Measuring consumer behavior using experimental data*

Philippe Février[†]and Michael Visser[‡]

First version September 2003
This version June 2005

Abstract

The hypothesis that the preferences of an individual can be represented by a utility function is at the center of economic theory. However, the main restrictions of the theory (the Slutsky conditions) are often rejected by empirical studies on micro data. This paper uses experimental data to analyze the main explanations of this result. Using the Generalized Axiom of Revealed Preferences (GARP), the subjects of the experiment are divided in two groups: GARP-consistent and GARP-inconsistent individuals. Two models, the translog model and a PIGLOG model, are then estimated for both groups separately and for the total sample. We find that the estimated parameters of the demand equations and tests of the Slutsky restrictions are not influenced by the presence of GARP-inconsistent individuals. Furthermore, the Slutsky restrictions are accepted for the PIGLOG model but rejected for the translog model. The rejection of the Slutsky conditions is therefore a consequence of a specification problem rather than an "irrationality" problem.

Keywords: Consumer behavior; Experimental economics; GARP tests; Slutsky restrictions; Microeconometrics.
JEL **Classification:** C12;C91;D12.

*The experiment on which this paper is based was designed and carried out with P. Combris, S. Issanchou and C. Lange. We are very grateful for their help. We also thank J. Abbring, and seminar participants at CREST, IDEI, the University of Bourgogne, the 8th World Congress of the Econometric Society (Seattle), and the 2000 ESA European Regional Meeting (Amsterdam), for their comments and suggestions.
[†]CREST, 28 rue des Saints Pères, 75007 Paris, France, Email: fevrier@ensae.fr.
[‡]INRA, 48 boulevard Jourdan, 75014 Paris , France. Email: michael.visser@ens.fr.

1 Introduction

The analysis of consumer behavior is at the center of economics. The neoclassical theory postulates that consumers have preferences that can be represented by a well defined utility function. An implication of this hypothesis is the symmetry of the matrix of substitution terms. However these Slutsky restrictions are often rejected by empirical demand studies on micro data (see for example Blundell, Pashardes and Weber, 1993).

Two main explanations can explain this rejection of the theory. First, since parametric models are typically used in the empirical studies, the rejection of the theory may be a consequence of bad functional specification. To overcome this problem, economists have recently tried to develop more complex and general parametric specifications in the analysis of consumer behavior. For instance, Banks, Blundell and Lewbel (1997) propose the Quadratic Almost Ideal Demand System to include non-linear income terms. Their demand system extends the previous ones, in particular the Translog model (Christensen, Jorgenson and Lau, 1975) and the Almost Ideal Demand System (Deaton and Muellbauer, 1980), which only allow for linear terms.

Second, the rejection may be a consequence of the fact that there simply does not exist a utility function which is compatible with the data. Unlike the previous explanation, the problem is not that the utility function (or equivalently the demand system) is mispecified, but rather that at the aggregate level no single utility function can fit the data. This can occur when there are non-rational individuals in the sample (whose presence perturb the estimation at the aggregate level). It can also occur even when all individuals are rational at the individual level, in which case the rejection comes from the fact that at the aggregate level the consumption patterns can not be represented by a utility function.

The objective of this paper is to empirically find out which of the two explanations is the most appropriate. We first test whether the individuals in our data set are utility-maximizers by applying revealed preference tests (the revealed preference approach to testing for consistency with utility-maximization is mainly due to Afriat (1967, 1973) and Varian (1982)). After establishing who are the GARP-consistent and the GARP-inconsistent individuals in our sample, we estimate two systems of demand equations: the frequently used translog demand system of Christensen, Jorgenson and Lau (1975), and a slightly different demand system that we derive using Lewbel's (1987) characterization theorem. Since we know who are the GARP-consistent and the GARP-inconsistent individuals in the sample, it is possible to identify the aggregate effects of these two groups on tests of the

Slutsky restrictions and on estimates of the demand equations. Using this approach, the effect of each group is decomposed which allows us to distinguish between the two explanations described above. We test in particular if the restrictions implied by the economic theory are accepted once the GARP-inconsistent subjects are excluded from the estimation sample, and we test whether the estimated coefficients of the demand equations are identical for the GARP-consistent and GARP-inconsistent individuals.

The data on individual purchase decisions that we use were generated in a laboratory experiment. During the experiment the subjects had to buy real products under several budget/price configurations. The experimental data are well suited for the objective of the paper and have a number of advantages over field data. In field data, like individual panel data for instance, it is typically the case that successive budget levels for an individual increase over time but prices remain relatively stable, implying that the power of revealed preference tests is low.[1] In contrast, we had full control over the prices and budget levels with which we confronted the participants of our experiment. The prices and budget levels were chosen so that the power of the tests against certain behavioral alternatives is very high given the relatively small number of different price/budget configurations. Another major advantage of our laboratory data is that the different product choices were made during a short span of time (one hour), so that unlike panel data it can reasonably be assumed that the underlying preference structure was the same for all the observed choices. Still another advantage is that all goods were observed in our laboratory environment, whereas in field data one typically observes only a subset of the commodities chosen by consumers. This means that, unlike studies based on field data, it is not necessary to make additional assumptions about the utility function in order to apply revealed preference tests.[2]

Our dataset also has an important drawback, namely that there are many observations with zero-expenditures on part of the goods. These so-called corner solutions are a natural consequence of the fact that the products in the experiment were measured on a very fine and detailed level. As is well known, the presence of corner solutions renders the estimation of demand systems complicated. The method of Lee and Pitt (1982) for instance

[1] See however the paper by Blundell, Browning and Crawford (2003). Using field data, they develop a method for choosing a sequence of total expenditures that maximizes the power of GARP tests with respect to a given preference ordering.

[2] Varian (1988) shows that if the set of goods from which a consumer chooses is larger than the set of observed goods, then any sequence of choices is compatible with utility maximization, i.e. the revealed preference theory puts no restrictions whatsoever on the observed data. Only if additional assumptions are made about the utility function, such as (weak) separability in the observed goods (see Varian (1983)), does the utility hypothesis have implications for subsets of goods.

requires, for each contribution of the likelihood function, the of multiple integrals (with the number of integrals equal to the number of goods not purchased). In spite of recent advances in simulation methods that allow highly-dimensional integrals to be approximated quite accurately, the empirical implementation of their approach would remain very complex in our case. We therefore propose a different estimation strategy which is much easier to implement because it avoids the evaluation of multiple integrals. The method amounts to estimating each demand equation separately by an iterative least squares procedure proposed by Blundell and Robin (1999).

Section 2 describes the experiment and contains a descriptive analysis of the data. Section 3 presents the theory, section 4 the results and section 5 concludes.

2 Data

We use data on individual purchase decisions that were generated in a laboratory.[3] Two slightly different experiments were carried out. The experiments will be referred to as Experiment 1 and Experiment 2.

A random sample of 120 individuals from the French city of Dijon participated in our experiments (To both experiments we allocated 60 individuals). In the first part of the experiment the participants were required to evaluate 6 real food products (six different type of orange juices described in Table 1). In the second part they were given the possibility to buy the products, under 5 different price/budget configurations.

Table 2 presents summary statistics for the socio-economic variables in our data set. The participants varied considerably in their observed characteristics. In both experiments the youngest person that participated was 19 years old, and the oldest 73 years. In Experiment 1 there were slightly more women than men, while in Experiment 2 the male participants were slightly in the majority. In both experiments there were single persons as well as individuals belonging to large households. In Experiment 2 the monthly household income varied between FFr1600 and FFr39040, and the average income was around FFr12500. In Experiment 1 the income ranged between FFr950 and FFr31600, and the mean income was around FFr14000.[4] In both experiments the average budget level for situations 1-4 was around FFr80. In situation 5 it was around FFr100 in Experiment 1, and around FFr90 in Experiment 2. According to the t-test, each variable appearing in Table 2 has the same mean in the two samples.[5]

[3]For a precise description of the experiment, see Février and Visser (2003).

[4]Here the descriptive statistics are based on 59 observations, since one person had not declared his/her income.

[5]The average values reported in Table 2 are quite close to French national statistics. In 1997 the mean age of individuals living in France was 38.13 years, and women made up

Table 3 reports mean prices and purchased quantities. In situation 1 the prices were equal to the market prices, so all individuals faced the same juice prices in that situation. In situations 2-5 the prices were individual-specific. Table 4 gives some additional information about the purchase behavior of the participants. To avoid too many details, the statistics of the variables are based on all observations, i.e. they are not calculated for each situation separately. Note that the subjects exhausted most of the budgets given to them: on average the participants of Experiment 1 only left 3% of their budget unspent, and those of Experiment 2 only 4%. In spite of the fact that the six products were fairly close substitutes, the subjects generally bought several juices at the same time: the expected number of different products bought in a situation was two and a half for participants of Experiment 1, and almost three for those of Experiment 2. Although the participants devoted the largest part of their budgets to either their most preferred product (Experiment 1) or their second most preferred product (Experiment 2), the expenditure shares for the less preferred juices were not negligeable.[6]

3 Theory

3.1 Revealed preference theory

In this subsection, we briefly sketch the revealed preference approach to testing for consistency with utility-maximization. Details can be found in Varian (1982). Suppose that we have a dataset of N individuals, and that there are S situations for each individual. Suppose there are K goods and let $p_s = (p_{1s}, ..., p_{Ks})'$ and $q_s = (q_{1s}, ..., q_{Ks})'$ denote the $K \times 1$ vectors of prices and associated quantities purchased by a consumer in situation s. Let q_s and q_t be two bundles of goods with $s, t \in \{1, ..., S\}$ and consider the following definitions:

1. q_s is strictly directly revealed preferred to q_t, written $q_s P^0 q_t$, if $p_s' q_s > p_s' q_t$
2. q_s is revealed preferred to q_t, written $q_s R q_t$, if there exists a sequence of bundles $(q_u, q_v, ..., q_w)$ such that $p_s' q_s \geq p_s' q_u$, $p_u' q_u \geq p_u' q_v, ..., p_w' q_w \geq p_w' q_t$

Varian (1982) introduced the Generalized Axiom of Revealed Preference (GARP):

52.70 % of the population; in 1990 the average number of persons per household was 2.57; in 1993 the average monthly household income was FFr14185. Source: INSEE, *Annuaire Statistique de la France, édition 1998.*.

[6]The subjects were asked to evaluate the six products at the beginning of the experiment. We are thus able to order the orange juices for each individual.

Definition 1. *A set of observations* (p_s, q_s), $s \in \{1, ..., S\}$, *satisfies GARP if* $\forall\ (s,t) \in \{1, ..., S\}$, $q_s R q_t$ *implies not* $q_t P^0 q_s$.

The equivalence between GARP and the existence of a utility function which rationalizes the data is shown by Afriat (1967) and Varian (1982):

Proposition 1. *A set of observations* (p_s, q_s), $s \in \{1, ..., S\}$, *satisfies GARP if and only if there exists a utility function u (continuous, concave and monotonic) that rationalizes the data, i.e. which verifies* $u(q_s) \geq u(q)$ *for all q such that* $p_s' q_s \geq p_s' q$.

To test if the set of observations of an individual is compatible with GARP, Varian described Warshall's algorithm. This algorithm is quick and easy to program. It is used in this paper to determine if an individual is GARP consistent or not.

3.2 Estimation of demand systems with binding nonnegativity constraints

This subsection explains how the two systems of demand equations that were mentioned in the introduction are estimated.

3.2.1 The translog demand system

First we consider the translog demand system that was introduced by Christensen, Jorgenson and Lau (1975).

Theory

Let m_s^i denote the budget level of individual i in situation s, and $v_{ks}^i = p_{ks}^i / m_s^i$ and $w_{ks}^i = p_{ks}^i q_{ks}^i / m_s^i$ the normalized price and the budget share of good k in situation s for individual i, $s \in \{1, ..., S\}$, $k = 1, ..., K$, $i = 1, ..., N$.

When the value taken by the indirect translog utility function for individual i in situation s is such that the corresponding optimal quantities are strictly positive for all k (an interior solution), an application of Roy's identity implies the following form for the budget share w_{ks}^i (see Christensen, Jorgenson and Lau, 1975)

$$w_{ks}^i = \frac{\alpha_k^i + \sum_{j=1}^K \beta_{kj} \log(v_{js}^i)}{\sum_{k=1}^K \alpha_k^i + \sum_{k=1}^K \sum_{j=1}^K \beta_{kj} \log(v_{js}^i)}. \tag{1}$$

The scalar parameters α_k^i and β_{kj} are the preference parameters of the underlying indirect utility function. Note that none of the preference parameters varies with the situation-specific index s. This reflects our basic hypothesis that the preference structure for a given individual remained constant during the course of the experiment. Note also that the parameter α_k^i is allowed to differ over individuals, while β_{kj} is assumed constant.

Since the parameters in the above share equation are only identified up to a multiplicative constant, a normalization of the parameters is necessary. A convenient normalization is $\sum_{k=1}^{K} \alpha_k^i = -1$ for all i. For an estimation reason explained below, we also impose the homogeneity restrictions, i.e. we impose the restrictions $\sum_{k=1}^{K} \beta_{kj} = 0$ for all j.

Finally, the parameter α_k^i is assumed to be of the form $\alpha_k^i = \alpha_{0k} + \alpha_{1k}' z^i + \varepsilon_k^i$, where α_{0k} is a scalar parameter, α_{1k} a vector of parameters, z^i a vector containing the observed characteristics of individual i, and ε_k^i a scalar random variable. The variable ε_k^i represents the effect of the omitted characteristics of individual i on the budget share of good k. The omitted characteristics are unobserved to us—which is why ε_k^i is considered as a random term—but known to individual i. The error terms are assumed to satisfy the two following standard assumptions: the vectors $\varepsilon^i = (\varepsilon_1^i, ..., \varepsilon_K^i)'$, $i = 1, ..., N$, are independent and follow the same distribution;[7] for each individual i, the variables $\varepsilon_1^i, ..., \varepsilon_K^i$ are independent from z^i and all normalized prices $v_{11}^i, ..., v_{KS}^i$.

Given the normalization, the homogeneity assumption and the chosen form for α_k^i, the share equation (1) becomes

$$-w_{ks}^i = \alpha_{0k} + \alpha_{1k}' z^i + \sum_{j=1}^{K} \beta_{kj} \log(v_{js}^i) + \varepsilon_k^i. \qquad (1')$$

As mentioned before, many points in our sample are not interior solutions. When for an individual i in situation s at least one of the observed quantities q_{ks}^i equals zero, the nonnegativity constraints are binding, which means that an application of Roy's identity is inappropriate, which in turn means that the budget share w_{ks}^i is not defined as in (1').

Neary and Roberts (1980) have shown that there nonetheless exists a vector of normalized virtual prices that exactly support the observed quantities q_{ks}^i, i.e. there exists virtual prices—equal to v_{ks}^i if the purchased quantity of good k is nonzero and smaller than v_{ks}^i otherwise—such that the nonnegativity constraints are no longer binding. This means that Roy's identity *evaluated at the virtual prices* yields the correct expression for the budget shares. In the appendix it is shown how the virtual prices can be calculated for the translog model. It also shown that Roy's identity evaluated at the virtual prices yields a share equation of the form

$$-w_{ks}^i = \alpha_{0k} + \alpha_{1k}' z^i + \sum_{j=1}^{K} \beta_{kj} \log(\tilde{v}_j(z^i, v_s^i, r_s^i, \theta)) + \tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta) \qquad (1'')$$

where $\tilde{v}_j(\cdot)$ is a function that has the vectors $z^i, v_s^i = (v_{1s}^i, ..., v_{Ks}^i)'$, and θ as its arguments. Here θ is defined as the vector containing all parameters of the demand system, that is $\alpha_{0k}, \alpha_{1k}'$, and β_{kj} for all $j, k = 1, ..., K$.

[7] This assumption does not exclude dependence between ε_k^i and ε_l^i.

The form of the function $\tilde{v}_j(\cdot)$ depends on the demand regime r_s^i. This scalar variable indicates which products are purchased and which are the ones not purchased by individual i in situation s, so that r_s^i can take the values $1, 2, ..., 2^K - 1$ (the regime where all products are purchased, the regime where only good 1 is not purchased, etc.).

In equation (1"), $\tilde{\varepsilon}_k(\cdot)$ is a function with ε^i and θ as its arguments, and its form depends on the demand regime r_s^i.[8] The conditional expectation $E(\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)|z^i, v_s^i, r_s^i)$ depends on r_s^i, but this problem can easily be circumvented by transforming the share equation (1"), so that all variables are measured as deviations from appropriately defined means.

Estimation method

The estimation of the demand system is not straightforward because the experimental sample contains many individuals with so-called corner solutions, i.e. individuals with zero expenditure on one or more products in a given situation.

Using the concept of virtual prices, Lee and Pitt (1982) proposed an estimation method that consists in transforming the binding nonnegativity constraints into nonbinding constraints. Their procedure requires, for each contribution to the likelihood function, the calculation of multiple integrals (with the number of integrals equal to the number of goods not purchased). Despite recent advances in simulation methods that allow precise approximations of highly-dimensional integrals, the empirical implementation of their approach would remain difficult. We therefore propose a different estimation strategy. Our method also uses the concept of virtual prices, but is much easier to implement because it avoids the evaluation of multiple integrals. The method amounts to estimating each demand equation separately using the iterative least squares procedure proposed by Blundell and Robin (1999). Apart from the relative computational simplicity of our method, another advantage is that unlike Lee and Pitt it is not necessary to fully specify the distribution of the error terms in the demand system.

The translog demand system to be estimated is made up of the share equations (1"), $k = 1, ..., K$ (as mentioned above, the share equations are transformed to sweep out the regime-specific constants; we prefer to keep the notation simple here, but give details on how the equations should be transformed in the appendix). The unknown parameters can be estimated by applying the iterated linear least squares method recently proposed by Blundell and Robin (1999). This method is applicable when the demand system possesses a conditional linearity property, that is when each share equation is linear in the parameters *conditional* on some function of the

[8]For notational simplicity, we write $\tilde{v}_j(z^i, v_s^i, r_s^i, \theta)$ instead of $\tilde{v}_{jr_s^i}(z^i, v_s^i, \theta)$, and $\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)$ instead of $\tilde{\varepsilon}_{kr_s^i}(\varepsilon^i, \theta)$.

explanatory variables and parameters of interest themselves.[9] This explains why the homogeneity hypothesis was made. When the homogeneity restrictions are not imposed, Roy's identity evaluated at the virtual prices leads to a share equation that is untractable compared to (1"). The share equation is then a ratio in which both the nominator and denominator depend on the error terms, and consequently the statistical inference can no longer be based on the relatively simple regression techniques.

The procedure is computationally attractive since it avoids having to estimate all equations of the demand system simultaneously. Instead, it amounts to estimating (iteratively) each share equation separately by ordinary least squares: given an initial value $\theta^{(0)}$ for θ, OLS regression is applied to each share equation, $\theta^{(1)}$ is obtained from the OLS estimates, and the iteration is repeated until numerical convergence. In the appendix, Blundell and Robin's Iterated Linear Least squares Estimator (ILLE) is precisely defined.

3.2.2 A PIGLOG demand system

A natural alternative demand system is the popular almost ideal demand system (Deaton and Muellbauer, 1980). However, in the presence of corner solutions, its share equations cannot be written in the form of regression equations (such as the translog shares (1")), and as a consequence the statistical techniques needed to estimate this demand system would be very complex.

Instead, using Lewbel's (1987) characterization theorem, we derive another demand system, that is simple and remains tractable in the presence of corner solutions, and that is actually quite similar to the almost ideal demand system. Like the almost ideal demand system, it is a member of the PIGLOG class, with demand equations of the form (partly using Lewbel's notation)

$$q_{ks}^i = ((\frac{\partial B}{\partial p_{ks}^i}/B) - \frac{\partial C}{\partial p_{ks}^i}\log(B))m_s^i + \frac{\partial C}{\partial p_{ks}^i}m_s^i\log(m_s^i)$$

where B (resp. C) is any twice differentiable, homogeneous of degree one (resp. zero) function of prices.[10]

Choosing $\log(B) = B^* - \sum_{j=1}^K \delta_j \log(p_{js}^i)$ and $C = \sum_{j=1}^K \gamma_j \log(p_{js}^i)$, we find, after some straightforward calculations, $w_{ks}^i = -(B^*\gamma_k + \delta_k) +$

[9] The system (1") clearly possesses this property, since, conditional on θ, each share equation is linear in the parameters.

[10] The indirect utility function underlying these demand equations is $f(\log(\log(m_s^i/B)) - C)$, where f is any monotonic function (see Lewbel, 1987).

$\sum_{j=1}^{K} \gamma_k \delta_j \log(p_{js}^i) + \gamma_k \log(m_s^i)$. Here the scalars B^*, γ_k and δ_k are the preference parameters of the underlying indirect utility function, with $\sum_{j=1}^{K} \gamma_j = 0$ and $\sum_{j=1}^{K} \delta_j = 1$, so that B and C are homogeneous functions.

Letting $B^* = b_0 + b_1' z^i + \xi^i$ (b_0 is a scalar parameter, b_1' a vector of parameters, and ξ^i a scalar random variable that is assumed independent from z^i, m_s^i and p_s^i), we obtain $w_{ks}^i = -(b_0\gamma_k + \delta_k + b_1'\gamma_k z^i) + \sum_{j=1}^{K} \gamma_k \delta_j \log(p_{js}^i) + \gamma_k \log(m_s^i) - \gamma_k \xi^i$, which can be rewritten as

$$w_{ks}^i = \alpha_{0k} + \alpha_{1k}' z^i + \sum_{j=1}^{K} \beta_{kj} \log(p_{js}^i) + \gamma_k \log(m_s^i) + \varepsilon_k^i. \tag{2}$$

Since these budget shares have the same form as the translog share equations (1'), the calculation of virtual prices is analogous, and, using obvious notation, Roy's identity evaluated at the virtual prices yields

$$w_{ks}^i = \alpha_{0k} + \alpha_{1k}' z^i + \sum_{j=1}^{K} \beta_{kj} \log(\tilde{p}_j(z^i, p_s^i, m_s^i, r_s^i, \theta)) + \gamma_k \log(m_s^i) + \tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta). \tag{2'}$$

The demand system made up of the above share equations possesses a conditional linearity property, so that the parameters can again be estimated by applying the iterated linear least squares method (after appropriately transforming the share equations).

3.2.3 Significance tests

The next section presents the estimation results of the demand systems (1") and (2'). The usual significance tests, and all other tests that are of interest in this paper (equality of the parameters for the GARP-consistent and GARP-inconsistent individuals, tests of the Slutsky restrictions, etc.), are based on the asymptotic variance of the ILLE. The error terms in both our models do not verify assumption 1 of Blundell and Robin (1999), and, as shown in the appendix, this implies that the asymptotic variance-covariance matrix in our case differs slightly from their's.

Concerning the Slutsky restrictions, we only test the symmetry of the Slutsky matrix. In the case of the translog demand system, this amounts to testing $\beta_{jk} = \beta_{kj}$ for all $j, k = 1, ..., K$. In the case of the PIGLOG demand system (2'), it can be shown that it amounts to testing $\alpha_{11}'/\gamma_1 = ... = \alpha_{1K}'/\gamma_K$ and $\beta_{1j}/\gamma_1 = ... = \beta_{Kj}/\gamma_K$ for all $j = 1, ..., K$.[11] So, in spite of the similarity between this demand system and the almost ideal demand

[11] There are also restrictions on the constants α_{0k}, $k = 1, ..., K$; however, since the constants are not identified from the transformed share equations, these additional restrictions cannot be tested.

system, the restrictions imposed by symmetry of the Slutsky matrix are very different.

4 Results

4.1 GARP consistency

We first give the results for the GARP test.[12] We find that 35 subjects out of 120, i.e., 29% of the subjects are GARP-inconsistent. This inconsistency rate is slightly lower than the ones found in other studies (37% for Cox (1997) and 42% for Sippel (1997)). We also estimate the power of the test against four types of random behavior. The power was 22%, 26%, 58% and 46% respectively. Cox and Sippel have reported the estimated power against only one type of random behavior. The estimated power obtained by Cox (he had 5 products and 7 situations) was 47% for the GARP-inconsistent individuals in his sample, and 51% for the GARP-consistent individuals. The estimated power obtained by Sippel (8 products and 10 situations) was 61%.

4.2 GARP-consistent and GARP-inconsistent subjects

Let us now turn to the estimation results of the demand systems.

Tables 5 and 6 present estimates of the parameters of respectively the translog model (1") and the PIGLOG model (2'). To study the impact of the GARP-inconsistent subjects, we report three sets of estimated coefficients: those based on the whole sample, those based on the subsample of GARP-consistent individuals, and those based on the subsample of GARP-inconsistent individuals.[13] Only the estimates of the key parameters are given: the βs in the case of the translog model, and the βs and γs in the case of the PIGLOG model.[14]

Table 5 shows that when estimation is based on the full sample, all own-price parameters and five (out of thirthy) cross-price parameters are

[12]For more results on GARP tests (power of GARP test, Afriat's efficiency index,...), see our related paper Féevrier and Visser (2003).

[13]Since there are $K = 6$ goods, there are potentially $2^K - 1 = 63$ different demand regimes. In the full sample, all regimes are observed, but there are 2 regimes with just one observation, so the estimation sample consists of $120 \times 5 - 2 = 598$ observations (because all variables are defined as deviations from regime-specific means, single observations do not contribute to the ILLE criterion that is minimized). In the GARP-consistent-only sample, 60 regimes are observed, 4 regimes have a single observation, so the sample size is 421. In the GARP-inconsistent-only sample, 51 regimes are observed, 8 regimes have a single observation, so the sample size is 167.

[14]The estimates of the coefficients associated with the variables in z can be obtained from the authors on request (included in z are all variables listed in Table 2 except the budget variable).

significant at the 5% level. When estimation is based on the subsample of GARP-consistent individuals, all own-price coefficients and four cross-price parameters are significant (note that apart from β_{25}, the significant cross-price parameters are also significant in the full sample case). When estimation is based on the subsample of GARP-inconsistent individuals, the results are substantially worse: only two own-price parameters are significant and none of the cross-price parameters.

From the results for the PIGLOG model, shown in Table 6, a similar picture emerges: many own-price and cross-price coefficients are significant when the statistical inference is based on either the full sample or the GARP-consistent-only sample (and again the sets of significant parameters are roughly the same in both cases), while there is hardly any significant coefficient when estimation is based on the GARP-inconsistent-only sample (only one coefficient is significantly different from zero).

Result 1. *GARP-inconsistent subjects have no impact on the estimation of the demand systems.*

For both models, the hypothesis that the demand system parameters differ for GARP-consistent and GARP-inconsistent individuals can be accepted at the 5% level, but the hypothesis that the parameters of the full sample differ from those of the GARP-consistent subjects cannot be rejected. Thus GARP-consistent and GARP-inconsistent individuals have different effects on the demand equations, but at the aggregate level the influence of the GARP-consistent subjects dominates since the results are statistically the same whether the GARP-inconsistent individuals are included in the sample or not.

This last result is confirmed by comparing the elasticities implied by the estimates based on the full sample with those based on the GARP-consistent-only sample.[15] Tables 7 and 8 give budget elasticities and uncompensated own-price elasticities for respectively the translog model and PIGLOG model.

For the translog model, the budget elasticity $\partial \log(q^i_{ks})/\partial \log(m^i_{ks})$ equals $1+\sum_{j=1}^{K} \beta_{kj}/w^i_{ks}$, and the uncompensated own-price elasticity $\partial \log(q^i_{ks})/\partial \log(p^i_{ks})$ equals $-1 - \beta_{kk}/w^i_{ks}$.

For the PIGLOG model the elasticities are $1+\gamma_k/w^i_{ks}$ and $-1+\beta_{kk}/w^i_{ks}$ respectively (all these elasticities are the elasticities corresponding to an interior solution).

The elasticities for the full sample (resp. the sample of GARP-consistent individuals) given in Tables 7 and 8 are computed at the average shares in the

[15] Since almost all the coefficients based on the GARP-inconsistent-only sample equal zero, elasticities for the GARP-inconsistent individuals are meaningless and are therefore not reported here.

complete sample (resp. the sample of GARP-consistent subjects), and since these averages are positive for all goods, the above formulas are appropriate.

For both models and both samples, all budget elasticities are positive and significant. Regarding the own-price elasticities, the results are also inherently the same: for both models and both samples, the own-price elasticities of products 1 to 5 are significantly negative; for the PIGLOG model the own-price elasticity of product 6 is insignificant for both samples; for the translog model this elasticity is also insignificant for the whole sample but is significantly negative once the GARP-inconsistent individuals are excluded from the sample.

All these results support the idea that GARP-inconsistent subjects do not alter the estimation of demand systems and that their behavior is assimilable to pure random behavior. Even if they represent around 30% of the population in our experiments, their behavior does not change (at the aggregate level) the estimations obtained from the pool of GARP-consistent individuals. In particular, this result leads to the conclusion that a rejection of the Slutsky restrictions is caused by a misspecification of the demand function, and not by the presence of "irrational" individuals.

4.3 Slutsky restrictions

Our final results concern the test results for symmetry of the Slutsky matrix. For the same reason as above, we only report the test statistics for the sample as a whole and the sample of GARP-consistent individuals.

Result 2. *The Slutsky restrictions are rejected for the translog demand system, but accepted for the PIGLOG demand system.*

As can be seen from Table 9, symmetry of the Slutsky matrix is rejected at the 5% level in the case of the translog model, for both samples. Note that the symmetry hypothesis is more strongly rejected when the test is based on the whole sample.[16]

For the PIGLOG model we find the inverse result: for both the full sample and the sample of GARP-consistent individuals, the test statistic (note that the two p-values are almost the same) indicates that the symmetry restrictions can easily be accepted.

In accordance with the above results, we thus find that the test for symmetry of the Slutsky matrix is not fundamentally affected by the presence

[16]Interestingly, the restrictions are also rejected in the case of the almost ideal demand system. We have estimated the almost ideal demand system under the *ad hoc* assumption that the price index is a linear function of the shares. In the presence of corner solutions, the model then has the same shape as models (1") and (2'), except that the share variables now appear on the r.h.s. of the share equations. In applying the ILLE and in testing the symmetry restrictions, we have ignored this endogeneity problem. This is clearly incorrect, and the test result should therefore be interpreted with caution.

of GARP-inconsistent individuals in the sample. Regardless of whether the test is based on a sample that includes or excludes GARP-inconsistent individuals, the implication of utility maximization is rejected in the case of the frequently used translog model, but accepted in the case of the alternative but simple PIGLOG model.

5 Conclusion

This paper tries to understand why the Slutsky restrictions are usually rejected in empirical studies. Using experimental data, we can divide the population in two groups : GARP-consistent individuals and GARP-inconsistent subjects. We thus study the impact of GARP-inconsistent individuals on the estimation of demand systems and test Slutsky restrictions.

Two systems of demand equations are estimated, the popular translog model and an alternative model (the PIGLOG model) that we derive using Lewbel's (1987) characterization theorem. The estimation results for both models show that almost all parameters for the GARP-inconsistent individuals are insignificant. We can thus conclude that the classical utility-based model cannot explain the consumption behavior of GARP-inconsistent subjects, neither at the individual level nor at the aggregate level.

For both models, a test of the hypothesis that the demand system parameters of the full sample are equal to those of the sample from which the GARP-inconsistent individuals are excluded is accepted. Also, the test for symmetry of the Slutsky matrix is not fundamentally affected by the presence of GARP-inconsistent individuals. These results lead us to the somewhat reassuring conclusion that at the aggregate level the "anomalies" made by the GARP-inconsistent individuals at the micro level cancel out on average.

The hypothesis of symmetry of the Slutsky matrix is rejected in the case of the frequently used translog model. The symmetry restriction is accepted in the case of the PIGLOG model. This model is as flexible as the almost ideal demand system, but has the advantage that it can be estimated easily in the presence of corner solutions. The result described in the previous paragraph suggests that the rejection for the translog model cannot be explained by the presence of GARP-inconsistent individuals. This rejection is rather a consequence of an incorrect specification of the utility function, as suggested by the results concerning the PIGLOG model.

Finally, it would be interesting to test the PIGLOG model introduced in this paper on field data to see if the Slutsky restrictions are accepted when using this specification.

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APPENDIX

A Calculation of virtual prices

We show how the virtual prices can be calculated only for the translog model, the procedures being similar for the PIGLOG model (3.4). Consider the regime where only good 1 is not purchased (by an individual i in situation s), i.e. $q^i_{1s} = 0$, $q^i_{ks} > 0$, $k = 2, ..., K$. The virtual price for good 1, vp^i_{1s}, is solved from the equation

$$0 = \alpha_{01} + \alpha'_{11} z^i + \beta_{11} \log(vp^i_{1s}) + \sum_{j=2}^{K} \beta_{1j} \log(v^i_{js}) + \varepsilon^i_1,$$

so that

$$\log(vp^i_{1s}) = -\frac{(\alpha_{01} + \alpha'_{11} z^i + \sum_{j=2}^{K} \beta_{1j} \log(v^i_{js}))}{\beta_{11}} - \frac{\varepsilon^i_1}{\beta_{11}}.$$

In this regime the virtual prices for the other goods equal the observed prices, i.e. $vp^i_{ks} = v^i_{ks}$, $k = 2, ..., K$. Consider next the regime where the first two goods are zero and all remaining goods are purchased. The virtual prices vp^i_{1s} and vp^i_{2s} are then solved from

$$\begin{pmatrix} \log(vp^i_{1s}) \\ \log(vp^i_{2s}) \end{pmatrix} = -\begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}^{-1} \left\{ \begin{pmatrix} \alpha_{01} + \alpha'_{11} z^i + \sum_{j=3}^{K} \beta_{1j} \log(v^i_{js}) \\ \alpha_{02} + \alpha'_{12} z^i + \sum_{j=3}^{K} \beta_{2j} \log(v^i_{js}) \end{pmatrix} + \begin{pmatrix} \varepsilon^i_1 \\ \varepsilon^i_2 \end{pmatrix} \right\}$$

and $vp^i_{ks} = v^i_{ks}$, $k = 3, ..., K$.

As can be seen, for both regimes, the logarithm of the virtual prices can be expressed as the sum of two terms. The first term depends only on the normalized prices and the observed characteristics of individual i, and the second term only on the unobserved variables. It is not difficult to show that this is true for all possible demand regimes: the logarithm of the virtual prices can always be written as the sum of a function of the explanatory variables and a function of the unobserved variables. It then follows that Roy's identity evaluated at the virtual prices (which amounts to replacing the observed prices by the virtual prices in the share equations (1')) yields the shares (1"). For example, when only good 1 is not purchased by individual i in situation s, and defining this regime as $r^i_s = 2$, we have

$$\begin{aligned} \log(\tilde{v}_1(z^i, v^i_s, r^i_s, \theta)) &= \log(\tilde{v}_1(z^i, v^i_s, 2, \theta)) \\ &= -\frac{(\alpha_{01} + \alpha'_{11} z^i + \sum_{j=2}^{K} \beta_{1j} \log(v^i_{js}))}{\beta_{11}} \end{aligned}$$

and $\log(\tilde{v}_j(z^i, v^i_s, 2, \theta)) = \log(v^i_{js})$, $j = 2, ..., K$. Furthermore

$$\tilde{\varepsilon}_k(\varepsilon^i, r^i_s, \theta) = \tilde{\varepsilon}_k(\varepsilon^i, 2, \theta) = \varepsilon^i_k - \frac{\beta_{k1} \varepsilon^i_1}{\beta_{11}}.$$

B The ILLE and its asymptotic properties

First we define the Iterated Linear Least squares Estimator (ILLE), as formulated by Blundell and Robin (1999), and give the asymptotic properties they have derived. We then show how our translog model fits in their framework, and how the asymptotic variance-covariance matrix of the ILLE must be slightly adapted. All procedures are identical for the PIGLOG model (3.4), and are therefore not described here.

Blundell and Robin consider (page 211, equation 1) the following demand system of K equations with T observations

$$y_{kt} = g(x_t, \theta)'\theta_k + u_{kt}, \quad k = 1, ..., K, \quad t = 1, ..., T \tag{3}$$

where y_{kt} is the dependent variable, x_t a vector of explanatory variables, u_{kt} an unobserved random variable, θ_k a vector of parameters with $\theta = (\theta_1^{'}, ..., \theta_K^{'})'$, and g a vector of functions of x_t and θ. To estimate the parameter θ, they suggest the following algorithm: given an initial value $\theta^{(0)}$ for θ, estimate each θ_k by regressing y_{kt} on $g(x_t, \theta^{(0)})$, compute $\theta^{(1)}$ from the K estimates, and repeat the iteration until numerical convergence. The $(p+1)$th iteration of their algorithm yields the following value for the parameter associated with the kth equation:

$$\theta_k^{(p+1)} = [G(\theta^{(p)})'G(\theta^{(p)})]^{-1}G(\theta^{(p)})'y_k$$

where $y_k = (y_{k1}, ..., y_{kT})'$ and $G(\theta)' = (g(x_1, \theta)...g(x_T, \theta))$. Noting $\widehat{\theta}$ the limit value of such recursive sequence, they show (page 213, theorems 1 and 2) that $\widehat{\theta}$ converges almost surely to the true value value θ, and that $\widehat{\theta}$ is asymptotically normally distributed:

$$\sqrt{T}(\widehat{\theta} - \theta) \rightarrow N(0, J^{-1}(\Sigma \otimes L)(J')^{-1}) \tag{4}$$

with $L = E[g(x_t, \theta)g(x_t, \theta)']$, $\Sigma = E(u_t u_t' | x_t)$, and

$$J = I_K \otimes L + E\left[\left(\Theta' \frac{\partial g(x_t, \theta)}{\partial \theta'}\right) \otimes g(x_t, \theta)\right]$$

where $u_t = (u_{1t}, ..., u_{Kt})'$, $\Theta = (\theta_1, ..., \theta_K)$, and I_K the identity matrix of dimension K.

Reconsider now our translog model (1"). As mentioned in the main text, the conditional expectation $E(\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)|z^i, v_s^i, r_s^i)$ depends on r_s^i (we assume that given r_s^i the expectation does not depend on z^i or v_s^i). The ILLE is therefore not applied to the equations (1"), but to their transformed counterparts. More precisely, to ensure that the error terms have conditional expectation equal to zero, all variables appearing on the l.h.s. and r.h.s. of (1") are redefined by substracting their means (over all individuals i' and s' such that $r_{s'}^{i'} = r_s^i$, that is all observations with the same demand regime as individual i in situation s). Denoting $R(r) = \{(i,s)$ such that $r_s^i = r\}$, the dependent variable in the transformed version of equation (1") is $-(w_{ks}^i - \frac{1}{card(R(r_s^i))}\sum_{(i',s')\in R(r_s^i)} w_{ks'}^{i'})$, the error term is $\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta) - \frac{1}{card(R(r_s^i))}\sum_{(i',s')\in R(r_s^i)} \tilde{\varepsilon}_k(\varepsilon^{i'}, r_{s'}^{i'}, \theta)$, etc... Note that the conditional (on all $z^{i'}, v_{s'}^{i'}, r_{s'}^{i'}$, $(i',s')\epsilon R(r_s^i)$) expectation of the transformed error term is indeed equal to zero. Note also that the transformation renders the notation very cumbersome, and we will therefore, for notational simplicity, proceed as if the ILLE is applied to the untransformed share equations (1").

By rewriting the share equation (1") as

$$-w_{ks}^i = \begin{pmatrix} 1 & z^{i\prime} & \log(\tilde{v}_1(z^i, v_s^i, r_s^i, \theta)) \cdots \log(\tilde{v}_K(z^i, v_s^i, r_s^i, \theta)) \end{pmatrix} \begin{pmatrix} \alpha_{0k} \\ \alpha_{1k} \\ \beta_{k1} \\ \vdots \\ \beta_{kK} \end{pmatrix} + \tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)$$

it is easy to see that the translog model fits into the formulation (3). Indeed, given the above form of the share equation, one can define a vector of functions g such that

$$-w_{ks}^i = g(z^i, v_s^i, r_s^i, \theta)'\theta_k + \tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta),\ k = 1, ..., K, \quad i = 1, ..., N,\ s \in \{1, ..., S\}.$$

Blundell and Robin's observation index t corresponds to the couple (i,s), the dependent variable y_{kt} to $-w_{ks}^i$, the explanatory variables x_t to $(z^{i\prime}, v_s^{i\prime}, r_s^i)'$, the parameter θ_k to $(\alpha_{0k}, \alpha_{1k}, \beta_{k1}, ..., \beta_{kK})'$, and the error term u_{kt} to $\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)$. The only difference with the framework of Blundell and Robin is that the error terms in our model are not necessarily independent. They assume that the error terms of observations t and t', u_t and $u_{t'}$, are independent, but the analogue assumption can clearly not be made in our case. Dependence between error terms can arise in our case because a given individual i appears more than once in the observations, and because of the above described transformations. Following the proofs of Blundell and Robin, it can be shown that the ILLE still converges almost surely to the true value θ when the number of individuals N goes to infinity and the number of situations is fixed, and that it is asymptotically normally distributed (here we assume that estimation is based on all S situations)

$$\sqrt{N}(\widehat{\theta} - \theta) \rightarrow N(0, \frac{1}{S}J^{-1}\Omega(J')^{-1}) \qquad (5)$$

where J is defined as above (except that $g(x_t, \theta)$ must be replaced by $g(z^i, v_s^i, r_s^i, \theta)$) and $\Omega = (\Omega_{kl})_{k=1,...,K;l=1,...,K}$ with

$$\Omega_{kl} = E\left(\lim_{N\to\infty} \frac{1}{SN}\sum_i \sum_{i'} \sum_s \sum_{s'} g(z^i, v_s^i, r_s^i, \theta) g(z^{i'}, v_{s'}^{i'}, r_{s'}^{i'}, \theta)' \tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)\tilde{\varepsilon}_l(\varepsilon^{i'}, r_{s'}^{i'}, \theta)\right).$$

Note the slight difference between Blundell and Robin's asymptotic variance-covariance matrix given in (4) and our's given in (5). In their case, the hypothesis $E(u_{kt}u_{lt'}|x_t, x_{t'}) = 0$ allows them to simplify the asymptotic variance

$$\Omega_{kl} = E\left(\lim_{T\to\infty}\frac{1}{T}\sum_t\sum_{t'} g(x_t,\theta)g(x_{t'},\theta)'u_{kt}u_{lt'}\right) = E(g(x_t,\theta)g(x_t,\theta)')\sigma_{kl}$$

and consequently $\Omega = \Sigma \otimes L$ (see 4). In our case, it can be shown that the covariance (induced by the transformations) between $\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)$ and $\tilde{\varepsilon}_l(\varepsilon^{i'}, r_{s'}^{i'}, \theta)$, $i \neq i'$, goes to zero as N goes to infinity, so that

$$\Omega_{kl} = E\left(\lim_{N\to\infty}\frac{1}{SN}\sum_i\sum_s\sum_{s'} g(z^i, v_s^i, r_s^i, \theta)g(z^i, v_{s'}^i, r_{s'}^i, \theta)'\tilde{\varepsilon}_k(\varepsilon^i, r_s^i, \theta)\tilde{\varepsilon}_l(\varepsilon^i, r_{s'}^i, \theta)\right).$$

An estimator of the asymptotic variance-covariance matrix given in (5) is $\widehat{V}_{as}\widehat{\theta} = \widehat{J}^{-1}\widehat{\Omega}\widehat{J'}^{-1}$ where

$$\widehat{J} = [I_K \otimes G(\widehat{\theta})']\frac{\partial(I_K \otimes G(\widehat{\theta}))\widehat{\theta}}{\partial\theta'}$$

and

$$\widehat{\Omega}_{kl} = \left(\frac{1}{SN}\right)^2\sum_i\sum_s\sum_{s'} g(z^i, v_s^i, r_s^i, \hat{\theta})g(z^i, v_{s'}^i, r_{s'}^i, \hat{\theta})'\hat{\varepsilon}_{iks}\hat{\varepsilon}_{ils'}$$

with $\hat{\varepsilon}_{iks} = -w_{ks}^i - g(z^i, v_s^i, r_s^i, \hat{\theta})'\hat{\theta}_k$. The estimator $\widehat{J}$ of J is the estimator introduced by Blundell and Robin (page 214), and the estimator $\widehat{\Omega}$ of Ω is White's estimator.

Table 1
The six products

Product	Information
1	Pure orange juice; bottle
2	Pure orange juice; cardboard pack; product from Morocco
3	Concentrated orange juice; bottle; guaranteed content of vitamin C
4	Concentrated orange juice; cardboard pack; product from Florida
5	Nectar; bottle; 55% of pure orange
6	Nectar; cardboard pack; 50% of pure orange

Table 2
Summary statistics socio-economic variables

	Experiment 1				Experiment 2			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Age in years	37.85	14.82	19	73	36.20	13.07	19	73
Gender (=1 if woman)	0.57	0.50	0	1	0.48	0.50	0	1
Size household	2.75	1.29	1	7	2.88	1.49	1	6
Income (in FFr)	13946.10	8454.53	950	31600	12305.25	7289.91	1600	39040
Budget level (in FFr) for situations 1, 2, 3, 4	80.75	39.32	30	155	75.17	41.78	30	150
Budget level (in FFr) for situation 5	98.42	21.79	65	130	92.67	19.90	65	135

Table 3
Mean prices (in FFr) and quantities: Experiment 1; Experiment 2

	Situation 1	Situation 2	Situation 3	Situation 4	Situation 5
			Prices		
Product 1	7;7	6.76;7.98	7.01;8.61	7.48;8.98	7.72;9.42
Product 2	11;11	14.41;13.02	15.29;13.98	14.82;13.18	15.49;13.92
Product 3	10;10	9.03;10.86	8.74;10.82	9.82;10.71	9.30;10.43
Product 4	5;5	6.13;4.43	6.08;4.23	5.73;4.72	5.51;4.53
Product 5	6;6	5.93;5.07	5.89;4.95	5.98;5.43	5.98;5.52
Product 6	3;3	2.63;3.19	2.68;3.02	2.72;2.96	2.87;2.87
			Quantities		
Product 1	2.15;2.97	2.08;2.78	1.35;2.83	2.23;2.45	2.76;3.30
Product 2	3.35;1.92	2.38;1.62	2.25;1.35	2.07;1.73	1.95;1.90
Product 3	0.67;1.45	0.53;1.17	0.47;1.00	0.33;0.83	0.77;0.95
Product 4	1.73;1.08	1.57;1.43	1.48;1.33	1.70;1.13	2.52;1.20
Product 5	1.15;0.82	1.03;1.18	1.47;0.88	1.45;0.75	1.62;0.95
Product 6	1.68;1.97	1.62;1.62	1.32;2.25	1.05;2.00	1.62;2.12

Table 4
Purchase behavior of participants

	Experiment 1				Experiment 2			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
(Budget level minus expenditure)/budget level	0.03	0.06	0	0.4	0.04	0.08	0	0.58
Number of different products purchased	2.56	1.03	1	5	2.84	1.13	1	6
Expenditure share of most preferred product	0.36	0.33	0	1	0.27	0.30	0	1
Expenditure share of second most preferred product	0.20	0.27	0	1	0.31	0.30	0	1
Expenditure share of third most preferred product	0.15	0.25	0	1	0.09	0.17	0	1
Expenditure shareof fourth most preferred product	0.07	0.18	0	1	0.08	0.16	0	1
Expenditure share of fifth most preferred product	0.07	0.17	0	1	0.14	0.24	0	1
Expenditure share of least preferred product	0.12	0.20	0	1	0.07	0.14	0	0.9

Table 5

Estimates of the parameters of the translog model (1")

Parameter	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
			All individuals			
β_{k1}	-0.196 (-5.562)	0.032 (0.983)	0.027 (0.839)	0.005 (0.167)	0.077 (2.509)	0.055 (1.295)
β_{k2}	0.018 (0.508)	-0.148 (-5.027)	0.012 (0.320)	0.049 (1.793)	0.045 (1.598)	0.024 (0.744)
β_{k3}	-0.005 (-0.127)	0.082 (1.887)	-0.177 (-5.213)	0.060 (1.936)	0.008 (0.267)	0.031 (0.854)
β_{k4}	0.094 (2.380)	0.005 (0.106)	-0.006 (-0.113)	-0.162 (-5.943)	-0.005 (-0.130)	0.072 (1.503)
β_{k5}	0.002 (0.036)	0.018 (0.326)	0.155 (3.803)	0.039 (0.866)	-0.0173 (-6.341)	-0.041 (-1.123)
β_{k6}	0.086 (2.299)	0.078 (1.998)	0.031 (0.624)	-0.019 (-0.480)	-0.026 (-0.488)	-0.151 (-4.737)
			Rational individuals			
β_{k1}	-0.146 (-2.647)	0.057 (1.016)	-0.026 (-0.598)	0.003 (0.078)	0.091 (2.547)	0.020 (0.552)
β_{k2}	-0.007 (-0.160)	-0.146 (-3.314)	0.068 (1.361)	0.027 (0.690)	0.024 (0.594)	0.034 (1.276)
β_{k3}	0.020 (0.453)	-0.019 (-0.330)	-0.145 (-2.500)	0.077 (1.791)	0.038 (1.261)	0.029 (0.780)
β_{k4}	0.097 (2.021)	0.021 (0.373)	0.041 (0.591)	-0.163 (-3.955)	-0.024 (-0.593)	0.028 (0.563)
β_{k5}	-0.092 (-1.515)	0.112 (1.978)	0.085 (1.763)	0.035 (0.688)	-0.127 (-3.455)	-0.013 (-0.399)
β_{k6}	0.102 (2.180)	0.078 (1.473)	-0.046 (-0.966)	0.035 (0.849)	-0.039 (-0.901)	-0.129 (-4.758)
			Irrational individuals			
β_{k1}	-0.129 (-2.791)	0.069 (1.117)	-0.003 (-0.022)	-0.008 (-0.129)	0.037 (0.844)	0.033 (0.790)
β_{k2}	-0.009 (-0.213)	-0.029 (-0.435)	-0.206 (-1.755)	0.031 (0.236)	0.169 (1.384)	0.046 (0.571)
β_{k3}	0.048 (0.507)	0.060 (0.362)	-0.083 (-0.374)	0.121 (0.511)	-0.060 (-0.476)	-0.085 (-0.601)
β_{k4}	0.078 (0.726)	0.067 (0.306)	-0.039 (-0.171)	-0.219 (-1.963)	-0.016 (-0.133)	0.129 (1.513)
β_{k5}	0.023 (0.635)	-0.046 (-0.810)	0.051 (0.637)	0.015 (0.345)	-0.059 (-1.152)	0.016 (0.499)
β_{k6}	-0.007 (-0.153)	-0.075 (-0.478)	0.227 (0.583)	-0.032 (-0.193)	-0.054 (-0.832)	-0.057 (-1.314)

Note: t-value in parentheses.

Table 6

Estimates of the parameters of the PIGLOG model (2')

Parameter	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
			All individuals			
β_{k1}	0.179 (4.724)	-0.045 (-1.347)	-0.003 (-0.103)	0.001 (0.011)	-0.114 (-4.022)	-0.016 (-0.400)
β_{k2}	-0.015 (-0.361)	0.153 (3.907)	-0.011 (-0.247)	-0.064 (-1.925)	-0.069 (-2.998)	0.007 (0.184)
β_{k3}	-0.001 (-0.012)	-0.073 (-1.781)	0.178 (5.507)	-0.067 (-1.926)	-0.015 (-0.453)	-0.023 (-0.736)
β_{k4}	-0.113 (-2.888)	0.001 (0.009)	0.017 (0.372)	0.166 (4.737)	-0.020 (-0.679)	-0.051 (-1.234)
β_{k5}	0.026 (0.657)	-0.011 (-0.264)	-0.126 (-3.579)	-0.033 (-0.913)	0.135 (4.832)	0.009 (0.362)
β_{k6}	-0.074 (-1.460)	-0.113 (-2.181)	-0.026 (-0.363)	-0.007 (-0.133)	0.007 (0.103)	0.213 (5.411)
γ_k	-0.012 (-0.264)	0.073 (1.537)	0.062 (1.349)	-0.021 (-0.441)	-0.115 (-3.792)	0.013 (0.439)
			Rational individuals			
β_{k1}	0.094 (1.846)	-0.036 (-0.829)	0.054 (1.586)	-0.004 (-0.102)	-0.108 (-2.501)	0.001 (0.035)
β_{k2}	-0.016 (-0.260)	0.187 (3.400)	-0.043 (-0.792)	-0.037 (-0.630)	-0.066 (-1.409)	-0.024 (-0.528)
β_{k3}	-0.015 (-0.344)	0.018 (0.314)	0.146 (2.646)	-0.099 (-2.222)	-0.025 (-0.675)	-0.025 (-0.743)
β_{k4}	-0.105 (-2.483)	-0.001 (-0.020)	-0.033 (-0.551)	0.143 (2.309)	0.011 (0.325)	-0.017 (-0.380)
β_{k5}	0.071 (1.917)	-0.074 (-1.898)	-0.063 (-1.993)	-0.024 (-0.724)	0.079 (2.176)	0.011 (0.441)
β_{k6}	-0.095 (-1.518)	-0.116 (-1.739)	0.061 (0.933)	-0.115 (-1.677)	0.071 (1.316)	0.195 (4.591)
γ_k	-0.060 (-1.186)	0.141 (3.153)	-0.005 (-0.103)	0.019 (0.311)	-0.072 (-2.438)	-0.023 (-0.909)
			Irrational individuals			
β_{k1}	0.156 (3.158)	-0.111 (-1.089)	0.005 (0.039)	-0.009 (-0.097)	-0.036 (-0.740)	-0.005 (-0.066)
β_{k2}	0.004 (0.120)	0.007 (0.133)	0.110 (0.571)	-0.019 (-0.264)	-0.081 (-0.427)	-0.021 (-0.359)
β_{k3}	-0.049 (-0.670)	-0.068 (-0.327)	0.062 (0.346)	-0.145 (-0.473)	0.095 (0.449)	0.105 (0.491)
β_{k4}	-0.084 (-1.257)	-0.092 (-0.658)	0.061 (0.394)	0.226 (0.904)	0.022 (0.186)	-0.132 (-1.095)
β_{k5}	-0.019 (-0.424)	0.035 (0.493)	-0.027 (-0.223)	-0.009 (-0.178)	0.043 (0.377)	-0.022 (-0.601)
β_{k6}	0.005 (0.096)	0.041 (0.432)	-0.123 (-0.460)	0.029 (0.310)	0.017 (0.297)	0.029 (0.482)
γ_k	-0.021 (-0.303)	0.016 (0.082)	-0.039 (-0.082)	-0.056 (-0.091)	0.003 (0.019)	0.056 (0.238)

Note: t-value in parentheses.

Table 7

Budget elasticities and own-price uncompensated elasticities for the translog model (1")

Elasticity	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
			All individuals			
Budget	1.000 (11.088)	1.131 (13.632)	1.119 (8.812)	0.905 (7.184)	0.731 (7.227)	0.949 (7.972)
Price	-0.546 (-6.725)	-0.717 (-12.787)	-0.501 (-5.256)	-0.449 (-4.878)	-0.364 (-3.637)	-0.271 (-1.768)
			Rational individuals			
Budget	0.939 (10.202)	1.199 (16.479)	0.932 (6.914)	1.050 (6.681)	0.862 (8.782)	0.849 (9.549)
Price	-0.663 (-5.202)	-0.721 (-8.571)	-0.589 (-3.584)	-0.446 (-3.179)	-0.533 (-3.938)	-0.376 (-2.869)

Note: t-value in parentheses.

Table 8

Budget elasticities and own-price uncompensated elasticities for the PIGLOG model (2')

Elasticity	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
			All individuals			
Budget	0.971 (8.932)	1.139 (12.530)	1.177 (8.979)	0.927 (5.638)	0.576 (5.164)	1.062 (7.509)
Price	-0.586 (-6.693)	-0.709 (-9.536)	-0.496 (-5.410)	-0.435 (-3.645)	-0.503 (-4.898)	0.026 (0.136)
			Rational individuals			
Budget	0.860 (7.310)	1.268 (14.919)	0.984 (6.570)	1.067 (4.945)	0.736 (6.801)	0.890 (7.381)
Price	-0.783 (-6.652)	-0.644 (-6.155)	-0.587 (-3.763)	-0.511 (-2.419)	-0.709 (-5.307)	-0.059 (-0.289)

Note: t-value in parentheses

Table 9

Test statistics for symmetry of the Slutsky matrix

	All individuals	Rational individuals	$\chi^2_{0.05}$(degrees of freedom)
Translog	58	49	25 (15)
PIGLOG	36	37	67 (50)