HABITS AND HETEROGENEITY IN DEMANDS: A PANEL DATA ANALYSIS*

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ABSTRACT

We examine demand behaviour for intertemporal dependencies, using Spanish panel data. We present evidence that there is both state dependence and correlated heterogeneity in demand behaviour. Our specific findings are that food outside the home, alcohol and tobacco are habit forming whereas clothing and small durables exhibit durability. We conclude that demand analyses using cross-section data that ignore these effects may be seriously biased. On the other hand, the degree of intertemporal dependence is not sufficiently strong to make composite `consumption' significantly habit forming, as has been suggested in some recent analyses.

***Keywords*:** Habits, State dependence, correlated heterogeneity.

1 Introduction.

Most theoretical models of consumption and demand assume that preferences are separable over time. Common observation suggests that some goods are habit forming and some that are traditionally classified as non-durables contain durable components. This would give rise to temporal non-separabilities which may have important implications for many outcomes of interest. For example, in the analysis of the effects of tax changes (for example, the duty on alcohol and tobacco) short run effects can be quite different from long run effects. As another example, from the macro literature, a number of papers have raised the possibility that significant habit formation for 'consumption' may help resolve some 'puzzles'. Examples include Campbell and Cochrane (1999), Constantinides (1990) and Boldrin, Christiano and Fisher (2001) for the equity premium puzzle; Carroll, Overland and Weil (2000) for the inability of standard endogenous growth models to explain the causal link from high growth to high savings seen in cross-country data and Fuhrer (2000) for consumption reactions to monetary shocks.

There is a long tradition of allowing for habits in demands (see Browning (1991) for a discussion and references to the earlier literature). Amongst other things, the early phase of the literature was notable for the careful theoretical treatment of rational, forward looking behaviour with one by-product being the first use of λ-constant (or Frisch) analysis which underlies widely used Euler equation methods. The early literature culminated in Spinneweyn (1981) which gives methods to effectively convert some intertemporally non-additive models into additive ones, by a suitable transformation of variables.[1] All empirical studies in this literature were based on macro data which makes it difficult to interpret the results and to see the implications for micro behaviour. One the other hand, we have only very limited panel demand data so that micro-based approaches are difficult to implement. Consequently there are very few micro-based studies examining habits for particular goods. Examples for single goods include tobacco, Jimenez-Martin, Labeaga and Lopez (1998) and food, Dynan (2000). For systems of demands, see Hayashi (1985) (who uses one wave following households for four periods) and for utility based demand systems see Meghir and Weber (1996) and Carrasco, Labeaga and Lopez-Salido (2004). The conclusions from these studies are somewhat mixed but there is generally some evidence of some habit formation for some goods.

When thinking about habits and intertemporal dependencies in preferences from a macro perspective, it is important to acknowledge that 'consumption' is a composite of many goods. Some of these are habit forming (and some exhibit some durability). In general the habituation of 'consumption' will depend on the mix of demands and their respective degrees of habituation. For example, smokers may exhibit more persistent consumption behaviour than otherwise similar non-smokers simply because one

[1] The procedure is the analogue of using stocks and user costs instead of purchases and prices in the neoclassical durables model.

of the goods they consume is habit forming. In section 2 we present a formal link between how habit forming individual goods are and the degree of habituation in consumption that is of interest to macroeconomists. We derive a simple formula that shows that the degree of habit formation for the composite commodity 'consumption' is the sum of the product of how habit forming the individual goods are and their respective budget shares. In our empirical work we use this formula to derive the degree of habit formation for consumption from estimates of the demands for specific goods. The degree to which consumption is habit forming is far smaller than that required for the macro studies referenced in the first paragraph.

When considering persistent behaviour we have to be careful to distinguish between three possible sources of persistence in behaviour: persistence of the environment, state dependence and heterogeneity. As is well known the latter two both lead to persistence but their causes and implications are very different. Consider, for example, smoking. It is clear that the probability of someone smoking in the current period is dependent on smoking behaviour in the past, but this could be because people are 'smokers' (heterogeneity) or because something induced them to start at some point and then they continue (state dependence). To have any chance of distinguishing between heterogeneity and state dependence we need panel data with several periods of observation for each household. In our empirical analysis we use Spanish data which gives demand information for between six and eight quarters. Using the same data source, Christensen (2004) tests for whether there are (correlated) fixed effects in demands and concludes that there are and that ignoring these leads to bias in estimates of parameters of interest, such as income elasticities. Here we explicitly test for the presence of dynamic dependencies over and above those induced by heterogeneity. In section 3 we present a conventional empirical demand analysis to show that even when we take account of the persistence of the environment, there is strong evidence of additional intertemporal dependencies. In section 4 we present a GMM based analysis that specifically allows for the different effects of heterogeneity and state dependence. Our broad conclusions are that even when we allow for correlated heterogeneity, there is evidence of state dependence. Conversely, even when we allow for state dependence there is evidence of correlated heterogeneity. We find that 'food outside the home' and 'alcohol and tobacco' are habit forming and 'clothing' and 'small durables' are durable; the other two goods, 'food at home' and 'non-durables and services' do not display any significant state dependence. These conclusions will not surprise any reader but they have implications for short run and long run responses. Moreover they indicate strongly that since the two habit forming goods represent a relatively small proportion of total expenditure, it is unlikely that there are strong habits for 'consumption' itself, whether or not we include the semi-durables. We show this formally using the framework developed in section 2.

2 Habits and consumption.

As discussed in the introduction, a number of papers have suggested that habit formation for consumption will resolve various puzzles in the macroeconomic literature. In each case it seems that substantial habit formation (in a sense to made explicit in the following paragraphs) is required to reconcile the macro theory with the macro evidence. One goal of this paper is to examine whether the degree of habit formation that we see in the micro data for individual goods is consistent with the amount required in the macro literature.

We consider first the one good case. Let c_t denote expenditure in period t and let 'actual consumption' in period t be given by:

$$z_t = c_t - \lambda c_{t-1} \tag{1}$$

where $\lambda \geq 0$. It is actual consumption that enters the current period felicity function, $u_t = v(z_t)$ rather than current expenditure. If $\lambda = 0$ then we have the conventional intertemporally additive model. If $\lambda > 0$ then the utility value of current expenditure, z_t, decreases as lagged expenditure increases. For example, if $c_t = c_{t-1}$ and $\lambda = 0.4$ then actual consumption is only 60% of current expenditure. A very convenient measure of the *relative loss* due to habits is given by:

$$\chi_t = 1 - \frac{z_t}{c_t} = \lambda \frac{c_{t-1}}{c_t} \tag{2}$$

The value of χ_t is bounded between zero and unity (if we restrict $z_t \geq 0$) with higher values denoting a worse loss. Along a constant consumption path, Boldrin *et al* (2001) require a value of $\lambda = \chi = 0.73$ for a representative agent to reconcile asset return data with a standard dynamic model. It is in this sense that we state that the degree of habit formation required in the macro literature is substantial.

Turning to the many good case, let the actual consumption of good i be given by:

$$z_{it} = c_{it} - \lambda_i c_{it-1} \tag{3}$$

In this formulation each good has its own habit persistence factor, λ_i. Total expenditure and total actual consumption are given by:

$$\begin{aligned} c_t &= \sum\nolimits_{i=1}^{n} c_{it} \\ z_t &= \sum\nolimits_{i=1}^{n} z_{it} = \sum\nolimits_{i=1}^{n} (c_{it} - \lambda_i c_{it-1}) \end{aligned} \tag{4}$$

The aggregate relative loss from habit formation is defined as before:

$$\chi_t = 1 - \frac{z_t}{c_t} = \frac{\sum \lambda_i c_{it-1}}{\sum c_{it}} \tag{5}$$

If we now set $c_{it} = c_{it-1} = c_i$ and divide each individual expenditure by total expenditure to give budget shares, $\omega_i = c_i/c$ (so that $\sum \omega_i = 1$) then we have that the relative loss from habits is given by:

$$\chi_t = \sum \lambda_i \omega_i \tag{6}$$

Thus the loss depends on the product of the importance of the good (the budget share) and the degree of habituation of that good. In the empirical analysis below we shall assume that the λ_i's are common across agents but the budget shares differ. Thus we will have a different loss value for each household h:

$$\chi_{ht} = \sum \lambda_i \omega_{hi} \tag{7}$$

This is intuitively sensible. For example, if tobacco has the highest degree of habituation then households with smokers will generally display more habituation in 'consumption' than households without smokers.

3 The dynamics of expenditure patterns.

3.1 The data and the dynamics of demand

The data set we use is a rotating panel from the Spanish Family Expenditure Survey (Encuesta Continua de Presupuestos Familiares, ECPF). This survey was conducted by the Spanish Statistics Office, and it was carried out from 1985, quarter I to 1996, quarter IV. Each household is retained for at most eight quarters with one-eighth of the sample being renewed in each quarter. The sample size of each wave is around 3,200 households. The ECPF provides very detailed information on expenditure, income and household characteristics; see Browning and Collado (2001) for a detailed description of the data set. The expenditure information is a mixture of diary information (for regularly purchased goods) and retrospective information (for infrequently purchased goods). For the purpose of this research, we consider couples with and without children, in which the husband is in full-time employment in a non-agricultural activity and the wife is out of the labor force. The restrictions on labour force status are to minimise the effect of non-separabilities between demand and labour supply. We only consider families reporting full information for at least six consecutive quarters. Our final sample consists of 2,449 households (18,188 observations). We aggregate the data on expenditures into six composite commodities: food-in (food at home); food-out (food outside the home); alct (alcohol and tobacco); clo (clothing); nds (other nondurables and services) and sdur (small durables such as books, toys, pillows, etc.).[2] Table 1 presents some descriptive statistics.

Our main concern is with the dynamics of demand patterns so we concentrate on an analysis of budget shares. A fourth-order vector autoregression for budget shares revealed that there are strong dynamic effects and

[2]In our data we do observe purchases of large durables but we do not observe the stocks, so we simply assume that the demands for the six goods we model is independent of the stock of large durables. This assumption has very little other than tradition and convenience to recommend it.

high persistence for shares. The high persistence could be due to a number of factors; we discuss here three of these[3]. First the environment the household faces (demographics, lifetime wealth and expectations, etc.) is persistent which in itself induces persistence.[4] Second, there may be persistent heterogeneity. Finally, there may be state dependence - either habits or durability. In the next two sub-sections we presents analyses which takes out first of these factors (persistence in the environment) by running conventional Engel curves in levels in which we condition on demographics and total expenditure.

3.2 Demand estimation in levels.

In this subsection we examine the dynamics of expenditure patterns taking as a benchmark a conventional quadratic-log formulation (the Engel curve form of the QAIDS (see Banks *et al* (1997)). We start from this since it is nowadays the overwhelming choice of functional form to model demands on micro data if we assume intertemporal separability. We are not primarily interested in price effects so we absorb any price effects into a full set of quarterly dummies, one for each of the 48 quarters of the survey (with one dropped to accommodate the constant). The resulting form for the budget

[3] Other possible candidates are that the planning period is shorter than the quarterly period that our data imposes on us (leading to time aggregation) or that it is longer.

[4] This is the fundamental idea that underlies the Euler equation approach to intertemporal allocation. Namely that a function of the consumption of different goods (the marginal utility of money) follows a martingale.

share for good i by household h in period t, ω_{iht}, is given by:

$$\omega_{iht} = \alpha_i + \beta_{i1} \ln x_{ht} + \beta_{i2} (\ln x_{ht})^2 + \sum_k \delta_{ik} z_{kht} + u_{iht} \tag{8}$$

where x_{ht} is total expenditure deflated by a price index and z_{kht} is a list of demographics and time and seasonal dummies. Specifically: we include the number of children and the number of adults in the household, and age and age squared of the husband. The seasonal dummies are a set of 32 weekly dummies that capture the period in the year in which the household is surveyed.[5] Our empirical strategy is to first present estimates of the coefficients of (8) for our six goods on the pooled data, using conventional identifying assumptions. Specifically, we instrument the two total expenditure terms with log and squared log real income, so that the model is just identified. Including expenditures on the two durable commodities (clothing and small durables) is, of course, questionable since they exhibit some durability. We note, however, that the results for the other goods are relatively independent of the inclusion of these goods in the total expenditure measure and we prefer to include them since their durability provides a useful check on the validity of our testing methods.

The results for the Engel curve analysis are presented in Table 2. After the rows for the coefficients we present a test for the joint significance

[5] We have checked all of the results below using other specifications to capture time and seasonal effects. Although some of the quantitative results are sensitive to the specification, the broad qualitative results do not vary with the specification.

of the total expenditure coefficients and the distribution of implied income elasticities. The results are typical for demand systems estimated on cross-section data: 'food at home' and 'alcohol and tobacco' are necessities, and the other four goods are luxuries (at the median). The estimated 'effects' of the demographics are also conventional. Thus there is no internal evidence from the cross-section information that there is any misspecification and here the analysis would usually stop. However, given that we have multiple observations for each household we can examine the dynamics of the residuals.

If there is unobserved, additive individual heterogeneity, the error term in equation (8) can be written:

$$u_{iht} = \lambda_{ih} + \varepsilon_{iht} \tag{9}$$

In this formulation we only allow for persistent heterogeneity in the intercept of each equation. As discussed in Browning and Carro (2006), this restriction on how heterogeneity enters is largely for convenience and it could well be that other parameters also display persistent heterogeneity. The artificiality of the assumption is particularly obvious when modelling budget shares: if we instead chose to model expenditures (budget share multiplied by total expenditure) then the fixed effect would be for the coefficient on total expenditure and not for the intercept. Despite this shortcoming, we continue with the conventional assumption as a first approach. Since ε_{iht} may be serially correlated we have:

$$E\left(u_{iht}u_{iht-s}\right) = \sigma_{i\lambda}^2 + E(\varepsilon_{iht}\varepsilon_{iht-s}) \tag{10}$$

Thus the extent of residual autocorrelation reflects both the variation in heterogeneity (the variance of the fixed effect) and the auto-correlation in ε. If there was solely a fixed effect then the autocorrelations should be constant, whereas if good i is habit forming then the autocorrelation should decrease with s to a positive constant. For durable goods, the sign of the autocovariances related to ε_{iht} will change with s,[6] and therefore the size of the autocorrelations will not necessarily be monotone with respect to s.

In Table 3 we present first to seventh-order autocorrelations of the residuals from the Engel curves. We also present tests for first order and second order serial correlation of the residuals proposed by Arellano and Bond (1991). These test statistics are asymptotically normally distributed and they indicate that there is positive first order and second order serial correlation in the residuals. The fact that the seventh order autocorrelation is also large suggests that there is some unobserved heterogeneity for all the goods; this confirms the analysis of Christensen (2004) who finds a significant fixed effect for most goods. As regards durability and habits, the results

[6] If an agent purchases a durable good today, her expenditure tomorrow will be lower but it will increase again at some point when the durable is replaced.

are inconclusive. It seems that for goods such as 'food-out' and 'alcohol and tobacco' the autocorrelations are larger than for the remaining goods, which might indicate habits. For small durables and clothing the autocorrelations are not monotone with respect to s, which is consistent with durability.

3.3 A formal test for intertemporal separability.

The analysis of the previous subsection establishes that there are highly significant dynamics over and above those usually allowed for in empirical demand analysis. In the next section we present a detailed analysis taking account of the possible presence of correlated heterogeneity. We finish this section with a formal test for intertemporal separability using the conditional demand approach of Browning and Meghir (1991). This test is based on the observation that if we have intertemporal separability then the demands in any period, conditional on total expenditure, should be independent of demands in other periods. This gives a very simple test for intertemporal separability by simply testing for the significance of lagged budget shares in our budget share equations. Once we allow for this dependence, we never found the squared total expenditure term to be 'significant' in any equations, so we drop it from our analysis.[7] In Appendix 1 we explain in detail, using a simple example, why the square of log total expenditure may have spurious explanatory power in a QAIDS specification that ignores tempo-

[7] The results below are unaffected by the inclusion of the insignificant square terms.

ral dependencies. This analysis shows that 'getting the dynamics right' is important since not doing so may introduce spurious non-linearities.

The augmented Engel curves take the form[8]:

$$\omega_{iht} = \alpha_i + \beta_i \ln x_{ht} + \gamma_i \omega_{iht-1} + \sum\nolimits_k \delta_{ik} z_{kht} + u_{iht} \qquad (11)$$

In the absence of unobserved individual heterogeneity[9], we can test for intertemporal separability by estimating the Engel curves (11) in levels and testing whether γ_i is equal to zero in each of the equations. Under the assumption that there are no fixed effects, we can use current and lagged income and lagged total expenditures as instruments for the Engel curves in levels. We estimate the equations by GMM, using as instruments log income and its square, lags one to five of log total expenditure and its square, and of log income and the square. The specification of the Engel curves include demographics and the full set of quarterly and week dummies used in Table 2. The results from the estimates are presented in Table 4. Taken at face value (that is, ignoring the possibility of correlated heterogeneity) these results indicate strong habits in 'non-durables and services', 'food-out' and 'alcohol and tobacco' and no durability or habits in 'food-in', 'clothing' and 'small durables'. This findings for clothing and small durables results are implau-

[8] The form given here is purely for testing purposes. Since it has different right hand side variables for different goods it can never satisfy adding-up and would not be a candidate for a 'structural' demand system.

[9] We consider testing for habits with allowance for unobserved correlated heterogeneity in the next section.

sible and are quite likely to be due to unobserved correlated heterogeneity: if the latter is present, then the lagged budget shares are picking up the omitted heterogeneity term. Furthermore, the Sargan test decisively rejects the instruments for 'food-in', 'alcohol and tobacco' and 'small durables', a further indication of dynamic misspecification. Thus the conclusion we take from this analysis of levels is that even when we allow for (first order) intertemporal dependencies, there is significant evidence of further intertemporal dependencies.

4 Estimation and testing

We turn now to testing for state dependence when there is unobserved correlated heterogeneity. If there is unobserved heterogeneity, and without further assumptions, the parameters of the Engel curves (11) are not identified. The standard approach is to first difference and then estimate. As is well known, the main drawback with this approach is that often we end up with weak instruments. That is, often the correlation between the instruments and the endogenous explanatory variables is close to zero so that it is often difficult to predict changes in the explanatory variables using the available set of instruments. An alternative, proposed by Arellano and Bover (1995) (AB), is to assume that the endogenous variables have a constant correlation with the household specific effects. This additional assumption, which is empirically testable, allows us to identify the model. If this assumption holds, lagged first differences of the endogenous variables are valid instruments for the Engel curves in levels. The estimation method suggested by AB is the Generalized Method of Moments (GMM) using both sets of instruments: lagged levels of the endogenous variables for the equation in first differences, and lagged first differences of the endogenous variables for the equation in levels. Then, the Sargan test of the overidentifying restrictions can be viewed as a test of whether the assumption of constant correlation between the endogenous variables and the household specific effects is satisfied

We adopt the AB procedure but first we carry out a test for underidentification, due to Arellano, Hansen and Sentana (1999). We focus on the linear instrumental variable model, and therefore, in this setting the underidentification test is a test of weak instruments. Arellano, Hansen and Sentana (1999) propose testing for underidentification by testing the overidentifying restrictions using the standard Sargan test in an augmented model. If the overidentifying assumptions in the augmented model are rejected the conclusion is that the instruments are not weak. Since this is not a familiar test we present a brief outline in Appendix 2.

5 Results

As discussed above, we use the GMM estimator proposed by Arellano and Bover (1995) to estimate the set of Engel curves (11) without the quadratic terms.[10] The set of instruments is the following:

- For the equation in first differences we use log total expenditure and the square lagged two to five, current log income and the square and lags one to five of log income and the square
- For the equation in levels we use first differences of log total expenditure and the square lagged one to four, first differences of log income and the squared in the current period and the lags from one to four.

We use the iterated version of AB in which we use the estimated coefficients to update the weighting matrix until the estimated coefficients in two consecutive iterations are very close.

The results from these estimates are presented in Table 5. The Sargan test does not reject the set of instruments at the 4% level for any of the goods but clothing and food-in are borderline. This provides evidence in favour of the additional assumption of constant correlation between log total expenditure and the individual effects and between log income and the individual effects. We also present the weak instruments test proposed by Arellano, Hansen and Sentana (1999) (see Appendix 2). The test statistic depends on the normalization used. To normalise we set the coefficient of the budget share to one and the coefficient of log total expenditure to zero,

[10] We have also estimated the set of Engel curves including log total expenditure squared but again none of the quadratic terms were significant. Therefore, there is no evidence of non linearities between budget shares and log total expenditures as has been found in other studies.

and in the other equation, the coefficient of the budget share to zero and the coefficient of log total expenditure to one. Recalling that a large Sargan statistic is evidence in favour of identification, the results indicate that there is no problem of weak instruments for any of our goods.

Regarding intertemporal separability, we find that lagged budget shares are significant for food-out, alcohol and tobacco, clothing and small durables, whereas for food-in and non-durables and services there is no evidence of state dependence once we control for unobserved heterogeneity. The positive coefficient of the lagged budget shares in the Engel curve for food-out and alcohol and tobacco is consistent with habit formation in those commodities. The negative sign on the Engel curve for clothing and for small durables reflects the durability of these two goods.

The estimated elasticities imply that food-in and alcohol and tobacco are necessities whereas food-out, clothing and small durables are luxuries. The elasticity of non-durables and services is very close to unity. These estimated elasticities are quite different from those reported in Table 2. For instance, the median income elasticity for food-in is 0.48 when we estimate a conventional Engel curve (see Table 2), whereas this elasticity is 0.7 when we properly account for unobserved heterogeneity (see Table 5). The fact that the income elasticity goes up when we account for unobserved heterogeneity is consistent with the 'taste for food-in' being negatively correlated with income.

Finally we present some results on the relative loss from habits. We have calculated the aggregate consumption relative loss from habit formation, χ_t, for each observation in our sample using (7). The first, fifth (median) and ninth deciles are 0.01, 0.076 and 0.14 respectively. We conclude that the relative loss implied by our estimation results is small for most households and is certainly never close to the value of 0.73 required by Boldrin et al (2001) to reconcile asset return data with a standard business-cycle model..

6 Conclusions.

The degree of habit formation in commodity demands is important for many policy questions. We have presented an empirical analysis of demand behaviour using panel data from Spain that indicates that there is significant correlated heterogeneity in demands for all goods (see also Christensen (2004)). Once we take account of this heterogeneity, we find that 'food outside the home' and 'alcohol and tobacco' are habit forming and 'clothing' and 'small durables' are durable. There is no evidence of state dependence for 'food at home' and 'non-durables and services'. A further important result is that once we take account of intertemporal dependencies budget share equations seem to be linear in log total expenditure; that is, the quadratic term in QAIDS forms may be spurious. Finally, we find that estimates of income elasticities are quite sensitve to allowing for unobserved correlated heterogeneity.

Our results suggest that a conventional composite consumption measure that includes clothing and small durables would not display very strong state dependence and certainly not enough to resolve the macro puzzles mentioned in the introduction. On the other hand, the results have significant implications for tax policies that change the relative prices of specific goods such as alcoholic beverages, tobacco and eating out. In general, long term responses to these changes will be larger (in absolute magnitude) than short run responses.

7 Tables.

Table 1: Descriptive statistics (budget shares)

	food-in	nds	food-out	alct	clo	sdur
Mean	0.3560	0.3283	0.1053	0.0330	0.1283	0.0492
St. dev.	0.1365	0.1343	0.0939	0.0354	0.1050	0.0707
Q25	0.2574	0.2301	0.0359	0.0060	0.0494	0.0028
Median	0.3473	0.3151	0.0822	0.0237	0.1067	0.0228
Q75	0.4422	0.4125	0.1509	0.0476	0.1834	0.0653

Table 2. QAIDS Engel curve estimates

	food-in	nds	food-out	alct	clo	sdur
lxtot	-43.2021	-61.7144	84.2816**	-65.5613***	52.6293	33.5669
	(54.8988)	(59.7230)	(39.6140)	(25.2667)	(40.5175)	(31.4366)
lxtots	0.9600	2.8515	-3.1728**	2.4216**	-1.8972	-1.1632
	(2.0873)	(2.2727)	(1.5070)	(0.9593)	(1.5430)	(1.1961)
nch	2.3780***	-1.2599***	-0.6562***	0.1007	-0.1935	-0.3691***
	(0.1995)	(0.2018)	(0.1337)	(0.0695)	(0.1192)	(0.0913)
nad	1.5448***	-1.9335***	1.1568***	0.5341***	-0.6396***	-0.6627***
	(0.2248)	(0.2528)	(0.1766)	(0.0861)	(0.1447)	(0.0977)
hage	1.1517***	-0.1027	-0.3046*	-0.2208***	-0.0586	-0.4650***
	(0.1919)	(0.2241)	(0.1575)	(0.0789)	(0.1285)	(0.0895)
hage2	-0.0102***	0.0006	0.0025	0.0020**	0.0005	0.0045***
	(0.0021)	(0.0025)	(0.0018)	(0.0009)	(0.0014)	(0.0010)
const	399.8490	360.9525	-543.8067**	450.1072***	-346.2537	-220.8484
	(358.5995)	(389.8414)	(258.3829)	(165.2332)	(264.2957)	(205.1685)
Chi-sq(2)+	555.97	219.29	6.60	47.18	26.97	75.23
p-value	0.0000	0.0000	0.0368	0.0000	0.0000	0.0000
Income elasticities						
Q25	0.31	1.30	0.93	-0.32	1.11	1.33
Median	0.48	1.40	1.11	0.42	1.24	1.80
Q75	0.58	1.56	1.42	0.83	1.53	3.18

Note: all coefficients and standard errors are multiplied by 100.

+ Test for the joint significance of the total expenditure coefficients.

Table 3. Autocorrelations of residuals

	food-in	nds	food-out	alct	clo	sdur
1st-order	0.3749	0.3548	0.4100	0.5906	0.1180	0.1290
2nd-order	0.3528	0.3340	0.3920	0.5755	0.1631	0.1025
3rd-order	0.3428	0.3233	0.3867	0.5550	0.1139	0.0734
4th-order	0.3891	0.3522	0.4012	0.5565	0.1980	0.1558
5th-order	0.3077	0.2791	0.3498	0.5236	0.1041	0.1120
6th-order	0.2584	0.2608	0.3353	0.5004	0.1262	0.0731
7th-order	0.2847	0.2459	0.3461	0.5009	0.1143	0.0702
Test for 1st-order serial correlation	20.327	21.198	19.862	17.424	10.453	9.318
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Test for 2nd-order serial correlation	19.410	19.936	19.219	17.308	13.702	8.836
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 4. Budget shares in levels

	food-in	nds	food-out	alct	clo	sdur
lxtot	-13.6345 ***	-0.2970	0.1397	-0.2064	3.1898 ***	2.9384 ***
	(1.0623)	(0.4470)	(0.5044)	(0.1298)	(0.5317)	(0.4510)
lagged budget share	0.0008	1.0082 ***	0.9901 ***	0.5937 ***	-0.0595	-0.1450
	(0.0579)	(0.0543)	(0.0914)	(0.0787)	(0.0712)	(0.0950)
nch	2.1385 ***	0.0670	0.0631	0.0346	-0.1611	-0.5532 ***
	(0.2494)	(0.1455)	(0.1170)	(0.0419)	(0.1854)	(0.1108)
nad	1.0843 ***	-0.2958 *	0.1167	0.1806 ***	-0.6532 ***	-0.5204 ***
	(0.2584)	(0.1513)	(0.1184)	(0.0550)	(0.1950)	(0.1417)
hage	0.7684 ***	-0.1997	0.0475	-0.1192 **	0.0362	-0.4017 ***
	(0.2106)	(0.1364)	(0.1012)	(0.0527)	(0.1647)	(0.1192)
hage2	-0.0061 ***	0.0020	-0.0005	0.0011 **	-0.0006	0.0036 ***
	(0.0023)	(0.0015)	(0.0011)	(0.0006)	(0.0018)	(0.0013)
const	187.5906 ***	12.2048 **	-2.2744	7.1016 ***	-26.4115 ***	-20.1491 ***
	(14.1638)	(5.4014)	(5.0855)	(2.4682)	(6.3137)	(4.5041)
Sarg. Test	53.10	11.26	8.60	62.74	8.60	19.02
df	9	9	9	9	9	9
p-value	0.0000	0.2581	0.4746	0.0000	0.4746	0.0251
Sort-run elast.						
Q25	0.46	0.99	1.01	0.87	1.17	1.36
Median	0.60	0.99	1.01	0.93	1.28	1.79
Q75	0.69	0.99	1.03	0.96	1.53	3.05
Long-run elast.						
Q25	0.46	1.87	1.86	0.68	1.16	1.32
Median	0.60	2.14	2.50	0.84	1.27	1.69
Q75	0.69	2.57	3.93	0.91	1.50	2.79
Instruments	lxtot(-1),lxtot(-2),lxtot(-3),lxtot(-4),lxtot(-5),ly,ly(-1),ly(-2),ly(-3),ly(-4),ly(-5)					

Note: all coefficients and standard errors but the lagged budget share are multiplied by 100.

Table 5. Iterated Arellano-Bover GMM

	food-in	nds	food-out	alct	clo	sdur
lxtot	-10.4360 ***	-0.9711	2.4451 **	-1.2733 ***	5.5732 ***	4.4151 ***
	(1.9042)	(1.8716)	(1.2255)	(0.4875)	(1.5803)	(1.0275)
lagged budget share	0.0245	0.1468	0.4102 ***	0.1723 **	-0.1132 **	-0.3167 ***
	(0.0459)	(0.0966)	(0.0953)	(0.0677)	(0.0541)	(0.0618)
nch	2.0234 ***	-0.5354 **	-0.3654 ***	0.0661	-0.2880	-0.6907 ***
	(0.2412)	(0.2296)	(0.1416)	(0.0636)	(0.1897)	(0.1234)
nad	0.4486	-0.1775	0.4908 **	0.3942 ***	-0.9466 ***	-0.7361 ***
	(0.3223)	(0.3326)	(0.2099)	(0.0985)	(0.2871)	(0.1930)
hage	0.5715 **	0.6454 ***	-0.2131	-0.2075 ***	-0.0706	-0.5410 ***
	(0.2388)	(0.2425)	(0.1474)	(0.0689)	(0.1898)	(0.1401)
hage2	-0.0041	-0.0070 ***	0.0019	0.0019 ***	0.0004	0.0050 ***
	(0.0026)	(0.0027)	(0.0016)	(0.0007)	(0.0021)	(0.0015)
const	151.5133 ***	25.5409	-22.1730 *	23.6900 ***	-52.3732 ***	-33.6156 ***
	(22.1229)	(20.9289)	(13.2100)	(5.9059)	(17.4310)	(11.3386)
Sargan test	103.09	92.49	75.44	73.15	104.28	93.74
df	81	81	81	81	81	81
p-value	0.0495	0.1800	0.6535	0.7208	0.0418	0.1575
Weak Ins test statistic	274.02	268.06	213.48	246.03	289.22	283.31
df	164	164	164	164	164	164
p-value	0.0000	0.0000	0.0056	0.0000	0.0000	0.0000
Sort-run elast.						
Q25	0.59	0.96	1.15	0.19	1.30	1.55
Median	0.70	0.97	1.26	0.60	1.50	2.18
Q75	0.76	0.98	1.51	0.77	1.93	4.08
Long-run elast.						
Q25	0.58	0.95	1.25	0.02	1.27	1.42
Median	0.69	0.96	1.44	0.51	1.45	1.90
Q75	0.76	0.97	1.86	0.72	1.84	3.34
Instruments						
Eq. in levels	dlxtot(-1),dlxtot(-2),dlxtot(-3),dlxtot(-4),dly,dly(-1),dly(-2),dly(-3),dly(-4)					
Eq. in first diff.	lxtot(-2),lxtot(-3),lxtot(-4),lxtot(-5),ly,ly(-1),ly(-2),ly(-3),ly(-4),ly(-5)					

Note: all coefficients and standard errors but the lagged budget share are multiplied by 100.

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Appendix 1: The bias arising from ignoring intertemporal dependencies.

Consider the model

$$y_t = \alpha y_{t-1} + \beta x_t + u_t$$

where u_t is white noise. Suppose that x_t follows a stationary $AR(1)$ process

$$x_t = \phi x_{t-1} + \varepsilon_t$$

When we estimate by OLS the regression of y_t on x_t and x_t^2, we are estimating the coefficients of the best linear predictor of y_t given x_t and x_t^2. This best linear predictor will be

$$E^*(y_t|x_t, x_t^2) = \gamma_1 x_t + \gamma_2 x_t^2$$

where

$$\begin{pmatrix} \gamma_1 \\ \gamma_2 \end{pmatrix} = \begin{pmatrix} E(x_t^2) & E(x_t^3) \\ E(x_t^3) & E(x_t^4) \end{pmatrix}^{-1} \begin{pmatrix} E(x_t y_t) \\ E(x_t^2 y_t) \end{pmatrix}$$

Let's now calculate $E(x_t y_t)$ as a function of the moments of x_t and the parameters of the model.

$$E(x_t y_t) = E(x_t(\alpha y_{t-1} + \beta x_t + u_t)) = \alpha E(x_t y_{t-1}) + \beta E(x_t^2) \tag{12}$$

and

$$E(x_t y_{t-1}) = E((\phi x_{t-1} + \varepsilon_t) y_{t-1}) = \phi E(x_{t-1} y_{t-1}) \tag{13}$$

substituting (13) in (12) and assuming that (y_t, x_t) is stationary. We have that

$$E(x_t y_t) = \frac{\beta E(x_t^2)}{1 - \alpha\phi}$$

Analogously we can also calculate calculate $E(x_t^2 y_t)$ as a function of the moments of x_t and the parameters of the model.

$$E(x_t^2 y_t) = E(x_t^2(\alpha y_{t-1} + \beta x_t + u_t)) = \alpha E(x_t^2 y_{t-1}) + \beta E(x_t^3) \tag{14}$$

and

$$\begin{aligned} E(x_t^2 y_{t-1}) &= E((\phi x_{t-1} + \varepsilon_t)^2 y_{t-1}) = E((\phi^2 x_{t-1}^2 + \varepsilon_t^2 + 2\phi x_{t-1}) y_{t-1}) & (15) \\ &= \phi^2 E(x_{t-1}^2 y_{t-1}) & (16) \end{aligned}$$

substituting (15) in (14) and assuming that (y_t, x_t) is stationary. We have that

$$E(x_t^2 y_t) = \frac{\beta E(x_t^3)}{1 - \alpha\phi^2}$$

Then

$$\begin{pmatrix} \gamma_1 \\ \gamma_2 \end{pmatrix} = \begin{pmatrix} E(x_t^2) & E(x_t^3) \\ E(x_t^3) & E(x_t^4) \end{pmatrix}^{-1} \begin{pmatrix} \frac{\beta E(x_t^2)}{1-\alpha\phi} \\ \frac{\beta E(x_t^3)}{1-\alpha\phi^2} \end{pmatrix}$$

and γ_2 will not be zero in general unless $E(x_t^3) = 0$ (or $\phi = 1$ which is rule out by the stationarity assumption).

$$\gamma_1 = k\beta \left(E(x_t^4) \frac{E(x_t^2)}{1 - \alpha\phi} - E(x_t^3) \frac{E(x_t^3)}{1 - \alpha\phi^2} \right)$$

$$
\begin{aligned}
\gamma_2 &= k\beta\left(-E(x_t^3)\frac{E(x_t^2)}{1-\alpha\phi} + E(x_t^2)\frac{E(x_t^3)}{1-\alpha\phi^2}\right) \\
&= k\beta E(x_t^3)E(x_t^2)\left(\frac{1}{1-\alpha\phi^2} - \frac{1}{1-\alpha\phi}\right) \\
&= -k\beta E(x_t^3)E(x_t^2)\frac{\alpha\phi * (1-\phi)}{(1-\alpha\phi^2)(1-\alpha\phi)}
\end{aligned}
$$

where k is the determinant of

$$
\begin{pmatrix} E(x_t^2) & E(x_t^3) \\ E(x_t^3) & E(x_t^4) \end{pmatrix}
$$

which is always positive. Then, the sign of γ_2 is the sign of $-\alpha\beta E(x_t^3)$ (provided that ϕ is positive). Regarding the size of γ_2, it will be larger if $\alpha > 0$ than if $\alpha < 0$

Appendix 2: The AHS test for underidentification.

Consider the linear model:

$$
w_i'\alpha = u_i, \quad E(z_i u_i) = 0 \tag{17}
$$

where w_i is a $(k+1)\times 1$ vector and z_i is an $r \times 1$ ($r \geq k$) vector orthogonal to the disturbance term, the so called vector of instruments. The orthogonality conditions can be written as the set of linear equations

$$
E(z_i w_i')\alpha = 0 \tag{18}
$$

If the rank of the matrix $E(z_i w_i')$ is k, the system has a unique-up-to-scale solution and the vector of parameters α is *identified* up to scale. The normalization most commonly used is to set the first coefficient of α to one so that $\alpha = (1, \beta')'$. However, if the rank of the matrix $E(z_i w_i')$ is smaller than k, the system does not have a unique (up-to-scale) solution and it is *underidentified*.

Suppose that the rank of $E(z_i w_i')$ is $k-1$; that is, model (17) is underidentified . Then, there exist two linearly independent vectors α and α^* such that

$$E(z_i w_i')\alpha = 0 \tag{19}$$
$$E(z_i w_i')\alpha^* = 0$$

and all the solutions of system (18) can be written as linear combinations of α and α^*. When the rank of $E(z_i w_i')$ is k, (that is, model (17) is identified), system (19) does not have two linearly independent solutions and, therefore, it is overidentified. Given this, testing the null hypothesis that the model is underidentified against the alternative that it is identified is equivalent to testing whether the system of equations

$$w_i'\alpha = u_i, \quad E(z_i u_i) = 0 \tag{20}$$
$$w_i'\alpha^* = v_i, \quad E(z_i v_i) = 0$$

is just identified against the alternative of overidentification. Notice that, given that α and α^* have to be linearly independent, to estimate this set of equations it is not enough to impose a normalization on each equation but we need to impose a further normalization to guarantee linear independence. Following Arellano, Hansen and Sentana (1999), we set one of the rows of (α, α^*) to $(1, 0)$ and another row to $(0, 1)$. Independently of the normalization used, the effective number of parameters is $2k - 2$ and therefore the number of overidentifiying restrictions is $2(r - k + 1)$. The test of weak instruments consists of estimating the system of equation in (20) by GMM and then testing the overidentifiying restrictions using the Sargan test. If the Sargan test rejects the null, then, system (20) is overidentified and therefore the original model (17) is identified. On the contrary, if the Sargan test does not reject the null, then, system (20) is identified and therefore the original model (17) is underidentified.