MARKET AND POLICY ISSUES
IN MICRO-ECONOMETRIC DEMAND MODELING
(draft)

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Paper prepared for presentation at the 107th EAAE Seminar
***"Modelling of Agricultural and Rural Development Policies".* Sevilla, Spain,**
January 29th -February 1st, 2008

Abstract

Micro-econometric demand modelling has been receiving an increasing attention in empirical research, mainly due to the increasing availability of micro-data. In this paper we provide a review of some relevant market and policy issues that can be analysed with the use of micro-data on demand. Problems arising from the treatment of micro-data are revised, mainly with reference to the standard neo-classical framework, although other approaches are also sketched. Finally, building on previous research, a dynamic model accounting for health issues, mainly obesity, is proposed for future research.

1. Introduction

Micro-econometric demand models analyse the economic behaviour of purchasing units (individuals and/or households) using individual-level data. As such, they provide a powerful tool in policy analysis since, by accounting for the heterogeneous behaviour of individuals agents, policy interventions can be better tailored according to their heterogeneous effects. Policy evaluation can be separated in two classes: the evaluation of a policy in place compared to other alternatives (the so-called *treatment effect*: for example the evaluation of a health-information program on food safety and health problems related on food on both participants and non participants in the program) and the evaluation of a policy in a new environment (Heckman, 2001). Furthermore, with respect to aggregate data, the use of micro-econometric models will provide a coherent tool to test economic theory (i.e. economic theory is founded on individual behaviour) and to explain empirical facts.

Demand models mainly have a microeconomic foundation, with rational agents seeking utility maximization and determining individual demand. In the past, most of the empirical work has been based on macroeconomic data (time-series analysis): the issue of aggregation (either across individuals or goods) has played a central role in both theoretical and empirical analysis, since the notion of a representative consumer (household) has been largely invoked to justify empirical analysis and testing of microeconomic theory using aggregated (macro) data. Of course, the issue of aggregation is still a relevant one: if we want to use results from empirical studies on demand as an input for (policy) simulation models, microeconomic information may be aggregated. However, micro-econometric demand models have shown the importance of heterogeneity in economic behaviour, something that cannot be fully accounted for by the notion of a representative consumer as in macroeconomic models (i.e. with aggregated data). The availability of micro-data has shown that 'identical individuals' (that is, individuals with the same observables characteristics) have different economic behaviour. This of course uncovers the role of unobservables (for example, tastes) in explaining microeconomic data, and requires that heterogeneity cannot be ignored in empirical research, unless serious consequences may arise.

Policy analysis as long as marketing research are often based on simulation models, either reduced form models or structural models (Bronnenberg et al., 2005). Micro-econometric demand models provide useful information mainly as an input for structural models, that's is models based on agents' optimizing behaviour. For policy and/or marketing simulation, it is crucial to refer to 'rich' models, in terms of their specification characteristics. For demand models it means that we may be willing to account for many variables (advertising, quality, information, and the related uncertainty), and their

effect on households' decisions: for example, micro-data at the store level (i.e. scanner data) may provide useful information on the role of in-store advertising/promotion with respect to other forms of advertising; on the other hand individual data provide useful tools to detect information issues, such as food safety. Then it is important to choose the best 'time' specification of the model, basically contrasting between static (one-period) and dynamic (multi-period) models: the consumption behaviour, also for non-durables goods such as food, appears to have a clear dynamic component, that can be the result of simple exogenous trends and/or myopic behaviour and/or intertemporal rational allocation models and 'inventory' levels in some 'good' (for example, health or knowledge).

2. Collecting the data

In the last years there has been an increasing use of microeconomic data (individual-level data) in demand analysis: cross-section data, longitudinal sample survey data, census data, ad-hoc sampling data, scanner data has been largely used in empirical analysis. Microeconomic data are distinguished between observational data (survey data, census data, scanner data) and experimental data (data from social or laboratory experiments) (Cameron and Trivedi, 2005, p. 39). Observational data are by far more common than experimental data: observational data can be obtained, as we said, from individual/household surveys and from census data; surveys can be conducted using different sampling procedures for the relevant population; institutions (National Bureau of Statistics and Government agencies), private companies and the researcher may be responsible for collecting data. *Observational data are collected without any attempt to control the characteristics of the sample data*. A key concept is that of representativeness of the sample: results must be evaluated according to the quality of the available data and can be extended to population only if a correct sampling procedure has been used.

Basically, we have two types of sampling procedure: *probability or random sampling* and *non-probability sampling*. In *probability* or *random sampling* we need to specify the *target population* (units to be sampled, geographical location, and temporal boundaries) and a *sampling frame*, a specific list that closely approximates all the individuals in the population. *Random samples* are important; they are most likely to yield a sample that truly represent the population.

Different *probability sampling procedures* can be used. *Simple random sampling*, where units are drawn uniformly from the population, with each individual having the same probability of being extracted; *systematic sampling*, a simple random sampling where individuals are sampled according to a sampling interval: it can be a good alternative to simple random sampling when we do not have a complete list for the population (e.g. in conducting a market research interviewing the customers of a store, we may select customers exiting from the store according to a sampling interval, i.e. one every *k* customers); *stratified sampling*, where the population is first divided in sub-populations (called *strata*), according to some criteria, and then random samples can be extracted from each strata, using simple random or systematic sampling; *cluster sampling*, where instead of using a single sampling frame, we can use a sampling design that involves multiples stages and clusters, thus the sampling procedure is to randomly sample cluster, first, and then to randomly sample elements within the sampled cluster. Cluster sampling can be conducted using weighted or unweighted procedures: weights will allow to have unbiased information on population parameters.

An alternative to random sampling is to use *non-probability sampling*: many 'self-made' samples are obtained in this manner. In fact often *convenience sampling* is adopted (e.g. a person 'randomly' selecting people to be interviewed in a certain location): biased sampling is likely (sampling is not made from the whole population and furthermore there is a selection bias); under convenience sampling it is important that empirical research will be correctly addressed. Also *quota sampling* is a widespread sampling procedure, especially in market research: the sample is constructed according to some categorical variables in the population (e.g. age, sex, etc): the sample will respect the joint distribution of the categorical variables in the population, with individuals not chosen randomly (biased sample).

In economic analysis, sampling may therefore produce a *selection error*, that can be decomposed into three parts: a *coverage error*, related to the possibility of effectively sampling (i.e. availability of the appropriate sampling frame) from the entire population; a *sampling error*, depending on the number of variables collected and affecting the sample size (i.e. the size of the sample depends on the joint distribution of the variables of interest); a *non-response error*, when selected individuals cannot be contacted or refuse to answer to the survey.

Biased samples (i.e. non representativeness) are thus possible in empirical analysis. For example, often consumer survey are conducted through direct interview to individuals, located at some point location (i.e. outside retailing stores); in this way there is a sort of response-based sampling, since only individuals purchasing at that chain-store will be selected (i.e. individuals within different retail channels will not be surveyed). Alternatively, selective sample may be the result of agents' behaviour: variables of interest may only be observed if agents have taken some choices, and there is no information about individuals not participating in some activities. This situation is known as a self-selection problem.

A further relevant issue, frequently occurring in consumer surveys, is that of a *sample selection bias*: it arises any time a rule other than a simple random sampling is used (Heckman, 2001); as a consequence there is a biased representation of the true population in the sample. This issue is a relevant one, in empirical analysis, since basically all empirical approaches can be affected by a selection bias issue. According to Heckman (2001), the selection bias can be interpreted in terms of a weighted function altering the distribution of variables of interest in the population: knowledge of the weighting function is necessary to recover the true population density. Empirical work must account for the selection bias problem, and new econometric tools have been introduced to this purpose. This issue is of extreme relevance in micro-econometric demand models: for example, non market participation (i.e. a zero response in consumption) may enter in the class of selection bias.

Finally, microeconomic data are different in quality with respect to aggregated time-series data, thus providing new challenges for econometricians. Heckman (2001) summarizes the main relevant issues encountered in the empirical analysis: [a] outcome variables can be discrete (for example dichotomous choice variables); [b] missing data are frequent, due to choices made by individuals (for example, goods are not purchased). The two issues may also overlap; for example, missing observations may be the result of a possible discrete outcome. Many empirical analyses have dealt with the issues of zero observation and/or missing observations. In micro-econometric demand models, for example, there may be a large number of zero observations, due to different reasons: [i] corner solutions, that is the individual/household does not consume the good at the actual prices and income (for example, the price is too high than the one at which the first unit of good is purchased); [ii] the individual/household is not interested to purchase the good, independently of prices and income (for example, the

individual/household will abstain from purchasing GM food); [iii)] infrequency of purchase: in the survey period the individual/household does not purchase the good. There are econometric tools able to treat the three different situations, although the problem is that it is not possible to a priori distinguish the source of a zero observation.

3. Issues in micro-econometric demand modeling.

3.1 Differences in microeconomic data and socio-demographic changing in population

There is an important difference between cross-section data and panel data (or even pseudo-panel data). Obviously, with cross-section data we can only evaluate differences within people at one point in time, while panel data allow to evaluate the dynamics in household behaviour through time. Panel data, when available, have obvious advantages over pure cross-section data: they may allow to decompose an average effect on consumption/expenditure among individuals, therefore explaining why individuals behave differently over time (Verbeek, 2004). Many of the available household surveys are based on a rotating panel, with a certain rotation/replacement rate (for example, a rotation rate of 20% may indicate that every household/individual is maintained in the sample for five surveying periods before being substituted); therefore it is common to build-up pseudo-panel data (see Fernandez-Villaverde and Krueger, 2007).. Therefore, assuming that the sample is representative of the population, we may consider that each randomly chosen household gives statistical information on the means of the group it belongs to (i.e. it is randomly chosen from the sub-population corresponding to that group); thus observed group means can be used to construct a 'complete' panel over a certain period. For example, the annual Consumer Expenditure Survey conducted by ISTAT in Italy uses a different random sample each year, therefore only groups of individuals can be observed through time (pseudo-panel). Thus, another important issue, although not always considered, with repeated cross-section data through time is related to the 'cohort' effect (Mori et al., 2006; Fernandez-Villaverde and Krueger, 2007): a 'cohort' is a 'group with fixed membership formed by individuals which can be identified as they show up in the surveys (Deaton, 1985; Kapteyn et al., 2005; Aristei et al., 2007). A common way to proceed is that of tracking households in surveys according to the age (date of birth) of the household's head. The cohort effect can have a considerable impact on consumption patterns, especially when addiction and/or habit forming in demand characteristics may be present.
The impact of relevant changing in demographics on demand analysis is a central issue; it is often argued that part of the relevant macro-trends shown by (food) consumption can be related to the evolution of demographic variables through time (for example aging, women labour, low fertility rates, and so on). Socio-demographic variables are usually collected in consumer surveys (level of education, place of living, family size, age, employment, etc.). Empirical demand analyses using micro-data have taken into account the incidence of demographics on consumption behaviour (Moro and Sckokai, 2000); usually demographics are introduced in empirical demand models as shifters (on the intercept term but also on behavioural parameters), mainly by means of dummy variables. A simple shifter can be interpreted as (see Denton et al., 1999):

$$DS = \sum_{i=1}^{m} h_i (DV_i)$$

where the demand shifter DS is made up as a linear combination of functions h_i of the m demographic variables DV_i; for example a shifter including a cohort effect can be given by[1]:

$$DS = h_1(\text{age}) + h_2(\text{year - of - birth}) + h_3(\text{trend}) + h_4(\text{size})$$

3.2 The role of unobservables

Consider a causal function (i.e. a demand function):

$$q = q(p, y, z, \omega)$$

where q represents consumption of the good, p and y are observable prices and income, z are other observables explanatory variables (i.e. demographics, quality, information, advertising) and ω are unobservable explanatory variables, affecting good consumption. Of course knowledge of the unobservables ω is required to evaluate the causal or treatment effect of a policy intervention (for example, a income tax or subsidy, a sin tax or a subsidy on food prices), unless simple specifications can be assumed (i.e. unobservables are additively separable in the causal function). Following Heckman (2001), there are different policy problems to be analysed, when a policy is introduced according to the observable variables, (p, y, z). A policy has been implemented in a population, providing measures on observable variables, and we want to evaluate its impact in a population with the same distribution of (p, y, z, ω); a policy has been implemented in a population, and we want to evaluate it in a population with a different distribution of (p, y, z, ω); and finally, a policy has never been implemented and we want to evaluate it in the population of interest. Of course, case 2 and 3 are the most challenging. For case 2 ('evaluate an old policy in a new regime'), we need to know the functional relation $q(\cdot)$ as long as the distribution of (p, y, z, ω) for the new population, although some simplifying assumptions can be invoked. Obviously, knowledge of the population of interest (i.e. the causal relation $q(\cdot)$ and the distribution of (p, y, z, ω)) is required in case 3. In practice, we need some information on variation effects on the new population. For example, in order to know the impact on consumption of a (sin) tax t on some 'fatting' food (i.e. a tax on p_{FF}) we need to know the possible reaction of individuals to tax variations, that is the (treatment) effect is given by (Heckman, 2001):

$$q(p_{FF}, p, y, z, \omega) - q(p_{FF} - t, p, y, z, \omega)$$

Suppose that we want to forecast the effect of introducing the tax; obviously we need to know the characteristics the function $q(p_{FF}, p, y, z, \omega)$, and in order to recover it from empirical estimation we need to identify structural parameters for the observable variables (this means, for example, that we need in-sample price variations for p_{FF}, in order to identify the effect of the tax on consumption, assuming the tax operating only through a price change); however, we also need assumptions on the distribution of the unobservables ω (for example, independence among (p, y, z) and ω).

The issue of unobservables variables is related to the issue of heterogeneity; in investigating micro-data the relevance of diversity and heterogeneity among individual agents has been made clear, further challenging the notion of an (aggregate) representative individual largely used in policy modeling with

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[1] Of course more sophisticated specifications of demographic variables can be obtained (see Lewbel, 1985).

macro-data. 'Otherwise observationally identical individuals make different choices' (Heckman, 2001): an empirical evidence of the considerable impact of unobservables on outcomes is given by the low R^2's in cross-section estimations (for example, also the presence of zero-responses in micro-data on consumption is one outcome of the impact of unobservables). Accounting for heterogeneity among individuals has been a major challenge in empirical analysis; the simplest model that may be traced to define the problem can be the following[2]: taking a simple demand function as $q(x,\omega)$, where $x \equiv (p,y,z)$, then unobservables may be simply introduced as affecting the intercepts of a linear model, that is for i^{th} individual :

$$q_h(x_h,\omega_h) = x_h^T \beta + \omega_h$$

also called the *individual-specific effects model* (see Cameron and Trivedi, 2003); basically, the model can be estimated empirically as a *fixed effects* (FE) *model* (ω_h are random variables potentially correlated with the observed regressors) or as a *random effects* (RE) *model* (ω_h are random variables independently distributed from observed regressors). In the FE model the ω_h accounts for the constant effect of unobservables (i.e. fixed unknown group-specific parameters); in the RE model the ω_h are assumed as drawings from a unique distribution, that is $\omega_h \sim (\omega, \sigma_\omega^2)$; therefore the model could also be rewritten as[3]:

$$q_h(x_h,\omega_h) = x_h^T \beta + \omega + u_h$$

Once the panel data is sufficiently long, several econometrics technique are available to estimate heterogeneous effects: developments has been made to deal with equation systems, non-linear models, unbalanced panel-data[4] (see Sckokai et al. 2008).

To summarise our discussion on specification issue a Marshallian demand function may take this very general form:

$$q_h(x_h,\omega_h) = (p_h|y_h)^T (\beta + \varpi_h + z_h^T \gamma) + \omega_h + z_h^T \alpha$$

in which the FE model and the RE model and demographic shifters in levels and slope coefficients can be included.

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[2] In this simple specification unobservables (i.e. individual-specific effects) affect outcomes basically as a shifter on the 'average' constant term (i.e. they can be interpreted as coefficients of individual dummy variables); of course, more complex specifications are possible, where individual-specific effects may affect also marginal responses (i.e. the vector β is individual specific). In terms of interpreting the model, the effect is similar to that of making slope coefficients β depending on values of observed variables (for example, demographics). In other terms we can model slope coefficients as $(\beta + \varpi_h)$.

[3] According to this formulation, in the FE models the random term of the estimated model is given by $\varepsilon_h \sim (0, \sigma_\varepsilon^2)$, while in the RE model is given by $(\varepsilon_h + u_h)$, where $\omega_h \sim (0, \sigma_\omega^2)$, an individual specific component constant over time.

[4] Unbalanced panel data are frequent in empirical work; unbalanced panel data substantially are incomplete panel data, since we do not have information on all units (i.e. individuals/households) for each year (for example, rotating panels provide unbalanced panel data).

3.3 The treatment of missing data (zero responses).

Depending on the source of the zero response, different models can be appropriated. Considering for simplicity the single-equation case, with only corner solutions (for example the existence of a reservation price), the most widely used approach is the Tobit model. Following the clear exposition in Angulo et al. (2007), in the Tobit model consumption can be defined as:

$$q = \begin{cases} q^* = z^T \kappa + \upsilon & \text{if } q^* > 0 \\ 0 \end{cases}$$

where q^* is the latent variable (incompletely observed), z is a vector of explicative variables, κ is a vector of parameters and υ is an appropriate error term.

Since a zero response may be also caused by infrequency of purchase (a transitory abstention from consumption due to different reasons), then the appropriate specification is an infrequency of purchase model: the decision of purchasing the good may be modeled as:

$$q = \begin{cases} \dfrac{q^*}{\Phi(D)} & \text{if } q^* = z^T \kappa + \upsilon > 0 \text{ and } D > 0 \\ 0 \end{cases}$$

where $D = x^T \tau + \varepsilon$ is an indicator of purchasing decision, with x a vector of explanatory variables for the decision of purchasing, τ is a vector of parameters and ε an appropriate error term, and $\Phi(D)$ is the standard normal cumulative distribution function (i.e. the probability of purchasing). Finally, the double-hardle model is suitable when the zero response may be also due to a complete abstention from the market; each individual takes two decisions: first the *participation decision* and then the *consumption* (*level of*) *decision*: the model can be expressed as:

$$q = \begin{cases} q^* & \text{if } q^* = z^T \kappa + \upsilon > 0 \text{ and } D = x^T \tau + \varepsilon > 0 \\ 0 \end{cases}$$

In a demand systems, things become more complicated, since the extension of the previous approach is not trivial. However, different approaches have been proposed to estimate demand systems, and many different routes are available at present. Although far from being exhaustive, a list of these approaches includes the Kuhn-Tucker approach (Wales and Woodland, 1983; Lee and Pitt, 1986: the demand system is derived from a random preference representation), the Amemiya-Tobin approach (Amemiya, 1974; Golan et al., 2001; Yen et al. 2003; Dong et al. 2004; the demand system is derived from a non stochastic preference representation with an error term added to the demand functions, and estimated using different techniques, such as generalized maximum entropy and simulated maximum likelihood estimation), or alternatively a number of less efficient estimators, such as a large class of two-step estimators (Heien and Wessells, 1990; Shonkwiler and Yen, 1999; Perali and Chavas, 2000; Yen 2005; Yen, 2005).

3.4 Inter-households comparisons: equivalence scales estimation

An important feature of micro-data is that they allow inter-household comparisons. Under different policy regimes it is important to identify the distributional effects on different households. In recent

years, for example, there is a growing concern about an 'increase of poverty' even within developed economies, and therefore policy intervention are requested, also in the food sector. Welfare comparisons among households require the use of equivalence scales[5]. Households' needs increase with the number of components[6]; however due to intra-households' economies of scale and members' heterogeneity, the increase is not proportional. Therefore it is obvious to weigh each component, i.e. to express any household in terms of *adult equivalents*: equivalence scales provide the weight for each additional member in the household[7]. Simply, an equivalence scale e is defined as:

$$e\left(z^1, z^0; p, u\right) = \frac{c\left(p, u, z^1\right)}{c\left(p, u, z^0\right)}$$

where $c(p, u, z)$ is the household expenditure function, indexed by demographics characteristics[8]. Micro-data (survey data) contain information to estimate the response of demand functions to demographic variability[9]; to estimate equivalence scales different empirical specifications are possible[10]. The demand-systems approach with micro-data has been extensively used to compute equivalence scales[11]; within this approach, a quite general specification (called *generalized equivalence-scales exactness*, *GESE*) has been recently proposed (see Donaldson and Pendakur, 2004)[12]: the cost function can be specified as:

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[5] Food shares have been largely used as an indicator of welfare (Engel method for equivalence scales): then, the ratio in the income of two different households having the same 'level of utility' (i.e. equivalent expenditures) is equal to the ratio of the incomes of two households having the same food share.

[6] Our brief discussion is centered on the household size; however, as it is clear by the formal analysis, equivalence scales can be used to account for any further demographic difference among households (for example, to account for disabled members).

[7] As an example, EUROSTAT has adopted a scale in which a weight of 1 is assigned to the household head (i.e. a one-person household), while the weight assigned to each additional member is 0.5 for an adult member and 0.3 for a child.

[8] For example, z^0 can be a household with two adults and z^1 a household with two adults and a child: then the ratio measures the (percentage) cost of a child.

[9] Equivalence scales cannot be obtained by household demand behaviour (*identification problem*), since the same behaviour is consistent with a non unique system of preferences (unique expenditure and/or indirect utility functions). Therefore recovering the expenditure function from demand behaviour implies further identification requirements (Blundell and Lewbel, 1991): for example, equivalence scales being independent of the utility reference level, that is:

$$c(p, u, z) = m(p, z) g(p, u)$$

and therefore:

$$e\left(z^1, z^0; p, u\right) = \frac{m\left(p, z^1\right)}{m\left(p, z^0\right)}$$

This property is called independence of the base (*IB*) or the equivalence-scale exactness (*ESE*).

[10] For example, the Barten- specification of the cost function, where demographics are introduced as commodity-specific scaling functions:

$$c(p, u, z) = c^*\left(\frac{p}{m(z)}, u\right)$$

leading to demand functions of the form:

$$q(p, y, z) = \frac{1}{m(z)} q\left(\frac{p}{m(z)}, y\right)$$

[11] An alternative route is the so called *subjective well-being* (*SWB*) approach; here the welfare level is approximated by a self-declared satisfaction level, and not inferred by reconstructing the expenditure function from observed consumption behaviour.

[12] Donaldson and Pendakur (2006) provide a further generalization, called *generalized absolute equivalence-scales exactness*, *GAESE*.

$$c(p,u,z) = m(p,z)g(p,u)^{n(p,z)}$$

where the function $n(p,z)$ is functionally dependent on $m(p,z)$.[13] Since by construction $m(p,z^0) = n(p,z^0) = 1$ (see Donaldson and Pendakur, 2004, for details), we can derive a (modified) expression for equivalence scales, defined as:

$$e(z^1, z^0; p, u) = m(p,z^1)g(p,u)^{[n(p,z^1)-1]}$$
$$= m(p,z^1)y^{1[n(p,z^1)-1]}$$

Accounting for identification restrictions on preferences, an empirical specification can be obtained; Donaldson and Pendakur (2004) use the quadratic almost ideal demand system (QAIDS) of Banks et al. (1997), that is derived as an extension of PIGLOG preferences (rank 3 demand system). The cost function is given by[14]:

$$\ln c(p,u,z) = \left[\ln a(p,z) + \left(\frac{u \cdot b(p,z)}{1 - u\lambda(p,z)} \right) \right]$$

and GESE implies that[15]:

$$\ln a(p,z) = n(p,z)\ln a(p,z^0) + \ln m(p,z)$$
$$b(p,z) = n(p,z)b(p,z^0)$$
$$\lambda(p,z) = \lambda(p,z^0)$$

As we said, equivalence scales can be used in different contexts; support policy program in food (i.e. food stamps) and also agricultural (market and non-market support) can be tailored according to their impact on inter-household distributional effects and on the definition of a threshold for poverty (a 'poverty line'), adjusted on households' differences; although the major issues are those related to poverty, especially in the LDCs, the policy impact on less favoured areas (i.e. rural development policies) is of great relevance also in developed countries.

3.5 Dynamics in demand models

An important issue in recent demand analysis is that of the existence of dynamics in demand models. One of the most common assumptions in demand analysis is that of time-separability, (i.e. inter-temporal weak separability); most demand models are specified as static models of demand, where each period outcome does not have any impact on other periods' outcomes (i.e. current consumption only depends on current prices and income). However the idea of the presence of some 'dynamics in (food) demand' has a long history in empirical demand analysis.

There has been a large body of the empirical literature dealing with the issue of structural change in preferences within food demand, mainly supporting the existence of a smooth or abrupt structural change; structural change has been firstly modeled as an exogenous trend in demand, and after many

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[13] Lemma 2 in Donaldson and Pendakur (2004) shows that:

$$n(p,,z) = \sum_j \frac{\partial \ln m(p,z)}{\partial \ln p_j}$$

[14] We have that $\ln a(p,z)$ is a translog aggregator function and $b(p,z)$ is a Cobb-Douglas aggregator function, while $\lambda(p,z)$ is a linear aggregator function.

[15] Note that we have simple tests for *GESE*, i.e. $\lambda(p,z) = \lambda(p,z^0)$, and *ESE*, i.e. $b(p,z) = b(p,z^0)$.

other alternative specifications have been used, allowing for stochastic and/or deterministic time-varying structural parameters in demand equations (see for example, Mazzocchi et al., 2006); as food consumption reaches saturation levels, as in developed countries, substitution effects prevail and the dynamics in food demand is driven by nutritional and service characteristics. An increasing attention is paid by consumers to food safety and health issues, and the link between health problems and diet; relevant and recurring food crises have affected food demand in the last years: an important policy and market issue is related to the long-run effect of food safety alarms, that is if they have to be considered as temporary or permanent. Malnutrition (over-nutrition) is a central issue in food and health policy, and obesity is becoming a growing concern, not only in the richest countries: a large share of the population of the most developed countries is affected by a weight-problem, with a relevant impact on public policy and transfer programs (health care); obviously, obesity shows a potential for addiction problems. An increasingly larger share of food expenditure is devoted to the consumption of food away from home, and this type of demand may be easily habit forming. But even 'marketing problems', like the effect of advertising on the consumption of goods, may have a dynamic component (Ackerberg, 2003). Furthermore, failures in empirical testing of the underlying economic theory can be an indication that consumer choices are taken in a dynamic context (LaFrance, 2001). Habit formation (and addiction)[16] and intertemporal non-separability in preferences have important 'aggregate' implications (see Browning and Collado, 2007); when we consider aggregate (composite) goods, we may find consumption persistence because some components may exhibit durability and/or habits over time.

In dynamic models (with habit formation) and panel data, it is also important to distinguish between heterogeneity and state-dependence (Heckman, 2001). In other words, if we observe a persistent behaviour in consumption (for example, high frequency and/or high level of consumption) two explanations are possible: first, the household/individual is intrinsically a frequent/high consumer (heterogeneity) or at some point 'something ' has induced a frequent/high consumption and this 'new habit' has been continuing (state-dependence). Empirical testing can be done, for example, according to the strategy proposed in Browning and Collado (2007); going back to the previous discussion, a possible (stochastic) demand functions can be specified as[17]:

$$q_{ht} = \left(p_{ht}\middle|y_{ht}\right)^{T}\beta + z_{ht}^{T}\alpha + \gamma q_{ht-1} + \omega_{h} + \varepsilon_{ht}$$

The model will present residual autocorrelation due to either heterogeneity or state-dependence; however, *constant* autocorrelations would arise if there were only effects due to heterogeneity, while habit formation will produce decreasing autocorrelations. Then, a test of intertemporal separability is a test on the significance of the γ coefficient in the demand specification, once we account for

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[16] Being very simple, in a model with habit formation demand functions include lagged dependent variables; in a model with rational addiction, also future values for the dependent variables must be included in the LHS (see for example Richards and Patterson, 2006 for an application).

[17] An interesting specification can be found in Richards and Patterson (2006), in their empirical research on obesity; in our context it reduces to specify a dynamic demand model like (heterogeneity and demographics are discarded):

$$q_{ht} = \left(p_{ht}\middle|y_{ht}\right)^{T}\beta + \omega_{h} + \gamma_{1}q_{ht-1} + \gamma_{2}q_{ht+1} + \lambda\Delta q_{h}$$

In this formulation, habit formation (or myopic addictive behaviour) is signalled by the coefficient γ_{1} being different from zero; further, a positive γ_{2} indicates rational addiction. The introduction of the term Δq_{ht}, specified as the (negative) deviation from mean consumption, may account for the role of adjustment costs in driving addictive behaviour.

heterogeneity: a significant coefficient will be an indication of state-dependence in consumption[18]. Dynamic specifications have been applying for many years in (food) demand estimation, developing the idea that individuals do not instantaneously adjust to a new equilibrium, as in a static model, but only in the long-run; therefore a short-run disequilibrium is possible due to many reasons (habit persistence, adjustment costs and/or inertia, incorrect expectations, misinterpretation of real price changes, and so on)[19].

3.6 Imperfect competition: estimation and policy simulation

A relevant topic in policy modeling is that of imperfect competition; there is in fact a strong evidence that food markets are not perfectly competitive and, in particular, there is a growing market power of retailers. Furthermore, even in international trade the issue is relevant: State Trading Enterprises may produce trade distortions by exerting market power in international market. Large models such as the AGLINK model of the OECD or the FAPRI model of the Centre for Agricultural and Rural Development commonly assume a perfectly competitive behaviour of all agents. Demand models can be used to estimate the degree of market power in a food supply chain, following the general framework of Hyde and Perloff (1998) and Gohin and Guyomard (2000). Demand Marshallian functions can be specified as $q_i = q_i(p, y)$, with any plausible functional form adopted for them. Assuming that firms in the supply chain may exert market power (for simplicity, we consider only the market power at the retailing level), thus profit maximising firms can exploit monopolistic/oligopolistic power by exploiting their impact on the (inverse) demand functions for each product, $p_i = p_i(q, y)$; from FOC of the profit maximisation (see Soregaroli et al., 2007), we obtain the following price transmission equation for each firm k :

$$p_h + \frac{1}{q_h^k} \sum_i \sum_j p_i q_i^k f_{ij} \theta_{jh}^k - \frac{\partial C^k(q^k)}{\partial q_h^k} = 0$$

where $f_{ij} = \frac{\partial p_i}{\partial q_j} \frac{q_j}{p_i}$ are price flexibilities, $\theta_{ih}^k = \frac{\partial q_i}{\partial q_h^k} \frac{q_h^k}{q_i}$ are conjectural elasticities of the kth on the final market and $C^k(q^k)$ the cost function. After adopting a parametric specification of the price transmission equation, parameter estimates can be obtained by estimating simultaneously the demand and price transmission systems of equations. Micro data can be useful in estimating models of this type, although in principle estimation may also be carried out by using aggregate data. For example, scanner data providing statistical information for purchases distinguished by brand can be used to estimate the degree of market power for different brands[20], including private labels or store brands.

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[18] Browning and Collado (2007), using Spanish data (rotating panel), found evidence that food away-from home, differently from food at home, exhibits habit formation. Furthermore, they found that expenditure (income) elasticities are quite sensitive to accounting for heterogeneity, especially for food at home.
[19] See Anderson and Blundell (1983) for a general representation of flexible dynamic demand systems and a testing procedure on dynamic behaviour (autoregressive/partial adjustment dynamic model vs. static model). Also, static demand models have been augmented to account for statistical properties of the data (i.e. non-stationarity of economic variables): error-correction (dynamic) models are then estimated using cointegration approaches (see, for example, Attfield, 1997).
[20] Alternative specifications for measuring market power are possible, with extensions towards oligopsonistic power: see for example Cotterill et al.,(2006).

The implication on policy analysis is straightforward; discarding market power in economic models for policy simulation and/or forecasting may produce even large distortions in responses, thus leading to incorrect or biased indication[21].

3.7 Marketing issues

Micro-econometric demand modeling may be useful also for market research; it is obvious that studies on households' behaviour accounting for demographic differences provide a potentially useful tool for market segmentation. Furthermore, in the same way, it is possible to exploit the same strategy (i.e. inclusion of other variables) to account for important marketing variables, like promotion, advertising, brands reputation, information, thus evaluating interventions made by firms and/or institutions. In this context it may become extremely relevant the availability of highly disaggregated data available at the marketing level. Panel data and scanner data are collected and elaborated by private firms (i.e. market research companies like A.C. Nielsen and I.R.I. Infoscan) and increasingly used in empirical analysis (see Capps, 1989, for a pioneer analysis, and Capps and Love, 2002).

One relevant issue in modern retail food markets is the role of private label and/or store brands, covering a large share of total sales. In this context it is important for marketing strategies, both for producing and retailing firms, to understand the sensitivity of consumers to price (i.e. price elasticities) and promotion policy, and the substitution effects among brands. Scanner (panel) data provide the required statistical information. The widespread demand system approach is extended to incorporate marketing variables. For example, in a recent analysis (Huang et al., 2007)[22], marketing variables are included in demand functions using a demand shifter on the constant term[23]: demand systems estimation then provides price elasticities for firm brands and private labels in the U.S cheese market[24].

Scanner (panel) data can be used also in different models. For example, models with discrete choice. However, when using data at the brand level it is also important to recognize that models of discrete choice may be misspecified for some goods if the single-unit purchase assumption of the most popular discrete choice models (for example, probit and/or logit models) is violated (Dubè, 2004). The random utility model, assuming a restriction on a single-unit purchase for the ith good, is given by:

$$u_i = A_i^T \beta - \gamma p_i$$

where A_i is a vector of the ith product attributes and p_i its price, while β is a parameter vector and γ is the marginal utility of money[25]. However, assuming that households in any shopping trip to the

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[21] For example, in Soregaroli et al. (2007), in a simulation model for the Italian dairy sector, the ratio between values of simulated endogenous variables (farm prices, consumer prices, consumption, trade) under the two frameworks (imperfect competition and perfect competition) varies from 0.0% to 13.8%.

[22] With a similar approach, Torrisi et al. (2006) estimated a demand for packaged red wine table in Italy differentiated by brand, using scanner data (I.R.I. Infoscan) within a demand system approach where the impact of marketing (a proxy for loyalty/promotion) and environmental variables is introduced as a shifter on the constant term (see above). The share of the private label was about 10-12% even in this very mature market.

[23] As for demographics, shifters could be imposed also on price parameters, thus hypothesizing that marketing variables could affect behavioural parameters in a more profound way; for example, this would produce a more complex impact of marketing strategies on brands' price elasticities.

[24] In this study a meta-analysis has been conducted on the estimated elasticities to detect their major determinants.

[25] Of course a random term must be added to the specification.

store may purchase a basket of different alternatives within a category (for example, carbonated soft drinks) in anticipation of a number J of future consumption occasions; in any of these occasions utility from consuming one of the I products in the category can be modeled as:

$$u_j = \left(\sum_{i=1}^{I} \vartheta_{ij} q_{ij} \right)^{\alpha}$$

where ϑ_{ij} represents the household's perceived quality for the alternative i in occasion j, and q_{ij} is the quantity chosen, while the parameter α provides curvature for the utility function. The perceived quality can be defined as:

$$\vartheta_{ij} = \max \left(0, A_i^T \beta_j \right)$$

Therefore, conditional on J, the total utility at each shopping trip is given by:

$$u = \sum_{j=1}^{J} u_j + z$$

where z represents other expenditure in the shopping trip. Therefore, by taking a shopping budget y, and substituting, we obtain:

$$u = \sum_{j=1}^{J} u_j - \sum_{j=1}^{J} \sum_{i=1}^{I} p_i q_{ij} + y$$

that clearly generalize the standard random utility model[26].

4. Experimental demand analysis

Another growing body of literature is that related to the use of 'experiments' in analyzing economic behaviour. There is of course a large difference in methods within this area of research, moving from so-called 'conventional lab experiment' to 'natural field experiment' (Harrison and List, 2004). Some important applications have been provided also for demand analysis; especially when we want to provide some policy and/or market indications about some new issues (for example, consumers' attitude towards new products or new characteristics) this approach may be the only feasible. Some recent applications can be found for Genetically Modified (*GM*) food (Rousu et al., 2004; Lusk et al. 2006), for food technologies, like food irradiation (Hayes et al., 2002; Nayga et al., 2006) or the use of antibiotics (Lusk et al., 2006), for environmentally certified food (Lusk et al., 2007), for health risks/food safety (Hammitt and Haninger, 2007). We wish however to emphasize that behavioral data from experimental methods may help in identifying parameters in structural policy simulation models. Mainly the interest is on measuring the willingness-to-pay (*WTP*) or to-accept (*WTA*) by consumers for the good of interest[27]. Experimental methods try to solve problems that can be encountered (i.e.

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[26] By using this model of multiple discreteness for carbonated soft drinks, with the inclusion of demographic effects and brand loyalty, Dubè (2004) found that the measurement of sensitivity of consumer demand to the marketing mix may be improved, evaluating for each brand ealsticities with respect to price, advertising and display.

[27] Obviously there are other important applications of experimental design analysis; for example, the conjoint analysis is a widespread tool in marketing research (see for example Jan et al., 2007 for an application on GM products).

biases in *WTP/WTA* estimates: *hypothetical bias*) when hypothetical questions are posed to individuals[28].

In an experiment, usually, some 'real' alternatives are involved. Basically, the experiments are based on models derived from consumer theory (i.e. individuals obtain utility from consuming goods and/or their characteristics). Experiments aim to 'create' new markets, not observable in reality. For example, the consumer's *WTP* can be elicited by setting an auction mechanism, (Melton et al., 1996; Lusk et al. 2006); or by conducting other types of field experiments (Nayga et al. 2006). As we said the experiments are associated with some real choices and the auction mechanism can be different (often, a second price auction is used, but also n^{th} price auctions can be employed, or even random n^{th} price auctions). The idea of an auction mechanism (for example, a second-price auction) is that of letting participants in the experiment bidding (for example for a GM vs a non-GM product), then the lowest (highest) bidder will accept (or pay) the second lowest (highest) bid. Normally, the auction is repeated for several rounds in order for participants to reveal their true preferences (thus bidding the 'true' amount), once realizing that being truthful is a dominant strategy. A second (n^{th}) price auction is largely used because it is weakly demand revealing and the market-clearing price is endogenous[29]. *WTP* and *WTA* can be used to evaluate the value for consumer of certain product characteristic, of food safety issue, of information and so on. For example (see Rousu et al., 2004), results from an experiment can be used to evaluate the value of information: by running an experiment on GM and non-GM food before and after the provision of information, its value for a single consumer (*VI*) can be evaluated as the change in consumer's surplus:

$$VI = \left(WTP_{GM} - P_{GM}\right) - \left(WTP_{nonGM} - P_{nonGM}\right)$$

Of course, data collected (for example, demographic characteristics) can be used in micro-econometric regression models to explain the determinants of *WTP/WTA* values. For example, (see Tegene et al., 2003) a censored regression analysis can be run to explain the difference in bid prices between GM and non-GM food $\left(WTP_{GM} - WTP_{nonGM}\right)$; in Lusk et al. (2006), a quantile regression method is used to explain the *WTA* GM food obtain from an auction mechanism; in Hammitt and Haninger (2007), maximum likelihood methods are employed to explain *WTP* for food risk reduction.

Alternative approaches to experimental methods are available; for example, Nayga et al. (2006) elicited *WTP* for irradiated food by using a dichotomous choice field experiment. The simplest environment is that in which the participant is confronted with some fixed cash amount and he must accept or pay it. The resulting model reflects discrete choices (McFadden, 1974; 1981), where a consumer chooses the alternative that maximizes utility: however, differently from auction methods, we do not have a 'precise' measure of the individual *WTP/WTA*. Alternatively, several applications of Contingent Valuation (CV) methods for detecting *WTP/WTA* can be found in the empirical literature; differently from field experiments based on a controlled environment and on real alternatives, CV methods usually survey a (random) sample from the population, collecting socio-economic information on the respondents; double-bounded models seem to provide a more efficient route (Hanemann et al., 1991; Nayga et al. 2006 uses a double bounded model with real alternatives; other recent applications in eliciting *WTP* can be found in Hammitt and Haninger, 2007, on reducing the

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[28] In Fox et al. (1998) and List and Shogren (1998) methods for calibrating results of hypothetical surveys with results from experimental auction markets have been proposed.

[29] However, evidence suggests that more rational behaviour can be obtained in more complex settings (such as a second price auction tournament; see Shogren, 2006).

probability of health risks in food; Lin et al., 2006, on GM foods in China)[30]. Adapting the model in Nayga et al. (2006), considering the alternative between GM and non-GM food, a consumer will accept/pay the proposed bid B, thus exchanging the two alternatives, if:

$$v(q^1, y \pm B) \geq v(q^0, y)$$

where v represents a (restricted) indirect utility function, while q^1 and q^0 are the two alternatives. In double-bounded models the elicitation process takes place in two stages: each participant is (randomly) confronted with two bids, where the level of the second bid is contingent on the response to the first bid[31].

The important issue is that by adopting this method it is not possible to know with certainty the real *WTP/WTA*, that is the value B^* for which $v(q^1, y \pm B^*) = v(q^0, y)$; therefore in this framework we must adopt probability choice models, i.e. modeling the $\Pr(\text{to accept } B) = \Pr(v(q^1, y \pm B^*) - v(q^0, y) \geq 0)$, according to a random utility-maximization response[32].

5. A dynamic model of demand with health (obesity) and quality issues

The current period utility of an individual is given by (Antle, 2001; LaFrance, 2001; Lakdawalla and Philipson, 2002 and 2005; Zhen and Wohlgenant, 2006):

$$U = u(F, C, H)$$

where F is food consumption, C is other goods' consumption and H is health.

First we may introduce habit forming in the model: habit formation implies time non-separable preferences, since current utility depends not only on current expenditure/consumption but also on a 'habit stock' (Dynan, 2000; Coppejans et al., 2007). Food consumption (i.e. food service, according to Zhen and Wohlgenant, 2006) is obtained through a production function:

$$F = f(X, q, S)$$

where X are the raw-food goods, q is a quality indicator, and S is the 'consumption capital', that is experience/knowledge obtained from the past. Individual health depends also on individual weight and food safety issues:[33]

$$H = h(W, k)$$

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[30] Alternatively, *WTP/WTA* in CV studies may be elicited with different methods; for example, a payment card method (Boccaletti and Moro, 2000), where participants are presented with a range of alternative bids and asked to identify their maximum *WTP*; or a randomized card sorting method, where alternative bids are written on separate cards, and cards are then randomly chosen and presented to the participant, who is asked to accept or reject any bid.

[31] For example, if the participant accepts the first bid B^1, then the second bid will satisfies $B^2 > B^1$, otherwise if the participant does not accept the first bid B^1, then the second bid will satisfies $B^2 < B^1$; obviously four different outcomes are possible.

[32] For example the probability that the participants will accept both bids can be defined as:

$$\Pr(B_a^1, B_a^2) = \Pr(B^1 \leq \max WTP, B^2 \leq \max WTP) = \Pr(B^2 \leq \max WTP) = 1 - \Phi(B)$$

where $\Phi(B)$ is the (cumulative) distribution function of the individual's true maximum *WTP*. Therefore a log-likelihood function for the survey participants can be constructed, based on probabilities for the different outcomes; ML methods can be used to estimate the model.

[33] As in Antle (2001) health may also depends on other variables, like medical expenditure and cautious behaviour.

where W is individual current weight and k is a (perceived) nutrition risk (food safety information). Regarding individual weight, following Lakdawalla and Philipson (2002), health is non-monotonic in weight: the individual has an 'ideal weight', W_0, and health is decreasing moving away from W_0. Transition equation for weight and consumption capital can be represented as:

$$\overset{o}{W} = (1-\delta)W + g(X,a)$$

$$\overset{o}{S} = X - \gamma S$$

where δ is a sort of 'weight depreciation rate' and γ is the consumption capital depreciation rate, while $g(X)$ is a (concave) function increasing in nutritional intake X and decreasing in physical activity a.[34]

The consumer problem is[35]:

$$\max_{X,C} \int_0^T e^{-\theta t} u(F,C,H)dt$$

$$s.t. \quad F = f(X,q,S)$$
$$H = h(W,k)$$
$$\overset{o}{W} = (1-\delta)W + g(X,a)$$
$$\overset{o}{S} = X - \gamma S$$
$$pX + C = y$$

where p is the price of the raw-food goods, y is disposable income and θ is the time discounting rate; or alternatively:

$$\max_X \int_0^T e^{-\theta t} u(f(X,q,S), y - pX, h(W,k))dt$$

$$s.t. \quad \overset{o}{W} = (1-\delta)W + g(X,a)$$
$$\overset{o}{S} = X - \gamma S$$

The problem value function J can be written as:

$$J(W,S) = \max_X \left\{ u(f(X,q,S), y - pX, h(W,k)) + e^{-\theta} J\left(\overset{o}{W}, \overset{o}{S} \right) \right\}$$

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[34] Note that, following Lakdawalla and Philipson (2002), physical activity p is not a choice variable but the results of a technological change in home and market activities. Also, we do not consider a model with 'addiction effects' although the extension is possible (Lakdawalla and Philipson, 2002). Simply, in models with rational addiction, commonly applied for tobacco and alcohol consumption, the current consumption depends on both past and future levels of consumptions (see, for example, Labeaga, 1999; for an application to obesity, see Richards and Patterson, 2006). Richards et al. (2007), adopting a refinement of the random utility model, found rational addiction in nutrients, taking it as a cause of the 'obesity epidemic'.

[35] Again, for simplicity, we have introduced the strong assumption that the budget constraint is given only by current income.

$$\text{s.t.} \quad \overset{\circ}{W} = (1-\delta)W + g(X,a)$$

$$\overset{\circ}{S} = X - \gamma S$$

and providing that all the curvature assumptions are satisfied then the first order condition is given by:

$$(u_F f_X - p u_C) + (J_W g_X - J_S) = 0$$

By interpreting J_i as the shadow price of the state variable i, and considering the first order condition we can rewrite it as:

$$J_W = \frac{(p u_C + J_S - u_F f_X)}{g_X}$$

Therefore the marginal benefit (shadow price) of weight is equal to marginal cost of spending resources in weight gain (Lakdawalla and Philipson, 2002). Consider for simplicity an 'aggregate' X, then the first order condition implicitly defines the optimal raw-food policy $\Phi(W,S;p,y,q,k)$. Food consumption (purchasing of raw food) will be reduced by an increase in weight, that is

$\Phi_W \equiv \dfrac{dX}{dW} < 0$, at the steady-state solution of the model. Although in a slightly simpler framework,

Lakdawalla and Philipson (2002) provide a discussion of the determinant of weight in the steady state.

5.1 The empirical specification

In order to derive an empirical model of demand we exploit the fact that there exists an indirect utility function v solving the static problem and dual to the direct utility function u:

$$v(p,y,q,k,W,S) = \max \begin{cases} u(F,C,H) & \text{s.t.} & F = f(X,q,S) \\ & & H = h(W,k) \\ & & pX + C = y \end{cases}$$

then the dynamic problem becomes:

$$V(p,y,q,k,W,S) = \max_X \int_0^T e^{-\theta t} v(p,y,q,k,W,S) dt$$

$$\text{s.t.} \quad \overset{\circ}{W} = (1-\delta)W + g(X,a)$$

$$\overset{\circ}{S} = X - \gamma S$$

where the function V is a dynamic indirect utility function (Arnade and Gopinath, 2006). The optimal value of the maximisation problem (the Bellman equation) is given by:

$$\theta V(p,y,q,k,W,S) = \max_X \{ v(p,y,q,k,W,S) + V_W[(1-\delta)W + g(X,a)] + V_S[X - \gamma S] \}$$

Then by setting a primal-dual problem as:

$$\min_{p,y,W,S} \{ \theta V(p,y,q,k,W,S) - v(p,y,q,k,W,S) - V_W[(1-\delta)W + g(X,a)] - V_S[X - \gamma S] \}$$

and we use this specification to derive dynamic demand functions. First we get first order conditions:

$$\theta V_p - V_{Wp} \overset{\circ}{W} - V_{Sp} \overset{\circ}{S} = v_p$$

$$\theta V_y - V_{Wy}\overset{o}{W} - V_{Sy}\overset{o}{S} = v_y$$

$$\theta V_W - v_W - V_{WW}\overset{o}{W} - V_{SW}\overset{o}{S} = 0$$

$$\theta V_S - v_S - V_{WS}\overset{o}{W} - V_{SS}\overset{o}{S} = 0$$

We use Roy's identity to get dynamic demand functions:

$$X = -\frac{v_p}{v_y} = -\frac{\theta V_p - V_{Wp}\overset{o}{W} - V_{Sp}\overset{o}{S}}{\theta V_y - V_{Wy}\overset{o}{W} - V_{Sy}\overset{o}{S}}$$

where the dynamic demand functions for raw-food material can be obtained by derivatives of the dynamic indirect utility function V; thus by resorting to an appropriate flexible functional form (for example, a second-order quadratic approximation as in Arnade e Gopinath, 2006) to approximate the function V we may obtain empirical specification for the Marshallian demands of n food categories:

$$V(p,y,q,k,W,S) = \alpha_0 + \sum_{i=1}^{n}\alpha_i \ln(p_i) + \beta_1 \ln(y) + \gamma_1 q + \gamma_2 k + \gamma_3 W + \gamma_4 S$$

$$+ \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_{ij}\ln(p_i)\ln(p_j) + \frac{1}{2}\beta_2 \ln(y) + \gamma_{11}q^2 + \gamma_{22}k^2 + \gamma_{33}W^2 + \gamma_{44}S^2$$

$$+ \sum_{i=1}^{n}\lambda_i \ln(p_i)\ln(y) + \sum_{i=1}^{n}\lambda_{i1}\ln(p_i)q + \sum_{i=1}^{n}\lambda_{i2}\ln(p_i)k + \sum_{i=1}^{n}\lambda_{i3}\ln(p_i)W + \sum_{i=1}^{n}\lambda_{i4}\ln(p_i)S$$

$$+ \pi_1 \ln(y)q + \pi_2 \ln(y)k + \pi_3 \ln(y)W + \pi_4 \ln(y)S$$

$$+ \gamma_{12}qk + \gamma_{13}qW + \gamma_{14}qS + \gamma_{23}kW + \gamma_{14}kS + \gamma_{34}WS$$

One of the main problems is of course that of data availability; in fact we do not have many empirical applications in estimating demand systems related to obesity issues (Asfaw, 2007). Often, we have a sort of approximating approach, where health/obesity issue are approximated through nutrient intake (see for example Arnade and Gopinath, 2006; Angulo and Gil, 2006; Richards and Patterson, 2006; Smed et al. 2007). The suggestion for future research is that of trying to combine (micro)-data from different sources or surveying new variables, registering information on measures of obesity, such as the BMI (Body Mass Index).

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