Semiparametric Estimation of Consumption Based Equivalence Scales - The Case of Germany

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Abstract

Consumption based equivalence scales are estimated by applying the extended partially linear model (EPLM) to the 1998 Income and Consumption Survey (EVS) of Germany. In this model the equivalence scales are identified from nonlinearities in household demand. The econometric framework should not therefore impose strong restrictions on the functional forms of household expenditure shares. The chosen semiparametric specification meets this requirement. It is flexible, it yields $\sqrt{N}-$consistent parameter estimates and it is consistent with consumer theory. The estimated equivalence scales are sometimes below and sometimes in the range of the expert equivalence scales of the German social benefits system.

Keywords: semiparametric estimation, wild bootstrapping, equivalence scales, social benefits

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1 Introduction

Recent reforms of the social security system in Germany lead to the merger of social benefits (Sozialhilfe) and unemployment assistance (Arbeitslosenhilfe) by the year 2005. When this reform takes effect, up to 1.7 million individuals[1] and their families will obtain *new* needs-oriented social benefits (Arbeitslosengeld II) in addition to the over 2.3 million employable individuals currently receiving similar social benefits. In contrast to the social benefits system, the system of *new* social benefits is intended to provide stronger incentives to the unemployed to search for and accept new jobs (Hartz, 2002). However, gross need for social benefits are continued to be calculated on the basis of equivalence scales and these therefore essentially drive the incentive scheme. This means that, finding appropriate values for the equivalence scales will assume even greater importance in the future. This paper provides estimates for this purpose by applying the estimator of Wilke (2003) to the most recent version of the German income and consumption survey. It is the first comprehensive application of this estimator. Previous work for Germany was done with parametric demand systems and older version of the data.

Equivalence scales are often used in welfare systems to compute households' need for financial support. These scales determine whether and to what extent households are eligible for social benefit transfer payments. To make things more precise, let us state what is usually understood as an equivalence scale:

> *Equivalence scales deflate household money income [. . .] according to household type to "calculate the relative amounts of money two different types of households require in order to reach the same standard of living".* (Muellbauer, 1977)

The purpose of social benefit transfer payments is to ensure that all households enjoy a minimum standard of living. If equivalence scales are incorrectly codified, the standard rates for social benefits will not coincide with their intended values. If transfer payments are too high, the respective household may receive more money than it needs to reach the minimum standard of living. On the other hand, if the value of the equivalence scales is too

[1]Note that the set of social benefits recipients and the set of unemployment assistance recipients are not disjoint.

low, the respective household may not be able to achieve the minimum standard of living. The standard rates must therefore be determined with great care.

Many theoretical and empirical contributions have already examined the issue of how to find a *reasonable* equivalence scale for this purpose. In most cases one of the following three approaches has been adopted.

In the first approach, "expert scales" are devised based on the opinion of social security experts. Table 1 presents two scales in this class. The standard rates of the German social benefits system and the so called OECD scales. The average gross needs in table 1 are the empirical numbers for Germany. Rates calculated from these numbers deviate from the standard rates because they also consists of expenses for housing, heating and general supplementary costs. In the case of Germany the expert scales are supported by several example calculations. The main criticism of this approach is its lack of theoretical justification which means that the resulting equivalence scales appear ad hoc to a large extent.

Table 1: Comparison of existing equivalence scales schemes

	German social benefits			OECD (1982)
	Standard rates*	Average gross needs**		
		West	East	
Single households				
without children (S0)	1.00	1.00	1.00	1.00
with one child (S1)	1.65	1.64***	1.68***	1.50
Couple households				
without children (C0)	1.80	1.58	1.62	1.70
with 1 child (C1)	2.45	2.04	2.11	2.20
with 2 children (C2)	3.10	2.47	2.58	2.70
with 3 children (C3)	3.75	2.92	3.03	3.20

* Federal Law for Social Benefits (BSGH), children of age 7-13

** Reporting date 1/JAN/2003, source: Federal Ministry of Health and Social Security

*** Child aged < 7

The second approach uses data about the satisfaction of a household with its income for the determination of subjective equivalence scales. A criticism of this method is that the results depend on subjective valuations. Other more objective criteria would be preferable. However, this method, does allow equivalence scales to be estimated with sophisticated econometric methods. See Bellemare, Melenberg and van Soest (2002) for a comparison of different estimators using the German Socio Economic Panel (GSOEP).

The third approach, -consumption based equivalence scales- is based on consumer theory. These scales are determined on the basis of households' consumption behavior. Empirical consumption based equivalence scales can be estimated using comprehensive cross section consumption data at the household level. This paper aims in estimating consumption based equivalence scales for Germany using the semiparametric estimator of Wilke (2003) and the 1998 income and consumption survey of Germany. In the past consumption based equivalence scales were mainly estimated using parametric linear demand systems. See for example Blundell and Lewbel (1991) for Britain and Merz and Faik (1995) for Germany. However, empirical evidence has shown that in many cases the demand functions of households are nonlinear, see for example Blundell, Paschardes and Weber (1993). An extension to nonlinear parametric or partially linear expenditure systems is straight and accounts for this misspecification. New developments in consumer theory show that this model choice may also be inappropriate if demographic variation is taken into account (Blundell, Duncan and Penkadur, 1998). In this light the parametric quadratic specification of Kohn and Missong (2003) for Germany appears crucial. Blundell et al. (1998) introduced a semiparametric approach, the so called extended partially linear model (EPLM) that is based on the work of Pendakur (1999). The equivalence scales are identified from the non-linearities in the demand functions. Linear and quadratic parametric demand functions do not allow for or heavily restrict the non linearities. Thanks to its nonparametric element the EPLM is more flexible than the parametric models in particular with respect to the non linearities. Wilke (2003) develops an implementable estimator for the EPLM and derives its theoretical properties. A small application with the British Family expenditure survey indicates that there is empirical evidence. In this paper the EPLM is applied to the 1998 German income and consumption survey (EVS) using Wilke's estimator. A new survey design of the EVS 1998 is a step towards less measurement error and more representativeness of the data compared to the previous versions. The paper therefore provides an application of a flexible estimator to the best data currently available. The model specification appears to be appropriate for a variety of estimations not only conditional on demographics but also by segmenting the data according to the lowest or highest quartile of the household net income. Most of the estimated average equivalence scales are lower than or equal to the expert scales used for the calculation of the gross needs for social benefits in Germany. However, the underlying approach also involves a degree of arbitrariness (Pollak and Wales, 1992, Kohn and Missong, 2003). Precise policy recommendations are not derivable because of certain arbitrariness in the modelling approach which is mainly due to intestable assumptions. Furthermore some estimation results are affected by selectivity of the compared data segments and large standard errors in some cases lead to impreciseness. Possible measurement errors due to commodity aggregation and due to misreporting behavior of the households may also affect the results. Nevertheless, the results can be considered to provide the first comprehensive empirical result for this class of models and most of the criticism applies to the majority of contributions in this field. The underlying model has the foundation of consumer theory and results are obtained from large data sets. These are the striking advantages compared to the other approaches for the determination of equivalence scales.

The paper is structured as follows: Section 2 presents the theoretical framework of the underlying consumer theory. Section 3 sketches the system of social benefits in Germany and explains the importance of equivalence scales. Section 4 introduces the econometric model for the estimation of the extended partially linear model. Section 5 describes the data, and the estimation results are presented in section 6. The last section concludes and provides suggestions for further research.

2 Consumer Theory

This section presents the underlying static microeconomic framework for the econometric analysis. Since we consider cross section data which should be recorded at a given point of time, we ignore calender time variations. The expenditure shares are given by

$$y = m(x, z, p),$$

where m is the vector of expenditure shares for commodities $j = 1, \ldots, J$, x is the log. of total expenditure, z is a household specific finite dimensional vector of observable characteristics and p is the $J \times 1$ vector of log prices. The equivalence scale between two groups z and z_0 is defined as $exp(\alpha(z, p))$. It can be identified from the respective cost functions $c(p, u, z)$ and $c(p, u, z_0)$, which correspond to the minimum expenditures in order to achieve a specific utility level u. More specifically, we have

$$\alpha(z, p, u) = lnc(p, u, z) - lnc(p, u, z_0),$$

where $\alpha(p, z)$ is the log. of the equivalence scale and z_0 denotes the reference group. Then household z requires $exp(\alpha(z, p, u))$ of the reference household's income to reach the same utility level u. Cost functions and expenditure shares are directly related because from Shepard's lemma we have $m(x, z, p) = \partial lnc(p, u, z)/\partial p$. This relationship suggest the identification of equivalence scales from consumption data. However, this approach involves the problem of not observing u but knowledge of the utility level is indispensable for welfare comparisons. This fundamental identification problem is not yet solved (Pollak and Wales, 1992). Stronger assumptions are required in order to induce that the equivalence scale do not depend on the utility level. Unfortunately, stronger assumptions like the independence of the base utility, i.e. $\alpha(z, p, u) = \alpha(z, p)$, have still a lack of empirical support. Kohn and Missong (2002) therefore conclude that "observed demand quantities do not suffice for a unique identification of equivalence scales – a fact that renders welfare comparisons impossible". Moreover, the utility arising from leisure is ignored by uniquely focusing on utility coming from consumption. Consequently, the leisure related part is not captured by a model that is solely estimated with consumption data. If we assume that utility is separable in consumption and leisure, we would only model and estimate the consumption-related utility element.

A variety of functional forms for expenditure shares are consistent with economic theory. A popular linear specification is the so called Price-Independent Generalized Logarithmic

(PIGLOG, see Muellbauer, 1976). This arises from indirect utility functions which are linear in the log. of total expenditure. Complete demand systems such as the AIDS (Deaton and Muellbauer, 1982) and the ELES (Lluch, 1973) are based on linear specifications of the expenditure shares. Nowadays, there is enough empirical evidence that this specification has to be generalized, since for many goods there is a nonlinear relationship. A simple generalization is the partially linear model (PLM) which includes as a special case the quadratic model. This class of models has attractive theoretical properties and there is empirical evidence for the quadratic specification (Blundell et al., 1993). More recently, Blundell et al. (1998) state that if the expenditure share of one commodity is PIGLOG than consumer theory induces the same property for all demand function in a demand system. As a consequence the nature of the PLM can drastically restrict the functional forms for all expenditure shares in order to be still consistent with consumer theory if the demand function for one single good is linear. For this reason demand systems based on expenditure shares belonging to the class of PLMs involve crucial functional form restrictions for the estimation of equivalence scales. There is also some evidence that this is relevant in an application since for example the expenditure share for food is linear in Britain (Blundell et al., 1998). Inspired by Pendakur (1999) and by the findings for Britain, Blundell et al. (1998) suggest an alternative system of expenditure shares that accounts for demographic decomposition, that is nonlinear in log of total expenditure and consistent with consumer theory. However, it requires the assumption that the equivalence scales are independent of the baseline utility. Given a smooth unknown function g_j, Blundell et al. (1998) state the following lemma for the extended partially linear model (EPLM):

If expenditure shares have the EPLM form:

$$m_j(x, z, p) = \frac{\partial \alpha(z, p)}{\partial p_j} + g_j(x - \alpha(z, p)), \tag{1}$$

then if the reference share equations

$$m_j(x, z_0, p) = g_j(x, p) \tag{2}$$

are consistent with consumer theory and $exp(\alpha(z, p))$ is weakly concave and homogeneous of degree zero in $exp(p)$, expenditure shares given by (1) are also consistent with consumer *theory.*

The derivation of the EPLM and further underlying theory can be found in Pendakur (1999) and in Blundell et al. (1998). It uses the main tools of dual theory and skillfully exploits the definition of baseline utility independent equivalence scales. Interestingly, the class of functionals in equation (1) belongs to the shape invariant models because we have simple vertical and horizontal (due to $\alpha(z,p)$) shifts of an unknown smooth function g_j. Apparently, the shape of the nonparametric function g_j may differ across the commodities, whereby $\alpha(z,p)$ does not. The horizontal shift $\alpha(z,p)$ is of particular interest because its exponential transformation, i.e. $exp(\alpha(z,p))$, is the equivalence scale. The EPLM is therefore a general theoretical model for the estimation of equivalence scales that are independent of the base utility. It requires very mild assumptions on the functional form of the reference share equations (2) and it identifies the equivalence scales from the non linearities in the demand functions. It therefore requires a flexible estimator in the empirical analysis that does not impose strong restrictions on the functional form of the derivatives of the expenditure shares.

Demographic group	#	average gross needs	average net entitlement	total gross needs	total net entitlements
All households	1.235.326	860	394	1.062.663 294	486.718.444
Single households					
without children	605.020	581	326	351.705.194	197.312.874
with 1 child (< 18 years)	190.696	919	429	175.219.574	81.790.457
with 2 children (< 18 years)	106.664	1.214	470	129.541.414	50.116.993
Couple households					
without children	120.819	893	407	107.836.320	49.117.174
with 1 child (< 18 years)	67.016	1.101	464	73.778.288	31.103.827
with 2 children (< 18 years)	52 523	1.336	489	70.181.561	25.691.999
more than 2 children (< 18 years)	44.365	1.756	559	77.905.957	24.804.852

Table 2: Some facts about German "Sozialhilfe" in 2001: regular means of subsistence. Gross needs and net entitlements are per month in euros. Source: Federal Statistical Office (2001), own calculations.

3 Equivalence Scales for Social Benefits - the Case of Germany

In Germany social benefits for more than 1.23 million households are mainly calculated according to a method based on equivalence scales. See table 2 for a descriptive overview of the year 2001. [2] Each household has a defined income requirement in order to achieve a minimum standard of living. The gross needs (Bruttobedarf) for social benefits should meet this amount. The calculation of the amount of gross needs is based on two parts: firstly, the standard rate (Regelsatz) that accounts for the demographic composition, i.e. the number of adults and the number of children living in the respective household, and secondly, payments for housing, heating and other supplementary general costs that are calculated on a case by case basis by a responsible administrator at the social assistance office. The net entitlements in table 2 correspond to the gross needs for social benefits minus the current income of the household. The net entitlements are the amount of money finally paid to the household.

The demographic composition of a household plays an essential role in determining the standard rates. For the latter the social planner computes the equivalent income between the demographic groups of households on the basis of an equivalence scale that is codified in the Federal Law of Social Benefits (BSHG). Table 1 presents the equivalence scales of the German social security system and the widely accepted "OECD (1982) scales". It also presents the demographic compositions that are subsequently considered for the estimations. It is evident that standard rates in Germany are higher than the OECD rates. If we look at the - empirically relevant - average gross needs, the opposite appears to be the case. The empirical scales computed from the average gross needs are lower than the OECD scales, with the exception of the scale between single person households and single people with a child. This interesting observation has not been noted to date in the related empirical literature about Germany, e.g. Merz and Faik (1995) and Kohn and Missong (2003). A plausible explanation for this is that the administrators at the social assistance offices expect larger

[2] Table 2 contains information about regular means of subsistence only. Households in specific circumstances, e.g. disabled, who receive social benefits are not included because it is not possible to identify these households in the data.

economies of scales in expenses for housing, heating and other supplementary costs of the household.

4 Econometric Model

The economic theory suggests that the EPLM would be an appropriate framework for the empirical analysis. The advantages of this semiparametric approach are also clear from the viewpoint of an econometrician: the risk of misspecification of the functional form of the expenditure shares is lower than for purely parametric models. At the same time the rate of convergence of the parameter of interest, e.g. of the equivalence scale parameter, is the same as in parametric frameworks $N^{1/2}$, where N is the number of observations. Purely nonparametric estimators are ruled out as possible alternatives as we intend to estimate a parameter of interest. In this paper we use the recently developed estimator of Wilke (2003) which is based on the work of Härdle and Marron (1990), which provides applicable solutions to the identification problems involved in this framework, and which has better finite sample properties.

Assume the availability of cross section data at a given point of time with given log prices p. Define $m_j^0(x) = m_j(x, z_0, p)$ as the share equation of the reference household type z_0 and $m_j^1(x) = m_j(x, z, p)$ for any $z \neq z_0$. According to the restrictions of the EPLM we may write equation (1) as (Blundell et al., 1998)

$$m_j^1(x) = a_j + m_j^0(x - \alpha), \tag{3}$$

where the function m_j^1 is a vertically and horizontally shifted translation of the reference function m_j^0. Our empirical focus is on the estimation of the parameter α, which corresponds to the log. of the equivalence scale. The parameter a_j reflects the elasticity of the equivalence scale with respect to the commodity price j. For the estimation of equation (3) we always compare two homogeneous subgroups of households. For each subgroup we have a sample of observations with different sample sizes N_0 and N_1. In order to identify the equivalence scale, we need a consistent estimate of α. Let us therefore introduce the estimation model and the identification conditions as given by Wilke (2003).

Suppose we have samples $(Y_{ji}, X_i)_{i=1,...,N_0}$ and $(S_{ji}, W_i)_{i=1,...,N_1}$ with $j = 1, ..., J$. Let us assume the following functional relationships:

$$\begin{aligned} Y_{ji} &= m_j^0(X_i) + U_{ji} \\ S_{ji} &= m_j^1(W_i) + V_{ji} \quad \text{for } j = 1, \ldots, J \end{aligned}$$

with $E(U_{ji}|X_l) = E(V_{ji}|W_l) = 0$ for all i, l and j. U_{ji} and V_{ji} have finite fourth moments and the pairs U_{ji}, V_{ji} are mutually independent. $X_i \in \mathcal{X}_1$ and $W_i \in \mathcal{W}$ are i.i.d random variables with realizations on compact sets with twice differentiable densities $f_x(x) > 0$ and $f_w(w) > 0$ for all x and w. Furthermore, let the true parameter values a_{j0} for $j = 1, \ldots, J$ and α_0 be in the interior of open subsets in $\mathbb{R}$. Let us denote the set $\{x - \alpha\} = \mathcal{W}_\alpha$ for all $x \in \mathcal{X}_1$. The following assumptions ensure the identifiability of the parameters: $\mathcal{W} \cap \mathcal{W}_\alpha$ is nonempty for all α. This condition implies that the two nonparametric functions overlap on their support for all α. There exists a j such that the function $m_j^0(x-\alpha)$ is not periodic on $\mathcal{W} \cap \mathcal{W}_\alpha$. This means that for at least one commodity there is no $\alpha \neq \alpha_0$ with $m_j^0(x - \alpha) = m_j^0(x - \alpha_0)$ for all $x - \alpha \in \mathcal{W} \cap \mathcal{W}_\alpha$. This is required for a unique solution in α. Furthermore, there exist a j such that the function $m_j^0(x - \alpha)$ is nonlinear on $\mathcal{W} \cap \mathcal{W}_\alpha$ for all α. This is required for the joint identification of a_j and α. Under some technical assumptions on the nonparametric estimates of m^0, m^1 and f, the solution to the problem

$$\min_{a,\alpha} L_{N_0,N_1}(a, \alpha) = \sum_{j=1}^{J} \frac{\int_{\mathcal{W}\cap\mathcal{W}_\alpha} [\hat{m}_j^1(x) - a_j - \hat{m}_j^\alpha(x)]^2 dx}{\int_{\mathcal{W}\cap\mathcal{W}_\alpha} \hat{f}_x(x) dx}, \tag{4}$$

yields consistent parameter estimates, where $\hat{m}_j^\alpha(x)$ denotes the nonparametric estimate of the function m_j^0 after shifting it horizontally by the parameter α.[3] Under further technical conditions the parameter estimates converge at rate $N^{1/2}$ and they are normally distributed (Wilke, 2003). We use here the HM4SE[4] which is an improved version of the Härdle and

[3]In fact the estimation objective function (4) does not involve the shape invariance restriction across all household types z because it is restricted to the comparison of two household types only. The equivalence scales could be estimated for all groups simultaneously by using $\hat{m}_j^0(x) = a_j' z + \hat{m}_j(x - \alpha' z)$, where a_j and α are column vectors of the length of the total amount of demographic groups and z is a dummy vector of the same length.

[4]HM4SE is introduced by Wilke (2003).

Marron (1990) estimator.[5] The estimator is implemented as follows:

1. Estimate the nonparametric functions m_j^0 and m_j^1 for $j = 1, \dots, J$. In our applications we use the Nadaraya-Watson estimator and the local linear smoother with constant bandwidths that are obtained with a plug-in method as given in Fan and Gijbels (1995). A parametric nonlinear least squares (NLS) estimator is also applied as a benchmark, which imposes a quadratic specification of the expenditure share.[6]

2. Estimate the parameters a_j given α by least squares, i.e.

$$\min_{a_j} \int_{\mathcal{W} \cap \mathcal{W}_\alpha} (\hat{m}_j^1(x) - a_j - \hat{m}_j^\alpha(x))^2 dx$$

   for any α and all j. Denote the estimate $\hat{a}_j^\alpha$.

3. Solve problem (4) numerically in α conditional on $\hat{a}_j^\alpha$ in order to obtain $\hat{\alpha}$. Denote the function $L_{N_0,N_1}(\alpha|a_\alpha)$ as the loss function in α.

4. $\hat{a}_j = \hat{a}_j^{\hat{\alpha}}$ for $j = 1, \dots, J$.

The least squares estimation in step three is not efficient, since the variance of the non-parametric estimators is a function depending on the location on the support where it is evaluated. This variance function might be estimated by (wild)-bootstrap and used for constructing weights in the least squares estimation.

The standard errors of the parameter estimates are computed from the empirical distribution of the parameter estimates obtained by wild bootstrapping. Wild bootstrapping in the EPLM is described in the appendix A I.

5 Data

The 1998 German Income and Consumption Survey (EVS) is used for the estimations. The survey data is based on 49,720 households from both west and east Germany with more

[5]Stengos and Wang (2002) and Pendakur (2004) use a penalizing function in order to overcome the finite sample difficulties.

[6]This specification restricts the nonlinearities to a constant. It is intended to serve as a check whether results are sensitive with respect to this restriction.

than 900 variables (demographic, consumption and income related). It is a quota sample with voluntary participation and is therefore not representative with regard to the whole population (Kühnen, 1999). Single people and blue-collar workers for example have a lower rate of reply. The same is true for households on either low or high incomes. Projection factors are available to generate representative results. The analysis in this paper does not use these factors as there is no obvious reason for doing so as the analysis is performed for homogenous demographic groups conditional on the level of household net income and or on the employment status of the household head. However, we can only assume that the observed consumption behavior in each of the segments is nevertheless representative for the whole population segment. It is also important to mention that the sample and census design have significantly changed from previous EVSs used for example by Merz and Faik (1995) and Kohn and Missong (2003). Due to the voluntary participation of the households and the generally long recording period of one year [7], attrition was too high in the past (Chlumsky and Ehling, 1997). For this reason the responsible Federal Statistical Office (Statistisches Bundesamt) reduced the recording period from one year to three months. In the author's view, this should also increase the quality of the observed variables. They should become more precise (due to higher motivation of the recording households). Moreover, the probability is greater that variables such as employment status, demographic decomposition and prices do not in fact vary, as the former are recorded by interviews at the beginning and at the end of the recording period only. For estimations we only use observations that are recorded in the second or in the third quarter of the year, i.e. during summer time, in order to wipe out calender time effects on the consumption structure of the households. In terms of commodity aggregation we are confronted with the following trade-off: if we use all possible consumption items available in the data (several hundred) there are insufficient observations and in many cases one commodity may substitute a very similar one. There is therefore no alternative but to work with some aggregated commodity groups. However, aggregation must be done carefully if it is not to induce a measurement error which could seriously bias the estimation results. For the estimation we consider 12 aggregated commodity groups which are presented in table 3. These groups are directly taken from the 1998 EVS data.

[7] There are also to some extend records on a monthly basis (Feinaufschriebe).

j	*Commodity group*		
1	Food	2	Clothing
3	Housing	4	Energy
5	Interior decoration	6	Health care
7	Transport	8	Communication
9	Leisure and travelling	10	Education
11	Board and lodging	12	Other goods

Table 3: The commodity groups used for the estimations.

The aggregation of the commodities is performed by the German Federal Statistical Office and the commodity categories are constructed such that each reflects a central need of the households. This categorization is harmonized with international standards, i.e. COICOP 1998.[8] It seems therefore reasonable to adopt this categorization for our purposes. However, it is not clear how much measurement error is imposed by this aggregation. Another source of error is the non response behavior of the households. Overall 8.5% of the $12 \times 49,720$ observed expenditures shares are zero. Zero entries in the data correspond to either zero expenditures or to missing values. While taking a closer look one finds that they are concentrated in some commodity groups such as "education" or "board and lodging". In the following analysis the zero entries are treated as zero expenditures because it is likely that many households do indeed have zero expenditures for goods such as "education". This assumption has an additional justification because participation in the survey is completely voluntary. Since we are interested in transfer payments for regular means of subsistence, we should restrict the following analysis to expenses for non-durables. This makes small modifications of the original commodity groups necessary because some groups contain expenses for durables, e.g. transport expenditures contain expenses for car purchases. Expenditures for durables[9]

[8]There are some minor deviations from the international standard which are mainly for comparative reasons with older issues of the EVS-data.

[9]Furnishing, medical devices, purchases of or reparation costs for cars, motor bikes or bicycles, purchases of leisure or electronic devices, musical instruments, jewelry, watches and precious metals. They amount of 0 – 94% of total household expenditure with mean 9.5% and median 4.3%. Expenditures for durables are lower for single households and they do not increase with the number of children.

are therefore subtracted. As already mentioned, only observations that are recorded during the summer quarters of the year are used.

The following demographic groups are used separately for the estimation of the equivalence scales: (S0,C0), (S1,C1), (S0,S1), (C0,C1), (C1,C2), (C2,C3)[10] conditional on the status of the head of the household (full time employed or non employed) and by distinguishing between the level of the household net income. These distinctions are made for the following reasons: the separation with respect to the employment status is done because households with non-employed household head (retired, unemployed) have typically income depending to certain extent on social security transfer payments. It is interesting to see whether the consumption behavior of households which rely on a social transfer scheme is different from the consumption behavior of households with working income. Unfortunately, not many households only receive social benefits (all other transfers schemes depend at least to some extent on the prior working income). For this reason the group of non-employed household heads is chosen with the drawback that a large number of these households has income related to prior working income. Nonetheless, this allows us to relate the consumption structure of demographic groups of households that are homogeneous with respect to the available leisure time. If leisure and consumption are perfectly separable and if in addition the design of social transfers payment schemes does not affect the behavior of households, the results should be identical for the two leisure-groups. A distinction between different net income levels may provide a rough idea whether the assumption of the independence of the base utility, i.e. $\alpha(u) = \alpha$, may have empirical evidence or not. For this reason estimations are also done separately for households in the lowest or in the highest quartile of the net income sample distribution. Everything equal, we could get a rough idea wether the estimated equivalence scales are invariant over the income level. The construction of the homogenous sub-samples revealed the sample size in some cells decreased such that reliable semiparametric estimations become impossible (see table 5 in the appendix). For this reason the single household with one child (S1) group is not considered in two cases. The analysis in this paper does not explicitly consider the age of children as it is the case in the German social security system, where the equivalence scale increases when the children become

[10]Again, the notation of table 1 is used.

older. This simplification ensures that there are still enough observations in a considerable proportion of the data segment considered (see table 5). At the same time it can affect the estimation results if there is some variation in average age over the data segments. In particular households with low net income have typically younger children than households with high net income (see table 7). Then, estimation results between the data segments are not therefore directly comparable if equivalence scales depend on the age of the children. In other cases, in particular for the nonemployed it is evident that sample composition of the compared demographic groups differ substantially (see tables 6 and 7). These selection issues can affect the estimation results and one should restrict attention to sample of similar composition. Since the size of the available data is not large enough it is impossible to overcome this difficulty with the underlying estimation approach.[11]

6 Estimation Results

The estimations reveal the appropriateness of the model specification in most cases (tables 9 and 11). The estimated change in the equivalent income for additional adults or additional children is in these cases in an economically plausible range ($0-100\%$). However, in the case of the first child the estimated equivalence scale is often below this range, i.e. it is negative (table 10). If we turn attention back to all the cases again, the shifted nonparametric functions appear at a glance to fit acceptably. The loss function possesses in most cases a unique minimum for plausible values of the equivalence scales, i.e. $c \in [0, ln2]$.[12] Tables 9-11 in the appendix report the detailed estimation results and present an extended coefficient of determination for the parametric part of the EPLM, the $\mathbf{eR}^2$ which is introduced in appendix A.II. Since the $\mathbf{eR}^2$ is mostly in the range $0.3 - 0.6$ it is evident that the simple transformation with two parameters yields a convincing fit for survey consumer data. This clearly indicates that large standard errors of the parameter estimates are driven by the

[11] Other characteristics such as sex of the household head are not considered for the same reason, whereby disability of household members is not observed. A skillful extension of the semiparametric approach that accounts for a variety of regressors remains for future research. Chen, Blundell and Kristensen (2003) move in this direction; however, their identification conditions are subjected to hardly any practical verification.

[12] Figures which illustrates this are available upon request from the author.

		Additional adult		*Additional child*	
		C0/S0	C1/S1	C2/C1	C3/C2
German social benefits					
Standard rates†		80%	49%	27%	21%
Average gross needs 2003	(west Germany)	58%	24%	21%	18%
OECD (1982)		70%	47%	23%	19%
Consumption based, EVS 1998					
Semiparametric estimation results					
Full sample		48 – 51%	25 – 28%	12%	12 – 15%
	lowest income quartile	–	–	9 – 13%	14 – 19%
	highest income quartile	47 – 57%	–	1 – 7%	–
Employed		54 – 59%	14 – 21%	11%	10 – 12%
	lowest income quartile	70 – 73%	–	12 – 13%	17 – 22%
	highest income quartile	73 – 78%	–	3 – 6%	–
Other results					
Merz and Faik (1995)		54%	43%	7%	6%
Kohn and Missong (2003)		66%	30%	11%	8%
Bellemare et al. (2002)		29 – 44%*	5 – 33%*	–	–

Table 4: Increase of equivalent income: comparison of selected point estimates (tables 9 and 11) to policy rules of table 1. † BSHG, children of age 7-13. * This is the range of point estimates spanned by the various methods; children of age 7-12 years.

variance of the first step nonparametric estimates. Therefore, it seems that the model (4) is appropriately specified for the EVS 1998. The reported standard errors are computed from the empirical distribution of 500 wild-bootstrap estimates. Note that each 12.000 Nadaraya-Watson and local linear smoothing estimates are performed in the bootstrap estimation of one standard error. In some cases the estimated parameters possess large standard errors and therefore have to be considered as of limited reliability. Standard errors are mainly driven by small sample sizes and in addition by different sample composition within and across the data segments that cannot be captured by the model. The chosen bandwidths are obtained by the plug-in method suggested in Fan and Gijbels (1995). The resulting bandwidths are mostly in the range $0.2 - 0.5$.[13] The choice of the bandwidth and the choice of the support for the nonparametric estimation affect the results. However, the sensitivity of the results was checked by weakly varying the boundaries of the support of the nonparametric functions.

A selection of the most reliable point estimates is presented in table 4. This compares them with the expert equivalence scales of the German social benefits system, the OECD equivalence scales, the empirical evident values computed from the gross needs and with the estimation results of Merz and Faik (1995), Kohn and Missong (2003) and Bellemare et al. (2002). The reported ranges of the estimation results are based on the two point estimates obtained (see tables 9-11) and are not therefore based on distributional information. It is apparent that the results are sometimes below the value suggested by the expert equivalence scales of the German social security system or by the OECD and that they are sometimes in the range of the expert scales. Intuitively, the estimated equivalence scales correspond to the increase in household income such that an average household is able to maintain the same standard of living if an additional member (adult or child) is added. The word *average* means that it is the empirical mean for all households of the respective data segments. It is therefore an estimate of the mean equivalence scale. The estimates cannot provide any information about a reasonable absolute amount of gross needs for social benefits for the single person household (S0).

[13] In a earlier version of this paper the bandwidth was chosen to be three times the optimal bandwidth. This high degree of oversmoothing was conducted in order to reduce the variance of the first step nonparametric estimates which was much greater when also including expenditures for durables. As a result the parameter estimates based on the two nonparametric estimators diverged to a greater extent.

Let us turn now to a more detailed discussion of the estimation results which are presented in detail in tables 9-11.

Choice of the first stage estimate The choice of the first stage estimator affects the results more strongly if it comes from a different class of estimators. In many cases the results for the two nonparametric estimators are pretty close, whereby the results for the parametric first stage estimator rather differ. In 17 cases the parametric benchmark estimate is smaller than the semiparametric $\hat{\alpha}$, in 6 cases it is in between and in 9 cases it is greater. If we look at the cases when it lies above it becomes clear that it is mainly in the first child case (6 of 9 cases fall into these segments). As it will be discussed below the estimation results are probably biased in the first child case due to selection issues in the data. If we therefore restrict the attention to the other cases one can conclude that the parametric approach often yields a smaller estimate of the equivalence scale. This is some evidence for a systematic estimation bias of the parametric benchmark estimator due to the strong restrictions on the non-linearities of the expenditure shares. The estimated wild bootstrap standard errors are often similar for the two nonparametric first stage estimates and there is no clear result pattern in the differences. In the parametric case the standard errors are often similar or smaller but we do not observe a clear advantage of the parametric estimator.

Employment status Results for employed and nonemployed household heads are rather different. Since there is quite a lot of heterogeneity within and across the groups compared, one cannot not directly infer that the employment status is the driving force behind differences in the results. Results for the employed are less likely affected by compositional effects and appear more reliable. The large standard errors and the low $\mathbf{eR}^2$ in the case of the nonemployed are probably due to different sample compositions of the data segments compared (tables 6-7). Results for the nonemployed are therefore not presented in table 4.

Additional adult An additional adult in a household without children requires an increase in equivalent income by $50 - 75\%$ and by up to 30% for households with one child if one ignores in both cases the results for the nonemployed which have large standard errors. The results with small standard errors provide us estimated equivalence scales weakly below the standard rates. Standard rates are in the range of the estimation results for the full sample and for the employed in the C0/S0 comparison. For C1/S1 the estimations are weakly below the standard rates.

Additional child The EPLM is very well specified for the comparison of C2 and C1 with an $\mathbf{eR}^2$ up to 0.85 and small standard errors. For the full sample and the employed the estimated equivalence scales are significantly below the standard rates. For the nonemployment group the standard errors are again quite large and also the $\mathbf{eR}^2$ falls below with a value of 0.4. For the C3/C2 comparison we obtain that lower bounds are slightly below and upper bounds are in the range of the standard rates. The results for the nonemployed are below the other results and they have again the largest standard errors. Sample compositions in terms of average age of the household head and average age of the children in the household are quite similar. For this reason we expect that there is only little heterogeneity across the groups. This explains the small standard errors of the results and the good fit of the model in the case of an additional child.[14]

First child Results for the first child in a household appear implausible, since estimates are sometimes negative. This is not because households decrease expenditures after the birth of the first child, since the average age of the first child is quite high (9 – 16 years old) in the underlying data segments. Other explanations such as different compositions with respect to other variables such as the age of the household heads compared seem to be more plausible. Moreover, if we think about preferences, the decision in favor of a child can be considered as a permanent decision against a high level of consumption. The model does not control for this heterogeneity in preferences and omitted variables. It also does not control for the employment status of the second adult in the household, which often changes in response to a child. All this may bias the estimation results in the first child case. For this reason they are not presented in table 4. Again the estimation results for the nonemployed have large standard errors and differ from the other groups.

[14] Additional segmentation with respect to the age of the children (<7, >12 or in between) did not improve the fit of the model and did not yield a clear result pattern.

Income level When considering the full set of estimation results, there is a weak tendency towards higher equivalence scales for households with lower net income. The income pattern is clearest in the case of additional children where we have the most precise estimates. The presented results therefore give indications that the level of household net income may have empirical relevance for the determination of equivalence scales. However, only better data and improvements in the model structure will answer the question whether the equivalence scale is independent of the income level or not.

7 Summary and Outlook

This paper presents a comprehensive empirical study of the semiparametric estimation of consumption based equivalence scales. Equivalence scales for Germany are estimated by applying Wilke's (2003) estimator for the extended partially linear model suggested by Blundell et al. (1998) to cross section EVS survey data for 1998 with almost 50.000 observations. The model identifies the equivalence scales from the nonlinearities in the expenditure shares of the households. The econometric framework accounts for that by keeping the expenditures shares nonparametric. It appears that this is important because a comparison with a parametric estimator reveals rather systematic differences in the results. For estimation purposes the data is segmented into homogenous groups of households according to the employment status of the household head or the level of net household income. The curse of dimensionality, heterogeneity with respect to ignored variables and the demanding computational approach are drawbacks in the adopted framework. However, it is found that estimated consumption based equivalence scales are weakly below the equivalence scales of the German social benefits system. In some cases the estimates appear to be precise and in other cases they suffer from large standard errors. In these cases the composition of the household groups compared differ considerably, which probably have an impact on the estimation results. Another source of bias maybe the measurement error due to the commodity aggregation and due to the misreporting behavior of the interviewed households. Moreover several assumptions of the underlying economic theory are hardly verified in an application.

The assumption of independence of the base utility is not formally checked but the estimated equivalence scales appear to be weakly higher for low income households. The adoption of a more general model structure that incorporates dynamic consumer theory may also have an impact on the results. These are several reasons why it is difficult to infer policy recommendations from the results. However, most of these weaknesses apply to a broad range of contributions in this research field.

The estimation results do not provide indications that on average the costs for additional persons in a household are not *at least* covered by the standard rates of German social benefits. In the light of recent decisions of the Federal Constitutional Court (Bundesverfassungsgericht) concerning the costs of children and growing discussion of demographic transitions in Germany, it is not apparent from the estimation results that equivalence scales need to be increased for households with children. Before attempting to infer policy recommendations from this class of models, the assumption that equivalence scales do not depend on household income should be solved. The results of this paper give indications for an income pattern but they lack of statistical significance. Moreover, some readjustments in the model specification may help to overcome the evident sample selection issues in the first child case and they may help reduce the noise in the data. Conditioning on the type of region (urban, rural etc.), where the respective household stays, or on west and east Germany did not improve the model fit and did not yield clear result patterns. This has already been checked by the author. While segmenting the data we are directly faced with the curse of dimensionality, i.e. the problem of running into data cells with low frequency. An extension to an estimation framework that overcomes some of these difficulties and that in addition accounts for endogeneity is therefore desirable. The recent paper by Blundell, Chen and Kristensen (2003) provides some interesting developments which may contribute soon to the applied literature.

Appendix:

A I: Wild bootstrapping in the EPLM

The idea of bootstrapping is to resample the observations several times and estimate the unknown regression functions and the unknown coefficients for each resample. This yields an empirical distribution for the parameter estimates of interest. However, naive resampling does not work in the EPLM because the conditions $E(U|X = x) = E(V|W = w) = 0$ would not be imposed. Therefore, wild bootstrapping is performed which induces the required conditions.

Let Q be a random variable with a two point probability distribution H:

$$Q = (1-\sqrt{5})U/2 \quad \text{with probability}(1+\sqrt{5})/2\sqrt{5}$$

and

$$Q = (1+\sqrt{5})U/2 \quad \text{with probability} \left(1-(1+\sqrt{5})\right)/2\sqrt{5}$$

This implies $E(Q|H) = 0$, $E(Q^2|H) = U^2$ and $E(Q^3|H) = U^3$.

Compute the residuals of the first step nonparametric estimation, i.e. $\hat{U}_{ji} = Y_{ji} - \hat{m}_j^0(X_i)$ and $\hat{V}_{ji} = S_{ji} - \hat{m}_j^1(W_i)$. Then Wild bootstrapping is then carried out as follows:

1. Compute $U_{ji}^* = Q\hat{U}_{ji}$ and $V_{ji}^* = Q\hat{V}_{ji}$ for all i and j.
2. Compute $Y_{ji}^* = \hat{m}_j^0(X_i) + U_{ji}^*$ and $S_{ji}^* = \hat{m}_j^1(W_i) + V_{ji}^*$ for all i and j.
3. Estimate m_j^{0*} and m_j^{1*} using the samples (Y_{ij}^*, X_i) and (S_{ij}^*, W_i) for all j.
4. Obtain bootstrap parameter estimates $\hat{a}^*$ and $\hat{\alpha}^*$.
5. Repeat steps one to four in order to get finitely many realizations of $\hat{a}^*$ and $\hat{\alpha}^*$.

The empirical distribution of $\hat{a}^*$ and $\hat{\alpha}^*$ is used to approximate the distribution of $\hat{a}$ and $\hat{\alpha}$. For further details concerning the wild-bootstrap method see Härdle and Mammen (1993). Härdle and Mammen (1993) suggest choosing a larger bandwidth for the pilot nonparametric estimates and an optimal bandwidth for the bootstrap estimates. In this paper the same bandwidth is used for the estimation of m_j and m_j^*. This is done for the simple reason of computational feasibility.

A II: Second stage $\mathbf{R}^2$ in the EPLM

This appendix introduces the extended coefficient of determination for the parametric transformation in the EPLM, the $\mathbf{eR}^2$. It determines how well the differences between the two sets of nonparametric functions $\hat{m}_0^j$ and $\hat{m}_1^j$ are explained by the parametric part of the model. However, it only incorporates the point estimates and ignores information about higher moments of the distribution of $\hat{m}_0^j$ and $\hat{m}_0^j$. Since a large part of the variance of the estimated coefficients is due to the variance of the first stage nonparametric estimates, the suggested $\mathbf{eR}^2$ cannot be seen as a general goodness of fit measure for the EPLM.

Let us denote $\bar{m}_0^j = \sum_i \hat{m}_0^j(x_i)$ and $\bar{m}_1^j = \sum_i \hat{m}_1^j(x_i)$ as the mean expenditure shares for commodity j. Then the coefficient of determination for commodity j is given by

$$\mathbf{R}_j^2 = \frac{\left[\sum_i \left(\hat{m}_1^j(x_i) - \bar{m}_1^j\right)\left(\hat{m}_\alpha^j(x_i) - \bar{m}_c^j\right)\right]^2}{\left[\sum_i \left(\hat{m}_1^j(x_i) - \bar{m}_1^j\right)^2\right]\left[\sum_i \left(\hat{m}_\alpha^j(x_i) - \bar{m}_\alpha^j\right)^2\right]}$$

which has the standard properties of the $\mathbf{R}^2$, i.e. it is the squared correlation between the nonparametric function $\hat{m}_1^j$ and its predicted value $\hat{m}_\alpha^j$ both evaluated at the observations. Note that the constant $\hat{a}_j$ cancels out. The $\mathbf{eR}^2$ is simply an average over the $\mathbf{R}_j^2$, i.e.

$$\mathbf{eR}^2 = \frac{1}{J}\sum_j \mathbf{R}_j^2.$$

A III: Tables

Table 5: Sample Size

	S0	S1	C0	C1	C2	C3
Full sample	5.714	882	7.727	3.531	4.589	1.321
quartile	1.429	221	1.932	883	1.147	330
Employed	2.460	380	3.349	2.886	3.968	1.091
quartile	615	–‡	838	722	992	273
Nonemployed	3.254	502	4.378	645	621	230

‡ not considered, too few observations

Table 6: Average age of household head

	S0	S1	C0	C1	C2	C3
Full sample	50.7	41.5	56.7	42.7	41.1	41.7
lowest income quartile	48.9	38.4	60.6	39.0	41.1	41.7
highest income quartile	52.5	45.6	53.9	47.0	44.9	44.3
Employed	38.8	42.3	45.0	41.7	40.8	41.4
lowest income quartile	34.1	–‡	43.2	37.8	37.7	39.0
highest income quartile	44.4	–‡	47.7	46.0	44.4	43.9
Nonemployed	59.7	40.9	65.6	46.9	43.2	43.2

‡ not considered, too few observations

Table 7: Average age of children

	S0	S1	C0	C1	C2	C3
Full sample	–	13.4	–	11.7	10.8	10.5
lowest income quartile	–	10.6	–	9.0	9.0	9.3
highest income quartile	–	16.0	–	14.2	13.1	12.1
Employed	–	15.6	–	11.4	10.7	10.4
lowest income quartile	–	–‡	–	8.5	8.9	9.2
highest income quartile	–	–‡	–	14.2	12.8	12.0
Nonemployed	–	11.7	–	13.0	11.6	10.9

‡ not considered, too few observations

Table 8: Employment status of the 2nd adult in the household

	S0	S1	C0	C1	C2	C3
Full sample						
full time employed	–	–	21%	17%	14%	6%
part time, other	–	–	14%	47%	49%	43%
nonemployed	–	–	65%	36%	37%	51%
Employed						
full time employed	–	–	43%	19%	14%	5%
part time, other	–	–	21%	49%	50%	43%
nonemployed	–	–	36%	32%	36%	52%

Table 9: Estimation results of the log of the consumption based equivalence scale, part I

Additional adult		C0/S0			C1/S1		
		NW[a]	LLS[b]	NLS[c]	NW[a]	LLS[b]	NLS[c]
Full sample	$\hat{\alpha}$	0.3915 (0.1036)[†]	0.4093 (0.0764)[†]	0.3444 ()	0.2136 (0.1098)	0.2492 (0.0809)	0.0740 (0.1291)
	eR^2	0.26	0.27	0.57	0.32	0.33	0.57
low income	$\hat{\alpha}$	–[§]	–[§]	0.4627 (0.1042)	–[§]	–[§]	−0.0917 (0.2624)
	eR^2			0.47			0.39
high income	$\hat{\alpha}$	0.3829 (0.0760)	0.4285 (0.0831)	0.4248 (0.0682)	–[§]	–[§]	0.2006 (0.1334)
	eR^2	0.29	0.30	0.64			0.50
Employed	$\hat{\alpha}$	0.4323 (0.0533)	0.4611 (0.0557)	0.4563 (0.0579)	0.1321 (0.2058)	0.1865 (0.1482)	0.0634 (0.1672)
	eR^2	0.30	0.31	0.61	0.24	0.29	0.58
low income	$\hat{\alpha}$	0.5305 (0.0978)	0.5459 (0.0904)	0.4269 (0.1242)	–[‡]	–[‡]	–[‡]
	eR^2	0.25	0.26	0.36			
high income	$\hat{\alpha}$	0.5465 (0.0639)	0.5769 (0.1114)	0.5425 (0.1085)	–[‡]	–[‡]	–[‡]
	eR^2	0.39	0.41	0.65			
Nonemployed	$\hat{\alpha}$	0.2551 (0.2488)	0.2551 (0.2044)	0.1968 (0.1025)	0.3945 (0.2180)	0.3861 (0.1746)	0.2589 (0.1679)
	eR^2	0.31	0.33	0.50	0.28	0.30	0.49

Wild bootstrap standard errors of $\hat{\alpha}$ in brackets

[a] Nadaraya-Watson 1st stage nonparametric estimate

[b] Local linear smoother 1st stage nonparametric estimate

[c] quadratic parametric 1st stage estimate

[§] no result available (boundary solution, misshaped objective function)

[†] results based on a 75% random sample (C0), otherwise too many observations

[‡] not considered, too few observations

Table 10: Estimation results of the log of the consumption based equivalence scale, part II

First child		S1/S0			C1/C0		
		NW[a]	LLS[b]	NLS[c]	NW[a]	LLS[b]	NLS[c]
Full sample	$\hat{\alpha}$	0.0445 (0.1035)	0.0668 (0.0840)	0.1574 (0.0885)	−0.0540 (0.0435)[†]	−0.0432 (0.0386)[†]	−0.0408 (0.0387)
	eR^2	0.27	0.29	0.60	0.28	0.29	0.27
low income	$\hat{\alpha}$	–[§]	–[§]	0.3973 (0.1701)	−0.0431 (0.0686)	0.0000 (0.0762)	−0.0673 (0.0742)
	eR^2			0.45	0.38	0.38	0.58
high income	$\hat{\alpha}$	0.0080 (0.1083)	−0.0080 (0.0935)	0.1631 (0.1301)	0.0121 (0.0629)	−0.0483 (0.0810)	−0.0342 (0.0635)
	eR^2	0.34	0.35	0.51	0.59	0.51	0.64
Employed	$\hat{\alpha}$	0.2384 (0.1867)	0.2831 (0.1672)	0.3574 (0.1473)	−0.1113 (0.0552)	−0.1113 (0.0549)	−0.0799 (0.0466)
	eR^2	0.18	0.22	0.41	0.57	0.55	0.63
low income	$\hat{\alpha}$	–[‡]	–[‡]	–[‡]	−0.1136 (0.3210)	0.0852 (0.2479)	−0.0317 (0.0733)
	eR^2				0.25	0.38	0.69
high income	$\hat{\alpha}$	–[‡]	–[‡]	–[‡]	0.0582 (0.0943)	0.0582 (0.0992)	−0.1251 (0.0921)
	eR^2				0.39	0.42	0.63
Nonemployed	$\hat{\alpha}$	−0.1970 (0.2813)	−0.1244 (0.2367)	−0.0900 (0.1730)	0.1850 (0.1028)	0.2081 (0.1048)	0.1020 (0.0786)
	eR^2	0.21	0.22	0.48	0.29	0.32	0.54

Wild bootstrap standard errors of $\hat{\alpha}$ in brackets

[a] Nadaraya-Watson 1st stage nonparametric estimate

[b] Local linear smoother 1st stage nonparametric estimate

[c] quadratic parametric 1st stage estimate

[§] no result available (boundary solution, misshaped objective function)

[†] results based on a 75% random sample (C0), otherwise too many observations

[‡] not considered, too few observations

Table 11: Estimation results of the log of the consumption based equivalence scale, part III

Additional child		C2/C1			C3/C2		
		NW[a]	LLS[b]	NLS[c]	NW[a]	LLS[b]	NLS[c]
Full sample	$\hat{\alpha}$	0.1102 (0.0350)	0.1102 (0.0352)	0.0683 (0.0357)	0.1392 (0.0663)	0.1160 (0.0557)	0.1142 (0.0512)
	eR^2	0.81	0.81	0.84	0.57	0.62	0.75
low income	$\hat{\alpha}$	0.1234 (0.0592)	0.0905 (0.0678)	0.0414 (0.0531)	0.1320 (0.1659)	0.1775 (0.1384)	0.1895 (0.0746)
	eR^2	0.58	0.59	0.76	0.27	0.28	0.64
high income	$\hat{\alpha}$	0.0069 (0.0731)	0.0691 (0.0598)	0.0435 (0.0626)	–[§]	–[§]	0.3339 (0.1682)
	eR^2	0.60	0.65	0.75			0.49
Employed	$\hat{\alpha}$	0.1036 (0.0356)	0.1036 (0.0369)	0.0803 (0.0343)	0.1168 (0.0543)	0.0973 (0.0508)	0.0764 (0.0484)
	eR^2	0.85	0.82	0.84	0.65	0.62	0.68
low income	$\hat{\alpha}$	0.1155 (0.0520)	0.1227 (0.0668)	0.0414 (0.0627)	0.1547 (0.1664)	0.1957 (0.1370)	0.2021 (0.0855)
	eR^2	0.58	0.60	0.77	0.29	0.29	0.67
high income	$\hat{\alpha}$	0.0297 (0.0571)	0.0535 (0.0527)	0.0521 (0.0583)	–[§]	–[§]	0.2151 (0.1386)
	eR^2	0.68	0.73	0.75			0.40
Nonemployed	$\hat{\alpha}$	0.2150 (0.2434)	0.2398 (0.2314)	0.1685 (0.1112)	0.0463 (0.3957)	0.0556 (0.2727)	0.1583 (0.1527)
	eR^2	0.41	0.39	0.61	0.44	0.48	0.72

Wild bootstrap standard errors of $\hat{\alpha}$ in brackets

[a] Nadaraya-Watson 1st stage nonparametric estimate

[b] Local linear smoother 1st stage nonparametric estimate

[c] quadratic parametric 1st stage estimate

[§] no result available (boundary solution, misshaped objective function)

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