What Do We Learn About Consumer Demand Patterns from Micro Data?

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The aim of this paper is to assess the importance of using micro-level data in the econometric analysis of consumer demand. To do this we utilize a time series of repeated cross sections covering some 4,000 households in each of 15 years. Employing a number of different aggregation procedures, we conclude that aggregate data alone are unlikely to produce reliable estimates of structural price and income coefficients. However, once certain "aggregation factors" as well as trend and seasonal components are included, an aggregate model is not necessarily outperformed across all demand equations in terms of forecasting ability. (*JEL* D12, C52, C31)

The purpose of this paper is to develop a complete consumer demand system based on a time series of individual household data and to use it to measure the biases introduced into the study of consumer demand behavior when aggregate data are used in place of the appropriate microeconomic data. We assess the suitability of aggregate data through the impact on income and price elasticities and by evaluating the ability of both micro- and aggregate-based models to forecast aggregate consumer demand. The biases, introduced by the use of aggregate data, depend upon the way that household characteristics interact with income and price effects and on departures of demand systems from linearity. We explore the structure of microeconomic demand systems and the role of household characteristics in the behavior of consumer demand both for the light this may shed on the pattern of future demands and for the implications this behavior has for issues of aggregation.

Consumer demand patterns typically found in micro data sets vary considerably across households with different household characteristics and with different levels of income. We model this variability by making intercept and slope parameters in the budget-share equations of our demand system depend on household characteristics and by allowing for nonlinear total log-expenditure terms. In fact, in theory-consistent demand systems it is total expenditure rather than disposable income that is allocated across goods. We find that this general framework leads to a well-specified data-coherent demand system, which is a quadratic extension of the popular "almost ideal" model of Angus S. Deaton and John Muellbauer (1980). The micro-level estimates are shown to be sensitive to the treatment of endogeneity of total expenditure and to the specification of interaction terms with household characteristics. In addition, this specification is also shown to possess many attractive features for the evaluation of aggregate models.

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The parameters estimated on individual household data can be used to evaluate price and budget elasticities for each household in the sample and to calculate summary elasticity measures, comparable in principle to what can be obtained by working with aggregate data. Using our data (the British Family Expenditure Survey, 1970–1984) we find evidence of systematic aggregation bias over the sample period, especially with regard to the measurement of income effects.

We also investigate the ability of our micro-level model and a similar model estimated on aggregate data to forecast aggregate budget shares over a 24-month postsample period. The aggregate model we adopt is estimated on the aggregated *micro* data from the same sample and, following Thomas M. Stoker (1986), includes some simple distribution measures as well as seasonal and trend components. It also adopts the flexible specification of income and price effects as indicated by the micro data. In an out-of-sample forecast comparison of *aggregate* share predictions, we show that for certain equations forecasts from the aggregate model can outperform a forecast based on aggregated micro predictions.

These findings are not surprising, for although the aggregate model neglects information on time-varying household characteristics and should therefore have worse forecasting performance, the inclusion of certain distributional measures can correct for aggregation bias. Moreover, the aggregate model explains the aggregate share directly. This latter point gives the aggregate model an advantage over the micro model in two distinct ways. First, the micro estimates assume an independent distribution of unobservable errors and thereby ignore any common components in the micro-level errors. To some extent this serves as another motivation for the inclusion of a large number of observable common characteristics in the micro model. Secondly, in order to generate an *aggregate* forecast of expenditure shares from the micro model a *weighted* sum of micro share forecasts is required, rather than a simple average. For example, the aggregate budget share of food is defined as the expenditure on food over the budget (or the total of nondurable expenditure) and is *not* the simple average of individual households' budget shares. Since the weights are likely to be endogenous at the micro level, the calculation of an unbiased forecast for the aggregate share from the micro model is shown to require careful treatment.

In Section I of this paper we discuss theoretical and econometric issues underlying our chosen micro-level model. We develop the concept of aggregation factors which can be used to detect likely sources of aggregation bias, and we discuss some issues that arise in using the micro results for forecasting. Section II presents econometric estimates and statistical tests for the micro model. In Section III we assess the importance of aggregation bias and relate it to the time-variability of the aggregation factors. Section IV presents the results of our comparison of forecasting abilities, and Section V concludes the paper.

I. The Modeling Framework

A. *The Specification of Individual Preferences*

We begin by considering an appropriate framework for the specification of preferences at the microeconomic level. Our objective is to model a broad set of nondurable commodities that are well recorded in our micro data source. To this end we characterize preferences such that, in each period t, household h makes decisions on how much to consume of these commodities conditional on various household characteristics and also conditional on the consumption levels of a second group of other (possibly less flexible) demands. This latter group contains housing, tobacco expenditures, some durables, and labor-market decisions which, together with household characteristics, we represent by $\mathbf{z}$.

The goods we model directly ($\mathbf{q}$) refer to food, clothing, services, fuel (household energy), alcohol, transport, and other nondurables. Clearly the relative amounts consumed of these commodities may well depend on the consumption of the second group of goods. Indeed, it is unlikely that the two "groups" are weakly separable in utility. Rather the second group acts much like demographic or locational variables affecting both the allocation of total expenditure to these goods *and* the marginal rate of substitution between them. As a result we define household utility over $\mathbf{q}_t^h$ for household h in period t conditional on the set of demographic and other conditioning variables $\mathbf{z}_t^h$ (see Martin J. Browning and Costas Meghir [1991] for a discussion of conditional demands and weak separability).

The household may wish to save or to borrow according to the way in which it evaluates present and future needs, and this determines how much expenditure to allocate to current consumption and in particular to goods $\mathbf{q}_t^h$. Expenditure allocated to these goods, denoted by m_t^h, is the first stage in a two-stage allocation process, and we shall be allowing for the endogeneity of m_t^h using the two-stage budgeting framework to suggest identifying instrumental variables.[1]

Letting q_{it}^h represent consumption of good i in period t, if utility is weakly separable across time then the allocation of expenditure to good i, conditional on $\mathbf{z}_t^h$, may be expressed as

$$(1) \qquad p_{it}q_{it}^h = f_i(\mathbf{p}_t, m_t^h; \mathbf{z}_t^h)$$

where f_i describes within-period preferences and $\mathbf{p}_t$ is the n-vector of period-t prices. Under (conditional) intertemporal weak separability, once m_t^h is chosen each f_i can be determined without reference to prices or incomes outside the period (Blundell and Ian Walker, 1986).

To describe individual household preferences we first abstract from differences in $\mathbf{z}_t^h$ and write the share of expenditure i in period t (out of m_t^h) for household h as

$$(2) \quad s_{it}^h = \alpha_i + b_0^i(\mathbf{p}_t) + \sum_{j=1}^{L} b_j^i(\mathbf{p}_t) g_j(x_t^h)$$

[1]These may contain price, income, seasonal, and demographic variables, as well as macro variables bearing on intertemporal substitution (like real interest rates) and macroeconomic indicators reflecting changes in expectations (like the unemployment rates).

where x_t^h is real total expenditure, $b_0^i(\mathbf{p}_t)$, $b_1^i(\mathbf{p}_t), \dots, b_L^i(\mathbf{p}_t)$ are zero homogeneous functions of prices and $g_j(x_t^h)$ are known polynomials in total real expenditure. The form of (2) is sufficiently general to cover many of the popular forms for Engel curves and demand systems. In particular, those of Holbrook Working (1943), Conrad E. V. Leser (1963), Deaton and Muellbauer (1980), and subsequent generalizations are generated with polynomials in the logarithm of real expenditure such as those in William M. Gorman (1981). Household characteristics may enter in a variety of different ways, the exact specification of which is primarily an empirical issue. Nevertheless, the specification of such variables will have a bearing on the form of the corresponding aggregate relationship, as we shall document below.

If we let M_t represent aggregate total household expenditure $(\Sigma_{h=1}^{H} m_t^h)$ and let μ_t^h equal the total expenditure share for household h (m_t^h / M_t), then the μ_t^h-weighted sum of individual budget shares s_{it}^h generates the aggregate share s_{it} exactly. This point provides another motivation for choosing preferences of form (2), since the equivalent aggregate relationship has the form

$$(3) \quad s_{it} = \alpha_i + b_0^i(\mathbf{p}_t) + \sum_{j=1}^{L} b_j^i(\mathbf{p}_t) \sum_{h=1}^{H} \mu_t^h g_j(x_t^h)$$

and estimation of the unknown parameters in $\alpha_i, b_0^i, \dots, b_L^i$ on aggregated data can proceed provided $\Sigma_h \mu_t^h g_j(x_t^h)$ can be constructed in each period t. Moreover, if the $g_j(x_t^h)$ do not depend on unknown parameters, estimation is possible on aggregate time-series data alone. As a result the class of preferences that generate (2) has been popular in the analysis of aggregation as is documented by Gorman (1981). Indeed, Gorman shows that if such preferences are utilized then the integrability conditions of demand theory require that the $n \times L$ coefficient matrix formed by $\alpha_i + b_0^i, b_1^i, \dots, b_L^i$ will have a rank no higher than three (see also Dale W. Jorgenson et al., 1980; Lawrence J. Lau, 1982; Robert Russell, 1983; Arthur Lewbel, 1989; John Heineke and Michael Shefrin, 1990).

To illustrate these points more explicitly, consider the following quadratic extension to Deaton and Muellbauer's (1980) "almost ideal" model (QUAIDS) which as we shall see represents the observed behavior in our Family Expenditure Survey data quite adequately. In this model $L=2$ and the g_j's are simply polynomial logarithmic terms so that (2) may be written as

$$(4) \qquad s_{it} = \alpha_i + b_0^i(\mathbf{p}_t) + b_1^i(\mathbf{p}_t)\ln x_t + b_2^i(\mathbf{p}_t)(\ln x_t)^2$$

where household superscripts have been omitted for simplicity. If we restrict the coefficients on $\ln x_t$ and $(\ln x_t)^2$ to be independent of prices, that is, $b_1^i(\mathbf{p}_t) = \beta_i$ and $b_2^i(\mathbf{p}_t) = \lambda_i$, then integrability, in particular, symmetry of the Slutsky matrix, requires $\lambda_i = \beta_i \varepsilon$; that is, the ratio of the coefficients on the income and squared terms in income must be the same for all commodities. In this case, (4) becomes

$$(5) \qquad s_{it} = \alpha_i + b_0^i(\mathbf{p}_t) + \beta_i\left[\ln x_t + \varepsilon(\ln x_t)^2\right]$$

and reduces the rank of the coefficient matrix defined above to two. For models of this form the *maximum* rank under symmetry is two. As a result, a test of symmetry in this model additionally requires a test of $\lambda_i = \beta_i \varepsilon$. The "almost ideal" model of Deaton and Muellbauer imposes the further restriction that $\varepsilon = 0$.

B. *Individual Household Characteristics, Seasonal Factors, and Aggregation*

With household data we also need to allow household preferences to depend on characteristics. The specific form we adopt for individual household-h preferences explicitly allows for the effect of the characteristics $\mathbf{z}$ on the polynomial coefficients in (4). In particular we write

$$(6) \qquad s_{it}^h = \alpha_{it}^h + \sum_j \gamma_{ij} \ln p_{jt} + \beta_{it}^h \ln x_t^h + \lambda_{it}^h (\ln x_t^h)^2$$

where the α_i^h, β_i^h, and λ_i^h parameters are allowed to vary with the household-h characteristics and other conditioning variables. For example, we write

$$(7) \qquad \alpha_{it}^h = \alpha_0 + \sum_k \alpha_{ik} z_{kt}^h + \sum_k \delta_k T_{kt}$$

in which we have also added a set of variables T_{kt} that are purely deterministic time-dependent variables, like seasonal dummies and time trends. The parameters λ_{it}^h and β_{it}^h are also allowed to vary in a similar fashion. Consistent aggregation proceeds, as in (3), by computing μ-weighted sums of all variables.

To illustrate the implications for aggregate analysis of these generalizations consider the simplification in which we write

$$(8) \qquad \beta_{it}^h = \beta_i + \beta_i^D D_{ht}$$
$$\lambda_{it}^h = \lambda_i + \lambda_i^D D_{ht}$$

where D_{ht} is simply a zero–one dummy representing, say, the presence of children in the household. In our empirical work we find a number of such interactions with the real expenditure terms to be significant. The consistently aggregated relationship may be written as

$$(9) \qquad s_{it} = \alpha_0 + \sum_j \gamma_{ij} \ln p_{jt} + \beta_i \ln X_t + \sum_k \delta_k T_{kt} + \beta_i \sum_h \mu_{ht} \ln(x_t^h / X_t) + \sum_k \alpha_{ik} \sum_h \mu_{ht} z_{kt}^h + \beta_i^D \sum_h \mu_{ht} D_{ht} \ln x_t^h + \lambda_i \sum_h \mu_{ht} (\ln x_t^h)^2 + \lambda_i^D \sum_h \mu_{ht} D_{ht} (\ln x_t^h)^2$$

where $X_t = \sum_h x_t^h / H_t$ is average total real expenditure (H_t is the number of households in period t) and $\mu_{ht} = m_t^h / M_t$ is each household's relative weight in expenditure terms. As before the aggregate s_{it}, the μ_{ht}-weighted sum of micro shares s_{it}^h, simply equals the share of aggregate expenditure on good i out of total aggregate expenditure M_t.

In (9), the first four terms are the aggregate data analogues of the micro model with seasonal components. The first μ_{ht}-weighted sum is the negative of Theil's entropy measure of real expenditure inequality. This represents one of the distributional measures that we include in our aggregate model to be described in Section III. The next term is the expenditure-weighted average of the relevant household characteristics entering the α_i parameters in (6).

The remaining three terms in (9) reflect precisely how interacting the $\ln x_t^h$ expenditure terms with household characteristics and adding the quadratic term $(\ln x_t^h)^2$ complicates consistent aggregation. For example, it is likely that the quadratic terms in $\ln x_t^h$ will have to be approximated in the aggregate representation by adding expressions in $(\ln X_t)^2$ and $\Sigma_h \mu_{ht}[\ln(x_t^h/X_t)]^2$. Indeed, these are the additional quadratic terms we enter in our aggregate model. However, a complete representation would also involve the double product of the entropy measure and $\ln X_t$. Taking these points together, it seems inevitable that the precise data requirements for aggregate models are unlikely to be met with the short time series of simple aggregates available in national accounts.

Even neglecting the quadratic terms, in order for (9) to be estimatable with aggregate data of the type generally available, one of the following supplementary hypotheses is needed (see Browning, 1987): the decomposition hypothesis in which all covariances between the z_{kt}^h's and the weights, μ_{ht}, in any given time-period t are zero; or the constancy hypothesis in which either the distributional indexes are time-invariant (strong form) or their time variation is fully captured by trend and seasonal components, T_{kt}'s (weak form).

While the decomposition hypothesis is unlikely to hold in practice, the weak version of the constancy hypothesis is worth careful empirical consideration. We could consider the following possibilities:

(a) each individual weighted sum of the z's is uncorrelated with the price and income variables;

(b) the linear combination of aggregation terms is uncorrelated with the price and income variables.

In principle, one can check whether requirement (a) or (b) is met by the variables as they are, or at least by their "filtered" counterparts (obtained by taking the residuals of their regressions on the constant and the T's).

As an alternative to this approach, we may directly assess the importance of this aggregation problem by relating the coefficients identified from an aggregate equation directly to the underlying preference parameters. From (9) the following equation could be estimated:

$$(10)\quad s_{it} = \alpha_0 + \sum_j \gamma_{ij} \ln p_{jt} + \beta_i \pi_{0t} \ln X_t + \sum_k \delta_k T_{kt} + \sum_k \alpha_{ik} \theta_{kt} \sum_h z_{kt}^h + \beta_i^D \pi_{2t} \bar{D}_t \ln X_t + \lambda_i \pi_{1t} (\ln X_t)^2 + \lambda_i^D \pi_{3t} \bar{D}_t (\ln X_t)^2$$

where $\bar{D}_t$ denotes the proportion of households with characteristic D in period t. Comparison with equation (9) shows that

$$(11a)\quad \theta_{kt} = \sum_h \mu_{ht} z_{kt}^h \Big/ \sum_h z_{kt}^h$$

$$(11b)\quad \pi_{0t} = \sum_h \mu_{ht} \ln x_t^h / \ln X_t$$

$$(11c)\quad \pi_{1t} = \sum_h \mu_{ht} (\ln x_t^h)^2 / (\ln X_t)^2$$

$$(11d)\quad \pi_{2t} = \frac{\pi_{0t} \sum_h D_{ht} \mu_{ht} \ln x_t^h}{\bar{D}_t \sum_h \mu_{ht} \ln x_t^h}$$

$$(11e)\quad \pi_{3t} = \frac{\pi_{1t} \sum_h D_{ht} \mu_{ht} (\ln x_t^h)^2}{\bar{D}_t \sum_h \mu_{ht} (\ln x_t^h)^2}.$$

If the θ_{kt} and π_{jt} *aggregation factors*, (11a)–(11e), are approximately constant over time (with the π_{jt}'s close to unity), we may expect unbiased estimates from an aggregate equation like (10). If the π_{jt}'s are constant and the θ_{kt} are functions only of the deterministic time-dependent variables T_{kt}, the parameters of the "aggregate" model may still be stable and the γ_{ij}'s will be consistently estimated.

C. *Econometric Analysis*

The first issue we consider relates to the occurrence of zero expenditures in the diary records. For the commodity groups we consider, these will most likely correspond to purchase infrequency. The problem of infrequent expenditures has its major effect on goods like clothing, transport, and possibly alcohol (we do not consider tobacco consumption or expenditures on durable appliances in this paper). It means that the theoretical concept of "consumption" differs from its measured counterpart "expenditure." As this discrepancy affects both the dependent variable and the total-real-expenditure variable $\ln x_t^h$, ordinary least-squares (OLS) estimates of the share equations are biased. However, instrumental-variable (IV) estimation (or more generally generalized method of moments [GMM] once heteroscedasticity is allowed for) permitting all terms in $\ln x_t^h$ to be endogenous removes this measurement-error problem. As we wish to treat $\ln x_t^h$ as endogenous, following the discussion above, we can use our IV or GMM estimates to obtain unrestricted consistent estimates for each equation. Homogeneity can also be checked at this stage since it is a within-equation restriction. Although each equation is estimated separately, adding-up and invariance are preserved for all of these linear estimators.

Turning to cross-equation restrictions, these can be imposed at a second stage using the minimum-chi-square (MCS) procedure (see Thomas Ferguson, 1958; Thomas J. Rothenberg, 1973). The attraction of the MCS estimator for microeconometric analysis of consumer behavior of the type pursued here relates to the separate stages of imposing within- and cross-equation restrictions.[2] At the first stage, consistent estimates of the parameters of each equation with restrictions confined to within equations (zero-degree homogeneity in prices, for example) are recovered. For a standard demand system (linear expenditure system [LES] or "almost ideal" and its generalizations, for example), this would involve estimating separate linear share equations as described above. As we have also mentioned, in our case we allow for the endogeneity of all $\ln x_t^h$ terms and of some other conditioning factors as well as considering the issue of general heteroscedasticity across households. These single-equation estimates together with their covariance matrix summarize all information available in the data concerning estimation of preference parameters. In effect they act as sufficient statistics for the purposes of demand-system estimation on the vast quantity of micro-level data. As a result the following second-stage restricted estimates attain asymptotic efficiency.

Denoting the vector of unrestricted parameters as $\boldsymbol{\phi}$, cross-equation restrictions (symmetry, for example) on $\boldsymbol{\phi}$ may be expressed as

$$\boldsymbol{\phi} = \mathbf{g}(\boldsymbol{\phi}^*). \tag{12}$$

To impose these restrictions the MCS method chooses an estimator $\hat{\boldsymbol{\phi}}^*$ so as to minimize the quadratic form

$$\hat{\boldsymbol{\phi}}^* = \arg\min[\hat{\boldsymbol{\phi}} - \mathbf{g}(\boldsymbol{\phi}^*)]'\boldsymbol{\Sigma}_{\phi}^{-1}[\hat{\boldsymbol{\phi}} - \mathbf{g}(\boldsymbol{\phi}^*)] \tag{13}$$

where $\hat{\boldsymbol{\phi}}$ is the vector of unrestricted estimates and $\boldsymbol{\Sigma}_{\phi}$ is its estimated variance-

[2]For very large samples, this method can allow a considerable computational saving over the standard restricted-maximum-likelihood estimator since the dimensions of the vector of unrestricted parameters can be significantly less than the number of observations.

covariance matrix.[3] This procedure is adopted in the estimation of the restricted micro-level estimates to which we now turn.

II. The Micro Data Estimates

A. *The Household Data*

In this study we adopt the estimation procedure described in the previous section to recover estimates of a seven-good model of demand from a pooled cross section over 15 annual time series covering more than 61,000 households. These data are drawn from the annual British Family Expenditure Survey (FES) for the years 1970–1984. In one form or another the FES has been the cornerstone of many empirical studies of consumer behavior at the micro level, including, for example, the papers by Anthony B. Atkinson and Nicholas Stern (1980) and Robert A. Pollak and Terence J. Wales (1978). In our demand system we have concentrated on seven broad commodity groups: food, alcohol, fuel, clothing, transport, services, and other. In terms of sample selection, the results of the illustration reported here refer to a sample of households whose head is more than 18 and less than 60 years of age and is not self-employed.[4] Further details are provided in Appendix A.

[3]The consistency of the resulting MCS estimator simply requires that the restrictions are correct and that $\hat{\phi}$ is a consistent estimator. Any positive-definite weight matrix can be used to replace Σ_{ϕ}^{-1}. However, where the correct weight matrix is used and where ϕ is derived from an efficiency single equation technique, the MCS estimator is asymptotically equal to the maximum-likelihood estimator, and the minimized value of the quadratic form in (13) is an optimal chi-square test of the restrictions.

[4]We also selected out the tails of the income distribution. In particular, we looked at the sample distribution of the logarithm of real net income and discarded the observations in the bottom and top 1 percent. This selection (based on an econometrically exogenous variable) is meant to remove the possibility that small outliers in the income distribution are responsible for the nonlinearity in the budget-share equations.

B. *The Estimated Models*

We now turn to the estimated parameters and implied elasticities of the individual-household expenditure allocations. We present estimates from the quadratic extension of the "almost ideal" demand system in which second-order terms in $\ln x^h$ are included as developed in Subsection I-B. In Table 1A the price and income coefficients that correspond to the γ_{ij}, β_i, and λ_i parameters of share equations are presented; these correspond to equation (6). In all equations, we consistently find that both the own- and the cross-price parameters are statistically significant. It should be noted that all $\ln x^h$ terms are treated as endogenous, and the restricted and unrestricted estimators are described in Subsection I-C, above.

Before considering the impact of household characteristics on the intercept terms α_i in (6), we should stress that the coefficients on the logarithm of real expenditure terms, $\ln x$ and $(\ln x)^2$, are also found to display seasonal and demographic variation. In particular, there is a different budget response if there are children in the household (the interaction term $C \times \ln x^h$ between a child dummy and real expenditure has an important impact on alcohol, fuel, clothing, and services) and if the head of the household is a white-collar worker (e.g., see the coefficient on $C \times \ln x^h$ in the food, transport, and services equations).

Appendix B presents the complete estimation results for the first two equations (the others are omitted for space reasons but are available from the authors upon request). These tables document the household characteristics that were allowed to influence the α_i intercept parameters in each share equation. Despite the large number of such characteristics, many of which have time variation, it is comforting to find that prices have a significant impact. The interpretation of the price parameters is probably best discussed in terms of elasticities, to which we turn below. However, the direct interpretation of the α_i coefficients in each share equation is quite simple. For example the estimated coefficient on variable CH02 indicates that an additional child of less than three years of age will, ceteris paribus, add 0.01935 to the share of expenditure on food. On the other hand, with the head of the household being unemployed (HUNEMP), even allowing for income differences the ceteris paribus fall in the share is 0.01329. Large significant effects are found for car ownership and the number of cars (DCAR and CARS) even though they are allowed to be endogenous. The interpretation of characteristics in the other equations follows in the same fashion. As one might expect, the impact of these "taste-shifter" variables differs quite substantially across commodity groups.

The results from Table 1A appear to be plausible, and in Table 1B we present some formal statistical diagnostics. The overidentification tests are constructed under two assumptions. In the first row, homoscedasticity is assumed, while in the second row this assumption is relaxed, and the GMM estimator proposed by Hal White (1982) is adopted. These results indicate two things: first, that the choice of instruments, described at the foot of Table 1B, is broadly valid; second, that adjusting for heteroscedasticity has little impact on the test statistics, suggesting that we have included sufficient household-specific interaction terms to account for heterogeneity in the error variances of the share equations.

A simple check for functional-form misspecification involves introducing a cubic term in $\ln x^h$ in each equation and testing for its insignificance. A standard t test (reported in the third row of the table) confirms that this extra nonlinearity is not needed. The test of the joint significance of the linear and quadratic $\ln x^h$ terms, on the other hand, displays the distance the data stand from homotheticity or unitary income elasticities in which expenditure shares would be independent of total outlay.

In estimation, we treated all terms in $\ln x^h$ and a number of household characteristics as endogenous and used instrumental variables. A formal exogeneity test can be constructed, and this strongly rejects the null hypothesis that our instrumental-variable estimates are insignificantly different from ordinary least-squares ones. In fact, the test statistic (which is a χ^2 with 12 degrees of freedom under the null hypotheses) rejects even if we adopt the less stringent Schwarz criterion (Gideon Schwarz, 1978), which optimally adjusts the size of the test as the number of observations increases. The presence of simultaneity bias in OLS estimates is also confirmed by our out-of-sample forecasts to be presented below, in which we find systematic forecast errors from equations based on OLS parameters.

The homogeneity tests reported in Table 1B indicate that we were unable to reject the homogeneity restrictions implied by the theory, an issue which has proved to be a major stumbling block for other demand studies, especially with results on aggregate data (see e.g., Deaton and Muellbauer, 1980). The fact that here the price parameters are quite precisely estimated adds to the importance of our results. Moreover, both in the Deaton and Muellbauer (1980) study and in many that followed (e.g., Gordon Anderson and Blundell, 1982), dynamic misspecification is suggested as the root cause of homogeneity rejections. As was noted earlier, the omitted characteristics in aggregate models implied from this study may evolve in a way that is captured by the introduction of dynamic adjustment or trend-like terms, a point also noted by Stoker (1986).

Finally, in Table 1B we present the test statistics relating to the symmetry hypothesis. This is separated into two parts reflecting the discussion of Subsection II-A. The first test statistic refers to the standard symmetry restriction on the γ_{ij} parameters. Although the test statistic is high, a comparison of the unrestricted parameter estimates with the γ-symmetry-constrained estimates of Table 1A indicates that very little is lost in imposing γ-symmetry. Given symmetry on these price terms, we can turn to the second condition required for symmetry in the complete system which was shown in equation (5) to require proportionality between the parameters on the $\ln x$ terms and their corresponding $(\ln x)^2$ counterparts. Although the sign pattern in Table 1A ap-

TABLE 1—THE QUADRATIC ALMOST-IDEAL DEMAND SYSTEM

A. *The* γ_{ij}, β_i, *and* λ_i *Coefficient Estimates:*

	Share equations					
Variable	(i) Food	(ii) Alcohol	(iii) Fuel	(iv) Clothing	(v) Transport	(vi) Services
γ_{i1}	0.1037	0.0188	−0.0334	−0.0231	−0.0131	0.0034
	(0.0126)	(0.0084)	(0.0074)	(0.0125)	(0.0147)	(0.0102)
γ_{i2}	0.0188	−0.0434	0.0468	0.0103	0.0050	−0.0063
	(0.0084)	(0.0108)	(0.0070)	(0.0100)	(0.0134)	(0.0101)
γ_{i3}	−0.0334	0.0468	0.0397	−0.0040	−0.0433	−0.0292
	(0.0074)	(0.0070)	(0.0086)	(0.0091)	(0.0107)	(0.0079)
γ_{i4}	−0.0231	0.0103	−0.0040	0.0376	−0.0284	−0.0386
	(0.0125)	(0.0100)	(0.0091)	(0.0179)	(0.0174)	(0.0119)
γ_{i5}	−0.0131	0.0050	−0.0433	−0.0284	0.0605	0.0266
	(0.0147)	(0.0134)	(0.0107)	(0.0174)	(0.0317)	(0.0169)
γ_{i6}	0.0034	−0.0063	−0.0292	−0.0386	0.0266	0.0387
	(0.0102)	(0.0101)	(0.0079)	(0.0119)	(0.0169)	(0.0166)
β_i	−0.0377	0.0891	−0.4433	0.2940	−0.1310	0.3829
	(0.1301)	(0.1066)	(0.0758)	(0.1389)	(0.2058)	(0.1481)
λ_i	−0.0076	−0.0017	0.0370	−0.0264	0.0151	−0.0273
	(0.0112)	(0.0092)	(0.0065)	(0.0120)	(0.0178)	(0.0128)
β_i(S3)	0.0561	0.1486	0.1561	−0.1383	−0.1299	−0.0758
	(0.0866)	(0.0705)	(0.0492)	(0.0922)	(0.1366)	(0.0975)
λ_i(S3)	−0.0053	−0.0134	−0.0123	0.0113	0.0111	0.0071
	(0.0070)	(0.0060)	(0.0042)	(0.0079)	(0.0118)	(0.0084)
$\beta_i(C)$	−0.0038	−0.0466	0.0386	−0.0297	−0.0009	0.0501
	(0.0122)	(0.0100)	(0.0070)	(0.0130)	(0.0193)	(0.0138)
$\lambda_i(C)$	0.0000	0.0060	−0.0054	0.0051	−0.0015	−0.0057
	(0.0016)	(0.0013)	(0.0009)	(0.0017)	(0.0025)	(0.0018)
β_i(WHC)	0.4024	0.0670	0.0190	−0.1053	−0.6504	0.4223
	(0.1436)	(0.1177)	(0.0830)	(0.1564)	(0.2263)	(0.1614)
λ_i(WHC)	−0.0349	−0.0041	−0.0005	0.0074	0.0548	−0.0356
	(0.0124)	(0.0101)	(0.0071)	(0.0135)	(0.0195)	(0.0639)

pears broadly to support this proportionality, the test statistic strongly rejects, and in our evaluation of the properties of this model we have decided not to present results with this restriction imposed.

C. *Price Aggregation*

In Table 2 we investigate the joint significance of the price terms by comparing a model with all prices included to one in which the deflated own price only is included. From the chi-square tests of the joint significance of the extra terms (A. Ronald Gallant and Jorgenson, 1979), it is clear that the cross-price terms are important.

D. *Model Elasticities*

Inspection of the parameter estimates for the estimated demand models reveals some general patterns. For example, services are a luxury while fuel is a necessity. Each household h will, however, have a different budget elasticity. In the context of the

TABLE 1—*Continued*.

B. *Test Statistics for Quadratic Almost-Ideal System:*

	Share equations						
Test	Food	Alcohol	Fuel	Clothing	Transport	Other	Services
Overidentification simple IV, $X^2_{[17]}$	50.65	54.75	110.86	58.41	37.54	27.98	33.95
Overidentification White IV, $X^2_{[17]}$	50.01	56.74	106.71	58.36	37.00	28.71	33.52
Functional form, t value	−0.043	2.319	1.772	−0.730	−0.863	−0.999	0.493
$\ln x_h$ terms, $X^2_{[8]}$ (Swz = 88.27)	23.20	153.12	117.52	37.21	63.76	34.72	160.30
Exogeneity (Wu-Hausman), $X^2_{[12]}$ (Swz = 132.41)	285.84	628.56	391.68	147.24	602.40	66.69	251.28
Homogeneity, t value	0.066	0.163	0.755	−0.581	−0.388	−0.095	0.597

Symmetry:
$\gamma_{ij} = \gamma_{ji}$, $X^2_{[15]} = 54.0364$
$\lambda_i = \varepsilon\beta_i$, $X^2_{[20]} = 115.9694$

Notes: Standard errors are given in parentheses; γ-symmetry constrained the estimates. Variables treated as endogenous in estimation: $\ln x, (\ln x)^2, C \times \ln x, C \times (\ln x)^2$, WHC$\times \ln x$, WHC$\times (\ln x)^2$, S3$\times \ln x$, S3$\times (\ln x)^2$, DTOB (=1 if there is a smoker in the household), CTOB, DCAR, and CARS (see Appendix A for further definitions). Instruments not included in the equation: professional, managerial, and teacher dummies, current and lagged durable prices, current prices of "other" and housing, lagged transport price, trending seasonals, lagged unemployment rates (1 and 12 months previous), lagged real lending and borrowing rates, net normal income ($\ln Y$), S1$\times \ln Y$, S2$\times \ln Y$, S3$\times \ln Y$, $(\ln Y)^2$, $C \times \ln Y$, $C \times (\ln Y)^2$, WHC$\times \ln Y$, WHC$\times (\ln Y)^2$, S3$\times (\ln y)^2$, dummy for three-day week (1974:1), $C \times$(age), $C \times$(age)^2, and (trend)^2. Swz is the critical value of the test statistic based on the Schwarz criterion.

quadratic model estimated above at reference prices this elasticity is defined as

$$(14)\qquad e_i^h = \left(\beta_i^h + 2\lambda_i^h \ln m^h\right)/s_i^h + 1.$$

As documented above our empirical specification allowed β_i^h and λ_i^h to vary with family composition and the occupation of the household head. Moreover, the budget elasticity is likely to exhibit substantial variation between households because it depends on the level of the budget itself. Also, as we can see from the impact of the many included characteristics, the predicted expenditure share s_i^h will vary across households. This variation of elasticities across the sample is a distinct advantage of using individual household-level data across time rather than aggregate time series, where often only a single elasticity estimate for all households in any period is given.

The uncompensated elasticity of good i with respect to the price of good j is given by

$$(15)\qquad e_{ij}^h = \left(\gamma_{ij}/s_i^h\right) - \left(\beta_i^h + 2\lambda_i^h \ln m^h\right)\left(s_j^h/s_i^h\right) - k_{ij}$$

where $k_{ij} = 1$ if $i = j$ and $k_{ij} = 0$ if $i \neq j$. The compensated price elasticity is simply

$$(16)\qquad \tilde{e}_{ij}^h = e_{ij}^h + e_i^h s_j^h.$$

Both (15) and (16) take into account the

TABLE 2—RESTRICTIONS ON CROSS-PRICE PARAMETERS

	Commodity						
Term	Food	Alcohol	Fuel	Clothing	Transport	Other	Services
A. *Unrestricted*:							
Food	0.106	0.029	−0.015	−0.057	0.013	−0.065	−0.011
	(0.017)	(0.013)	(0.009)	(0.017)	(0.026)	(0.012)	(0.018)
Alcohol	−0.059	−0.029	0.039	0.009	0.059	−0.036	0.018
	(0.017)	(0.014)	(0.010)	(0.018)	(0.027)	(0.013)	(0.019)
Fuel	−0.040	0.038	0.047	−0.025	−0.039	0.009	0.011
	(0.017)	(0.013)	(0.009)	(0.017)	(0.026)	(0.012)	(0.019)
Clothing	0.037	−0.003	−0.013	0.054	−0.039	0.052	−0.016
	(0.022)	(0.018)	(0.012)	(0.023)	(0.035)	(0.016)	(0.025)
Transport	−0.093	0.006	−0.058	−0.013	0.118	−0.008	0.048
	(0.025)	(0.020)	(0.014)	(0.026)	(0.038)	(0.019)	(0.027)
Services	0.038	−0.009	−0.040	−0.019	0.002	0.018	0.010
	(0.017)	(0.014)	(0.010)	(0.018)	(0.027)	(0.013)	(0.019)
$\ln x$	−0.021	0.057	−0.302	0.177	−0.026	−0.082	0.196
	(0.083)	(0.068)	(0.047)	(0.088)	(0.131)	(0.061)	(0.094)
$(\ln x)^2$	−0.017	0.000	0.037	−0.025	0.012	0.007	−0.015
	(0.011)	(0.009)	(0.006)	(0.012)	(0.018)	(0.008)	(0.013)
$C \times \ln x$	−0.006	−0.057	0.045	−0.027	−0.013	−0.005	0.063
	(0.015)	(0.012)	(0.009)	(0.016)	(0.024)	(0.011)	(0.017)
$C \times (\ln x)^2$	0.001	0.011	−0.009	0.007	−0.000	0.002	−0.011
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
B. *Grouping Restrictions*:							
Own price	0.127	−0.035	0.073	0.028	0.012	0.026	0.054
	(0.011)	(0.009)	(0.007)	(0.013)	(0.035)	(0.014)	(0.018)
$\ln x$	−0.095	0.113	−0.354	0.137	−0.140	−0.102	0.194
	(0.080)	(0.063)	(0.047)	(0.084)	(0.130)	(0.057)	(0.089)
$(\ln x)^2$	−0.005	−0.007	0.043	−0.020	0.024	0.011	−0.018
	(0.011)	(0.009)	(0.006)	(0.011)	(0.018)	(0.008)	(0.012)
$C \times \ln x$	−0.011	−0.052	0.045	−0.031	−0.014	−0.009	0.066
	(0.015)	(0.012)	(0.009)	(0.016)	(0.024)	(0.011)	(0.17)
$C \times (\ln x)^2$	0.001	0.010	−0.009	0.008	−0.000	0.003	−0.011
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)
Share:	0.348	0.067	0.085	0.102	0.178	0.103	0.117
GJ(5):	11.04	20.80	104.90	28.48	14.44	34.12	6.19

Notes: Standard errors are given in parentheses. The retail price index for these components is used as a general deflator throughout. GJ(5) is the test statistic from χ^2 tests of the joint significance of the extra terms (Gallant and Jorgenson, 1979).

TABLE 3—PRICE AND BUDGET ELASTICITIES

A. *Budget Elasticities Computed at the Average Shares and Household Characteristics:*

	Commodity					
Estimator	Food	Alcohol	Fuel	Clothing	Transport	Services
GMM	0.608	2.290	0.838	0.917	1.201	1.448
	(0.07)	(0.28)	(0.15)	(0.24)	(0.20)	(0.22)
OLS	0.574	1.290	0.409	1.994	1.329	1.207
	(0.01)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)

B. *Compensated Price Elasticities:*

	Commodity					
Commodity	Food	Alcohol	Fuel	Clothing	Transport	Services
Food	−0.354	0.122	−0.012	0.034	0.141	0.128
	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)
Alcohol	0.627	−1.582	0.785	0.255	0.254	0.024
	(0.13)	(0.16)	(0.11)	(0.15)	(0.20)	(0.15)
Fuel	−0.048	0.618	−0.448	0.054	−0.331	−0.226
	(0.09)	(0.08)	(0.10)	(0.11)	(0.13)	(0.09)
Clothing	0.116	0.169	0.045	−0.526	−0.103	−0.264
	(0.12)	(0.10)	(0.09)	(0.18)	(0.17)	(0.12)
Transport	0.271	0.095	−0.157	−0.058	−0.483	0.267
	(0.08)	(0.08)	(0.06)	(0.10)	(0.18)	(0.09)
Services	0.375	0.013	−0.162	−0.226	0.405	−0.554
	(0.09)	(0.09)	(0.07)	(0.10)	(0.27)	(0.14)
OLS compensated own-price elasticities:						
	−0.429	−1.537	−0.445	−0.686	−0.488	−0.667
	(0.04)	(0.16)	(0.10)	(0.17)	(0.17)	(0.13)

C. *Uncompensated Price Elasticities:*

	Commodity					
Commodity	Food	Alcohol	Fuel	Clothing	Transport	Services
Food	−0.564	0.081	−0.064	−0.028	0.032	0.056
	(0.04)	(0.02)	(0.02)	(0.04)	(0.05)	(0.03)
Alcohol	−0.163	−1.735	0.590	0.024	−0.156	−0.247
	(0.17)	(0.16)	(0.11)	(0.15)	(0.22)	(0.16)
Fuel	−0.337	0.562	−0.519	−0.031	−0.481	−0.325
	(0.13)	(0.09)	(0.10)	(0.11)	(0.15)	(0.10)
Clothing	−0.200	0.108	−0.033	−0.619	−0.267	−0.372
	(0.14)	(0.10)	(0.09)	(0.18)	(0.18)	(0.12)
Transport	−0.143	0.015	−0.259	−0.179	−0.698	0.125
	(0.10)	(0.08)	(0.06)	(0.10)	(0.19)	(0.10)
Services	−0.125	−0.084	−0.286	−0.372	0.146	−0.725
	(0.11)	(0.09)	(0.07)	(0.10)	(0.28)	(0.14)

TABLE 3—*Continued.*

D. *Distribution of Uncompensated Own-Price Elasticities by Total Expenditure:*

Expenditure group	Commodity					
	Food	Alcohol	Fuel	Clothing	Transport	Services
Low 5 percent	−0.671 (0.017)	−1.79 (0.095)	−0.680 (0.020)	−0.468 (0.070)	−0.553 (0.161)	−0.667 (0.079)
6–10 percent	−0.647 (0.023)	−1.72 (0.093)	−0.641 (0.034)	−0.554 (0.065)	−0.561 (0.191)	−0.731 (0.076)
11–25 percent	−0.622 (0.018)	−1.65 (0.053)	−0.599 (0.027)	−0.581 (0.036)	−0.615 (0.104)	−0.721 (0.056)
Middle 50 percent	−0.556 (0.020)	−1.57 (0.037)	−0.486 (0.026)	−0.625 (0.020)	−0.727 (0.051)	−0.737 (0.030)
76–90 percent	−0.472 (0.070)	−1.53 (0.101)	−0.369 (0.082)	−0.642 (0.051)	−0.810 (0.093)	−0.739 (0.057)
Top 10 percent	−0.324 (0.239)	−1.48 (0.149)	−0.425 (0.159)	−0.626 (0.103)	−0.925 (0.149)	−0.712 (0.094)
All	−0.514 (0.033)	−1.55 (0.031)	−0.479 (0.025)	−0.625 (0.018)	−0.798 (0.042)	−0.729 (0.022)

E. *Distribution of Budget Elasticities by Total Expenditure:*

Expenditure group	Commodity					
	Food	Alcohol	Fuel	Clothing	Transport	Services
Low 5 percent	0.788 (0.032)	2.378 (0.206)	0.510 (0.034)	1.470 (0.118)	0.762 (0.192)	2.598 (0.315)
6–10 percent	0.752 (0.030)	2.251 (0.206)	0.545 (0.045)	1.235 (0.089)	0.904 (0.148)	2.146 (0.239)
11–25 percent	0.708 (0.021)	2.118 (0.113)	0.610 (0.029)	1.114 (0.048)	1.041 (0.061)	1.867 (0.130)
Middle 50 percent	0.591 (0.030)	1.947 (0.079)	0.852 (0.031)	0.913 (0.031)	1.209 (0.039)	1.371 (0.048)
76–90 percent	0.424 (0.128)	1.859 (0.226)	1.296 (0.100)	0.758 (0.088)	1.355 (0.143)	1.038 (0.075)
Top 10 percent	0.096 (0.549)	1.736 (0.328)	1.829 (0.228)	0.602 (0.235)	1.478 (0.310)	0.722 (0.290)
All	0.501 (0.069)	1.884 (0.069)	1.057 (0.050)	0.822 (0.037)	1.310 (0.052)	1.162 (0.066)

Note: Numbers in parentheses are standard errors.

Stone-index approximation for the total expenditure deflator $\ln P = \Sigma_i s_i^h \ln p_i$ and exhibit variation between households.

Table 3A–C reports the elasticities as defined above computed at the average shares and household characteristics. A comparison with the OLS row displays the importance of allowing for endogeneity in the total-expenditure terms. In the matrix of compensated price elasticities (Table 3B), it can be observed that own-price effects are large and negative while the cross-price effects are generally positive. Moreover, all the eigenvalues of the Slutsky matrix (evaluated at mean expenditure levels) were found to be negative. This shows a close adherence to concavity and taken together with the above results suggests, perhaps surprisingly, that integrability conditions are not too much at odds with observed micro behavior.

To illustrate the variation of elasticities across households, parts D and E of Table 3 report the uncompensated own-price and budget elasticities for households grouped by total expenditure. An interesting result in this table is the budget elasticity reversal in the case of several goods. In some cases this may reflect genuine changes in the perception of need at different income levels; for example, clothing is perceived to be a luxury at low income and a necessity at high income. In other cases it may reflect changes in the type of good consumed at different income levels; for example, the elasticity reversal of demand for transport probably reflects demand for public transport (a necessity) by the poor as opposed to demand for private motoring (a luxury) by the rich. The differences in the budget elasticities in Table 3E are reflected in the variation of the uncompensated own-price elasticities in the first part of the same table.

III. An Empirical Evaluation of Aggregation Bias

As was noted in the discussion of aggregation bias in Section I, the empirical model estimated on micro data does not lend itself to the simplest forms of aggregation for two reasons. First there are the quadratic terms in the logarithm of real expenditure, and second there are interaction terms between the demographic variables and the real expenditure terms. It is however possible to assess the type of results that would emerge if an empirical investigator tried to estimate share equations for the relevant groups of commodities on aggregate data.

A first possibility for our hypothetical investigator would be to follow the aggregation procedure described by equation (9) in Subsection I-B and appropriately weight *all* right-hand-side variables by the share of individual total expenditure in aggregate total expenditure. Given the large number of interaction terms in the micro model, this approach would generally be ruled out by a lack of degrees of freedom in the aggregate model. Even if a guide to which variables would be important in the aggregate model were possible, it is unlikely that such exactly aggregated variables would be available over the complete time series. As a result we adopt a more parsimonious option in which household characteristics are ignored, and each budget share is regressed on the logarithm of prices, the log of average real expenditure and its squared term, seasonal components, trend terms, and the simple linear and quadratic entropy distribution measures to capture the basic aggregation effects also described in the discussion of equation (9) above.

This analysis utilizes aggregated *monthly* Family Expenditure Survey data over the exact same time period as used in the micro analysis. We include monthly time dummies which together with the price terms, the total expenditure terms, the two entropy measures of distributional change, a temperature measure, and a trend term result in 23 explanatory factors for each aggregate expenditure share equation. In contrast to the micro model the corresponding exogeneity test suggested little need to account for the potential endogeneity of $\ln x$ terms. As a result, the aggregate demand system is estimated using the standard seemingly unrelated regressions estimator on the constructed monthly time-series data base, and it is these results that we present in what follows.

Although the entropy measures, the trend terms, and the seasonal components are included, it is impossible to include all terms suggested by the micro model. However, it is interesting to ask whether the omitted factors in this aggregate model induce any dynamic misspecification and if so whether it is sufficient to invalidate the homogeneity hypothesis. To address the issue of dynamic misspecifications we calculated the LM test of autocorrelation. The test assesses the importance of misspecification over own and

Table 4—Elasticities from the Aggregate Model

A. *Budget Elasticities:*

Estimator	Food	Alcohol	Fuel	Clothing	Transport	Services
GMM	0.547 (0.13)	0.621 (0.42)	0.569 (0.31)	0.903 (0.43)	1.855 (0.40)	1.806 (0.53)

B. *Compensated Price Elasticities:*

Commodity	Food	Alcohol	Fuel	Clothing	Transport	Services
Food	−0.417 (0.05)	0.063 (0.03)	0.034 (0.03)	0.040 (0.05)	0.148 (0.06)	0.162 (0.05)
Alcohol	0.322 (0.17)	−1.260 (0.20)	0.482 (0.15)	0.352 (0.18)	0.697 (0.25)	−0.132 (0.19)
Fuel	0.136 (0.13)	0.380 (0.12)	−0.492 (0.15)	0.057 (0.14)	−0.293 (0.18)	−0.014 (0.13)
Clothing	0.963 (0.16)	−0.349 (0.12)	−0.359 (0.12)	−1.107 (0.20)	0.346 (0.20)	0.081 (0.15)
Transport	0.754 (0.12)	0.087 (0.09)	0.071 (0.09)	0.035 (0.11)	−0.871 (0.25)	0.116 (0.15)
Services	0.706 (0.13)	0.155 (0.11)	0.124 (0.10)	0.267 (0.13)	0.124 (0.05)	−0.906 (0.03)

C. *Uncompensated Price Elasticities:*

Commodity	Food	Alcohol	Fuel	Clothing	Transport	Services
Food	−0.605 (0.08)	0.026 (0.03)	−0.013 (0.03)	−0.015 (0.05)	0.050 (0.08)	0.098 (0.05)
Alcohol	0.108 (0.31)	−1.301 (0.21)	0.429 (0.15)	0.289 (0.19)	0.585 (0.33)	−0.206 (0.23)
Fuel	−0.060 (0.24)	0.341 (0.12)	−0.540 (0.15)	0.000 (0.15)	−0.395 (0.25)	−0.081 (0.17)
Clothing	0.651 (0.20)	−0.409 (0.11)	−0.436 (0.12)	−1.198 (0.19)	0.184 (0.22)	−0.026 (0.16)
Transport	0.115 (0.14)	−0.038 (0.09)	−0.087 (0.09)	−0.152 (0.12)	−1.203 (0.26)	−0.103 (0.16)
Services	0.083 (0.17)	0.034 (0.11)	−0.030 (0.10)	0.085 (0.13)	−0.199 (0.12)	−1.119 (0.07)

D. *Budget-Elasticity Differences Between Micro and Aggregate Models:*

Estimator	Food	Alcohol	Fuel	Clothing	Transport	Services
GMM	−0.003 (0.04)	1.353 (4.37)	0.372 (2.04)	−0.683 (2.46)	−0.090 (0.37)	−0.149 (0.51)

TABLE 4—*Continued.*

E. *Compensated-Price Elasticity Differences Between Micro and Aggregate Models:*

	Commodity					
Commodity	Food	Alcohol	Fuel	Clothing	Transport	Services
Food	0.074	0.050	−0.040	−0.056	0.022	−0.020
	(1.16)	(0.98)	(0.92)	(0.65)	(0.14)	(0.19)
Alcohol	0.255	−0.293	0.269	−0.076	−0.407	0.146
	(0.65)	(1.31)	(1.19)	(0.17)	(0.50)	(0.27)
Fuel	−0.161	0.212	0.070	−0.069	−0.064	−0.156
	(0.53)	(1.11)	(0.50)	(0.20)	(0.10)	(0.37)
Clothing	−0.192	−0.051	−0.058	−0.054	0.105	0.083
	(0.72)	(0.28)	(0.35)	(0.27)	(0.19)	(0.23)
Transport	0.042	−0.152	−0.030	0.059	−0.060	0.064
	(0.27)	(1.58)	(0.35)	(0.35)	(0.26)	(0.30)
Services	−0.060	0.082	−0.112	0.071	0.098	−0.023
	(0.26)	(0.62)	(0.87)	(0.28)	(0.20)	(0.09)

Chi-square values for joint tests:
Compensated price elasticities: 14.66 [$d.f. = 21$]
Budget elasticities: 29.66 [$d.f. = 6$]

Notes: Numbers in parentheses are standard errors in parts A–C and t statistics in parts D and E.

cross autocorrelation in the error terms at first, third, and twelfth orders. Only in fuel and transport was there an indication of dynamic misspecification. Moreover the aggregate model did not reject price homogeneity.

For policy purposes it may be more useful to compare elasticities. Parts A–C of Table 4 provide the aggregate model elasticities evaluated at the sample means. Parts D and E compare these with the elasticities obtained directly from micro data reported in Table 3 by presenting their differences and the t values associated with these differences. The joint chi-square test for budget elasticities indicates a rejection of equality. Interestingly there is less evidence of bias in the price elasticities, although some differences are relatively large. However, given that relative prices are only time-varying and given that the aggregate model includes seasonals, trend, and entropy terms, this may not be surprising.

It is hard to predict circumstances under which the estimated price and income effects from the aggregate models will give a reliable picture of the underlying microeconomic behavior. Some guidance on this topic may come from looking at the ratios of μ-weighted averages to simple averages of the explanatory variables used in the micro level. These correspond to the θ_k aggregation factors in the consistently aggregated model (10) of Section I. Those variables for which the ratios are uncorrelated with prices and income do not require direct inclusion in the aggregate model. If their simple averages over time are either constant, or trend-like, they can be omitted altogether.

Table 5 presents selected results of regressions of some θ's on trend, prices, and real expenditure, which confirm that the simple demographic variables may cause major problems in identifying price and especially income effects from aggregated data alone. The column headed CH1116, representing the effect of older children aged 11–16, shows that, for some demographic characteristics, the ratio of μ-weighted average to simple average is fairly constant. However, in all other cases considered there are nonnegligible correlations with price

TABLE 5—REGRESSION OF SELECTED θ_k'S ON PRICES AND REAL EXPENDITURE

	θ						
Variable	CH1116	$(AGE)^2$	ADLTNR	WHC	YORK	OWNER	DCAR
PFOOD	0.047	0.141	0.105	−0.007	0.019	−0.854	−0.037
	(0.207)	(0.103)	(0.094)	(0.162)	(0.344)	(0.139)	(0.072)
PALCL	−0.030	0.109	0.092	0.681	0.519	0.202	0.190
	(0.205)	(0.102)	(0.093)	(0.160)	(0.341)	(0.138)	(0.071)
PFUEL	−0.018	0.014	−0.283	−0.040	0.289	−0.175	−0.163
	(0.197)	(0.098)	(0.089)	(0.154)	(0.328)	(0.132)	(0.069)
PCLOTH	0.080	−0.053	−0.148	−0.047	0.555	−0.021	−0.037
	(0.257)	(0.128)	(0.116)	(0.200)	(0.427)	(0.172)	(0.089)
PTRPT	−0.069	0.083	−0.018	0.166	1.150	0.164	−0.133
	(0.281)	(0.141)	(0.128)	(0.219)	(0.468)	(0.189)	(0.098)
PSERV	−0.000	−0.150	0.129	−0.333	−1.203	0.019	0.042
	(0.204)	(0.102)	(0.093)	(0.159)	(0.340)	(0.137)	(0.071)
$\ln x$	−1.819	2.151	−1.316	0.003	3.451	−3.018	−2.321
	(1.593)	(0.795)	(0.721)	(1.242)	(2.647)	(1.069)	(0.553)
$(\ln x)^2$	0.138	−0.164	0.101	0.002	−0.271	0.229	0.177
	(0.122)	(0.061)	(0.055)	(0.095)	(0.202)	(0.082)	(0.042)
Mean:	1.175	0.919	1.181	1.128	0.931	1.107	1.133
R^2:	0.206	0.114	0.227	0.393	0.160	0.241	0.330
DW:	1.863	1.878	2.001	2.057	2.150	1.908	1.907

Notes: Monthly regressions over 15 years. All regressions include an intercept, a time trend, and 11 monthly dummies. Standard errors are given in parentheses. See Appendix A for definitions of variables. DW is the Durbin-Watson statistic.

(e.g., see the ADLTNR equation) and expenditure terms, particularly in the case of home owners (OWNER).

The case of the coefficients on the real expenditure terms is more complex. As our analysis in Section I revealed, consistent parameter estimates of these coefficients can be obtained only if the π aggregation factors of equations (11b)–(11e) are constant and close to unity. By their nature, the π's are unlikely to be unity. For example, π_0 is the ratio of the weighted average of $\ln x$ to the logarithm of the simple average of real expenditure. As the weights are given by an increasing function of $\ln x$, this ratio will typically exceed 1. The same applies for π_1 (involving the square of real expenditure). The case is less clear-cut for the π_2 and π_3 ratios, which include demographic-related characteristics (households with children and households whose head is a white-collar worker). In this case, π is the ratio of the (weighted) average of the product to the product of the (weighted) averages. It will exceed 1 if the demographic characteristic in question is positively correlated with total real expenditure.[5]

Figure 1 presents graphs of the variations of the π_0 and π_2 ratios over time (π_2^c relates to presence of children, π_2^w to

[5]This statement needs qualifying though. From equation (11),

$$\pi_0 = \sum_h \mu_h \ln x^h / \ln X$$

$$= \left(\frac{\Sigma_h \mu_h \ln x^h}{H^{-1}\Sigma_h \ln x^h} \right) \left(\frac{H^{-1}\Sigma_h \ln x^h}{\ln(\Sigma_h x^h / H)} \right)$$

where H is the total number of households. In the text, we argued that the first ratio is at least 1; however, Jensen's inequality implies that the second will be 1 at most. In practice, the second ratio is fairly stable and close to unity.

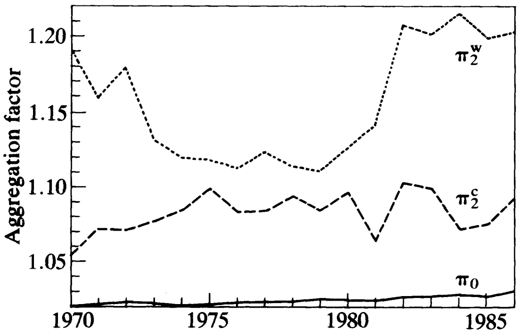

FIGURE 1. AGGREGATION FACTORS: TERMS INVOLVING ln(x)

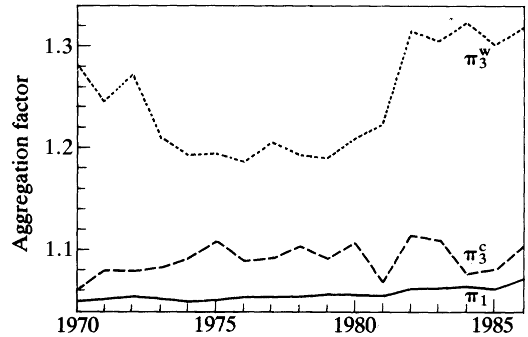

FIGURE 2. AGGREGATION FACTORS: TERMS INVOLVING ln(x) SQUARED

white-collar workers). Since these aggregation factors are not dependent on any estimated parameters, this figure not only covers the within-period sample but also 24 months of postsample information which will be used for a forecast comparison in the next section. It clearly shows that only in the case of π_0 is there limited variability. In practice, we could take a given value of π_0 and use it to scale down parameter estimates obtained using aggregate data. Whenever the π's are time-varying the estimated parameters in the aggregate model are likely to be unstable. It appears that this will occur for all the other expenditure terms. This is particularly systematic for the interaction between $\ln x$ and the white-collar dummy. The time-series variation of π_2^w suggests that there has been high positive correlation between being a white-collar worker and overall expenditure in the early 1970's and early 1980's, and a much lower one in the mid-to-late 1970's.

In Figure 2 the aggregation factors relating to $(\ln x)^2$ (i.e., π_1 and π_3) are presented. Again the white-collar worker variable, π_3^w, shows systematic time-series variation. Together these results indicate that differences in the distribution of expenditures between and across households of different types can lead to systematic time variation in aggregate model parameters. It is worth noting, however, that there is less variation in the postsample period, which may make it less likely that any systematic instability will be observed over this period. With this in mind we turn, in the next section, to the comparison of forecasts of aggregate shares from an aggregate model to those generated from the (weighted) sum of micro model forecasts over this period.

IV. Forecast Performance

In assessing the forecast performance of the micro and aggregate specifications we are naturally drawn to compare postsample predictions of *aggregate* behavior. As we noted earlier there are likely to be factors that mitigate the efficiency and bias considerations derived in the previous section when aggregate forecast performance is compared. First, the micro model, in assuming independent variation in unobservable factors across households, will not necessarily produce the best fit in the time-series domain. Second, since *weighted* summation is required to calculate the aggregate share and since the weights are most likely endogenous, one has to be careful to remove any resulting bias at the summation stage. Finally, our aggregate model described in Section III is estimated on the aggregated micro data and includes distribution, trend, and seasonal components to minimize aggregation bias.

Since our estimation period ends in 1984, we decided to consider out-of-sample forecast performance for the 24 months in the 1985 and 1986 Family Expenditure Survey data. In line with Section II, we also decided to maintain use of the instrumental-

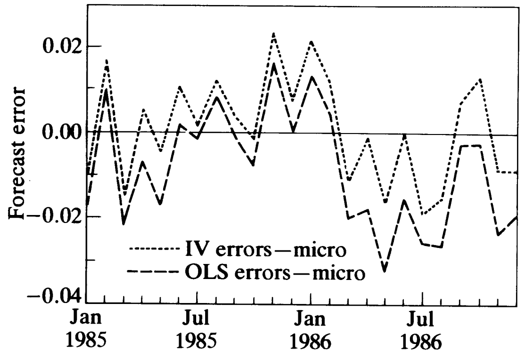

FIGURE 3. ESTIMATOR FORECAST PERFORMANCE: MICRO TRANSPORT SHARE EQUATION

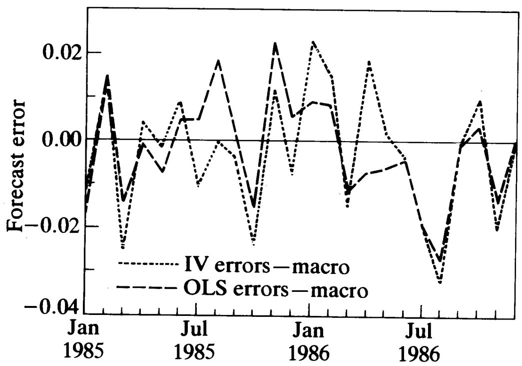

FIGURE 4. ESTIMATOR FORECAST PERFORMANCE: MACRO (AGGREGATE) TRANSPORT SHARE EQUATION

variable (GMM) estimated micro system. Figure 3 uses the transport equation as an example of the persistent bias over the forecast period that is present in the micro OLS estimates. The other micro equations display a bias of similar magnitudes. For the aggregate model, this bias is less evident. In Figure 4 the corresponding forecast error for the transport equation is reported and supports our view that the standard OLS estimator should be used for the aggregate model. As we noted above in comparison with the micro model, the within-sample exogeneity test statistics are small.

The comparative precision in forecast performance is presented in Table 6. We turn first to the mean forecast error over the 24-month period. The individual household forecasts have to allow for the endogeneity of the $\ln x$ terms and the μ weights. To account for the endogeneity of terms in $\ln x$ we include the estimated reduced-form residuals, which is equivalent to forecasting with the structural restrictions imposed. Note however that to construct the forecast of the aggregate share the μ-weighted sum is required. Since this sum includes the weighted sum of micro error terms, the forecast will only be unbiased if the error terms are uncorrelated with the weights. However, since $\mu_t^h \equiv x_t^h / X_t$, accounting for the endogeneity of the terms in $\ln x$ and $(\ln x)^2$ as described above all but purges the correlation between the error terms and the μ weights.

Table 6A shows the close accordance of the forecasts from the two models. This is further displayed in Figures 5–11, where the monthly forecast errors are presented. On these aggregate monthly data the micro model does not always dominate, only outperforming the aggregate model for clothing, transport, "other" goods, and services. This pattern is confirmed when the post-sample (Table 6B) and the within-sample root-mean-square-error criteria (Table 6C) are computed.

One further comparison is also useful. As we pointed out in the Introduction, the aggregate model has an apparent built-in advantage, in that it works directly with μ-weighted shares. One way to evaluate the empirical importance of this issue is to look at the forecast performance of both models when simple averages are used. While the resulting average share has no obvious economic meaning, this aggregation procedure simplifies the task of computing standard errors of the forecasts. Indeed, the standard errors in Table 6A are based on this simple average.

Table 6D presents our results. Once again, forecast errors are not universally

TABLE 6—FORECASTING PERFORMANCE

Model	Commodity						
	Food	Alcohol	Fuel	Clothing	Transport	Other	Services
A. *Mean Forecast Error, μ-Weighted Averages of Budget Shares:*							
Micro	−0.00323	−0.00520	−0.00163	−0.00299	0.00599	−0.00103	0.00808
	(0.00125)	(0.00092)	(0.00089)	(0.00122)	(0.00183)	(0.00094)	(0.00129)
Aggregate	0.00148	0.00443	−0.00442	−0.00299	−0.00429	−0.00457	−0.01040
	(0.00441)	(0.00259)	(0.00249)	(0.00415)	(0.00696)	(0.00443)	(0.00589)
B. *Root-Mean-Square Error, Postsample:*							
Micro	0.00936	0.00704	0.00612	0.00980	0.01252	0.00640	0.01829
Aggregate	0.00745	0.00484	0.00432	0.00988	0.01251	0.00745	0.02046
C. *Root-Mean-Square Error, Within Sample:*							
Micro	0.00643	0.00427	0.00414	0.00746	0.01090	0.00590	0.01110
Aggregate	0.00664	0.00414	0.00388	0.00640	0.01070	0.00544	0.00945
D. *Mean Forecast Error, Simple Averages of Budget Shares:*							
Micro	−0.00560	−0.00514	−0.00486	−0.00163	0.00080	−0.00267	0.00790
	(0.00125)	(0.00092)	(0.00089)	(0.00122)	(0.00183)	(0.00094)	(0.00129)
Aggregate	−0.00328	0.00181	−0.00273	−0.00202	−0.00227	−0.00398	0.01250
	(0.00441)	(0.00259)	(0.00249)	(0.00415)	(0.00696)	(0.00443)	(0.00589)

Note: Standard errors are given in parentheses.

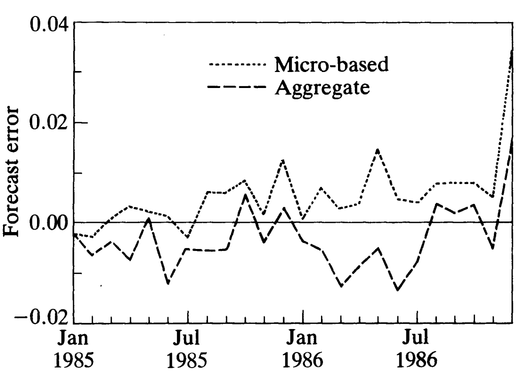

FIGURE 5. FORECAST ERRORS: FOOD SHARE EQUATION

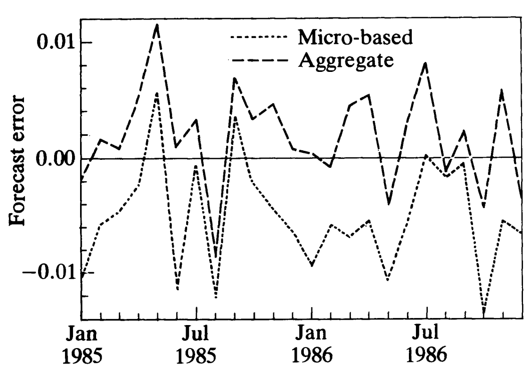

FIGURE 6. FORECAST ERRORS: ALCOHOL SHARE EQUATION

smaller for either the micro or the aggregate model, thus showing that μ-weighting alone does not give the aggregate model an edge over the micro model. A simple test for zero forecast mean often rejects the null for both models when the micro-model standard errors are used and fails to reject when the macro standard errors are instead employed.

V. Conclusions

In assessing the relationship between models of consumer demand based on mi-

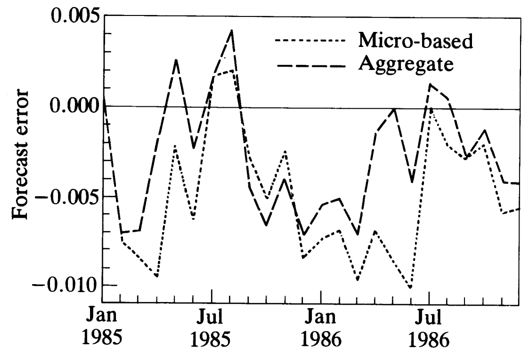

FIGURE 7. FORECAST ERRORS: FUEL SHARE EQUATION

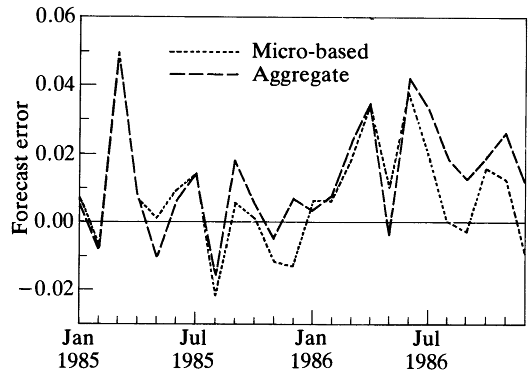

FIGURE 10. FORECAST ERRORS: SERVICES SHARE EQUATION

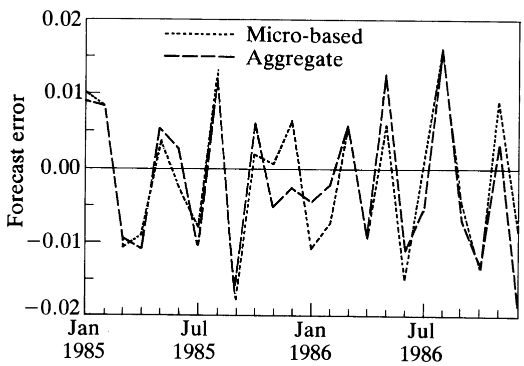

FIGURE 8. FORECAST ERRORS: CLOTHING SHARE EQUATION

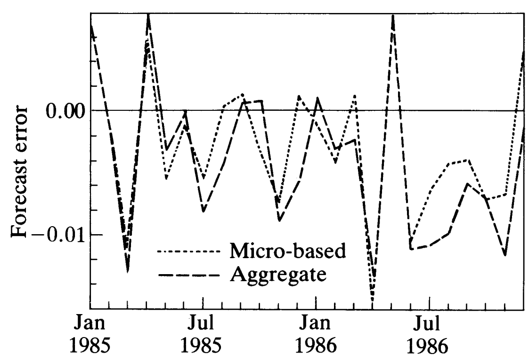

FIGURE 11. FORECAST ERRORS: OTHER GOODS SHARE EQUATION

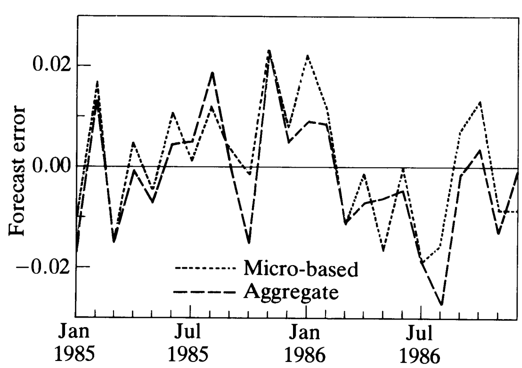

FIGURE 9. FORECAST ERRORS: TRANSPORT SHARE EQUATION

cro and aggregate data, it is important to establish the presence of nonlinearity in the micro-level Engel curves and the need for interactions with household-specific characteristics, since either of these would rule out simple linear aggregation. In our sample of U.K. survey data, pooled over 15 years, we find strong evidence of both. In particular, we find that goods may change with income from luxury to necessity, a possibility ruled out in many commonly used demand systems. In comparison to previous studies in this area, we do not find that price homogeneity is rejected, while the own- and cross-price variables are strongly significant.

From our results we can draw certain implications for work on aggregate data. Even ignoring the interactions of total expenditure with individual characteristics, aggregate models that explain demands in terms of price and total-expenditure variables exclude many important aggregation factors such as the proportion of total expenditure associated with particular family size, tenure group, or employment status. These factors change over time in a way that may well be correlated with real total expenditure and relative price movements, often making it difficult to identify the separate effects from aggregate data or to test theoretical hypotheses concerning price and income terms.

For our sample, the estimated price elasticities were found to be similar in micro and aggregate equations, while the estimated income elasticities differed significantly. In general, our results imply that a comparison of aggregate estimates either across different time periods or across different countries in which the income distribution is not constant may display coefficient instability. To help assess the likely occurrence of parameter instability and systematic differences in parameter estimates according to the level of aggregation, we propose a set of computable aggregation factors. These are purely data-dependent and only relate to observable household characteristics and components of the income distribution.

In terms of *ex post* aggregate forecasting ability, we find that the micro-based model does not unambiguously outperform a similarly specified aggregate model that simply includes some basic distributional measures. We interpret this unexpected result as a consequence of the stability of the aggregation factors over our postsample period. Indeed, when the aggregation factors do not vary or evolve in a predictable way, our analysis has shown that the aggregate-data model is useful both for forecasting and for the evaluation of the aggregate consequences of public-policy experiments.

Appendix A: Data Description

Table A1 describes the variables used in the empirical analysis. The logarithm of real expenditure ($\ln x$) is defined as total group expenditure divided by the individual-specific Stone price index. Other endogenous variables in the share equations are: interactions of real expenditure with child dummy ($C \times \ln x$), with zero-sum summer dummy ($S3 \times \ln x$), and with white-collar dummy ($WHC \times \ln x$); log real expenditure squared ($[\ln x]^2$) and its interactions with the above dummies ($C \times [\ln x]^2$, $S3 \times [\ln x]^2$, and $WHC \times [\ln x]^2$); car-ownership indicator (DCAR), number of cars owned (CARS), smoker-in-the-household indicator (DTOB), and the interaction of DTOB with the children dummy (CTOB).

Table A1—Sample Means (Estimation Sample: April 1970–December 1984; Number of Observations = 61,984)

Variable	Description	Mean	Standard deviation	Minimum	Maximum
POTH	ln(price, other goods)	0.08760	0.06504	−0.05404	0.2053
PFOOD	ln(price, food) − POTH	−0.04293	0.05159	−0.14583	0.0550
PALCL	ln(price, alcohol) − POTH	−1.00667	0.57715	−1.88871	−0.0916
PHOUS	ln(price, housing) − POTH	−0.12021	0.11349	−0.27241	0.0956
PFUEL	ln(price, fuel) − POTH	−0.53703	0.41322	−1.21319	−0.0231
PDUR	ln(price, durables) − POTH	0.36416	0.16344	0.03932	0.5972
PCLOTH	ln(price, clothing) − POTH	0.06801	0.03541	−0.00394	0.1552
PTRPT	ln(price, transport) − POTH	−0.81562	0.52112	−1.64700	−0.0721
PSERV	ln(price, services) − POTH	−0.01743	0.04330	−0.09593	0.0933

TABLE A1—*Continued*

Variable	Description	Mean	Standard deviation	Minimum	Maximum
RPI	ln(retail price index)	1.35017	0.53120	0.49103	2.0901
INTR	building-society deposit rate	713.66748	158.66119	475	1,050
MORG	building-society mortgage rate	1,099.53149	203.63988	800	1,500
PDUR(−12)	PDUR lagged 12 months	0.83554	0.42563	0.18149	1.4083
PTRPT(−12)	PTRPT lagged 12 months	1.27883	0.55916	0.45044	2.1129
DLAY	number of degree-days	580.79721	19.25561	76	1,274
S1	first-quarter dummy	0.23834	0.42607	0	1
S2	second-quarter dummy	0.24726	0.43142	0	1
S3	third-quarter dummy	0.25705	0.43701	0	1
D3DAY	1974, S1	0.01387	0.11697	0	1
FEB	February dummy	0.07770	0.26760	0	1
MAR	March dummy	0.08263	0.27533	0	1
MAY	May dummy	0.08370	0.27694	0	1
JUN	June dummy	0.07938	0.27033	0	1
AUG	August dummy	0.08496	0.27882	0	1
SEP	September dummy	0.08634	0.28088	0	1
NOV	November dummy	0.09264	0.28992	0	1
XMAS	December dummy	0.08007	0.27140	0	1
WHC	white-collar dummy	0.34932	0.47676	0	1
PROF	professional dummy	0.11140	0.31463	0	1
MANAG	manager dummy	0.11085	0.31395	0	1
TEACH	teacher dummy	0.03862	0.19270	0	1
HUNEMP	head unemployed	0.10782	0.31015	0	1
ROOMS	number of rooms	5.10943	1.29643	1	16
MC	married couple	0.79109	0.40653	0	1
WW	working wife	0.49726	0.50000	0	1
DCAR	car dummy	0.67316	0.46906	0	1
CARS	number of cars	0.82646	0.70038	0	7
FR	refrigerator dummy	0.90999	0.28619	0	1
CH	central-heating dummy	0.54604	0.49788	0	1
LA	local-authority tenant	0.31665	0.46517	0	1
RENT	private rented, unfurnished	0.07066	0.25626	0	1
RENTF	rented, furnished	0.04514	0.20761	0	1
NORENT	rent-free	0.02612	0.15949	0	1
OOM	owner occupier, mortgage	0.43574	0.49586	0	1
OOO	owner occupier, outright	0.10569	0.30744	0	1
RAT	ln(rateable value)	3.26047	0.65676	−0.87547	5.8021
TREND	quarterly trend	30.99806	16.93330	2	60
TRSQ	TREND squared	1,247.61193	1,080.20464	4	3,600
EX	total expenditure	6,894.03947	5,839.59646	190.83330	86,386.0000
WALCL	alcohol share	0.06693	0.07774	0.00000	0.7522
WFOOD	food share	0.34774	0.12500	0.00000	1.0000
WFUEL	fuel share	0.08451	0.06077	−0.15178	0.8228
WCLOTH	clothing share	0.10190	0.10293	0.00000	0.7619
WTRPT	transport share	0.17854	0.14531	−0.05107	0.9493
WOTH	other-goods share	0.10359	0.07102	0.00000	0.8795
WSER	services share	0.11679	0.10390	−0.08520	0.9578
LP	Stone price index	−0.74908	0.52705	−1.79247	−0.0150
DCHIL	children dummy	0.56355	0.49595	0	1
RL	real lending rate	−0.03470	0.04769	−0.16566	0.0478
RB	real borrowing rate	−0.00199	0.02113	−0.13362	0.0915
URATE1	unemployment rate, 1-month lag	0.07944	0.04222	0.02917	0.1652
URATE12	unemployment rate, 1-year lag	0.07188	0.03859	0.02917	0.1652
ADLTNR	number of adults −1	1.12003	0.75800	0	4
ADTSQ	ADLTNR squared	1.82902	2.53083	0	16
FEMNR	number of females	1.07545	0.48267	0	5
DTOB	tobacco expenditure > 0	0.66885	0.47063	0	1

TABLE A1—*Continued*

Variable	Description	Mean	Standard deviation	Minimum	Maximum
CTOB	DCHIL × DTOB	0.38494	0.48658	0	1
NORTH	regional dummy	0.06579	0.24792	0	1
YORKHUMB	regional dummy	0.09486	0.29303	0	1
EASTMIDL	regional dummy	0.07036	0.25575	0	1
EANGLIA	regional dummy	0.03511	0.18405	0	1
GRLONDON	regional dummy	0.11874	0.32348	0	1
SOUTHWES	regional dummy	0.06873	0.25299	0	1
WALES	regional dummy	0.05156	0.22114	0	1
WESTMIDL	regional dummy	0.09974	0.29965	0	1
NORTHWES	regional dummy	0.11821	0.32286	0	1
SCOTLAND	regional dummy	0.09732	0.29639	0	1
CH02	children aged 0–2	0.18531	0.44233	0	5
CH35	children aged 3–5	0.19102	0.45059	0	4
CH610	children aged 6–10	0.33280	0.64576	0	5
CH1116	children aged 11–16	0.36071	0.69386	0	6
CH1718	children aged 17–18	0.02447	0.15945	0	2
S1S	S1 × TREND	7.35753	15.33367	0	57
S2S	S2 × TREND	7.48245	15.50919	0	58
S3S	S3 × TREND	7.95171	16.10686	0	59
AGE	age of head − 40	0.58912	11.29241	−22	20
AGESQ	AGE squared	127.86351	116.91232	0	484
EARNNR	number of earners	1.68239	0.84920	0	5
RETNR	number of retired	0.03094	0.18056	0	2
CAGE	AGE × DCHIL	−1.33854	6.76473	−22	20
CAGESQ	CAGE squared	47.55200	81.42646	0	484
$\ln x$	ln(EX) − LP − 3.4	5.89889	0.54445	2.36429	8.8515
$(\ln x)^2$	$\ln x$ squared	35.09300	6.39670	5.58987	78.3493
$C \times \ln x$	DCHIL × $\ln x$	3.35531	2.97508	0.00000	8.6092
$C \times (\ln x)^2$	DCHIL × $(\ln x)^2$	20.10906	18.22439	0.00000	74.1186
S3 × $\ln x$	(S1 − 0.25) × $\ln x$	0.04215	2.58969	−2.09966	6.6386
S3 × $(\ln x)^2$	(S1)0.25) × $(\ln x)^2$	9.02969	15.70177	0.00000	78.3493
WHCLRX	WHC × $\ln x$	2.10478	2.89034	0.00000	8.3986
WHCLRXS	WHC × $(\ln x)^2$	12.78401	17.86466	0.00000	70.5370
CH1	CH × S1	0.12955	0.33581	0	1
CH2	CH × S2	0.13465	0.34135	0	1
CH3	CH × S3	0.14123	0.34826	0	1
AGE1	AGE × S1	0.15710	5.51526	−22	20
AGE2	AGE × S2	0.15664	5.61082	−22	20
AGE3	AGE × S3	0.13634	5.72748	−22	20
$\ln Y$	ln(net normal income)	6.65565	0.72528	4.34489	8.4608
$(\ln Y)^2$	$\ln Y$ squared	44.82366	9.61067	18.87804	71.5857
S1 × $\ln Y$	(S1 − 0.25) × $\ln Y$	−0.07886	2.85079	−2.11521	6.3167
S2 × $\ln Y$	(S2 − 0.25) × $\ln Y$	−0.02500	2.88039	−2.11521	6.3354
S3 × $\ln Y$	(S3 − 0.25) × $\ln Y$	0.04880	2.92818	−2.11521	6.3314
S3 × $(\ln Y)^2$	(S3 − 0.25) × $(\ln Y)^2$	11.55005	20.24554	0.00000	71.2644
WHC × $\ln Y$	WHC × $\ln Y$	2.39898	3.30074	0.00000	8.4540
WHC × $(\ln Y)^2$	WHC × $(\ln Y)^2$	16.64977	23.42595	0.00000	71.4708
C × $\ln Y$	DCHIL × $\ln Y$	3.75420	3.34555	0.00000	8.4608
C × $(\ln Y)^2$	DCHIL × $(\ln Y)^2$	25.28721	23.32740	0.00000	71.5857
SGLPAR	single-parent dummy	0.05322	0.22448	0	1
AGRIC	agriculture dummy	0.01452	0.11962	0	1
MFGSEC	manufacturing dummy	0.28910	0.45349	0	1
TXTSEC	textile dummy	0.02552	0.15771	0	1
FUESEC	fuel dummy	0.27005	0.44399	0	1
SERSEC	services dummy	0.32510	0.46845	0	1
UNC	unclassified dummy	0.07530	0.26389	0	1

Appendix B: The GMM Estimated Demand System

Variable	Food equation: Parameter estimate	Food equation: Standard error	Alcohol equation: Parameter estimate	Alcohol equation: Standard error
Intercept	0.94108	0.42506	−0.20103	0.35461
PFOOD	0.08215	0.01735	0.03607	0.01518
PALCL	−0.02861	0.01786	−0.03684	0.01561
PFUEL	−0.04957	0.01765	0.04124	0.01524
PCLOTH	−0.02508	0.02319	−0.00344	0.02011
PTRPT	−0.08735	0.02596	0.00235	0.02249
PSERV	0.04249	0.01852	−0.01050	0.01604
CH02	0.01935	0.00162	−0.00174	0.00137
CH35	0.02260	0.00159	−0.00610	0.00134
CH610	0.02873	0.00144	−0.00711	0.00123
CH1116	0.03178	0.00181	−0.00920	0.00153
CH1718	0.01921	0.00384	−0.00778	0.00317
FEMNR	-8.98×10^{-4}	0.00248	−0.04106	0.00209
AGE	0.00140	8.51×10^{-5}	-5.42×10^{-4}	7.53×10^{-5}
AGESQ	-2.78×10^{-5}	8.21×10^{-6}	7.96×10^{-6}	7.23×10^{-6}
ADLTNR	0.07796	0.00878	−0.00236	0.00746
ADTSQ	−0.01069	0.00192	0.00266	0.00164
WHC	−0.82597	0.47465	−0.34611	0.37933
EARNNR	−0.01617	0.00221	0.01093	0.00191
HUNEMP	−0.01329	0.00359	−0.00485	0.00309
RETNR	0.00218	0.00300	0.00511	0.00258
SGLPAR	0.04272	0.01021	−0.01401	0.00877
NORTH	−0.00316	0.00302	0.02025	0.00268
YORK	−0.00133	0.00243	0.01236	0.00211
NORTHWES	−0.00424	0.00252	0.01284	0.00220
EASTMIDL	-7.51×10^{-4}	0.00197	0.00884	0.00169
WESTMIDL	−0.00113	0.00178	0.01109	0.00151
EANGLIA	0.00035	0.00316	0.00022	0.00250
GRLONDON	0.02194	0.00406	−0.00189	0.00347
WALES	0.00173	0.00246	0.00731	0.00210
SOUTHWES	−0.00890	0.00241	0.00344	0.00197
SCOTLAND	0.00538	0.00311	0.00781	0.00272
S1	0.00922	0.00506	0.00010	0.00443
S2	0.01144	0.00643	0.00477	0.00564
S3	−0.16281	0.28657	−0.40436	0.21647
FEB	0.00338	0.00217	0.00122	0.00188
MAR	0.00431	0.00211	−0.00123	0.00181
MAY	0.00048	0.00203	−0.00121	0.00177
JUN	0.00098	0.00214	−0.00169	0.00183
AUG	−0.00713	0.00221	0.00183	0.00190
SEP	−0.00716	0.00240	0.00196	0.00209
NOV	−0.00285	0.00210	−0.00248	0.00183
XMAS	−0.00591	0.00313	0.00982	0.00273
DLAY	-1.09×10^{-5}	7.34×10^{-6}	-5.34×10^{-6}	6.43×10^{-6}
TREND	-5.36×10^{-4}	0.00022	0.00026	0.00019
ROOMS	0.00088	0.00051	-9.83×10^{-4}	0.00042
LA	−0.00351	0.00438	0.00618	0.00375
RENT	−0.00356	0.00305	0.00596	0.00265
RENTF	−0.00865	0.00380	0.01128	0.00328
NORENT	−0.00305	0.00367	0.00107	0.00296
OOM	−0.00284	0.00172	0.00442	0.00138
FR	-1.20×10^{-4}	0.00380	−0.01033	0.00333
CH	0.00039	0.00218	6.67×10^{-5}	0.00191
DCAR	−0.12533	0.04164	0.00898	0.03499
CH1	−0.00318	0.00234	0.00171	0.00208
CH2	−0.00548	0.00231	−0.00254	0.00206
CH3	−0.00758	0.00242	-3.27×10^{-4}	0.00215
AGE1	-4.14×10^{-4}	0.00011	-1.80×10^{-4}	0.00009

APPENDIX B—*Continued.*

Variable	Food equation: Parameter estimate	Food equation: Standard error	Alcohol equation: Parameter estimate	Alcohol equation: Standard error
AGE2	-4.45×10^{-4}	0.00010	-2.11×10^{-4}	9.18×10^{-5}
AGE3	-2.07×10^{-4}	0.00012	-8.60×10^{-5}	0.00010
MC	0.02474	0.00448	−0.00930	0.00391
WW	0.00810	0.00241	−0.01168	0.00208
AGRIC	−0.00709	0.00571	−0.00541	0.00455
MFGSEC	0.00045	0.00150	0.00661	0.00128
TXTSEC	0.00609	0.00327	0.00153	0.00287
FUESEC	0.00406	0.00143	0.00570	0.00121
UNC	−0.00326	0.00463	0.00899	0.00394
DTOB	0.02240	0.01351	0.04157	0.01163
CTOB	0.04410	0.02465	0.06887	0.02133
RAT	−0.00430	0.00210	−0.00621	0.00183
CARS	0.08626	0.02144	−0.01828	0.01765
$\ln x$	−0.04935	0.14705	0.11137	0.12287
$(\ln x)^2$	−0.00762	0.01279	−0.00352	0.01068
$S3\times\ln x$	0.06889	0.09980	0.14933	0.07550
$S3\times(\ln x)^2$	−0.00650	0.00862	−0.01350	0.00652
$C\times\ln x$	−0.00199	0.01307	−0.04566	0.01142
$C\times(\ln x)^2$	-2.07×10^{-4}	0.00175	0.00597	0.00153
$WHC\times\ln x$	0.28516	0.16485	0.09975	0.13220
$WHC\times(\ln x)^2$	−0.02462	0.01420	−0.00697	0.01142
R^2:		0.2998	0.1388	
Dependent-variable mean:		0.3477393	0.0669326	

Note: See Table A1 for definitions of variables.

APPENDIX C: THE DETERMINANTS OF REAL EXPENDITURE

In Table C1 we report the estimated parameters for the equation describing the logarithm of total household real expenditure in terms of prices, demographic variables, other socioeconomic characteristics, income, and macroeconomic indicators. The following macroeconomic variables are used: national male unemployment rate lagged 1 and 12 months, defined throughout on a new count basis; and building-societies mortgage and deposit rates, lagged 12 months, net of actual current annual inflation. While the unemployment rate is used for everybody, the mortgage rate is only applied to households who are owner-occupiers. These variables also act as instrumental variables for the total expenditure variables in the demand system. This "real" consumption function shows considerable impact of prices (PFOOD, PALCL, etc.), demographics, some other characteristics, and log disposable normal income ($\ln Y$). As described above, this equation is best interpreted as a household-specific consumption function describing how a given price or income change will affect total real expenditure by each household.

TABLE C1—THE "CONSUMPTION FUNCTION" (DEPENDENT VARIABLE = $\ln x$)

Variable	Parameter estimate	Standard error
INTERCEPT	0.3854774	0.29519597
PFOOD	−0.3139564	0.09501118
PALCL	0.0886517	0.13714167
PFUEL	−0.2078526	0.10998859
PCLOTH	−0.2521109	0.16597644
PTRPT	0.0647888	0.12959347
PSERV	−0.3245401	0.08740673
POTH	−1.0252135	0.22031144
PHOUS	−0.0569460	0.05792697

TABLE C1—*Continued*

Variable	Parameter estimate	Standard error
PDUR	−0.0239695	0.17070763
PROF	0.0162932	0.006792808
MANAG	0.0426338	0.006865871
TEACH	0.00309731	0.009277766
PDUR(−12)	0.0861247	0.12685792
PTRPT(−12)	0.1193048	0.12620202
WHCNNYS	0.00867847	0.005186131
CNNYSQ	−0.00209989	0.000703825
CH	0.0234325	0.006307244
CH1	−0.00224398	0.008851906
CH2	0.00369860	0.008753436
CH3	−0.00456267	0.008687769
AGE1	0.00060721	0.000368853
AGE2	0.00125135	0.000365610
AGE3	0.00078590	0.000362279
S3NNYSQ	−0.00462336	0.005193668
CH02	0.0118976	0.004525959
CH35	0.0255787	0.003874054
CH610	0.0225738	0.002843022
CH1116	0.0432165	0.002947156
CH1718	0.1538818	0.009951139
EARNNR	0.0166535	0.006439010
RETNR	−0.0621062	0.009224938
WHCNNY	−0.1190711	0.06973416
MFGSEC	−0.0141660	0.004059250
TXTSEC	−0.0213891	0.009675972
FUESEC	−0.00754604	0.004089064
UNC	0.0726466	0.01230823
CAGE	0.00047970	0.000338549
CAGESQ	0.0000022676	0.000030578
CNNY	0.0152325	0.005214606
FEMNR	−0.0358637	0.004224383
NNYSQ	0.0102070	0.003558024
S1	0.0148602	0.05451964
S2	−0.0851755	0.05598739
S3	−0.2282000	0.22890123
FEB	0.0245062	0.007923524
MAR	0.0607857	0.007976353
MAY	0.0180066	0.007244820
JUN	0.01860135	0.00778398
AUG	−0.04131475	0.00737680
SEP	−0.06957354	0.00771556
NOV	0.05255358	0.00704951
XMAS	0.18918554	0.00752299
DLAY	0.000048067	0.00002804
TREND	0.009623142	0.00280230
TRSQ	−0.000024976	0.00002995
AGE	−0.000982634	0.00029744
AGESQ	−0.000109518	0.00001937
ADLTNR	0.29192512	0.0100687
ADTSQ	−0.03942827	0.00207085
FR	0.08938080	0.00572080
RENTF	0.04658696	0.00947843
ROOMS	0.01398228	0.00154915
NORENT	0.04033130	0.0108811
LA	−0.04333731	0.00564932
RENT	0.01114839	0.00738821
OOM	−0.06181822	0.00564029
NORTH	−0.006764908	0.00760934
YORKHUMB	−0.007784608	0.00667785

TABLE C1—*Continued*

Variable	Parameter estimate	Standard error
EASTMIDL	−0.01850154	0.00686182
EANGLIA	−0.01675933	0.00869490
GRLONDON	0.03407035	0.00560985
SOUTHWES	−0.01341849	0.00661599
WALES	0.01961687	0.00772153
WESTMIDL	−0.01125650	0.00628050
NORTHWES	0.009373691	0.00573247
SCOTLAND	0.03738412	0.00694795
D3DAY	−0.01417704	0.0147996
S1S	0.000557293	0.00039763
S2S	−0.000453689	0.00038109
S3S	−0.000145479	0.00037380
URATE1	0.19539975	0.3700711
URATE12	−0.47325186	0.2303028
RL	−0.24149299	0.1086953
RB	−0.29735390	0.1343964
$S1 \times \ln Y$	−0.01430351	0.00924498
$S2 \times \ln Y$	0.01354067	0.00917326
$S3 \times \ln Y$	0.07380839	0.0689631
HUNEMP	−0.09139814	0.00858824
SGLPAR	0.09265308	0.00922584
AGRIC	−0.02728242	0.0133799
WHC	0.41059024	0.2328521
MC	−0.01995567	0.00820081
WW	−0.01135298	0.00724470
RAT	0.006177528	0.00404807
$\ln Y$	0.51580274	0.0424016

Root-mean-square error: 0.3622302
R^2: 0.5580
Adjusted R^2: 0.5574
Dependent-variable mean: 5.898886

Note: Definitions of variables are given in Table A1.

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