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Habits and Heterogeneity in Demands: a Panel Data Analysis

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Habits and heterogeneity in demands: a panel data analysis.[1]

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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.

1 Introduction.

The dynamics of consumption behaviour occupies a central position in many debates in economics. Usually it is assumed that preferences are additive over time but a number of recent papers have raised the possibility that significant habit formation for 'consumption' may help resolve some 'puzzles'. (see, for example, Campbell and Cochrane (1999), Carroll, Overland and Weil (2000), Dynan (2000) and Fuhrer (2000)). As well as these explicitly macro perspectives, the degree of intertemporal dependence is also important for the validity of any results using demand estimates that assume intertemporal separability. 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. When thinking about habits and intertemporal dependencies in preferences, it is important to acknowledge that 'consumption' is a composite of many goods which differ across agents and some of which are durable and some of which may be habit forming. In general the habituation of 'consumption' will depend on the mix of demands. For example, smokers may exhibit more persistent consumption behaviour than otherwise similar non-smokers simply because one of the goods they consume is habit forming. In this paper we explicitly consider the extent of intertemporal dependencies in demand behaviour.

There is a long tradition of allowing for habits in demands (see Browning (1991) for a discussion and references of 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 it is fair to say that no one finds effects that are anywhere near strong enough to resolve the problems for 'consumption' raised in the papers listed in the previous paragraph. Nonetheless, there is some evidence of intertemporal dependencies for individual goods and it is this that we address in this paper.

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

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 t 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. Our approach is to first consider the dynamics of demands in a time series analysis which does not make explicit use of demand theory. We then present empirical demand analysis to consider the specific contributions of environmental persistence, state dependence and heterogeneity. Our broad conclusions are that even when we allow for correlated heterogeneity (a ‘fixed effect’), 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 readers 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.

2 The dynamics of expenditure patterns.

2.1 The data and the dynamics of demand

The data set 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]

Our main concern is with the dynamics of demand patterns so we concentrate on an analysis of budget shares. Table 1 presents a fourth-order vector autoregression (VAR(4)) for the levels of budget shares. We have estimated each equation separately by OLS. For each good the right hand side variables are the first four lags of all budget shares, except those for 'nds'. The latter are dropped to accommodate adding-up and the equation for 'nds' is also dropped. It will be seen that there are strong dynamic

[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.

effects and high persistence. The high persistence could be due to a number of factors. First the environment the household faces (demographics, lifetime wealth and expectations, etc.) is persistent which in itself induces persistence.[3] Second, there may be 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.

2.2 A utility based demand levels system.

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

$$\omega_{iht} = \alpha_i + \beta_{i1} \ln x_{ht} + \beta_{i2} (\ln x_{ht})^2 + \sum\nolimits_k \delta_{ik} z_{kht} + u_{iht} \qquad (1)$$

[3] 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.

where x_{ht} is total expenditure deflated by a price index and z_{kht} is a list of demographics and time and weekly 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.[4] Our empirical strategy is to first present estimates of the coefficients of (1) 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 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

[4] 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.

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 (1) can be written:

$$u_{iht} = \lambda_{ih} + \varepsilon_{iht} \tag{2}$$

Since ε_{iht} may be serially correlated we have:

$$E\left(u_{iht}u_{iht-s}\right) = \sigma_{i\lambda}^2 + E(\varepsilon_{iht}\varepsilon_{iht-s}) \tag{3}$$

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,[5] and therefore the size of

[5] 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.

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). This 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 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 might indicate durability.

2.3 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 careful account of the possible presence of correlated heterogeneity. We finish this section with a formal tests 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. This already suggests that 'getting the dynamics right' is important since not doing so may introduce spurious non-linearities. The augmented Engel curves take the form[6]:

$$\omega_{iht} = \alpha_i + \beta_i \ln x_{ht} + \gamma_i \omega_{iht-1} + \sum\nolimits_k \delta_{ik} z_{kht} + u_{iht} \tag{4}$$

In the absence of unobserved individual heterogeneity, we can test for intertemporal separability by estimating the Engel curves (4) in levels and testing whether β_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

[6]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.

1. The results from the estimates are presented in Table 4. If the assumption of no fixed effect were correct, the results in Table 4 will indicate very 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 latter result is very implausible and is very likely driven by unobserved correlated heterogeneity: if there is the latter, 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.

3 Estimation and testing

3.1 Testing for weak instruments.

We turn now to testing for state dependence when there is unobserved heterogeneity. If there is unobserved heterogeneity, and without further assumptions, the parameters of the Engel curves (4) are not identified. However, identification can be achieved by taking first differences to eliminate the household specific effects and then using lagged values of the endogenous variables as instruments. The main problem with this approach is that, in general, it is often difficult to predict changes in the explanatory variables using the available set of instruments; that is, the correlation between the instruments and the endogenous explanatory variables is close to zero. If this is the case, the instruments are said to be weak and the model is under-identified or close to be underidentified.[7] Another alternative, proposed by Arellano and Bover (1995), 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 Arellano and Bover (1995) uses 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.

We adopt the Arellano and Bover 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. Since this is not a familiar test we present here a brief outline for the linear model:

$$w_i'\alpha = u_i, \quad E(z_i u_i) = 0 \tag{5}$$

[7] We have estimated the set of Engel curves in equation (1) in first differences and the results point out to a potential poor instruments problem. We calculated very large standard errors and implausible point estimates for the estimated elasticities.

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

$$E(z_i w_i')\alpha = 0 \tag{6}$$

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 (5) is underidentified . Then, there exist two linearly independent vectors α and α^* such that

$$\begin{aligned} E(z_i w_i')\alpha &= 0 \\ E(z_i w_i')\alpha^* &= 0 \end{aligned} \tag{7}$$

and all the solutions of system (6) can be written as linear combinations of α and α^*. When the rank of $E(z_i w_i')$ is k, (that is, model (5) is identified), system (7) 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

$$
\begin{aligned}
w_i'\alpha &= u_i, \quad E(z_i u_i) = 0 \\
w_i'\alpha^* &= v_i, \quad E(z_i v_i) = 0
\end{aligned} \tag{8}
$$

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 (8) by GMM and then testing the overidentifiying restrictions using the Sargan test. If the Sargan test rejects the null, then, system (8) is overidentified and therefore the original model (5) is identified. On the contrary, if the Sargan test does not reject the null, then, system (8) is identified and therefore the original model (5) is underidentified.

4 Results

As discussed above, we use the GMM estimator proposed by Arellano and Bover (1995) to estimate the set of Engel curves (4) without the quadratic terms.[8] 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.

The results from these estimates are presented in Table 5. The Sargan test does not reject the set of instruments at the 5% level for any of the goods but clothing. 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). The test statistic depends on the normalization used, therefore, we use two different normalizations to check the robustness of our results. Normalization 1 corresponds to setting in one equation the coefficient of the budget

[8] 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.

share to one and the coefficient of log total expenditure to zero, and in the other equation, the coefficient of the budget share to zero and the coefficient of log total expenditure to one. Normalization 2 corresponds to setting in one equation the coefficient of the budget share to one and the coefficient of the lagged budget share to zero, and in the other equation, the coefficient of the budget share to zero and the coefficient of the lagged budget share 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 food-in, alcohol and tobacco, clothing and small durables. For non-durables and services and food-out the result provide slight evidence of weak instruments depending on the normalization used.

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. 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.

5 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 'nondurables and services'. This suggests 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 prices of goods such as alcoholic beverages, tobacco and eating out relative to other goods. In general, long term responses to these changes will be larger (in absolute magnitude) than short run responses.

6 Tables.

Table 1

VAR(4)

	food-in	food-out	alct	clo	sdur
w(t-1)	0.2417***	0.2118***	0.2529***	0.0848***	0.1294***
	(0.0144)	(0.0142)	(0.0148)	(0.0132)	(0.0150)
w(t-2)	0.2077***	0.1889***	0.2217***	0.1705***	0.0649***
	(0.0139)	(0.0131)	(0.0168)	(0.0129)	(0.0114)
w(t-3)	0.1774***	0.1716***	0.1615***	0.0722***	0.0409***
	(0.0139)	(0.0139)	(0.0156)	(0.0119)	(0.0114)
w(t-4)	0.2524***	0.2253***	0.2084***	0.1989***	0.1842***
	(0.0133)	(0.0145)	(0.0161)	(0.0134)	(0.0150)
Food-in feedback from	food-out***, alct**, clo***, sdur***				
Food-out feedback from	alct***, clo***, sdur***				
Alct feedback from	food-in***, food-out***, clo***, sdur*				
Clo feedback from	food-in***, food-out***, alct***, sdur***				
Sdur feedback from	food-in***, food-out***, clo***				

Table 2

	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 values are multiplied by 100.

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

	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	0.0008	1.0082***	0.9901***	0.5937***	-0.0595	-0.1450
share	(0.0579)	(0.0543)	(0.0914)	(0.0787)	(0.0712)	(0.0950)
nch	1.0843***	-0.2958*	0.1167	0.1806***	-0.6532***	-0.5204***
	(0.2584)	(0.1513)	(0.1184)	(0.0550)	(0.1950)	(0.1417)
nad	0.7684***	-0.1997	0.0475	-0.1192**	0.0362	-0.4017***
	(0.2106)	(0.1364)	(0.1012)	(0.0527)	(0.1647)	(0.1192)
hage	-0.0061***	0.0020	-0.0005	0.0011**	-0.0006	0.0036***
	(0.0023)	(0.0015)	(0.0011)	(0.0006)	(0.0018)	(0.0013)
hage2	187.5906***	12.2048**	-2.2744	7.1016***	-26.4115***	-20.1491***
	(14.1638)	(5.4014)	(5.0855)	(2.4682)	(6.3137)	(4.5041)
const	0.2164	-2.3806	-1.0619	-0.9870**	-1.6425	-0.5331
	(1.3972)	(2.2214)	(1.4350)	(0.4047)	(1.3779)	(1.0093)
Sargan 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
Short run income elasticity						
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 income elasticity						
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

Table 5

	food-in	nds	food-out	alct	clo	sdur
lxtot	-10.2905***	-1.3736	2.8511**	-1.3104***	5.5527***	4.6048***
	(1.9351)	(1.9652)	(1.3271)	(0.5001)	(1.5868)	(1.0466)
lagged budget	0.0216	0.1107	0.3789***	0.1571**	-0.1197**	-0.3081***
share	(0.0464)	(0.0984)	(0.0997)	(0.0694)	(0.0542)	(0.0628)
nch	0.4369	-0.1355	0.4533*	0.3985***	-0.9362***	-0.7650***
	(0.3289)	(0.3543)	(0.2320)	(0.1019)	(0.2891)	(0.1952)
nad	0.5515**	0.7280***	-0.2480	-0.2154***	-0.0669	-0.5505***
	(0.2460)	(0.2621)	(0.1703)	(0.0743)	(0.1925)	(0.1411)
hage	-0.0039	-0.0079***	0.0022	0.0020**	0.0004	0.0051***
	(0.0027)	(0.0029)	(0.0019)	(0.0008)	(0.0021)	(0.0015)
hage2	150.1821***	30.0620	-26.1584*	24.3895***	-52.1436***	-35.7823***
	(22.4692)	(22.0534)	(14.4013)	(6.0485)	(17.5138)	(11.5477)
const	0.9234	2.0268	1.4061	-0.2085	-2.9939***	-1.0845
	(1.1858)	(1.2626)	(0.9619)	(0.2461)	(1.0672)	(0.8604)
Sargan Test	100.45	89.27	74.67	67.45	104.66	92.73
df	81	81	81	81	81	81
p-value	0.0705	0.2479	0.6766	0.8594	0.0397	0.1757
Weak Instrument test						
Normalization 1	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
Normalization 2	331.52	185.28	173.82	225.44	309.78	240.45
df	164	164	164	164	164	164
p-value	0.0000	0.1222	0.2850	0.0010	0.0000	0.0001
Short run income elasticity						
Q25	0.59	0.94	1.17	0.16	1.30	1.57
Median	0.70	0.96	1.30	0.58	1.50	2.24
Q75	0.77	0.97	1.59	0.76	1.93	4.21
Long run income elasticity						
Q25	0.58	0.93	1.28	0.01	1.27	1.44
Median	0.70	0.95	1.49	0.51	1.44	1.94
Q75	0.76	0.96	1.95	0.72	1.83	3.46

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