Elasticities of Food Demand in Germany – A Demand System Analysis Using Disaggregated Household Scanner Data

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Abstract

This paper presents price and income elasticities of food demand for Germany. Using disaggregated household scanner data and the Quadratic Almost Ideal Demand System (QUAIDS). The QUAIDS is modified to account for censoring and include household demographics. Furthermore, a two-stage budgeting approach is used to more accurately reflect households' purchasing behaviour. Having disaggregated data also allowed to include convenience aspects into the demand system. High expenditure elasticities are found for fruits and nuts and meat, fish and eggs. The highest own-price elasticity is found for beverages. At the second stage, the bread toppings group reveals new insights into demand relations between cold cuts, cheese and other spreads. Cold cuts have both the highest expenditure and own-price elasticity. Cross-price elasticities indicate mostly complementary relations between cold cuts and other bread toppings. Comparing different income groups shows that expenditure elasticities of raw foods or basic ingredient foods tend to decrease as income increases, whereas expenditure elasticities of foods that require minimal or no preparation tend to increase with income. In conclusion, this study stresses the need for regularly updated elasticities of food demand that reflect up-to-date consumption behavior.

Key words

food demand, elasticities, Germany, QUAIDS

1 Introduction

Elasticities of food demand allow an assessment of consumer reactions to changes in prices and incomes. Many evaluations of food or nutrition related problems, therefore, required accurate estimates of the elasticities of food demand. To estimate, for example, the effects of a tax on a food's carbon footprint, a measure discussed recently by experts and the public that can help reduce greenhouse gas emissions, it is essential to know how consumers react to increases in the prices of foods with higher carbon footprints and which foods they might substitute should a tax be imposed. If the elasticities of food demand are used as a decision tool by experts and policy makers, it is important that they reflect up-to-date consumption behavior. In order to observe all substitution effects, it is also important that the elasticities cover the widest possible range of foods while simultaneously providing a high degree of detail.

Existing studies on food price elasticities for Germany have focused on estimating complete systems of food demand using highly aggregated food groups, such as cereals, meat, fruits, or vegetables (GRINGS, 1993; HAEN et al., 1982; HENNING and MICHALEK, 1992; MICHALEK and KEYZER, 1992; THIELE, 2001; THIELE, 2008; THIELE, 2010; WILDNER 2001). Some of them also looked at individual categories of foods such as meat and analyzed the demand for the different products of the food group (e.g., pork or beef) (HENNING and MICHALEK, 1992; THIELE, 2008; WILDNER, 2001). The work of JONAS and ROOSEN (2008) and SCHRÖCK (2012) focused on the demand for organic and conventional milk. The demand for different fruits and vegetables was studied by BURREL and HENNINGSEN (2001) and SCHRÖCK (2013). BRONNMANN (2016), BRONNMANN et al. (2016) as well as NIELSEN et al. (2011) focused on the demand for fish and seafood.

As shown in the short literature review, some studies have estimated the elasticities of food demand in Germany. However, those considering the complete food basket are based on older data from 2003 (THIELE (2008) and THIELE (2010)). These elasticities are still used in recent studies, for example, to estimate the effects of a tax on unhealthy foods (EFFERTZ, 2017) or the effects of a tax on animal products to reduce carbon emissions (WBAE AND WBW, 2016). However, in order to update previous studies, this analysis estimates new elasticities using contemporary methodologies and a unique set of household scanner data. The data cover the complete food basket of households and provide highly disaggregated information on individual foods. The highly disaggregated data enable the use of a two-stage budgeting approach reflecting households' consumption decisions more accurately than those used in previous studies. A further advantage of the dataset and its high level of disaggregation of foods is that actual

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prices are available. Most previous studies estimated elasticities of demand based on data with information on expenditures and quantities for food groups from which unit values and, in a second step, quality adjusted prices could be derived following COX and WOHLGENANT (1986). Using the real prices of purchased food is one of the strengths of this analysis.

In the following section, the demand model used in this study is briefly outlined. In Section 2, a detailed description of the dataset is given, and the estimation strategy and its issues are described. In Section 3, the results are presented and discussed. Section 4 concludes the paper.

2 Data and methods

2.1 Data

The data source for this study is a consumer panel conducted by the GfK Group, a German market research institution. The data contain information on the food purchases of 13,131 representative German households from January to December of 2011. Stratified random sampling based on demographic and geographic targets is used to select households for the panel. Households were selected based on their geographic and demographic characteristics in accordance with the German Micro-Census, an annual random sample of 1% of the German population. Households participating in the sample were asked to document all purchases for home consumption for at least 10 months of the year.

To aid in the data collection, households were provided with a barcode scanner. Articles with a barcode were scanned directly by the households. For purchases without a barcode, such as products purchased at weekly markets or butcher shops, households received a codebook with extra barcodes. By this means, household food purchases are documented at the highest possible disaggregated level, which makes the dataset especially suitable for demand analyses. In 2011, a total of 12,408,473 food purchases were documented. However, as the manual scanning procedure is very labor intensive, it is conceivable that some purchases were not scanned by the households. To ensure data quality, households whose number of scanned products decreased significantly during the data collection period, were excluded by the GfK.

For each of the approximately 12 million food purchases, information, such as quantity, price, brand, and type of store where the food was purchased, was available. Additionally, the dataset has information about each household's socio-demographic characteristics. These include income, household size, number of children by age group in the household, age and education of the head of the household, and information about the person mainly responsible for the food purchases in the household. Information on the socio-demographic characteristics of the households are collected once a year using a standardized questionnaire. Descriptive statistics of the socio-demographic characteristics considered relevant for the present study are presented in Table 1.

Table 1. Definition and descriptive statistics of the variables used in the analyses

	Mean	SD
Monthly household equivalence income of the low-income group in 1000 Euros: The low-income group comprises households whose equivalence income is in the first equivalence income quartile	0.752	0.198
Monthly household equivalence income of the medium income group in 1000 Euros: The medium-income group comprises households whose equivalence income is in the second and third equivalence income quartile	1.361	0.211
Monthly household equivalence income of the high-income group in 1000 Euros: The high-income group comprises households whose equivalence income is in the fourth equivalence income quartile	2.340	0.517
Single household, male: dummy variable set to one if the household comprises of a single male person, otherwise zero	0.10	0.30
Single household, female: dummy variable set to one if the household comprises of a single female person, otherwise zero	0.13	0.33
Number of children aged 0 to 6	0.16	0.46
Number of children aged 7 to 13	0.24	0.58
Number of children aged 14 to 17	0.07	0.27
Lower education: dummy variable set to one if the principal wage earner has finished 9 years of elementary school but does not have additional professional training (Hauptschule ohne Berufsausbildung), otherwise zero	0.26	0.44
Higher education: dummy variable set to one if the principal wage earner has university degree (Fachhochschule/ Hochschule/ Staatsexamen), otherwise zero	0.31	0.46

Source: Own calculations based on the representative GfK consumer panel dataset.

2.2 Modelling a two-stage budgeting process

The very detailed data enable the modeling of a two-stage budgeting approach reflecting households' consumption decisions more accurately than those used in previous studies. At the first stage, foods were divided into 15 major food groups, and at the second stage, two selected major groups were further divided into subgroups. In line with the basic idea of the budgeting process, we put those food items together which, from the consumer perspective, are most likely the closest substitutes. For example, one of the major groups formed in this study is "bread toppings" consisting of cheese, cold cuts, cream cheese, etc. Many previous studies classified cheese into a group called "milk and dairy products", whereas cold cuts were assigned to "meat and meat products". However, our approach is justified because cheese is more likely to be a substitute for cold cuts than for fluid milk. It should be noted, that the demand system estimated in this study focusses on how households allocate their food budgets to individual food groups. The decision on how much of the household income is spent on food is made at an earlier stage, where households decide on how much of their income is spent on broad expenditure categories such as housing, transport and food etc.

2.2.1 The QUAIDS

To model consumer behavior, the quadratic almost ideal demand system (QUAIDS) proposed by BANKS et al. (1997) was used. The QUAIDS model is a generalization of the popular almost ideal demand system (AIDS) by DEATON and MUELLBAUER (1980). It includes squared logarithmised expenditure as an additional regressor. This allows any given good to be a necessity at one level of expenditure but a luxury good at another level of expenditure. Furthermore, this allows for greater flexibility of the Engle curves and for demands to be rank three as theory predicts. The demand for each food group is defined as a function of food expenditures and prices:

$$w_{ih} = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_{jh} + \beta_i \ln\left\{\frac{m_h}{a(\mathbf{p}_h)}\right\} + \frac{\lambda_i}{b(\mathbf{p}_h)} \left[\ln\left\{\frac{m_h}{a(\mathbf{p}_h)}\right\}\right]^2 \tag{1}$$

for $i = 1, 2, 3,\ldots, k$, $j = 1, 2, 3,\ldots, k$ and $h = 1, 2, 3,\ldots, n$ with i and j referring to the i-th and j-th food group and h referring to the h-th household. Nominal expenditure is denoted by m and $\mathbf{p}$ denotes an k-dimensional price vector. Ln $a(\mathbf{p}_h)$ is the transcendental logarithmic function

$$\ln a(\mathbf{p}_h) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln p_{jh} + \frac{1}{2}\sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln p_{ih} \ln p_{jh} \tag{2}$$

and $b(\mathbf{p}_h)$ the Cobb-Douglas price aggregator

$$b(\mathbf{p}_h) = \prod_{i=1}^{k} p_{ih}{}^{\beta_i} \tag{3}$$

The adding-up, homogeneity, and Slutsky symmetry restrictions are given by:

$$\sum_{i=1}^{k} \alpha_i = 1 \quad \sum_{i=1}^{k} \beta_i = 0 \quad \sum_{i=1}^{k} \gamma_{ij} = 0$$
$$\sum_{i=1}^{k} \lambda_i = 0 \text{ and } \gamma_{ij} = \gamma_{ji} \tag{4}$$

for all $i, j = 1, 2, 3,\ldots, k$.

2.2.2 Considering socio-demographic variables

Because income, in particular, affects how households react to price changes, the demand system was estimated separately for three different income groups. The assignment of a household to an income group is based on households' equivalence income. Using the modified OECD equivalence scale (HAGENAARS et al., 1994), the first adult in the household is assigned a weight of 1.0. Every additional adult in the household and every child aged 14 and older gets a weight of 0.5. Children younger than 14 are weighted at 0.3. The equivalence income is calculated by dividing the household income by the sum of the equivalence values of the household. Using quartiles of the equivalence income, households in the first quartile belong to the low-income group, households in the second and third quartiles form the medium income group, and households in the fourth quartile comprise the high-income group.

Further factors affecting the demand for foods were considered in the QUAIDS model using RAY'S (1983) demographic scaling. RAY assumes that each household faces an expenditure function of the form:

$$e^h(u, \mathbf{p}, \mathbf{z}) = m_0(\mathbf{p}, \mathbf{z}, u) \times e^R(u, \mathbf{p}) \tag{5}$$

where u refers to a reference level of utility, $\mathbf{z}$ is a vector of s household characteristics and $c^R(u,\mathbf{p})$ is the cost function of a reference household. The cost function is scaled by the function $m_0(\mathbf{p},\mathbf{z},u)$ to obtain the cost function of a household. According to Ray, $m_0(\mathbf{p},\mathbf{z},u)$ consists of two multiplicative factors: a component $\overline{m}_0(\mathbf{z})$ that measures increases in costs as a function of $\mathbf{z}$ without controlling for changes in the consumption pattern and $\psi(\mathbf{p},\mathbf{z},u)$ that controls for changes in relative prices and consumed goods (POI, 2012). This results in the form of $m_0(\mathbf{p},\mathbf{z},u)$ as follows.

$$m_0(\mathbf{p},\mathbf{z},u) = \bar{m}_0(\mathbf{z}) \times \psi(\mathbf{p},\mathbf{z},u) \tag{6}$$

To parameterize $\bar{m}_0(\mathbf{z})$, this study follows RAY (1983) and POI (2012):

$$\bar{m}_0(\mathbf{z}) = 1 + \boldsymbol{\rho}'\mathbf{z} \tag{7}$$

where $\boldsymbol{\rho}'$ is a vector of parameters to be estimated. Following POI (2012), $\psi(\mathbf{p},\mathbf{z},u)$ takes the following form:

$$\ln \psi(\mathbf{p},\mathbf{z},u) = \frac{\prod_{j=1}^{k} p_j^{\beta_j}\left(\prod_{j=1}^{k} p_j^{\boldsymbol{\eta}_j'\mathbf{z}} - 1\right)}{\frac{1}{u} - \sum_{j=1}^{k} \lambda_j \ln p_j}, \tag{8}$$

with $\boldsymbol{\eta}_j$ being the j-th column of a $s \times k$ parameter matrix $\boldsymbol{\eta}$. The advantage of this specification is that the budget share equations in the QUAIDS model with demographics are similar to those in a model without demographics (POI, 2012). Following POI's (2012) approach to incorporate demographic characteristics in a demand system, the model described in equation 1 was modified as follows:

$$w_{ih} = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_{jh} + (\beta_i + \boldsymbol{\eta}_i'\mathbf{z}_h) \ln\left\{\frac{m_h}{\bar{m}_0(\mathbf{z}_h) a(\mathbf{p}_h)}\right\} + \frac{\lambda_i}{b(\mathbf{p}_h) c(\mathbf{p}_h, \mathbf{z}_h)} \left[\ln\left\{\frac{m_h}{\bar{m}_0(\mathbf{z}_h) a(\mathbf{p}_h)}\right\}\right]^2, \tag{9}$$

with $c(\mathbf{p}_h, \mathbf{z}_h) = \prod_{j=1}^{k} p_{jh}^{\boldsymbol{\eta}_j'\mathbf{z}_h}$. The modifications require an additional restriction in the form of $\sum_{j=1}^{k} \eta_{dj} = 0$ for $d = 1, \dots, s$.

2.2.3 Treatment of zero observations

Zero observations are a common issue when using household data, especially at a disaggregated level because not all households consume every product. These corner solutions will lead to biased estimation results when ignored. There are multiple ways for dealing with zero observations when estimating a demand system. Many of them are, however, either difficult to implement or computationally expensive, especially when using large datasets. Currently, the two-step approach by SHONKWILER and YEN (1999) is widely used to correct for censoring in demand systems. In this method, a probit model is estimated to derive correction terms (in the form of probability density functions and cumulative density functions), which are included in the demand system's budget share equations. However, the approach of SHONKWILER and YEN was shown to lack efficiency (TAUCHMANN, 2005) and includes the problem that the adding-up restriction (see equation 4) cannot be imposed via parametric restrictions (GARCÍA-ENRÍQUEZ and ECHEVARRÍA, 2016; YEN, LIN, and SMALLWOOD, 2003)[1]. The problems associated with this are, among others, described by YEN, LIN, and SMALLWOOD (2003) and by GARCÍA-ENRÍQUEZ and ECHEVARRÍA (2016). Because of the drawbacks of SHONKWILER and YEN's method, this study uses an approach that addresses the problems of both the SHONKWILER and YEN method. TAUCHMANN (2010) proposed a consistent generalized Heckmann-type estimator to account for censoring. Suppose that there is a latent system of equations characterized as (TAUCHMANN, 2010)[2]:

$$w_{ih}^* = f(\mathbf{x}_h \boldsymbol{\theta}_i) + \varepsilon_{ih}, \tag{10a}$$

$$d_{ih}^* = \mathbf{z}_h \boldsymbol{\pi}_i + \nu_{ih}, \tag{10b}$$

where w^*_{ih} and d^*_{ih} are latent variables with i referring to the i-th good and h referring to the h-th household, $\mathbf{x}_h$ and $\mathbf{z}_h$ are vectors of exogenous variables for the h-th household, and $\boldsymbol{\theta}_i$ and $\boldsymbol{\pi}_i$ are vectors of parameters to be estimated. The observed variables are given as follows.

$$d_{ih} = \begin{cases} 1 \; if \; d_{ih}^* > 0 \\ 0 \; if \; d_{ih}^* \le 0 \end{cases} \tag{11a}$$

$$w_{ih} = d_{ih} * w_{ih}^* \tag{11b}$$

To construct TAUCHMANN's consistent generalized Heckmann-type estimator, a multivariate probit model is estimated, and the results are used to build a correction term as follows.

$$M_{jh} = \xi_{ih} \phi(\mathbf{z}_h' \hat{\boldsymbol{\pi}}_i) \frac{\Phi^{k-1}(\tilde{\mathbf{A}}_{jh}, \tilde{\mathbf{R}}_{jh})}{\Phi^{k}(\mathbf{z}_h' \hat{\boldsymbol{\pi}}_1, \dots, \mathbf{z}_h' \hat{\boldsymbol{\pi}}_k)} \tag{12}$$

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[1] The approach of SHONKWILER and YEN modifies the demand system's budget share equations as follows: $w_{ih} = \Phi(\mathbf{z}_h'\boldsymbol{\pi}_i) f(\mathbf{x}_h \boldsymbol{\theta}_i) + \sigma_i \phi(\mathbf{z}_h'\boldsymbol{\pi}_i) + \varepsilon_{ih}$, where $f(\mathbf{x}_h\boldsymbol{\theta}_i)$ refers to the functional form of the demand system (in the case of a QUAIDS model, the right hand side of equation 1), $\Phi(\mathbf{z}_h'\boldsymbol{\pi}_i)$ and $\phi(\mathbf{z}_h'\boldsymbol{\pi}_i)$ are estimated by a probit model and replaced with $\Phi(\mathbf{z}_h'\hat{\boldsymbol{\pi}}_i)$ and $\phi(\mathbf{z}_h'\hat{\boldsymbol{\pi}}_i)$ in the estimation. Using this specification and the QUAIDS model, adding-up can no longer be imposed with parametric restrictions because $\sum_{i=1}^{k} \alpha_i \Phi(\mathbf{z}_h'\boldsymbol{\pi}_i) \neq 1$ (GARCÍA-ENRÍQUEZ and ECHEVARRÍA, 2016).

[2] In the following section, we follow the notation of GARCÍA-ENRÍQUEZ and ECHEVARRÍA (2016) when describing the method used to account for zero observations.

For $i = 1, 2, 3,\dots, k$; $\xi_{ih} \equiv 2d_{ih} - 1$ indicates truncation from above or below; $\phi(\cdot)$ is the univariate standard normal probability density function, $\hat{\boldsymbol{\pi}}_i$ denotes the maximum likelihood estimates of the vector $\boldsymbol{\pi}_i$, and $\Phi^k(\cdot)$ is the cumulative density function of the x-variate standard normal distribution; $\widetilde{\mathbf{A}}_{jh}$ is a vector of k-1 elements $\xi_{lh} \frac{\left(\mathbf{z}_h'\hat{\boldsymbol{\pi}}_l - s_{lj}^{vv}\mathbf{z}_h'\hat{\boldsymbol{\pi}}_j\right)}{\left\{1-\left(s_{lj}^{vv}\right)^2\right\}^{0.5}}$, $l = 1, 2, 3,\dots, k$; $l \neq j$. $\widetilde{\mathbf{R}}_{jh}$ is defined as $\mathbf{K}_{jh}\mathbf{R}_{jh}\mathbf{K}_{jh}$, where $\mathbf{K}_{jh}$ is a diagonal matrix with diagonal elements ξ_{lh} $l \neq j$. The matrix $\mathbf{R}_{jh}$ is the partial conditional correlation matrix $Cor(v_h | v_{jh})$. Compared to the model described in equations 11a and 11b which conditions only on d_{ih} the correction term in equation 12 conditions on the entire selection pattern $d_h = [d_{1h},\dots,d_{kh}]'$ (GARCÍA-ENRÍQUEZ and ECHEVARRÍA, 2016). Using the correction term proposed by TAUCHMANN each QUAIDS budget share equation includes k correction terms to correct for censoring.

To correct for censoring, the correction terms were estimated based on equation 12 and then, to correct for censoring, were added as additional regressors to the modified QUAIDS shown in equation 9, resulting in equation 13.

$$w_{ih} = d_{ih}\Bigg(\alpha_i + \sum_{j=1}^{k}\gamma_{ij}\ln p_{jh} + (\beta_i + \boldsymbol{\eta}_i'\mathbf{z}_h)\ln\left\{\frac{m_h}{\overline{m}_0(\mathbf{z}_h)a(\mathbf{p}_h)}\right\} + \frac{\lambda_i}{b(\mathbf{p}_h)c(\mathbf{p}_h,\mathbf{z}_h)}\left[\ln\left\{\frac{m_h}{\overline{m}_0(\mathbf{z}_h)a(\mathbf{p}_h)}\right\}\right]^2\Bigg) + d_{ih}\sum_{j=1}^{k}\upsilon_{ij}M_{jh} + d_{ih}\tilde{\varepsilon}_{ih}, \tag{13}$$

with $\tilde{\varepsilon}_{ih} = \varepsilon_{ih} - E(\varepsilon_{ih}|d_h)$. The inclusion of the weighting variable d_{ih} causes every household that has not bought all the food groups to be excluded from the estimation sample. The model in equation 13 was estimated using iterative feasible generalized nonlinear least squares, which is equivalent to maximum likelihood estimation (POI, 2008). The model shown in equation 13 was estimated for all 15 highly disaggregated food subgroups in the second stage of the two-stage budgeting approach. In contrast, the foods in the first stage are highly aggregated, so censoring was not a problem and, therefore, equation 9 was estimated. To avoid singularity of the covariance matrix in the estimation, a system of k–1 equations was estimated, and the parameters of the k-th equation were recovered by using the restrictions applied to the system. It is important to note that, in contrast to the method of SHONKWILER and YEN, the censoring correction term is the same for every budget share equation. Thus, the estimated system is invariant to the equation dropped. Stata's *nlsur* command was used to estimate the demand system (STATACORP, 2019).

2.2.4 Deriving elasticities

The elasticities of prices and expenditures were estimated based on the formulae in POI (2012). To estimate elasticities for the first stage (second stage), equation 9 (13) is first differentiated with respect to ln m and ln p_j, respectively, to obtain:

$$\mu_i = \frac{\delta w_i}{\delta\ln(m)} = \beta_i + \boldsymbol{\eta}_i'\mathbf{z} + \frac{2\lambda_i}{b(\mathbf{p})c(\mathbf{p},\mathbf{z})}\left\{\ln\left[\frac{m}{\overline{m}_0(\mathbf{z})a(\mathbf{p})}\right]\right\} \tag{14}$$

$$\mu_{ij} = \frac{\delta w_i}{\delta\ln p_j} = \gamma_{ij} - \mu_i\left(\alpha_j + \sum_k\gamma_{jk}\ln p_k\right) - \frac{\lambda_i(\beta_j + \boldsymbol{\eta}_j'\mathbf{z})}{b(\mathbf{p})c(\mathbf{p},\mathbf{z})}\left\{\ln\left[\frac{m}{\overline{m}_0(\mathbf{z})a(\mathbf{p})}\right]\right\}^2 \tag{15}$$

The expenditure elasticity, as well as the Marshallian and Hicksian price elasticities are:

Expenditure elasticity: $e_i = \frac{\mu_i}{w_i} + 1$, (16)

Marshallian price elasticity: $e_{ij}^U = \frac{\mu_{ij}}{w_i} - \delta_{ij}$, and (17)

Hicksian price elasticity: $e_{ij}^C = e_{ij}^U + w_j e_i$, (18)

where $\delta_{ij} = 1$ if i=j and $\delta_{ij} = 0$ otherwise.

As a change in the price of a good of a subgroup (e.g., bread toppings) may not only affect the demand for other goods in that subgroup but also of the goods in all other subgroups (e.g., meat, fish, and eggs), unconditional elasticities that explicitly account for the two-stage budgeting approach were calculated following CARPENTIER and GUYOMARD (2001). The authors use an approximation to the Slutsky substitution terms that are assumed to be weakly separable. Denoting the superscript as representing the major food group and the subscript as representing the subgroup of foods, the unconditional expenditure, Marshallian and Hicksian elasticities are:

$$e_{iM} \approx e_{iM}^I\, e^{IM}, \tag{19}$$

$$e^{U}_{ij} \approx \delta^{IJ} e^{UI}_{ij} + w^{J}_{j} e^{I}_{iM} e^{J}_{jM} \left(\frac{\delta^{IJ}}{e^{J}_{jM}} + e^{UIJ} \right) + w^{J}_{j} w^{J} e^{IM} e^{I}_{iM} (e^{J}_{jM} - 1), \quad (20)$$

$$e^{C}_{ij} \approx \delta^{IJ} e^{CI}_{ij} + w^{J}_{j} e^{CIJ} e^{I}_{iM} e^{J}_{jM}, \quad (21)$$

where e^{I}_{iM} is the expenditure elasticity for good i conditional on expenditure for group I, e^{IM} is the expenditure elasticity for major food group I with respect to total expenditure (M), e^{UI}_{ij} is the Marshallian elasticity of demand for good i with respect to price j, e^{UIJ} is the Marshallian elasticity of demand for major food group I with respect to major food group price J, e^{CIJ} is the Hicksian elasticity of demand for major food group I with respect to major food group price J, δ^{IJ} is Kronecker's delta (1 if $I = J$; 0, otherwise), w^{J}_{j} is the budget share of good j, and w^{J} is the budget share of major food group J.

3 Results and discussion

Households' reaction to changes in food prices depend strongly on income. Lower income households react differently to changes in food prices and expenditures than higher income households as the percentage of total household income dedicated to food as well as the mix of foods a household consumes may vary from one income group to another. To address this unobserved heterogeneity in demands that is correlated with income which is not captured by the QUAIDS (LEWBEL and PENDAKUR, 2009), separate estimations were conducted for the three different income groups. The income groups are defined in Table 1. In the following description of the results, the focus is mainly on the medium-income group. This group is then compared with the high- and low-income groups. All results are based on household purchases for home consumption; therefore, inferences cannot be made about food demand outside of home purchases.

3.1 Budget shares of the food groups

Table 2 gives an overview of the 15 major food groups. Medium-income households spent, on average, the highest amount of their food budget on cold cuts, cheese, and spreads (21.1%). Other categories with high budget shares were beverages (mean budget share of 12.2%), meat, fish, and eggs (12.2%), and sweets and salty snacks (11.3%). Following the two-stage budgeting approach, two of the major food groups were split up to examine food consumption at a disaggregated level. These are the meat, fish, and eggs subgroup with a share of 51% of red meat, and the bread toppings subgroup which consists to the largest extent of cold cuts (53.7%) and cheese (27.3%). These groups were chosen for a more detailed analysis because, in particular, meat is one of the most commonly examined food groups in demand systems (FEMENIA, 2019) and was also the subject of previous estimations of food elasticities in Germany (THIELE, 2001; THIELE 2008; WILDNER, 2001).

Table 2. Means and standard deviations of the food groups used in the demand systems

			Budget Shares	
			Mean	**Std. Dev**
1	Cereals, bakery products		0.078	0.048
2	Potatoes, pasta, rice		0.027	0.018
3	Fruits, nuts		0.073	0.049
4	Vegetables		0.072	0.040
5	Meat, fisch, eggs		0.122	0.064
	5_1	Beef	0.126	0.136
	5_2	Pork	0.321	0.200
	5_3	Beef/Pork mixed	0.064	0.093
	5_4	Poultry	0.208	0.168
	5_5	Fish	0.135	0.155
	5_6	Eggs	0.146	0.150
6	Fats; oils		0.034	0.022
7	Bread toppings		0.211	0.072
	7_1	Cold cuts	0.537	0.172
	7_2	Tinned and cured fish	0.044	0.061
	7_3	Cheese	0.273	0.137
	7_4	Savoury spreads[1]	0.086	0.074
	7_5	Sweet spreads[2]	0.060	0.074
8	Ready to heat components[3]		0.026	0.022
9	Ready-made meals		0.028	0.034
10	Sauce, gravies, dressings		0.020	0.015
11	Desserts		0.032	0.028
12	Sweets, salty snacks		0.113	0.061
13	Beverages		0.122	0.063
14	Milk, milk drinks		0.032	0.032
15	Other foods[4]		0.009	0.009

Notes: Mean budget shares for foods in all subgroups are conditional on the group expenditure.
[1] e.g. Curd cheese with herbs, cream cheese.
[2] Jam, marmelade, honey and hazelnut spread
[3] e.g. Fish fingers, meat in breadcrumbs, frozen vegetables with sauce.
[4] Salt, herbs, spices, broth, vinegar and other condiments.
Source: Own calculations based on the representative GfK consumer panel dataset.

3.2 First stage estimates

In the parameter estimation of the first stage of the QUAIDS model, 382 parameters were estimated, of which 255 were statistically significant at the 5% level.[3] Uncompensated price and expenditure elasticities of the 15 food groups derived from the parameter estimates are presented in Table 3[4] for the medium-income group. Compensated price elasticities, which disregard the income effect and display only the substitution effect, are shown in Table 4.

Table 3 shows that all expenditure elasticities were positive and statistically significant. Most food groups were normal goods as the expenditure elasticities for nine out of 15 groups were positive but below unity. Fruits and nuts (G3), vegetables (G4), meat, fish, and eggs (G5), fats and oils (G6), bread toppings (G7), and sweet and salty snacks (G12) had expenditure elasticities of 1 or higher, which indicates that they were considered "luxury" goods by the households. All own-price elasticities were negative and statistically significant. Cereals and bakery products had the lowest own-price elasticity (–0.211) indicating a relatively inelastic demand, whereas the highest elasticities were found for fruits and nuts (–0.955), sauces, gravies, and dressings (–1.004), and beverages (–1.065). The low elasticity of cereals and bakery products are consistent with the results of previously estimated elasticities for this group in Germany (THIELE, 2008) and is also consistent with the findings of a recent review of food demand elasticities published in this journal (FEMENIA, 2019). Based on the own-price elasticities of various studies, FEMENIA computed a weighted-average own-price elasticity for cereals of –0.33. Comparing the uncompensated and the compensated own-price elasticities shows that, as expected, the compensated elasticities are always smaller. The largest differences can be observed for cereals and bakery products (G1), meat, fish, and eggs (G5), and bread toppings (G7). For these three groups, an increase in price means a comparatively high loss of real income. The cross-price effects were relatively small in many cases, however, more than 70% of both the uncompensated and compensated cross-price elasticities were statistically significant. For the uncompensated cross-price effects, the values were mostly negative indicating that a price increase of a food group leads to consumption reductions not only in the respective food group but also in other food groups. This is particularly valid for cereals and bakery products (G1), meat, fish, and eggs (G5), and for bread toppings (G7), as it is in these three groups that the highest negative cross-price values are found. This is consistent with the previous observation that an increase in the prices of these three groups causes comparatively great losses in real income. However, in the compensated cross-price elasticities, many values are positive indicating substitutive relationships between products. Most substitutes exist for beverages (G13), bread toppings (G7), and sweets and salty snacks (G12). Comparatively strong substitutive relationships were, for example, found between bread toppings (G7) and meat, fish, and eggs (G5) and between ready-made meals (G9) and ready-to-heat components (G8).

3.3 Second stage estimates

In this study, two of the 15 main groups, meat, fish, and eggs and bread toppings, were divided into subgroups. Table 5 shows the unconditional uncompensated and unconditional compensated elasticities for the meat, fish, and eggs group. All expenditure elasticities are significant and positive. The highest value is for pork, indicating that a one percent increase in the expenditure for meat, fish, and eggs increased expenditure for pork by 1.161%. The lowest expenditure elasticity is for the mixed beef and pork group. In general, the elasticity values for the different types of meat are lower than those found in previous studies (THIELE, 2001; THIELE 2008; WILDNER, 2001).

All own-price elasticities are negative and statistically significant. Mixed beef and pork have the highest absolute own-price elasticity, followed by pork and beef. A one percent increase in the price of mixed beef and pork (which is mainly minced meat) reduces the demand for this food group by 0.783 percent. Prior estimations for Germany (THIELE, 2008; WILDNER, 2001) or other countries (ANDREYEVA et al., 2010; FEMENIA, 2019) had results that showed that they all found meat demand to be relatively inelastic. However, in this study, the values were –0.1 and –0.2 percentage points lower than those found in previous studies. This could possibly be attributed to differences in food group construction; in contrast to this study, most prior studies included cold cuts in the meat group, and therefore, cold cuts could act as a further substitute to other types of meat. In general, more substitution possibilities between products reduce the average own-price responses of product aggregates (EALES and UNNEVEHR, 1988).

[3] The parameter estimates can be obtained from the authors upon request.

[4] To make Tables 3 and 4 more readable, the standard errors are not reported but can be obtained from the authors upon request.

Table 3. Uncompensated (Marshallian) price elasticities and expenditure elasticities of main food groups (first stage) for medium-income households

	Quantity \ Price	G1 Cereals, bakery prod.	G2 Potatoes, pasta, rice	G3 Fruits, nuts	G4 Vege-tables	G5 Meat, fish, eggs	G6 Fats, oils	G7 Bread toppings	G8 Ready to heat comp.	G9 Ready-made meals	G10 Sauces, gravies, dressings	G11 Desserts	G12 Sweets, salty snacks	G13 Beverages	G14 Milk, milk drinks	G15 Other foods
G1	Cereals, bakery products	**-0.211***	-0.024*	-0.038*	-0.079*	-0.121*	-0.086*	-0.130*	-0.060*	-0.042*	-0.039*	-0.072*	-0.026	0.042*	-0.087*	-0.015*
G2	Potatoes, pasta, rice	-0.065*	**-0.732***	-0.026	-0.048*	-0.131*	-0.067*	-0.019	0.080*	0.066*	0.056*	-0.009	-0.033	0.007	-0.022	0.005
G3	Fruits, nuts	-0.048*	-0.014*	**-0.955***	0.006	-0.083*	0.010	-0.046	-0.032*	-0.033*	0.023*	-0.068*	0.069*	0.087*	-0.007	0.004
G4	Vegetables	-0.087*	-0.020*	0.012	**-0.699***	-0.030	-0.003	-0.134*	-0.028*	0.009	0.021*	-0.062*	-0.010	0.036*	-0.026*	0.017*
G5	Meat, fish, eggs	-0.083*	-0.033*	-0.048*	-0.022	**-0.619***	-0.053*	-0.003	0.020*	0.001	-0.014*	-0.023*	-0.127*	-0.041*	-0.026*	0.008*
G6	Fats, oils	-0.200*	-0.056*	0.028	-0.006	-0.184*	**-0.408***	-0.031	-0.036*	-0.110*	-0.049*	0.069*	-0.061*	0.064*	-0.045*	0.012*
G7	Bread toppings	-0.049*	-0.004	-0.010	-0.046*	0.006	-0.005	**-0.665***	-0.049*	-0.055*	-0.004	-0.050*	-0.032*	-0.012*	-0.020*	-0.006*
G8	Ready to heat components	-0.176*	0.086*	-0.077*	-0.072*	0.116*	-0.044*	-0.381*	**-0.619***	0.110*	0.046*	0.050*	0.074*	-0.009	0.004	-0.008
G9	Ready-made meals	-0.103*	0.067*	-0.063*	0.037	0.035	-0.125*	-0.367*	0.102*	**-0.595***	0.020	0.071*	0.134*	-0.046*	0.064*	-0.027*
G10	Sauce, gravies, dressings	-0.154*	0.076*	0.091*	0.077*	-0.074*	-0.083*	-0.036	0.057*	0.023	**-1.004***	0.026	-0.099*	0.019	0.063*	0.038*
G11	Desserts	-0.173*	-0.008	-0.144*	-0.134*	-0.074	0.075*	-0.319*	0.038*	0.058*	0.017	**-0.479***	0.079*	0.034*	0.095*	-0.023*
G12	Sweets, salty snacks	-0.020	-0.010	0.050*	-0.007	-0.131*	-0.018*	-0.062*	0.014*	0.027*	-0.018*	0.021*	**-0.840***	0.001	-0.008	-0.012*
G13	Beverages	0.026*	0.000	0.059*	0.022*	-0.032*	0.019*	-0.019*	-0.005*	-0.017*	0.003	0.008*	0.003	**-1.065***	0.000	0.003*
G14	Milk, milk drinks	-0.208*	-0.019	-0.006	-0.054*	-0.085*	-0.046*	-0.126*	0.001	0.051*	0.039*	0.094*	-0.022	0.004	**-0.579***	-0.013*
G15	Other foods	-0.110*	0.019	0.048*	0.147*	0.134*	0.053*	-0.091*	-0.019	-0.083*	0.085*	-0.073*	-0.121*	0.064*	-0.040*	**-0.819***
	Expenditure elasticities	0.987*	0.936*	1.086*	1.003*	1.064*	1.013*	1.000*	0.900*	0.795*	0.979*	0.959*	1.014*	0.994*	0.970*	0.805*

Note: Elasticities were calculated at the means of price, expenditure and demographic variables according to equations 16 and 17. Elasticities significant at the 5% level are marked with a star. Standard errors are not included for the sake of better readability but are available from the authors upon request.
Source: Own calculations based on the representative GfK consumer panel dataset.

Table 4. Compensated (Hicksian) price elasticities of main food groups (first stage) for medium-income households

		G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15
Quantity \ Price		Cereals, bakery prod.	Potatoes, pasta, rice	Fruits, nuts	Vege-tables	Meat, fish, eggs	Fats, oils	Bread toppings	Ready to heat compon.	Ready-made meals	Sauces, gravies, dressings	Desserts	Sweets, salty snacks	Beverages	Milk, milk drinks	Other foods
G1	Cereals, bakery products	**-0.133***	0.003	0.034*	-0.008	-0.001	-0.053*	0.078*	-0.034*	-0.014	-0.020*	-0.040*	0.086*	0.162*	-0.055*	-0.005
G2	Potatoes, pasta, rice	0.009	**-0.706***	0.043*	0.020	-0.017	-0.035*	0.178*	0.104*	0.093*	0.075*	0.021	0.074*	0.120*	0.009	0.014*
G3	Fruits, nuts	0.037*	0.016*	**-0.876***	0.084*	0.050*	0.047*	0.183*	-0.004	-0.002	0.044*	-0.033*	0.192*	0.219*	0.028*	0.014*
G4	Vegetables	-0.008	0.007*	0.086*	**-0.627***	0.092*	0.031*	0.077*	-0.002	0.037*	0.041*	-0.029*	0.103*	0.158*	0.007	0.027*
G5	Meat, fish, eggs	0.000	-0.004	0.030*	0.054*	**-0.489***	-0.017*	0.221*	0.047*	0.031*	0.007	0.011	-0.007	0.088*	0.009	0.018*
G6	Fats, oils	-0.120*	-0.028	0.102*	0.066*	-0.061*	**-0.374***	0.182*	-0.010	-0.081*	-0.029	0.102*	0.054*	0.187*	-0.012	0.022*
G7	Bread toppings	0.029*	0.023*	0.064*	0.026*	0.128*	0.029*	**-0.454***	-0.023*	-0.027*	0.016*	-0.018*	0.081*	0.110*	0.012	0.003
G8	Ready to heat components	-0.105*	0.111*	-0.012	-0.007	0.226*	-0.013	-0.192*	**-0.596***	0.135*	0.064*	0.079*	0.176*	0.100*	0.033*	0.000
G9	Ready-made meals	-0.041	0.089*	-0.005	0.094*	0.132*	-0.098*	-0.199*	0.122*	**-0.572***	0.036*	0.097*	0.224*	0.050*	0.090*	-0.020*
G10	Sauce, gravies, dressings	-0.077*	0.103*	0.162*	0.148*	0.046	-0.049	0.170*	0.082*	0.050*	**-0.985***	0.058*	0.012	0.138*	0.095*	0.047*
G11	Desserts	-0.098*	0.018	-0.074*	-0.065*	0.043	0.108*	-0.117*	0.062*	0.085*	0.036*	**-0.448***	0.187*	0.150*	0.126*	-0.014*
G12	Sweets, salty snacks	0.059*	0.018*	0.124*	0.066*	-0.007	0.016*	0.151*	0.040*	0.056*	0.002	0.053*	**-0.725***	0.124*	0.025*	-0.002
G13	Beverages	0.104*	0.027*	0.132*	0.094*	0.089*	0.053*	0.190*	0.021*	0.011*	0.023*	0.040*	0.116*	**-0.944***	0.033*	0.012*
G14	Milk, milk drinks	-0.132*	0.007	0.065*	0.016	0.033	-0.013	0.078	0.026	0.078*	0.058*	0.126*	0.088	0.122*	**-0.548***	-0.004
G15	Other foods	-0.047	0.041*	0.107*	0.205*	0.233*	0.080*	0.078	0.001	-0.060*	0.101*	-0.047*	-0.030	0.162*	-0.014	**-0.811***

Note: Elasticities were calculated at the means of price, expenditure and demographic variables according to equations 17 and 18. Elasticities significant at the 5% level are marked with a star. Standard errors are not included for the sake of better readability but are available from the authors upon request.
Source: Own calculations based on the representative GfK consumer panel dataset.

Table 5. Unconditional price and expenditure elasticities of meat, fish and eggs (second stage) for medium-income households

Quantity \ Price	Beef	Pork	Beef/pork mixed	Poultry	Fish	Eggs
Uncompensated (Marshallian) price elasticities						
Beef	**-0.510***	0.080	-0.009	-0.106*	0.089*	-0.057*
Pork	0.026	**-0.666***	0.092*	-0.066*	-0.099*	0.003
Beef/Pork mixed	-0.020	0.492*	**-0.783***	0.006	-0.143*	0.005
Poultry	-0.066*	-0.100*	0.000	**-0.500***	0.045*	-0.012
Fish	0.083*	-0.230*	-0.067*	0.070*	**-0.393***	-0.030
Eggs	-0.054*	0.027	0.002	-0.014	-0.031	**-0.441***
Compensated (Hicksian) price elasticities						
Beef	**-0.497***	0.113*	-0.003	-0.085*	0.102*	-0.043
Pork	0.044*	**-0.621***	0.101*	-0.037*	-0.080*	0.022
Beef/Pork mixed	-0.009	0.520*	**-0.777***	0.024	-0.132*	0.017
Poultry	-0.050*	-0.060*	0.008	**-0.474***	0.062*	0.005
Fish	0.097*	-0.194*	-0.060*	0.094*	**-0.378***	-0.015
Eggs	-0.042	0.059	0.008	0.007	-0.017	**-0.428***
Expenditure elasticities						
	0.837	1.161	0.724	1.036	0.927	0.838

Note: Conditional elasticities were calculated at the means of price, expenditure and demographic variables according to equations 16, 17 and 18. Unconditional elasticities were calculated based on equations 19, 20, and 21. Elasticities significant at the 5% level are marked with a star. Standard errors are not included for the sake of better readability but are available from the authors upon request.
Source: Own calculations based on the representative GfK consumer panel dataset.

The cross-price elasticities are mainly negative in the uncompensated price elasticities. These results are consistent with previous findings which also showed mainly complementary relations between different types of meat (THIELE, 2008; YEN and LIN, 2006; COFFEY et al., 2011; LAMBERT et al., 2006) The largest cross-price elasticities were found for pork; a one percent increase in the price of pork increases the demand for mixed beef and pork by 0.492 percent and a decrease in the demand for fish by –0.210 percent. When households obtain an income compensation as expressed by the Hicksian elasticities, there is an additional positive cross-price effect with beef with a value of 0.113.

Table 6 reports unconditional uncompensated and unconditional compensated elasticities for the bread toppings group. The highest own-price elasticity could be found for cold cuts (–0.768) followed by

Table 6. Unconditional price and expenditure elasticities of bread toppings (second stage) for medium-income households

Quantity \ Price	Cold cuts	Fish	Cheese	Savoury Spreads	Sweet Spreads
Uncompensated (Marshallian) price elasticities					
Cold cuts	-0.768*	-0.030*	0.009	0.012	0.016*
Tinned and cured fish	-0.324*	-0.413*	0.133*	0.050	0.038
Cheese	0.077*	0.022*	-0.638*	-0.048*	0.006
Savoury spreads	0.130*	0.026	-0.153*	-0.570*	-0.009
Sweet spreads	0.186*	0.034	0.046	-0.007	-0.676*
Compensated (Hicksian) price elasticities					
Cold cuts	-0.643*	-0.020*	0.073*	0.032*	0.030*
Tinned and cured fish	-0.240*	-0.406*	0.176*	0.063	0.047
Cheese	0.183*	0.031*	-0.584*	-0.031*	0.017
Savoury spreads	0.234*	0.034	-0.100*	-0.553*	0.002
Sweet spreads	0.257*	0.040	0.082	0.004	-0.668*
Expenditure elasticities					
	1.108*	0.739*	0.939*	0.914*	0.628*

Note: Conditional elasticities were calculated at the means of price, expenditure and demographic variables according to equations 16, 17 and 18. Unconditional elasticities were calculated based on equations 19, 20, and 21. Elasticities significant at the 5% level are marked with a star. Standard errors are not included for the sake of better readability but are available from the authors upon request.
Source: Own calculations based on the representative GfK consumer panel dataset.

sweet spreads (–0.676) and cheese (–0.638). The comparatively high elasticity values for cold cuts and cheese could be caused by their large budget shares, which are more than 54% for cold cuts and 27% for cheese (see Table 2). For the cross-price elasticities, about half of the estimated values were significant at the 5% level. Most significant values are positive showing that a considerable number of the individual products of this group are substitutes for each other. This indicates that creating a bread toppings group, as done in this study, is appropriate. Comparatively strong substitutive relationships exist for cold cuts and cheese; when the price of cold cuts increases, the households consume more cheese, savory spreads, and sweet spreads, and when the price of cheese increases, the households switch to tinned and cured fish.

3.4 Comparison of households with different incomes

Because households with different incomes react differently to changes in food prices, the Marshallian own-price and the expenditure elasticities of the medium-income households are compared with the low- and high-income households in Table 7. The definitions of the income groups appear in Table 1.

Table 7. Uncompensated (Marshallian) own-price elasticities and expenditure elasticities: a comparison of low-, medium-, and high-income households

		Expenditure elasticities			Own-price elasticities			Budge Shares		
		Low	Medium	High	Low	Medium	High	Low	Medium	High
						All Foods				
1	Cereals, bakery products	1.025	0.987	1.108	-0.305	-0.211	-0.228	0.077	0.078	0.078
2	Potatoes, pasta, rice	0.871	0.936	0.825	-0.816	-0.732	-0.731	0.028	0.027	0.025
3	Fruits, nuts	1.043	1.086	1.010	-0.933	-0.955	-0.977	0.063	0.073	0.080
4	Vegetables	1.029	1.003	0.918	-0.717	-0.699	-0.695	0.065	0.072	0.077
5	Meat, fish, eggs	1.048	1.064	0.905	-0.671	-0.619	-0.486	0.118	0.122	0.121
6	Fats, oils	1.034	1.013	1.079	-0.404	-0.408	-0.450	0.035	0.034	0.030
7	Bread toppings	1.025	1.000	1.095	-0.650	-0.665	-0.691	0.205	0.211	0.217
8	Ready to heat components	0.879	0.900	0.972	-0.677	-0.619	-0.589	0.028	0.026	0.024
9	Ready made meals	0.927	0.795	0.813	-0.685	-0.595	-0.517	0.033	0.028	0.029
10	Sauce, gravies, dressings	0.948	0.979	0.886	-1.062	-1.004	-0.856	0.021	0.020	0.019
11	Desserts	0.925	0.959	1.045	-0.434	-0.479	-0.528	0.033	0.032	0.032
12	Sweets, salty snacks	1.039	1.014	1.102	-0.869	-0.840	-0.937	0.117	0.113	0.106
13	Beverages	0.943	0.994	0.902	-1.060	-1.065	-1.052	0.131	0.122	0.119
14	Milk, milk drinks	0.964	0.970	1.016	-0.784	-0.579	-0.522	0.036	0.032	0.032
15	Other foods	0.834	0.805	0.716	-0.818	-0.819	-0.831	0.009	0.009	0.010
								1,000	1,000	1,000
						Meat, fish, eggs (unconditional)				
	Beef	0.771	0.837	0.762	-0.410	-0.510	-0.643	0.100	0.126	0.153
	Pork	1.154	1.161	1.207	-0.672	-0.666	-0.665	0.340	0.321	0.273
	Beef/Pork mixed	0.763	0.724	0.665	-0.805	-0.783	-0.748	0.074	0.064	0.053
	Poultry	1.038	1.036	1.064	-0.520	-0.500	-0.486	0.222	0.208	0.192
	Fish	0.917	0.927	0.951	-0.327	-0.393	-0.487	0.119	0.135	0.166
	Eggs	0.823	0.838	0.896	-0.383	-0.441	-0.532	0.145	0.146	0.162
								1,000	1,000	1,000
						Bread toppings (unconditional)				
	Cold cuts	1.137	1.108	1.208	-0.790	-0.768	-0.860	0.541	0.537	0.505
	Tinned and cured fish	0.698	0.739	0.956	-0.432	-0.413	-0.605	0.035	0.044	0.048
	Cheese	0.980	0.939	1.029	-0.817	-0.638	-0.628	0.275	0.273	0.299
	Savoury spreads	0.868	0.914	0.962	-0.536	-0.570	-0.391	0.084	0.086	0.091
	Sweet spreads	0.664	0.628	0.765	-0.758	-0.676	-0.686	0.065	0.060	0.058
								1,000	1,000	1,000

Note: Standard errors are not included for the sake of better readability but are available from the authors upon request. Low-income households: Households in the lowest quartile of weighted per capita (using the modified OECD scale) household income. High-income households: Households in the highest quartile of weighted per capita income.
Source: Own calculations based on the representative GfK consumer panel dataset.

In most cases, households with low incomes react more elastically to price changes than the average household. This is plausible, because households with lower incomes face stricter budget constraints and, thus, have to react more strongly to price changes than richer households do. This finding is in accordance with Engel's and Bennet's law (TIMMER et al., 1983). Comparatively large differences in own-price elasticities were found for milk and milk drinks, beef, and cheese. Comparatively large differences in the own-price elasticities for beef were also found by THIELE (2008).

According to Bennet's law, expenditures for staple foods and basic ingredients decrease with income and, in contrast, expenditures for meat, fruits, vegetables and convenience foods increase. As the food groups used in this study are homogeneous with respect to their level of processing and convenience (e.g., groups such as vegetables, fruits, and nuts, or meat, fish, and eggs contain predominantly raw foods that require a lot of preparation time, whereas groups such as ready-made meals or desserts contain only foods that need little preparation effort before consumption), Table 7 can also be used to compare the demand structure for foods of different convenience levels.

The expenditure elasticities of foods with a low convenience level (raw foods or basic ingredient foods) tend to decrease as income increases (groups 2, 3, 4, 5, and 6), whereas expenditure elasticities of foods with a higher convenience level (foods that require minimal or no preparation) tend to increase with income (groups 1, 7, 8, 11, and 12). These results are consistent with the findings of many previous studies on convenience food consumption that also found a positive association between income and expenditures for convenience foods (HARRIS and SHIPTSOVA, 2007; OKRENT and KUMCU, 2016; SHEELY, 2008). The higher demand for convenience foods in high-income households might be for different reasons; maybe they place a higher value on leisure time (HARRIS and SHIPTSOVA, 2007), have the financial means to substitute time for money (MANCINO and NEWMAN, 2007), or have a higher opportunity cost of time (BONKE, 1996; SENNAUER, 2001). Interestingly, the ready-made meals do not follow the pattern of other convenience foods in this study. A possible explanation is that high-income households substitute ready-made meals for food away from home consumption, which is more expensive but requires no preparation time (HARRIS and SHIPTSOVA, 2007). Because the dataset only includes food purchases for at home consumption, this association could not be investigated here, but would be an interesting subject of future demand analyses for Germany.

4 Summary and outlook

This study presented a new set of elasticities of food demand in Germany which can, among others, be used for simulations of policy interventions. A two-stage demand system was estimated using a dataset of highly disaggregated food purchases of a representative sample of German households and a quadratic AIDS augmented to account for censoring and to include demographic variables. Elasticities for the first stage as well as two subgroups of the second stage (the meat, fish, and eggs and the bread toppings groups) were presented. Consistent with previous estimates for Germany and with prior international studies, the demand for cereals and bakery foods was found to be price inelastic. The demand for beverages, however, had the highest price elasticity. At the second stage, increases in the price of pork caused major adjustment reactions. In the bread toppings group, which was composed differently to that in previous demand studies, cold cuts and cheese had relatively high own-price elasticities. In these two food groups, many cross-price relationships were found. The comparison of the expenditure elasticities of different income groups indicated that, compared with low-income households, high-income households were less income elastic for foods with a lower convenience level, but more price elastic for foods with a higher convenience level. One reason for the comparatively high preferences for more convenient foods could be the higher opportunity costs of these households.

The novelties of the estimation of food demand elasticities in this study include methodological improvements (e.g., in the way of handling missing observations) and in using a very disaggregated data set, including new food groups such as convenience foods. The study showed that using disaggregated food groups that include food trends such as convenience products delivers valuable information about consumer behavior. As food and demographic trends continue to influence food demand, updated elasticities should be provided regularly in order to provide a solid basis for, for example, policy intervention simulations. In future studies, it would be interesting to include further trends, such as food away from home consumption and the consumption of meat substitutes.

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