Demographic vs Expenditure Flexibility in Engel curves

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Abstract

We consider the e¤ects of demographic and expenditure variables on consumer demand in a system of Engel curves using a smooth coe¢cient semiparametric model where the expenditure e¤ects on the budget shares vary nonparametrically with continuous demographic variables such as the age of head and number of children in the household. This model is used together with a linear semiparametric and a polynomial parametric model to investigate the extent to which demographic e¤ects can be reparameterised into expenditure e¤ects and vice versa, and …nd an appropriate Engel curve speci…cation. Our …ndings, based on UK micro data, suggest that with a smooth coe¢cient semiparametric model there is no need for nonlinear logarithmic expenditure e¤ects in the budget shares. Furthermore, we …nd evidence of a trade-o¤ between demographic and expenditure e¤ects in Engel curves and that a rank-2 system of Engel where the logarithmic expenditure e¤ects are allowed to vary with demographic characteristics either nonparametrically or as a third degree polynomial function cannot be rejected againts a rank-3 (quadratic logarithmic) model.

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1 Introduction

There has been considerable interest in econometrics in developing models that incorporate both parametric and nonparametric components. The regression relationship is usually expressed in terms of variables that enter parametrically because they are known to interact with the dependent variable in a speci…c way, and those that enter nonparametrically since there is no a-priori reason for them to follow a particular pattern.

In the context of Engel curves most empirical studies allow demographic and other household characteristics to enter parametrically and expenditure to enter nonparametrically. This is because knowledge of the expenditure e¤ect on demand is of primary concern in analysing consumer behaviour and welfare and the use of nonparametric methods is part of the e¤ort to …nd appropriate ways of modelling this e¤ect in empirical applications. In particular, investigators have been interested in the rank of demand system, the maximum dimension of the expenditure space spanned by Engel curves, given that demand systems with a rank above three cannot be integrable (Gorman 1981, Lewbel 1991).

This paper is motivated by the empirical …nding that while the rank of Engel curves tends to be above three in studies that do not control for demographic heterogeneity in preferences (Grodal and Hildenbrand 1992, Hildenbrand 1994 and Kneip 1994), it becomes three or two when either (a) a relatively small, demographically homogeneous subset of data is used (Lewbel 1991, Banks, Blundell and Lewbel 1997, Donald 1997 and Hausman, Newey and Powell 1995); or (b) the e¤ects of demographic heterogeneity are removed using a semiparametric estimation technique (Lyssiotou, Pashardes and Stengos 1999). These …ndings suggest that the e¤ects of demographic characteristics on consumer demand may not be as uncomplicated as commonly assumed and a search for an appropriate Engel curve speci…cation may have to place as much emphasis on avoiding a-priori restrictions on demographic e¤ects as it does on the expenditure e¤ects.

To examine this issue, we employ a smooth coefficient model combining parametric and nonparametric components: the large number of household characteristics typically captured by binary variables (genter, housing location and tenure, occupation etc.) enter linearly while a important continuous demographic variables such as the age of the household head and/or the number of children, are allowed to directly affect the coefficients of the model. Thus, unlike the linear semiparametric model, the smooth coefficient approach yields expenditure effects that vary with consumer characteristics. In fact, it is a special case of a varying coefficient model offering a particular way of combining parametric and nonparametric components, see Fan and Zhang (1999), Cai, Fan and Li (2000) and Cai, Fan and Yao (2000). Li et al. (2001) used such a model to estimate the production function of the non-metal mineral industry in China.

The framework of analysis in the paper is a system of Engel curves that vary with a vector of exogenous characteristics z_h and the logarithm of the budget level y_h. For a given good, the observed Engel curve (budget share) w for household h can be written as,

$$w(z_h, y_h) = a(z_h) + d(z_h) f(y_h) \tag{1}$$

where $a(z_h)$, $d(z_h)$ and $f(y_h)$ are unknown functions. We shall use (1) to discuss and investigate empirically:

(i) appropriate empirical specifications for the $a(z_h)$, $d(z_h)$ and $f(y_h)$ functions,

(ii) the extent to which z_h can be reparameterised into y_h effects and vice versa, and

(iii) the behavioural and welfare implications of such reparameterisations.

Various approaches to searching for an empirically adequate specification of Engel curves can be seen as special cases of (1). For example, the restriction $d(z_h) = 1$, yields the Additively Separable Regression model used by Lyssiotou, Pashardes and Stengos (2002). If we also assume that $a(z_h) = z_h'\alpha$, where z_h is of dimension $p \times 1$ and a an unknown parameter of dimension $p \times 1$, we obtain the semiparametric partially linear model (Engle et. al. 1986, Robinson 1988 and Stock 1989),

$$w_h = z_h'\beta + f(y_h) + u_h. \tag{2}$$

This model has been used in the literature to recover the accurate specification of the Engel curve relation (Blundell, Duncan and Pendakur 1998).

The smooth coefficient semiparametric model considered in this paper is also a special case of (1). Unlike (2), however, is parametric in $f(y_h)$ and nonparametric in $a(z_h)$ and $d(z_h)$,

$$w_h = a(z_h) + y_h d(z_h) + \varepsilon_h. \tag{3}$$

We use (3) to investigate whether the presence of unrestricted demographic effects in the empirical specification bears on the effects of y_h. We also use this model as a benchmark to test the empirical performance of the Engel curves of the Quadratic Logarithmic model (Lewbel 1990, Banks, Blundell and Lewbel 1997), a rank-3 demand system generally found through (2) to be an empirically adequate parametric specification.

Comparison of results obtained from the linear and smooth coefficient semiprametric models can yield conclusions about the extent to which demographic flexibility can help reduce expenditure flexibility but cannot tell us how (2) and (3) perform relative to (2), the specification in which they are nested. To find how higher demographic and higher expenditure flexibility fare against a model that has both we shall assume that $a(z_h)$; $d(z_h)$ and $f(y_h)$ in (1) have polynomial functional form and how a decrease in demographic flexibility (lowering the degree of the $a(z_h)$ and $d(z_h)$; polynomials) compares with a decrease in expenditure flexibility (lowering the degree of $f(z_h)$) in terms of fitting the data. This parametric tests can also help investigate whether higher order terms in $a(z_h)$ and $d(z_h)$ can be parameterised into higher order terms in $f(y_h)$; and vice versa; and if so which parameterisation is statistically more adequate on empirical grounds.

The next section presents the basic structure of a smooth coefficient semiparametric model as applied to Engel curves and reports empirical results obtained from the application of this model to UK individual household data drawn from the 1980 Family Expenditure Survey. Section 3 describes the parametric model used in our analysis and also reports results obtained from the same dataset. Section 4 concludes the paper.

2 Demographic vs expenditure nonparametric effects

As in the previous section, w_h denotes the dependent variable, z_h be $p \times 1$ and y_h a one-dimensional variable. We write (3) as

$$\begin{aligned} w_h &= (1, y_h) \begin{pmatrix} \alpha(z_h) \\ d(z_h) \end{pmatrix} + \varepsilon_h \\ &= Y_h^T \xi(z_h) + \varepsilon_h \end{aligned} \tag{4}$$

where $\xi(z_h) = (\alpha(z_h), d(z_h))^T$ is a smooth but unknown function of z_h. One can then estimate $\xi(z_h)$ at each point z using a local least squares approach, where

$$\begin{aligned} \hat{\xi}(z) &= [(n\theta^p)^{-1} \sum_{h=1} Y_h Y_h^T K(\frac{z_h - z}{\theta})]^{-1} \{(n\theta^p)^{-1} \sum_{h=1} Y_h w_h K(\frac{z_h - z}{\theta})\} \\ &= [D_n(z)]^{-1} A_n(z) \end{aligned} \tag{5}$$

and $D_n(z) = (n\theta^p)^{-1} \sum_{h=1}^{n} Y_h Y_h^T K(\frac{z_h - z}{\theta})$, $A_n(z) = (n\theta^p)^{-1} \sum_{h=1}^{n} Y_h w_h K(\frac{z_h - z}{\theta})$, is a kernel function and $\theta = \theta_n$ is the smoothing parameter for sample size n.

The intuition behind the above local least-squares estimator is straightforward.. Let us assume that z is a scalar and $K(.)$ is a uniform kernel. In this case the expression for $\hat{\xi}(z)$ becomes

$$\hat{\xi}(z) = [\sum_{|z_h - z| \le b} Y_h Y_h^T]^{-1} \sum_{|z_h - z| \le b} Y_h w_h \tag{6}$$

In this case $\hat{\xi}(z)$ is simply a least squares estimator obtained by regressing w_h on Y_h using the observations of (Y_h, w_h) that their corresponding z_h is close to z $(|z_h - z| \le \theta)$. Since $\xi(z)$ is a smooth function of z, $|\xi(z_h) - \xi(z)|$ is small when $|z_h - z|$ is small. The condition that nb^p is large ensures that we have sufficient observations within the interval $|z_j - z| \le b$ when $\xi(z_h)$ is close to $\xi(z)$. Therefore, under the conditions that

$b \to 0$ and $nb^p \to \infty$, one can show that the local least squares regression of w_h on Y_h provides a consistent estimate of $\xi(z)$. In general it can be shown that

$$\sqrt{nb^p}\,(\hat{\xi}(z) - \xi(z)) \to N(0, \Omega)$$

where Ω can be consistently estimated.

We apply this method to estimate a system of Engel curves consisting of six categories of non-durable goods: food, alcohol, fuel, clothing, other goods and services. The data are drawn from the 1980 UK Family Expenditure Survey and include all two-adult households whose head is under retirement age and not self-employed. The size of the sample is 1305 observations. For each household, in addition to expenditure on each of the six categories of goods above, we have information about a large number of demographic and other characteristics, such as the family size and age composition, the sex, employment and economic position of members, the geographical location and housing tenure, the ownership of cars, domestic appliances and other durables etc. Specifically we use a model that is a simple generalization of equation (4), where we allow for some of the demographic characteristics (in particular the ones that are described by dummy variables) to enter the regression function separately. We denote these variables as z_{1h}, whereas the demographic characteristic of interest, denoted by z_{2h}, is allowed to enter the regression function nonparametrically as an argument of the coefficient $\xi(\cdot)$ in equation (4).

The regression function that we estimate is written as

$$\begin{aligned} w_h &= z_{1h}^T \gamma + (1, y_h, y_h^2) \begin{bmatrix} \alpha(z_{2h}) \\ \beta(z_{2h}) \\ \lambda(z_{2h}) \end{bmatrix} + \varepsilon_h \\ &= z_{1h}^T \gamma + Y_h^T \xi(z_{2h}) + \varepsilon_h \qquad (7) \end{aligned}$$

where $\xi(z_{2h}) = (\alpha(z_{2h}), d(z_{2h}))^T$ where $d(z_{2h}) = (\beta(z_{2h}), \lambda(z_{2h}))$ and $Y_h^T = (1, y_h, y_h^2)^T$. The z_{2h} variables that we use include the age of household head and the number of children; hence $p = 1$. We find that either of these two characteristics gives us very similar results and they are sufficient to capture by themselves any nonlinearity in expenditure effects due to heterogeneity that arise in the specification of the Engel curves that we examine.

The diagrams in Figures 1-4 show how $\alpha(z_{2h})$; $d(z_{2h})$ $\lambda(z_{2h})$ in (7)vary with the age of the household head for food, alcohol, fuel and clothing. The function $\alpha(z_{2h})$; is represented by the continuous line, $d(z_{2h})$ by the long-segments discontinuous line and $\lambda(z_{2h})$ by the short-segments discontinuous line. The striking feature of these diagrams is that $\lambda(z_{2h})$ are very close to zero throughout the age range in all the diagrams, whereas $d(z_{2h})$ and $\lambda(z_{2h})$ exhibit substantial variation over age.

The results in Figures 1-4 suggest that when the age effects on consumer demand are allowed to enter nonparametrically, a rank-2 system of Engel curves may not be statistically inadequate. To investigate this finding further, we compare the predicted budget shares at different log-expenditure levels obtained from the smooth coefficient model (7), with the results obtained from the linear semiparametric model, as defined by (2). The results of this comparison are shown in the diagrams of Figures 5-8. The continuous line represents the predictions of the rank-2 smooth coefficient model and the discontinuous line the predictions corresponding to the linear semiparametric model. As seen from the diagrams, the predictions from the two models are close to each other except for the extremes of log-expenditure distribution: for food, fuel and clothing the two models differ at the lower end of the log expenditure distribution, whereas for alcohol they differ at the upper end of the log expenditure distribution.

One conclusion emerging from the diagrams of Figures 5-8 is that for a wide range of expenditure, it makes no difference in terms of prediction whether one uses a linear in logarithmic system of Engel curves where the log expenditure effects vary nonparametrically with age or a system of Engel curves that are parametrically linear in demographic characteristics and nonparametric in log expenditure. This trade off between demographic and expenditure flexibility in the system of Engel curves under consideration is investigated further using a parametric approach in the next section.

However, the differences in predictions obtained from two models at the extremes of log expenditure distribution raises the question whether these differences are statistically significant and if so which of the two models is more appropriate. To answer this question we use the one-sited t-statistic described in the Appendix to test the rank-3 quadratic logarithmic system of Engel curves given by equation (13), found elsewhere to be a statistically adequate empirical model, against the smooth coefficient model (7) considered in this paper. The value of this statistic is calculated at 3.7651, whereas its critical value at 5% significance level is 1.1051. This suggests that the rank-3 quadratic logarithmic model is rejected against the rank-2 smooth coefficient model.

3 Demographic vs expenditure effects in parametric models

The analysis in the previous section shows that when the effects of demographic variables enter Engel curves nonparametrically, there is no need for quadratic logarithmic expenditure effects in these curves. This suggests that it may be possible to also do away with the same effects in a parametric specification of Engel curves if the demographic effects enter in a functionally flexible manner.

To investigate this point we allow the $a(z_h); d(z_h)$ and $f(y_h)$ functions in (1) to have the following polynomial :

$$a(z_h) = \sum_{m=0}^{M} a_m z_{2h}^m; \quad d(z_h) = \sum_{k=0}^{K} d_k z_{2h}^k; \text{ and } f(y_h) = \sum_{r=1}^{R} f_{r-1} y_h^{r-1} \qquad (8)$$

where z_{2h} are as defined in the previous section.

Then, for $M = 1; K = 1$ and $R = 2$ we have the rank-2 budget share equation system corresponding to the Almost Ideal (AI) demand system of Deaton and Muellbauer (1980)

$$w(z_h; y_h) = \delta_0 + \delta_1 z_{2h} + (\beta_0 + \beta_1 z_{2h}) y_h \qquad (9)$$

where $\delta_0 = a_0 + d_0 f_0$; $\delta_1 = a_1 + f_0 d_1$; $\beta_0 = f_1 d_0$; and $\beta_1 = f_1 d_1$: If $K = 0$, then $\beta_1 = 0$ and changes in the budget budget level have a uniform effect on demand across households with different characteristics z_{2h}:

Also, for $M = 1, K = 1$ and $R = 3$ we have the rank-3 budget share equation system corresponding to the Quadratic Almost Ideal Demand System (QUAIDS) of Banks, Blundell and Lewbel (1997)

$$w(z_h, y_h) = \delta_0 + \delta_1 z_{2h} + (\beta_0 + \beta_1 z_{2h}) y_h + (\lambda_0 + \lambda_1 z_{2h}) y_h^2 \qquad (10)$$

where $\lambda_0 = f_2 d_0$, and $\lambda_1 = f_2 d_1$.

In the empirical analysis below we investigate these and more complicated systems resulting for choosing higher values for M, K and R with a view to finding whether there is competition between greater demographic flexibility (larger values for M and K) and log expenditure flexibility (larger values for R). Indeed, this is a likely phenomenon because, as is well known, z_{2h} and y_h tend to be correlated in the data, e.g. the household budget increases with the number of children in the family.

To see this let $E(y_h z_h) = \gamma_{zy} E(y_h^2)$ where γ_{zy} is the regression coefficient part of z_{2h} on y_h. Then (9) can be written as

$$E(w) = \delta_0 + \delta_1 E(z_{2h}) + \beta_0 E(y_h) + \beta_1^* E(y_h^2) \qquad (11)$$

where $\beta_1^* = \gamma_{zy} \beta_1$ making the demand system appear as a rank-3. Given the significance of β_1, one may not reject the empirical hypothesis that (11) is a rank-3 model if γ_{zy} is significant.

The opposite, however, is also true, e.g. the rank of the demand system can be understated if log expenditure is parameterised as demographic flexibility, e.g. replacing $E(y_h z_h) = \gamma_{yz} E(z_h^2)$ where γ_{yz} is the regression coefficient part of y_h on z_h. Then (10) can be written as a rank-2 demand system

$$E(w) = \delta_0 + \delta_1 E(z_{2h}) + \beta_0 E(y_h) + \beta_1' E(z_{2h}^2) + \lambda_0 E(y_h^2) + \lambda_1' E(z_{2h}^2) \qquad (12)$$

where $\beta_1' = \beta_1 \gamma_{yz}$ and $\lambda_1' = \lambda_1 \gamma_{y^2 z}$. In this case, when $\lambda_0 = 0$ the demand system can be mistaken for a rank-2 in empirical application.

To investigate the arguments above on empirical grounds, we define z_{2h} to be the age of the household head and estimate the system of Engel curves (1) assuming $M = 3, K =$

3; and $R = 3$; i.e. a rank-3 specification with up to cubic demographic effects everywhere. Also, we condition on a number of other household characteristics, besides the age of household head, included in vector z_{1h} and found by previous studies to significantly affect demand behavior. We then use this specification as our maintained hypothesis to test alternative assumptions about the degrees of the polynomials (8). Table 1 reports the p-values corresponding these tests. As seen form the p-values corresponding to the rank-2 demand system, a system of Engel curves with linear logarithmic expenditure effects cannot be rejected against the rank-3 model at the 5% significance level if these effects are allowed to vary with; (i) age and its square ($K = 2$) and the intercept of the budget share equations also include the same variables ($M = 2$); or (ii) age, its square and its cubic ($K = 3$) and the intercept of the budget share equations includes age ($M = 1$):

It is clear from the results reported in Table 1 than age effects on the budget shares can be reparameterised in logarithmic expenditure effects, and vice versa. For example, a rank-2 model with up to cubic age effects in the intercept and logarithmic expenditure effects varying with age and age square ($R = 2$; $M = 3$; $K = 2$) has the same p-value when tested against the null, as a rank-3 model with age effects in the intercept and linear and quadratic logarithmic expenditure effects varying with age and age square ($R = 3$; $M = 1$; $K = 2$):

4 Conclusion

This paper investigates two prominent features of micro-level Engel curves expressed in budget share form: nonlinearity and heterogeneity of the logarithmic expenditure effects. This investigation is performed using nonparametric and parametric methods.

For the nonparametric analysis we use a smooth coefficient semiparametric model, a member of the varying coefficient models. In this model the nonparametric components relate to the effects of demographic characteristics (age and children), unlike the linear semiparametric model where the nonparametric component corresponds to the effects of logarithmic expenditure. The empirical results based on UK household data for six commodities show that with a smooth coe¢cient semiparametric model there is no need for nonlinear logarithmic expenditure e¤ects in the budget shares. This, together with the …nding that the smooth coe¢cient and linear semiparametric models yield similar predictions over a wide expenditure range suggests that there can be a trade-o¤ between allowing more ‡exibility in the demographic and expenditure e¤ects in Engel curves. However, at the extremes of expenditure distribution the two models suggest considerably di¤erent consumer behaviour. Notably, the rank-3 quadratic logarithmic system of Engel curves, where the logarithmic expenditure e¤ects are not allowed to vary with demographic characteristics, is rejected against the rank-2 smooth coe¢cient model.

Further investigation of the extent to which there is a trade o¤ between demographic and expenditure e¤ects in Engel curves and the implications of these for the empirical speci…cation of Engel curves is conducted using a parametric model where these effects are allowed to enter in a polynomial form. The results rea…rm the …ndings of the nonparametric investigation in the sense that a system of linear logarithmic cannot be rejected against a quadratic logarithmic system of Engel curves when the expenditure e¤ects are allowed to interact with a cubic age function. The empirical results from the parametric analysis also suggest that age e¤ects on the budget shares can be reparameterised in logarithmic expenditure e¤ects, and vice versa.

The …nding that ignoring nonlinear interactions of demographic characteristics with logarithmic expenditure can be responsible for nonlinear logarithmic expenditure e¤ects in a system of Engel curves can have important policy implications. For example, mistaking age as expenditure e¤ects on the budget share of fuel can result in wrong calculation of weather related bene…ts paid to old age pensioners. The study of such implications is an interesting topic for further research.

Appendix

We will present below a test statitistic that was used by Li et al. (2001). In our implementation we will use a bootstrap version of this test. Let y_i denote the dependent variable, and let x_i be $p \times 1$ and z_i be $q \times 1$ vectors of exogenous variables. Consider the following linear model

$$
\begin{aligned}
w_h &= z_1^T \gamma(z_i) + \alpha_0(z_{2h}) + y_h^T d_0(z_{2h}) + y_h^{2T} \lambda_0(z_{2h}) + \varepsilon_h \\
&= z_1^T \gamma(z_i) + Y_h^T \xi_0(z_{2h}) + \varepsilon_h \qquad (13)
\end{aligned}
$$

where $\xi_0(z_{2h}) = (\alpha_0(z_{2h}), d_0(z_{2h}), \lambda_0(z_{2h}))^T$ is a smooth known function of z, denoted by the subscript 0.

We can test the adequacy of (A1), the H_0, against the smooth coefficient semiparametric alternative (7) using the following test statitistic.

$$
\begin{aligned}
\hat{I}_n &= \frac{1}{n^2\theta^p} \sum_h \sum_{h \neq s} Y_h^T (w_h - Y_h^T \hat{\xi}_0(z_{2h})) Y_s (w_s - Y_s^T \hat{\xi}_0(z_{2s})) K\left(\frac{z_{2s} - z_s}{\theta}\right) \\
&= \frac{1}{n^2\theta^p} \sum_h \sum_{h \neq s} Y_h^T Y_s \hat{u}_h \hat{u}_s K\left(\frac{z_{2s} - z_s}{\theta}\right)
\end{aligned}
$$

where $\hat{u}_h$ denotes the residual from parametric estimation (under H_0). It can be shown that under H_0, $J_n = n\theta^{p/2} \hat{I}_n / \hat{\sigma}_0 \longrightarrow N(0,1)$, where $\hat{\sigma}_0$ is a consistent estimator of the variance of $\hat{I}_n$, see Li et al (2001). It can be shown that the test statistic is a consistent test for testing H_0 (equation (??)) against H_1 (equation (7)). We use a bootstrap version of the above test statistic, since boostrapping improves the size performance of kernel based tests for functional form, see Zheng (1996) and Li and Wang (1998).

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Table 1:

P-values of various specifications tested against a rank-3 model with up to cubic demographic effects

Polynomial degree		P-value	
M	K	Rank-2	Rank-3
3	3	0.2577	
3	2	0.3158	0.8773
3	1	0.0318	0.0968
2	3	0.3521	0.8152
2	2	0.1899	0.5176
2	1	0.0218	0.0642
1	3	0.0617	0.0458
1	2	0.0356	0.3060
1	1	0.0107	0.0221

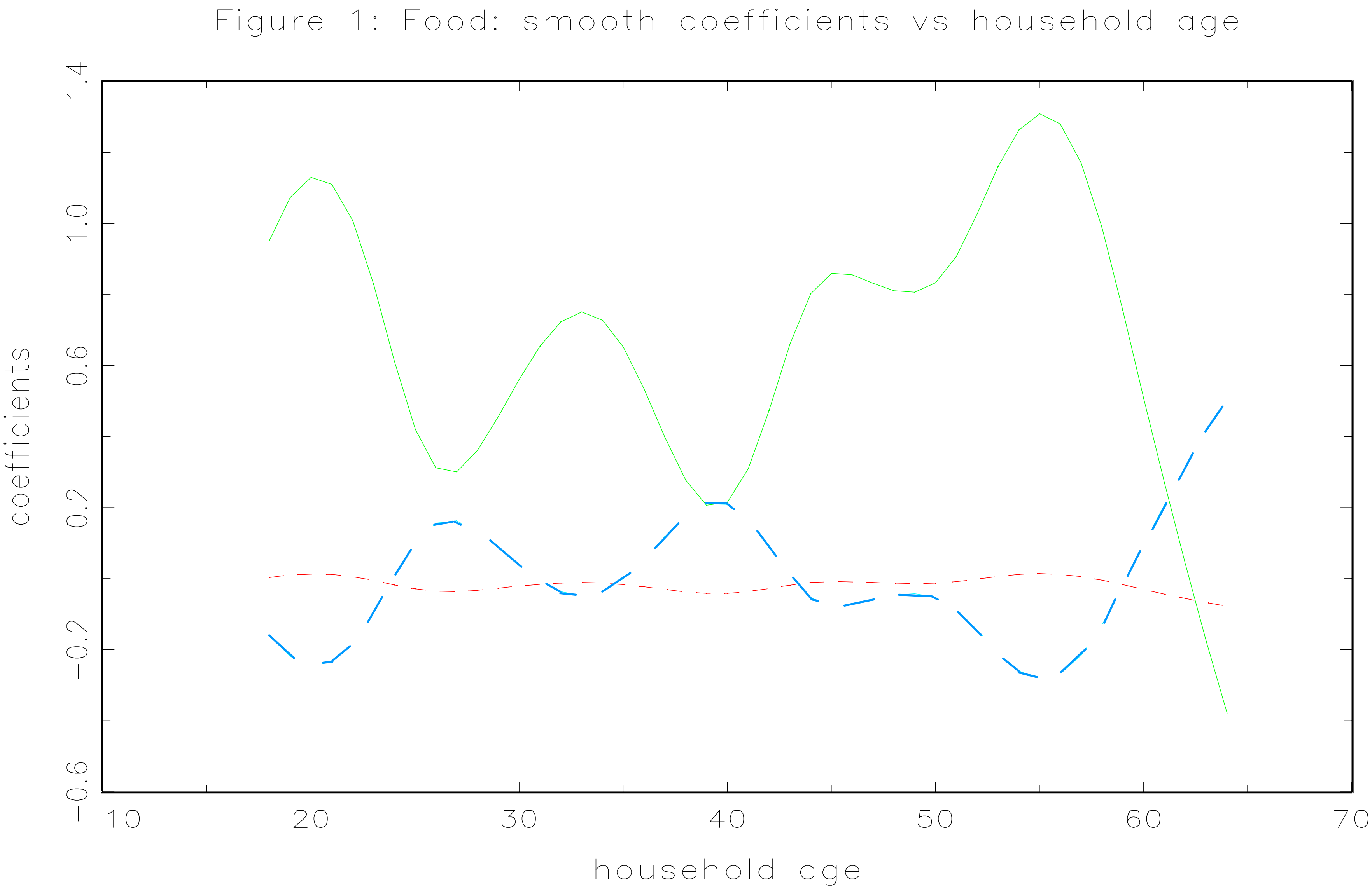


Figure 1: Food: smooth coefficients vs household age
coefficients
household age
1.4
1.0
0.6
0.2
−0.2
−0.6
10
20
30
40
50
60
70

Figure 2: Alcohol: smooth coefficients vs household age

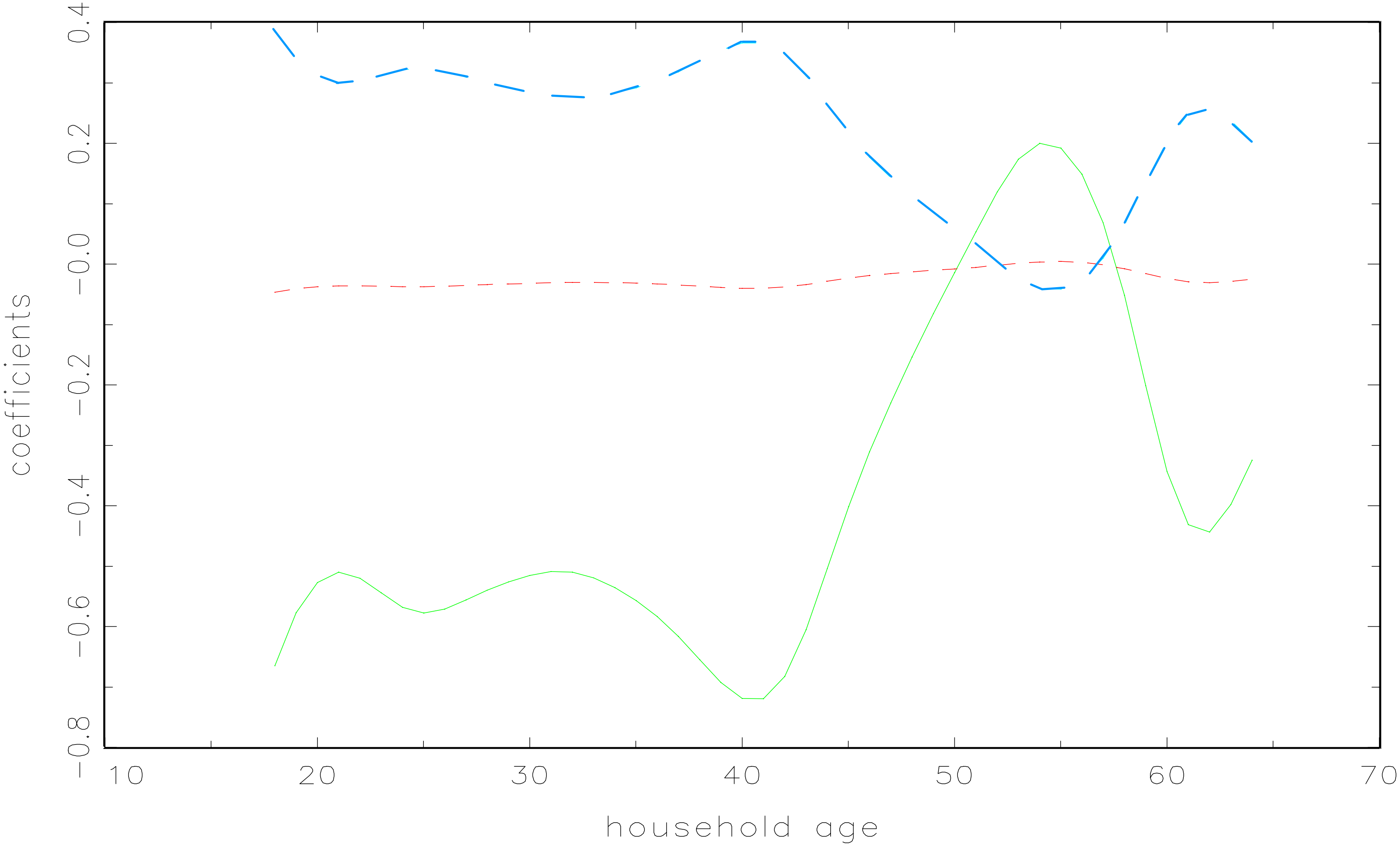


Figure 3: Fuel: smooth coefficients vs household age

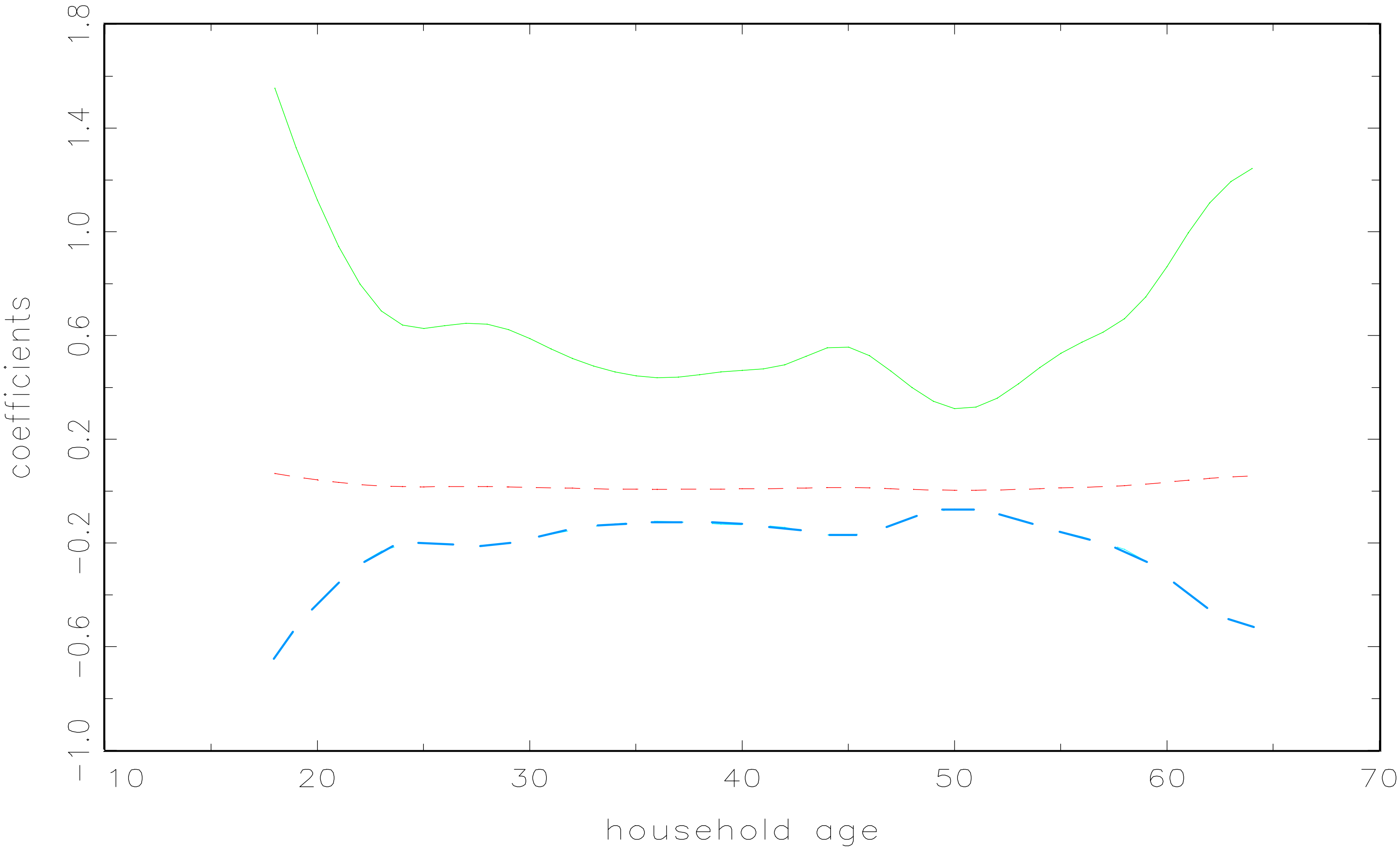


Figure 4: Clothing: smooth coefficients vs household age

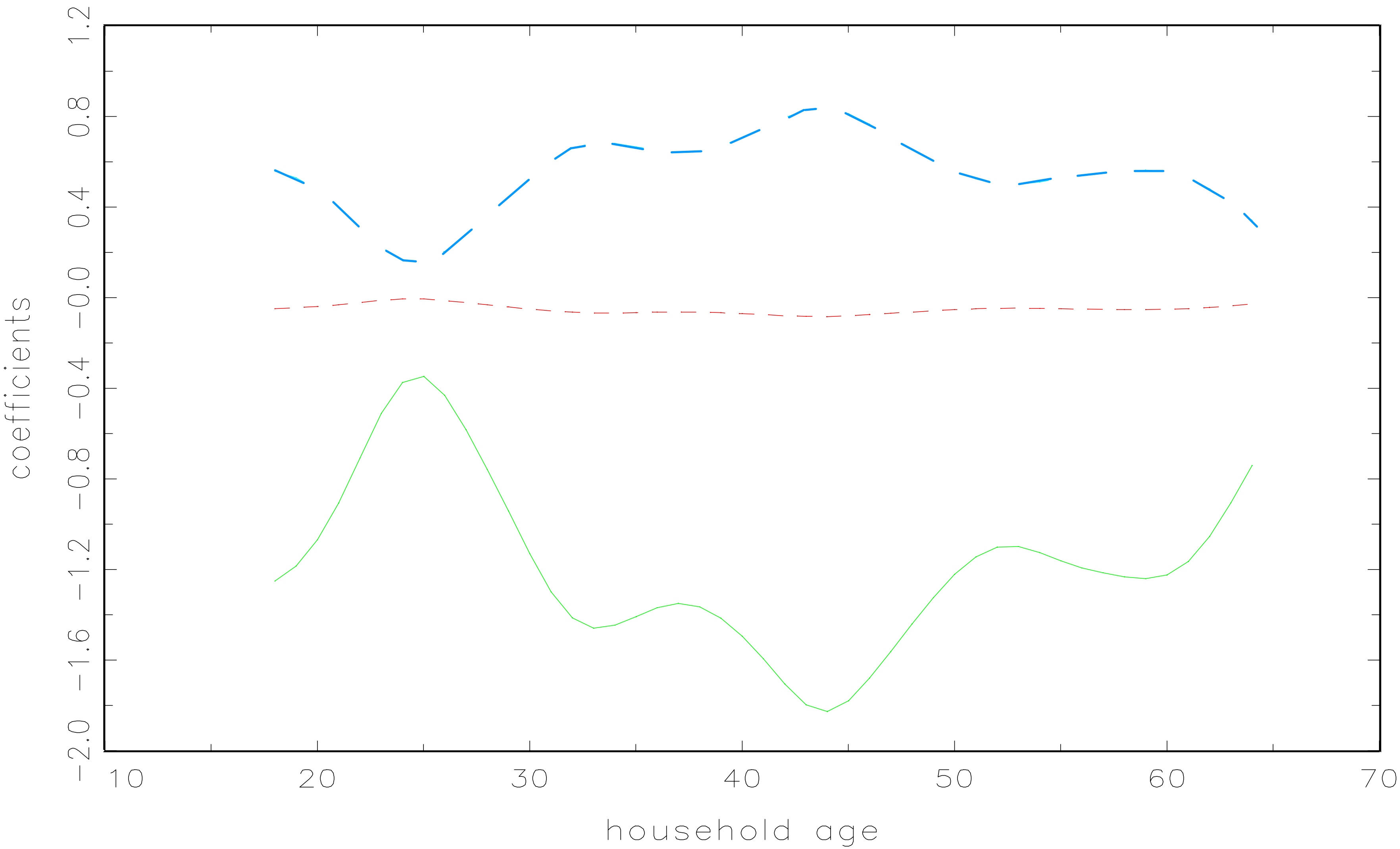
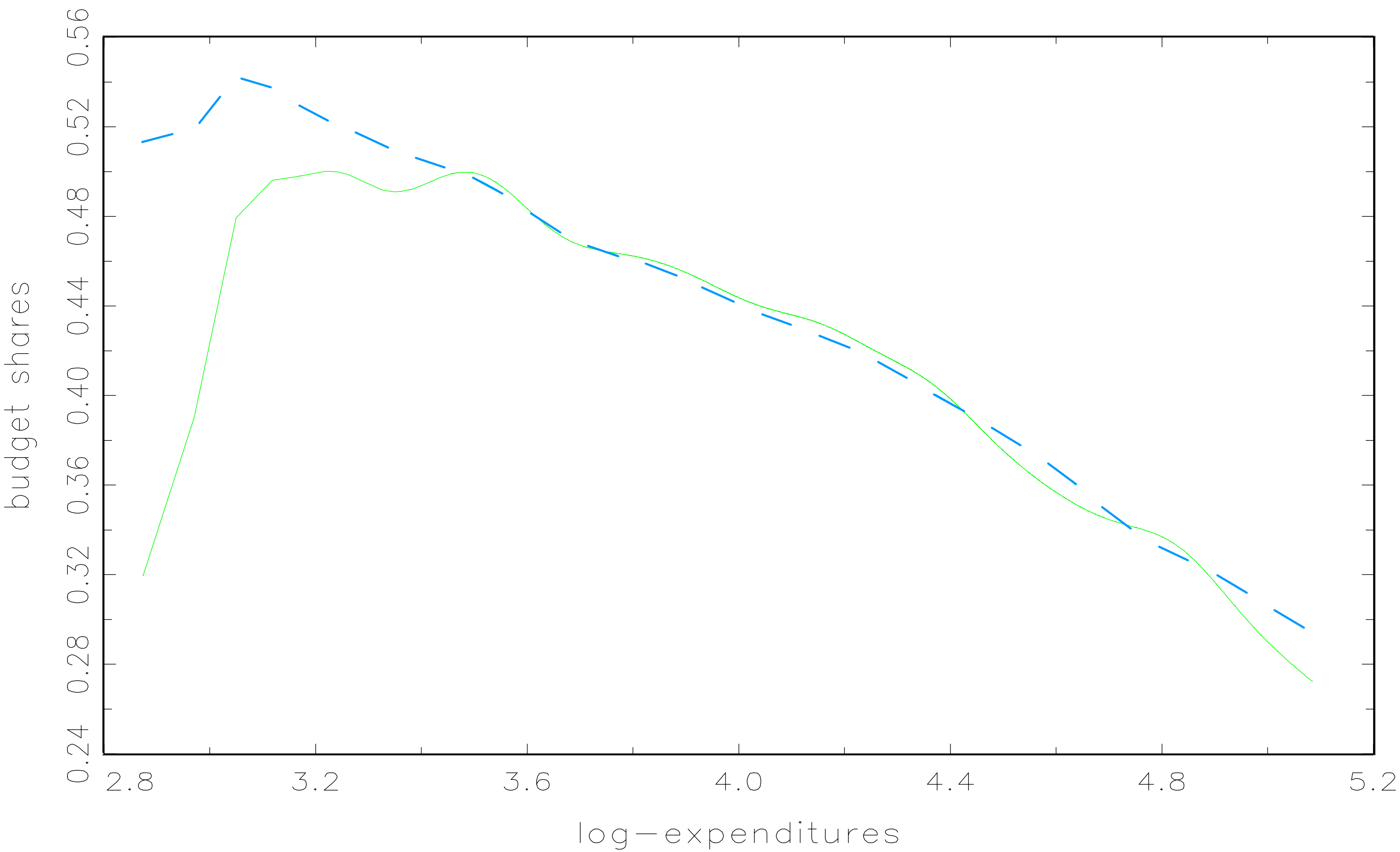


Figure 5: Food Engel Curves: Smooth Coefficient and Standard Semiparame



gure 6: Alcohol Engel Curves: Smooth Coefficient and Standard Semiparam

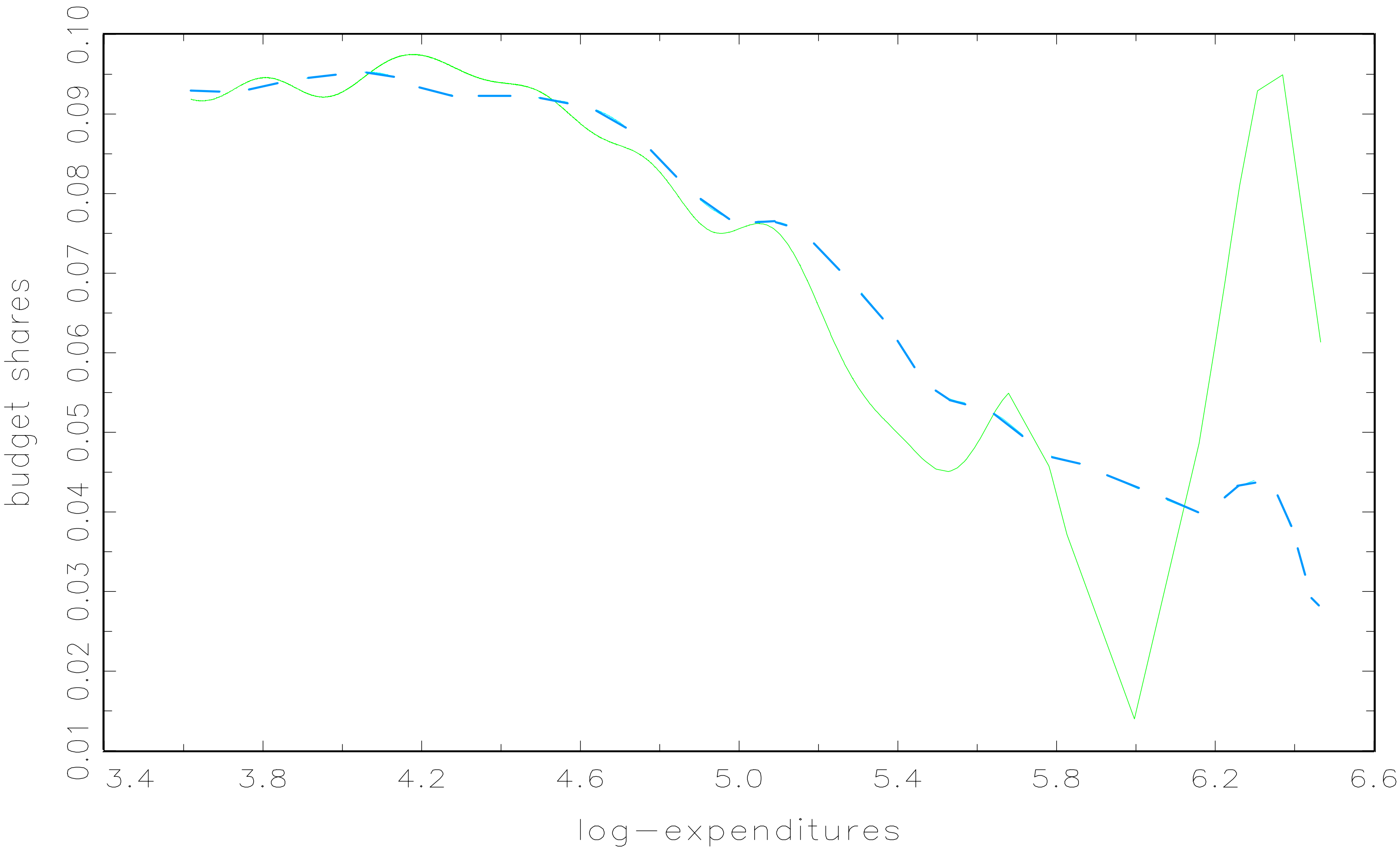
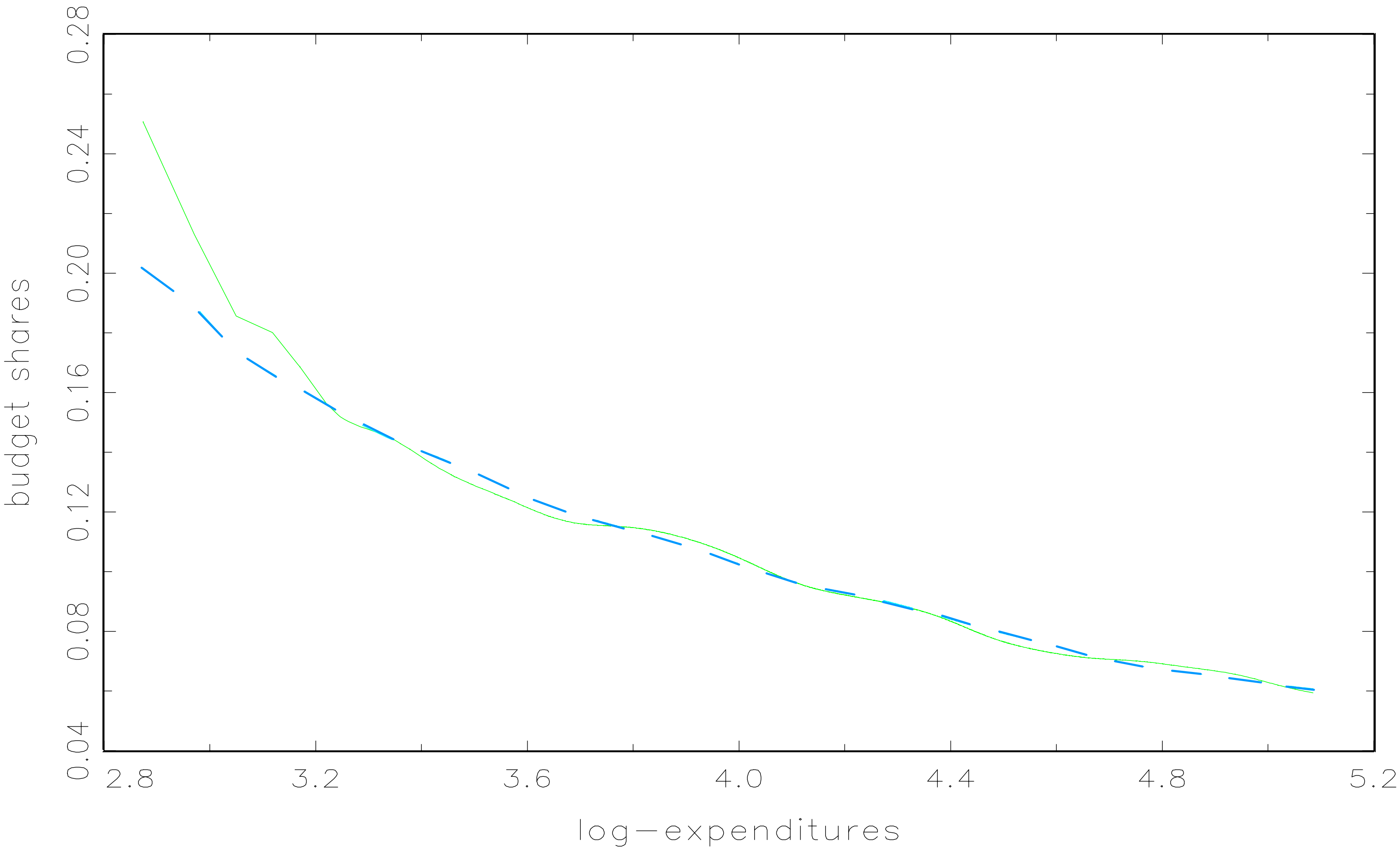


Figure 7: Fuel Engel Curves: Smooth Coefficient and Standard Semiparame



gure 8: Clothing Engel Curves: Smooth Coefficient and Standard Semiparar