabilities. The usual assumption is invoked that value functions represent a difference compared to the value function of one of the products, which is normalized to zero. The first condition to identify value functions is that mapping $\Gamma_i$ should be invertible resulting in

$$\Gamma_i^{-1}(\sigma_i(0|s),...,\sigma_i(J|s)) = (\Pi_i(1,s),...,\Pi_i(J,s)).$$

In case the choice model is a game then $\Pi_i(y_i,s)$ are expected utilities (denoting choices of individuals by $y_i$) formed in the following way:

$$\Pi_i(y_i,s) = \sum_{y_{-i}} \sigma(y_{-i}|s) \Pi_i(y_i,y_{-i},s), \tag{16}$$

where $y_{-i}$ represents a vector of choices made by all other individuals but $i$ and $\Pi_i(y_i,y_{-i},s)$ is the underlying value function which specifies the dependence of individual utilities on the choices made by other agents. Identifying $\Pi_i(y_i,y_{-i},s)$-s will be problematic because given choice $y_i$ and $\sigma(y_{-i}|s)$-s there are $(J+1)^{N-1}$ undetermined values of $\Pi_i(y_i,y_{-i},s)$ to sum to a single value of $\Pi_i(y_i,s)$. The basic insight of BHKN (2006) is that if one can make exclusion restrictions on $\Pi_i(y_i,y_{-i},s)$-s in a manner that individual decision are conditional on only a subset of observable information. Then $\Pi_i(y_i,s)$ will vary with those information not included in the individual decision rules. To see this formally denote by

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$s_i$ the subvector of observable information that is only entering individual utilities and by $s_{-i}$ all other observable information. Then (16) becomes:

$$\Pi_i(y_i, s_{-i}, s_i) = \sum_{y_{-i}} \sigma\left(y_{-i}, | s_{-i}, s_i\right) \Pi_i(y_i, y_{-i}, s_i) \tag{17}$$

A sufficient condition for identification is if there are $(J+1)^{N-1}$ points in the support of the distribution of $s_{-i}|s_i$ and that $\sigma(\cdot)$ is invertible. Therefore estimating discrete games boils down to the question of what kind of restrictions can be made on the variables entering the indirect utility functions.

It is instructive to fit the model of Brock and Durlauf (2003) into this framework. The first major point is that Brock and Durlauf (2003) do not aim to identify the $\Pi_i(y_i, y_{-i}, s_i)$-s, they simply provide identification conditions for $\Pi_i(y_i, s_{-i}, s_i)$. Their starting point is the **expected indirect utility** function as it was shown above. That this is sufficient in their case, is due to the specific formulation of their choice model. The variation in choice probabilities required for estimation comes from the variation of intergroup choice probabilities. There are, nevertheless implicit exclusion restrictions in the model of Brock and Durlauf (2003): by excluding contextual effects $(E(\mathbf{z}_{ig}|\mathbf{x}_g))$ they assume that only $i$-specific $\mathbf{z}_{ig}$-s influence the individual utilities. Therefore the identification assumption is that the personal attributes of other people in the group do not affect the choice of the individual directly, only through the conditional choice probabilities.

## 3.4  Proposed Empirical Model

The discussion about identification highlighted two crucial elements for identification: non-linearity and exclusion restrictions. Non-linearity of the brand choice model derives directly of describing choice among a discrete number of alternatives. Nevertheless the functional form has to be flexible enough in order to avoid identification based on the functional specification. Concerning the question of exclusion restrictions I will assume that individual attributes of other consumers do not influence brand choice directly. Moreover it is plausible to assume that expectations are relevant only about the behavior of the own socioeconomic reference group, and that label effects are assumed to be homogeneous across brands. Taking these into account the choice model to be estimated is the following:

$$D_{ijt} = \Lambda\left(\mathbf{x}'_{jt}\boldsymbol{\beta}_i + \gamma_j + \alpha\left[E_g(\sum_{j=1}^{J} L_{jt}D_{jt})\right]L_{jt} + \delta L_{jt}\right), \tag{18}$$

where $g$ is an index of socioeconomic groups and $\boldsymbol{\beta}_i$ are random taste parameters in the style of ABBP (2005).

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