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Demand Reactions in Food Retailing

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List of abbreviations

(IT)3SLS	(Iterative) Three-Stage Least Squares
AIDS	Almost Ideal Demand System
CBS	Central Bureau of Statistics demand system
ESL	Extended shelf life
FD(L)AIDS	First Differenced (Linear) Almost Ideal Demand System
GODDS	Generalized Ordinary Differenced Demand System
LES	Linear Expenditure System
NBR	National Bureau of Research demand system
(IT)SUR	(Iterative) Seemingly Unrelated Regression
TL	Translog model
UHT	Ultra-high treatment
UV	Unit value

Publication and submission record

The present work is submitted as a cumulative thesis, based on three publications:

1. Widenhorn, A. and Salhofer, K. (2014a). Using a Generalized Ordinary Differenced Demand System to Estimate Price and Expenditure Elasticities for Milk and Meat in Austria. German Journal of Agricultural Economics 63: 109-124.

2. Widenhorn, A. and Salhofer, K. (2014b). Price Sensitivity Within and Across Retail Formats. Agribusiness 30: 184–194.

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Zusammenfassung

Das Hauptziel der vorliegenden Arbeit ist die Schätzung von Nachfragereaktionen im Lebensmitteleinzelhandel. Hierbei stehen Preis- und Einkommenselastizitäten im Vordergrund. Diese werden für verschiedene Produktgruppen geschätzt und zwischen unterschiedlichen Formaten des Lebensmittel-einzelhandels verglichen. Darüber hinaus werden Konsumentenentscheidungen hinsichtlich des Einkaufs in unterschiedlichen Formaten des Lebensmitteleinzelhandels (Discounter gegenüber Supermärkten) modelliert. Die Ergebnisse liefern wertvolle Einsichten für den Lebensmittelmitteleinzelhandel, die Politik und modellbasierte Politikberatung. Den Kern dieser publikationsbasierten Dissertation bilden drei Artikel.

Der erste Artikel „Using a Generalized Differenced Demand Model to Estimate Price and Expenditure Elasticities for Milk and Meat in Austria" basiert auf einem sehr allgemeinen und flexiblen Nachfragemodell, welches bekannte Modelle wie das Almost Ideal Demand System (AIDS), das Rotterdam Modell, das Central Bureau of Statistics (CBS) Modell und das National Bureau of Research (NBR) Modell beinhaltet. Dieses allgemeine Modell wird auf verschiedene Produktgruppen und Budgetierungsansätze angewandt. Als Ergebnis zeigen sich hierbei für höhere Produktaggregationsstufen erwartungsgemäß schwächere Reaktionen auf Preisänderungen. Die Schätzungen verdeutlichen außerdem die Bedeutung unterschiedlicher Budgetierungsansätze. Es wird insbesondere gezeigt, dass sich Unterschiede in den Ergebnissen zwischen Nachfragestudien deutlich verringern können, wenn unterschiedliche Budgetierungsstrukturen berücksichtigt werden.

Im zweiten Artikel „Price Sensitivity Within and Across Retail Formats" werden Konsumentenreaktionen in den beiden wichtigsten Formaten des Lebensmitteleinzelhandels, in Supermärkten und Discountern, gegenübergestellt. Diese Fragestellung wurde bisher kaum erforscht. Insbesondere gehe ich der Frage nach, ob Preisreaktionen bei Milchprodukten zwischen Kunden von Discountern und Supermärkten statistisch signifikante Unterschiede aufweisen. Überdies wird die Wechselwirkung von Preisänderungen zwischen den beiden Formaten untersucht. Die Ergebnisse deuten darauf hin, dass zwischen Discounter- und Supermarktkunden in der Tat signifikante Unterschiede in den Reaktionen auf Preisänderungen bestehen. Dies

gilt sowohl für Preisänderungen innerhalb eines Einzelhandelsformates, als auch für Preisänderungen zwischen den Formaten. Für Preisänderungen bei Trinkmilch ergeben sich signifikante Nachfragereaktionen zwischen den Formaten, was die mögliche Rolle dieses Produkts als Lockartikel unterstreicht.

Im dritten Artikel „Differentiation in Demand with Different Food Retail Formats“ werden potenzielle Unterschiede in den Verhaltensmustern der Kunden von Discountern und Supermärkten auf zwei wesentliche Aspekte hin untersucht. Einerseits wird erörtert, welche Haushaltscharakteristika die Wahrscheinlichkeit erhöhen, dass beim Einkauf ein Discounter einem Supermarkt vorgezogen wird. Andererseits werden für neun verschiedene Produktgruppen, jeweils in Discountern und Supermärkten und unter Berücksichtigung von Kaufwahrscheinlichkeiten, Preiselastizitäten geschätzt. Die Ergebnisse liefern weitere Hinweise auf signifikante Unterschiede in den Preiselastizitäten für verschiedene Formate. Zusätzlich deuten die Resultate darauf hin, dass die Nachfrage in Supermärkten signifikant stärker auf Preisänderungen innerhalb der Supermärkte reagiert als dies für die Nachfrage in Discountern bei Discounter-Preisänderungen der Fall ist. Andererseits jedoch fallen Nachfragereaktionen in Discountern auf Preisänderungen in Supermärkten tendenziell stärker aus als jene in Supermärkten bei Preisänderungen in Discountern. Es wird außerdem ersichtlich, dass einkommens- und bildungsschwächere Haushalte eine höhere Präferenz für Discounter aufweisen, während jüngere Konsumenten zwar eine hohe Präferenz für Discounter besitzen, jedoch einen kleineren Anteil ihres Budgets dort ausgeben.

Insgesamt lassen sich zwei wesentliche Punkte festhalten. Zum einen wird in dieser Dissertation gezeigt, dass Vergleiche zwischen Nachfrageuntersuchungen stets die methodische Sensibilität der empirischen Ergebnisse beachten sollten, insbesondere hinsichtlich des Budgetierungsansatzes. Andererseits belegt diese Arbeit auch, dass eine getrennte Betrachtung verschiedener Einzelhandelsformate eminent wichtig für die präzise Schätzung von Nachfragereaktionen sein kann.

Abstract

The main purpose of this study is to estimate consumers’ demand reactions in food retailing. To this end, price and income elasticities are of primary interest. These elasticities are estimated for various product groups and compared between different food retail formats. In addition, consumers’ choices are modeled in regard to food retail formats (supermarkets versus discounters). The results provide valuable decision support for food retailing, policymakers and policy modellers. This cumulative, publication-based dissertation refers to three of the candidate’s publications.

The first essay „Using a Generalized Differenced Demand Model to Estimate Price and Expenditure Elasticities for Milk and Meat in Austria” is based on a very general and flexible demand model, which nests several well-known models including the Almost Ideal Demand System (AIDS), the Rotterdam model, the Central Bureau of Statistics (CBS) and the National Bureau of Research (NBR) model. This general model is applied to different product groups and different budgeting structures. Estimation results indicate that demand reactions, as expected, turn less strong the more aggregated the product groups are. Beyond this, the estimation results stress the importance of the underlying budgeting structure in demand models. It is shown that differences in the estimated elasticities of demand between studies may downsize remarkably once the same budgeting structures are considered.

In the second essay „Price Sensitivity Within and Across Retail Formats“, consumer demand reactions are compared between the two most important food retail formats, “conventional” supermarkets and discounters. This question has been largely neglected in literature so far. In particular, I investigate whether consumer responses to milk price changes are statistically different for discounters and supermarkets. Beyond this, price reactions across formats are considered as well, i.e. demand reactions in discounters to price changes in supermarkets and vice versa. Results indicate that significant differences between price reactions in supermarkets and those in discounters do exist. This holds true for both, inner-format reactions to price changes and responses to price changes across retailing formats. With regard to demand reactions to price changes for drinking milk, significant responses across formats illustrate the potential of drinking milk as a loss-leader product.

As far as the third essay „Differentiation in Demand with Different Food Retail Formats“ is concerned, potential differences in consumer behaviour for different food retail formats are analyzed regarding two main aspects. On the one hand, I analyze the factors which influence a household’s likeliness to prefer shopping at a discounter to shopping at a supermarket. On the other hand, price elasticities of demand are estimated for nine different product groups in discounters and supermarkets, applying a method which includes the individual purchase probabilities.

Results provide further indications for significantly different price elasticities between different retail formats. Beyond, supermarket demand is found to be more responsive to inner-format price changes than demand in discounters. However, demand reactions in discounters related to price changes in supermarkets are stronger than those in supermarkets when discounter prices are changed. Apart from this, results show that households with low levels of income and education are more likely to visit discounters, whereas younger people have a high preference for discounters despite spending less of their budget in discounters.

Altogether, two main results can be emphasized. First, comparisons of demand studies must keep in mind the potential for any study’s sensitivity to model and budget structure specification. Second, this study strongly points at the necessity to estimate demand reactions for each food retail format separately, whenever data availability allows for it.

1. Demand Reactions in Food Retailing – An overview

1.1. Background

Today, most empirical studies on consumer price and income responsiveness are based on econometric estimates of demand and income elasticities, a concept introduced by Alfred Marshall in 1890. One of this concept's most appealing features is its independence from underlying currencies or scaling units of any form. Possibly due to this handiness, studies in food retailing have made extensive use of elasticities of demand ever since they were initiated more than one hundred years ago. Noticeably, the popularity of elasticity estimates in food retailing has anything but diminished over the course of time, despite all structural changes and methodological innovations. Altogether, knowledge of elasticities of demand for food products is important in many respects (Okrent and Alston 2011).

As an example, elasticities of demand have been estimated for several purposes of taxation, such as the taxation of food types associated with type 2 diabetes and obesity. Here, elasticities of demand are highly valuable in view of many health sectors' massive potential for cost savings (Malik et al. 2006, Vartanian et al. 2007), and hence important for many countries worldwide. Denmark's temporarily introduced "fat tax" in 2011, Hungary's "junk food tax" of the same year or France's so-called "Nutella tax" in 2012 are just a few further examples of cases in which governments have tried to anticipate changes in consumer demand following price changes of particular products (Washington Post 2012).

Accordingly, a multitude of studies have estimated elasticities of demand for sugared, sweetened or other high-fructose products. In an attempt to summarize these elasticity estimates for the U.S., Powell et al. (2013) find that price elasticities of demand may vary considerably for different types of healthy and unhealthy products. Particularly, demand for fast food products in the U.S. is not very responsive to price changes, while this is also true for fruits and vegetables. At the same time however, U.S. consumers tend to adjust their demand more strongly for price changes of sugared beverages.

The importance of elasticities of demand is further reflected in a variety of studies on product attributes such as organic vs. non-organic products (e.g. Choi and Wohlgenant 2012, Monier et al. 2009, Dhar and Foltz 2005, Glaser and Thompson 2000). With this respect, empirical evidence usually suggests that price elasticities for organic products are significantly higher. According to Ritson and Brennan (2008), price elasticities for organic products are commonly about double the size of those of the corresponding non-organic products.

Another issue for which elasticities of demand are of crucial importance is the evolution of private labels as opposed to national brands (e.g. Bezawada and Pauwels 2013, Jonas and Roosen 2008, Bontemps et al. 2008, Akbay et al. 2005). Reviewing 73 articles on private labels, Hyman et al. (2010) find that price elasticities are generally not the same for national brand products and private label products. On top of this, they state that households with different income constraints are characterized by different price elasticities for private label- and national brand products, a finding also paralleled by Akbay et al. (2000).

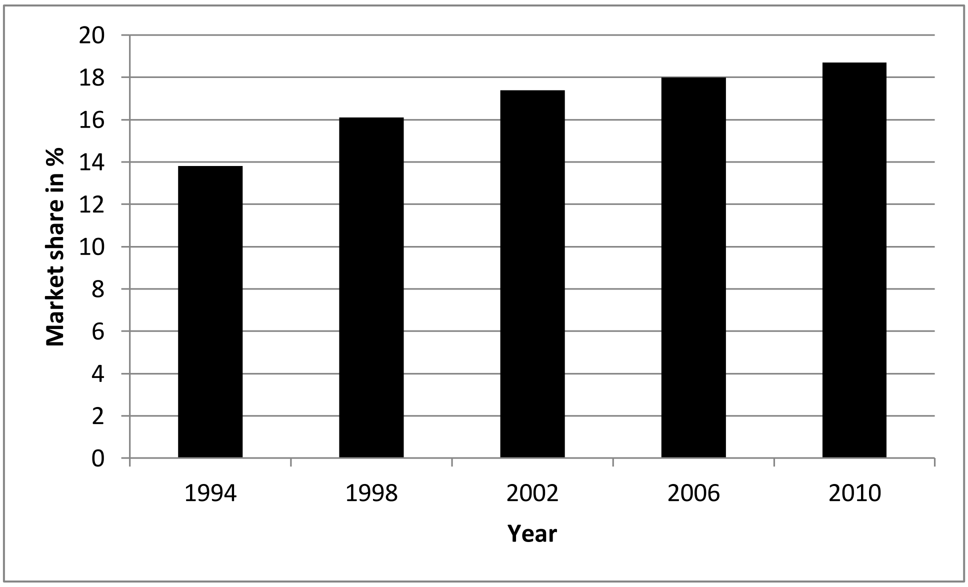
Relating to this, when looking at elasticities of demand from an international viewpoint, one also finds different elasticities of demand for countries with different levels of per-capita income (Muhammad et al. 2011). With gradually developing per-capita income levels, it hence seems that elasticities of demand may change over time, even when the same sample of people is considered. For instance, Andreyeva et al. (2010) provide an overview on U.S. studies estimating price elasticities of demand for various product groups over a period of about seventy years. Interestingly, quite some variation in the results of the included 160 studies can be found, while Andreyeva et al. (2010) state that parts of this variation could be attributed to the choice of demand models. However, for some product groups, the methodological choice is not found to have a significant impact on the estimates, suggesting that other factors such as heterogeneous consumer behavior might play an important role as well. In fact, Grunert (2003) points out that consumer reactions in food retailing are subject to a complex set of dynamic individual and cultural factors.

Owing to the diversity of consumer preferences, food retailers have established several food retail formats to target different types of consumers (Ahlert et al. 2005).

This important development however, has so far not been thoroughly analyzed as to potential differences in elasticities of demand for different food retail formats. In other words, while distinct elasticities of demand have been found for products with different attributes, very little is known about the relationship between elasticities of demand and different retail formats.

In terms of food retail formats today, various formats have become popular in different regions of the world. Possibly the most noticeable trend in Europe occurred for discount stores over the last decades. An example of a typical European discounter, sometimes also referred to as hard discounter, is ALDI. Discounters usually offer a limited sales area and a smaller variety in assortment as compared to supermarkets (Berman and Evan 2006). As part of their strategy, most hard discounters also offer a comparably high percentage of private-label products (Bustillo and Timothy 2010). The two main hard-discounters worldwide, ALDI and Lidl, are now active on more than 20 European markets, and belong to the top 25 retailers of the world (Nielsen 2007). Looking at the 20 main food retail markets of Europe, discounters have increased their overall market shares (Nielsen Grocery Universe 2012), as depicted in Figure 1.

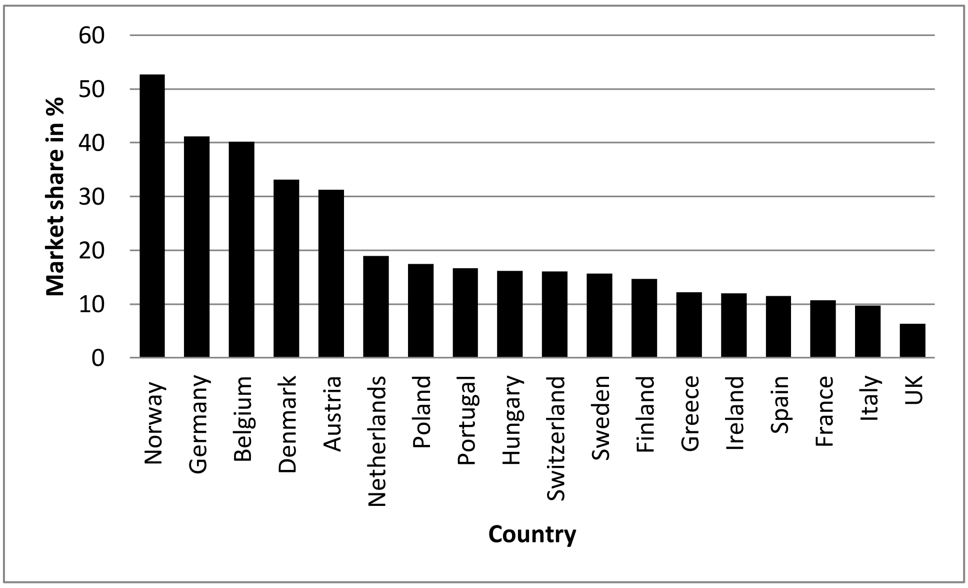
Figure 1: Overall market shares of discounters in Europe, between 1994 and 2010



Source: Nielsen Grocery Universe 2012

Despite this general trend, considerable variation in the format's importance can be observed for different countries and regions in Europe (Figure 2).

Figure 2: Market shares of discounters in Europe in 2010, by country



Source: Nielsen Grocery Universe 2012

While it seems reasonable to assume that different consumer preferences have driven the success of the discount format, the factors which influence consumer preferences are disputable. For example, households' economic situations might enforce different degrees of cost-awareness, or it might be that consumers are largely heterogeneous in their attitudes towards price and quality in general. In any case, the question would be, whom to typically expect in different types of retail formats. Related to this, it also seems questionable whether a generalization over consumers of different retail formats is admissible.

Apart from changes in food retailing and consumer preferences, economic theory and estimation methods have also been extended over time. To this matter, Okrent and Alston (2011) stress the importance of technical considerations when assessing the precision of estimated elasticities of demand. Thus, factors such as statistical techniques, assumed models and functional forms, datasets used, food product aggregations and separability structures can also affect results significantly.

Considering the models to estimate elasticities of demand, the Almost Ideal Demand System (AIDS) by Deaton and Muellbauer (1980), the Rotterdam model by Theil (1965), the linear expenditure system (LES) by Stone (1954) and the translog (TL) model by Christensen et al. (1975) are among the most popular ones (Barnett and Kalonda-Kalyama 2012, Clements and Selvanathan 1988). Aside from these, several others have been developed, such as the Quadratic AIDS model (Banks et al., 1997), models that allow imposing curvature restrictions (Ryan and Wales 1998) or dynamic models (Anderson and Blundell 1983). The availability of various models has lead to several comparative studies (e.g. Barnett and Seck 2008, Meyer et al. 2011). Overall, there seems to be no single model which can generally be considered optimal, and the suitability of a model seems to depend rather on data than on universal criteria (Matsuda 2005).

Furthermore, most empirical studies on food demand would not be feasible without a certain degree of separability, due to data limitations. Generally, separability of goods implies that consumers first allocate their budget for broad product groups and afterwards turn to the budget allocation for less aggregated sub-groups. While various forms of separability assumptions exist, the most commonly applied one is weak separability, also because strong separability cannot be expected to hold in most empirical applications (Okrent and Alston 2011). Any group or subgroup of goods is weakly separable from the rest of groups, if the utility from consumption of this groups solely depends on characteristics within the group, not on characteristics observed in other groups. Under this assumption, the number of parameters to be estimated is reduced, since demand for any group can be estimated in isolation. However, the resulting estimates for any sub-group are conditional on the budget allocated to product groups at higher levels of aggregation. Hence, the assumed budgeting structure is closely related to the assumptions in terms of separability of goods. If single budgeting stages are considered, or higher stages of budgeting are excluded, e.g. if one excludes the choice of how much to spend on food or on meat, milk etc. in general, there are implicit assumptions on the relationships between elasticities of demand at different budgeting stages. For example, it is implicitly ignored that price changes of sub-categories to some extent change the price level of the category as a whole (Edgerton

1997). As an alternative to ignoring these kinds of indirect effects, multiple budgeting stages can be combined after estimation, as proposed by Edgerton (1997) and Carpentier and Guyomard (2001). In addition to an improvement in precision, the inclusion and combination of all stages of budgeting allows for assessing the impacts of changes in macroeconomic factors such as changes in GDP or taxation (Bouamra-Mechemache et al. 2008). However, possibly depending on e.g. budget shares of considered sub-categories, available data or on the focus on either policy or corporate decisions, estimates from different budgeting structures are presented in the literature (e.g. Glaser and Thompson 2000, Yu and Abler 2009), implying different formulas underlying the estimates for elasticities of demand.

1.2. Aim of this study

The main purpose of this study is to analyze elasticities of demand as to their validity when different food retail formats and different estimation approaches are considered. As a crucial part, the need for differentiation will be studied in terms of discount stores on the one side and more traditional retail formats, such as supermarkets, on the other. Alongside, consumer heterogeneity is also investigated in terms of factors influencing a household's preference for the discount format and overall spending in discounters. Estimation is carried out applying different demand models and different assumptions on the structure of budgeting. By this, factors causing variation in results shall be examined, both in terms of modeling and in terms of data aggregation.

Estimations refer to the Austrian food retail market, whereas some comparisons to Germany and other European markets are also presented. In summation, three main objectives are pursued in this study:

1) To estimate demand reactions for different food retail formats, with a focus on differences between discounters on the one hand and more traditional retailers such as supermarkets on the other.

2) To analyze factors of format choice, aggregate format spending and format-switching potential.
3) To evaluate the sensitivity of estimates with regard to assumptions on budgeting structures.

1.3. Procedure and Structure

All key questions of this study are addressed through three empirical essays. The first essay, Widenhorn and Salhofer (2014a), is referred to as E1 in the sequel, whereas the second essay, Widenhorn and Salhofer (2014b) will be called E2, and Widenhorn and Salhofer (2014c) is equivalent to the third essay, E3. In E1, a rather aggregated viewpoint on elasticities of demand in Austria is taken. In this regard, the focus is put on general modeling issues, different models included in one nesting model and the impact of alternations in the assumed budgeting structure. Thereafter, in E2, consumer demand is separated by discount stores on the one hand and more traditional formats such as supermarkets on the other. Both inner-and cross-format reactions are estimated, and their statistical dissimilarity is tested for in the process.

Next, in E3, differences in demand reactions across retail formats are further investigated, with the extension to a number of nine product groups in each formats and the inclusion of sociodemographic factors in the estimation. At this point, a different modeling approach is used, tailored for household panel data and issues of censoring and selection mechanisms. As far as household sociodemographics are concerned, format choice factors will be given particular attention. Here, overall budget portions allocated to discounters on the one hand and supermarkets on the other are also analyzed.

The structure of this study is as follows: At first, an overview on foundations of demand theory is provided, in Chapter 2. More precisely, Chapter 2.1 elaborates on some theoretical underpinnings when estimating elasticities of demand, whereas Chapter 2.2 describes a nesting model, which is applied in E1 and E2. Alongside with the estimation of demand reactions, some theoretical restrictions can be imposed in the course of the estimation. These restrictions are explained in Chapter 2.3. In Chapter 2.4.ii, a selection model is characterized, which serves to filter out determinants of store format choice and aggregate spending in E3. Beyond, Chapter 2.4.iv includes a censoring model used to check for dissimilarity of demand reactions for a wider array of product groups in E3. Chapter 3 then gives a summary of E1. In Chapter 4, a summary of E2 is provided, and Chapter 5 contains a summary of E3. Chapter 6 summarizes and highlights the main findings of all the three essays.

2. Background on demand theory

2.1 Theoretical approaches to model consumer demand

Analyzing consumer demand implies the aim of capturing the behavior of a representative consumer or household as accurately as possible. Microeconomic theory offers two related concepts to accomplish this task: Utility maximization and expenditure minimization (Barten 1993). In any case, the consumer is assumed to comply with a set of preference axioms. These axioms need to be satisfied in order to allow for defining and making mathematical use of utility functions and portraying rational behavior (Autor 2010). Most importantly, it is required that a consumer's preferences are complete, transitive and continuous. Completeness refers to consumers being able to establish a preference ordering, while transitiveness requires consumers to be consistent in their choices. Continuity is satisfied if a consumer has a smooth preference order, i.e. a preference order without any "kinks" (Kirman 1992). Beyond, for utility-based models to yield reliable information, preferences are assumed to be stable over time. In addition, consumers need to have complete information on their available choices at all times.

This being said, two additional axioms are accepted if a utility function is meant to serve as the basis for a demand function (Okrent and Alston 2011). Mainly, consumer preferences need to be non-satiated, meaning that consumers would generally prefer possessing higher quantities of any good. Second, consumer preferences should be strictly convex, which entails strictly quasiconcave utility functions. The latter are necessary in order to obtain a maximum when solving the utility optimization problem.

The above axioms provided, a straightforward way to model consumer demand is to establish a utility-maximizing framework. In doing so, it is assumed that consumers seek to maximize their level of satisfaction through consumption of goods, while their choices are constrained by a limited budget (Mas-Colell et al. 1995). Each consumer solves the following maximization problem:

$$max_{\{q_1,\dots q_N\}} u(q_1, \dots, q_N) \ \ s.t. \sum_{i=1}^{N} p_i q_i \ \leq M \tag{1}$$

where q_i is the consumed quantity of good i, p_i is the price of good i , u refers to consumer's utility and M to each consumer's budget. Hence, the consumer chooses her optimal consumption quantity ${q_i}^*$ for each good i, depending on prices p_i and budget M:

$$ {q_i}^* = q_i(p_1, \dots, p_N, M) \tag{2} $$

The choices from equation (2) are observable, and they are usually referred to as Marshallian, or uncompensated, demand functions. When inserted into the utility function u, the utility at optimal choices, $u({q_1}^*, \dots, {q_N}^*)$, represents the indirect utility function. The term indirect is used because utility depends on quantities chosen, but these in turn depend on prices and expenditure. Thus, the indirect utility function depends indirectly on prices and expenditures, and it can be written as:

$$ v\ (p_1, \dots, p_N, M) = u(\boldsymbol{q}^*(p_1, \dots, p_N, M)) \tag{3} $$

with $\boldsymbol{q}^*$ as the vector of optimal choices for goods 1 to N.

Alternatively to specifying equation (1), one can start directly from specifying an indirect utility function to obtain the optimal choices ${q_i}^*$. In this case, Marshallian demand functions ${q_i}^*$ can be recovered from the indirect utility function through application of Roy's identity:

$$ q_i^*(p_1, \dots, p_N, M) = -\frac{\partial v(p_1,\dots,p_N,M)/\partial p_i}{\partial v(p_1,\dots,p_N,M)/\partial M} \tag{4} $$

Yet another popular starting point is to consider a consumer's expenditure minimization problem. Here, it is assumed that consumers wish to maintain a certain utility level, while looking for the lowest possible level of expenditure. Hence, this approach does not foreclose the concept of utility functions, nor does it contradict utility maximization. It is straightforward to see that a consumer who maximizes her utility would not be doing so if she had not optimized her expenditure, a rationale commonly known as duality.

With the consumer's desired optimal utility level $u(\boldsymbol{q}^*)$, the expenditure minimization problem takes the following form:

$$ min_{\{q_1,\dots q_N\}} \sum_{i=1}^{N} p_i q_i \quad s.t.\, u(\boldsymbol{q}) \geq u(\boldsymbol{q}^*) \tag{5} $$

Solving problem (5), one obtains the optimal consumption quantities $h_i^*(p_1, \dots, p_N, u)$, which can be used to derive the so-called expenditure function $e(p_1, \dots, p_N, u)$. The optimal quantities h_i^* are referred to as Hicksian, or compensated, demand functions. They are, however, unobservable in reality, and reflect only the change induced directly by alternations in prices. Thus, the indirect effect regarding a change in income whenever prices are changed is neglected for h_i^*. Starting out from the expenditure function $e(p_1, \dots, p_N, u)$, the Hicksian, compensated demand functions can also be derived through Shephard's Lemma:

$$h_i^* = \frac{\partial e(p_1, \dots, p_N, u)}{\partial p_i} \tag{6}$$

The Hicksian and Marshallian demand functions can be connected as follows:

$$h_i^*(p_1, \dots, p_N, u) = q_i\big(p_1, \dots, p_N, e(p_1, \dots, p_N, u)\big), \forall\, i = 1, \dots, n \tag{7}$$

$$q_i(p_1, \dots, p_N, M) = h_i^*\big(p_1, \dots, p_N, v(p_1, \dots, p_N, M)\big), \forall\, i = 1, \dots, n \tag{8}$$

Based on this relationship, the Slutsky equation can be obtained, yielding the following term (Mas-Colell et al.1995):

$$s_{ij} = \frac{\partial h_i^*(p_1, \dots, p_N, u)}{\partial p_j} + \frac{\partial q_i(p_1, \dots, p_N, M)}{\partial M}\, q_j(p_1, \dots, p_N, M) \tag{9}$$

In equation (9), s_{ij} denotes the change in demand for any good i in response to a change in the price of good j, also showing the connection between unobserved Hicksian demand functions and observable Marshallian demand reactions to price and income changes.

So far, two related starting points were mentioned to model Marshallian demand: Specification of (1) or (4), which can be used to obtain Marshallian optimal quantities q_n^*. Alternatively, a third option is provided by Theil (1965), who starts from differentiating equation (2) to obtain a differential double-log function of the following form:

$$d\ln q_i = \lambda_i\big(d\ln M - \textstyle\sum_{j=1}^{N} d\ln p_j\big) + \textstyle\sum_{j=1}^{N} \pi_{ij}\, d\ln p_j \tag{10}$$

λ_i is the expenditure elasticity of demand for good i, while π_{ij} is the Hicksian price elasticity of demand. For $i = j$, π_{ij} refers to the own-price elasticity of good i, while it captures a cross-price elasticity for $i \neq j$. Natural logarithms are represented by ln and d indicates that a variable is used in first differences. Models based on equation (10) are often called Rotterdam demand models.

2.2 The Generalized Ordinary Differenced Demand System (GODDS)

Despite their straightforward foundation, Barten (1993) notes that models based on a specification of direct utility functions (1) possess several inconvenient features. In short, their estimation can turn complicated and empirically restrictive. Barten (1993) developed a way to nest the approaches of specifying an expenditure function on the one hand (5) and a differential demand system on the other (10). This nesting model is used in E1 and E2. It nests the AIDS, in first differenced form (called FDLAIDS hereafter), a Rotterdam model, plus two intermediary demand models, the Central Bureau of Statistics (CBS) model and the National Bureau of Research (NBR) model. Okrent and Alston (2011) refer to it as the Generalized Ordinary Differenced Demand System (GODDS). The four elementary models of the GODDS can be denoted as follows:

Rotterdam: $w_i d\ln q_i = \lambda_i d\ln Q + \sum_{j=1}^{N} \pi_{ij} d\ln p_j$ (11)

FDLAIDS: $dw_i = \psi_i d\ln Q + \sum_{j=1}^{N} \gamma_{ij} d\ln p_j$ (12)

CBS: $w_i(d\ln q_i - d\ln Q) = \psi_i d\ln Q + \sum_{j=1}^{N} \pi_{ij} d\ln p_j$ (13)

NBR: $(dw_i + w_i d\ln Q) = \lambda_i d\ln Q + \sum_{j=1}^{N} \gamma_{ij} d\ln p_j$ (14)

In equations (11) to (14), all other Greek letters are parameters to be estimated and $d\ln Q$ is the Divisia Volume Index, which is defined as follows:

$d\ln Q = \sum_{\mathrm{i}=1}^{\mathrm{N}} (w_i\, d\ln q_i)$ (15)

According to Barten (1993) and Eales et al. (1997), the four basic models in equations (11) to (14) are nested as follows:

$$dw_i = (\beta_i + \varphi_1 w_i)d\ln Q + \sum_{j=1}^{N}\left[\theta_{ij} - \varphi_2 w_i(\delta_{ij} - w_j)\right]d\ln p_j \quad (16)$$

The parameters to be estimated are the constant price coefficient θ_{ij}, the expenditure coefficient β_i, and the model's nesting parameters φ_1 and φ_2, whereas δ_{ij} represents the Kronecker Delta (δ_{ij} = 1 for i = j, 0 otherwise). While the price coefficient θ_{ij} is composed of $\theta_{ij} = \varphi_2\gamma_{ij} + (1 - \varphi_2)\pi_{ij}$, the expenditure coefficient β_i is given as $\beta_i = \varphi_1\psi_i + (1 - \varphi_1)\lambda_i$ (Okrent and Alston 2011).

All of the four nested models are used in differenced form, where Gao and Shonkwiler (1993) note that difference models are preferable in the sense that spuriously desisting from differencing induces more severe falsifications than the use of differencing in cases in which it would not have been necessary.

The GODDS has the benefit that the nested models' adequacy (11 to 14) can be compared to each other and to the superordinate nesting model itself (16). As a key feature of the GODDS, different values for the nesting parameters can be hypothesized to test which of the nested models is most suitable for the data at hand. Generally, the nesting parameters correspond to each of the sub-models according to the restrictions outlined in Table 1. In case none of the nesting parameter restrictions is affirmed, the less restrictive GODDS itself can be applied (Xie et al. 2009, Matsuda 2005).

Table 1: Sub-models of the GODDS and corresponding parameter restrictions

	φ_1	φ_2
FDLAIDS	0	0
Rotterdam	-1	1
CBS	0	1
NBR	-1	0

Note: φ_1 and φ_2 are the nesting parameters of the GODDS. For example, if the hypothesis that $\varphi_1 = -1$ and $\varphi_2 = 0$ is not rejected, the NBR can be applied instead of the GODDS itself.

When applying the GODDS in E1 and E2, elasticities of demand are computed subsequent to parameter estimation. For the models included in the GODDS, elasticities of demand are defined as described in Table 2:

Table 2: Price and expenditure elasticity for all potential models of the GODDS

Model	Expenditure elasticity	Marshallian, Uncompensated price elasticity	Hicksian, Compensated price elasticity
FDLAIDS	$1 + \frac{\psi_i}{w_i}$	$\frac{\gamma_{ij} - \psi_i w_j}{w_i} - \delta_{ij}$	$\frac{\gamma_{ij}}{w_i} + w_j - \delta_{ij}$
Rotterdam	$\frac{\lambda_i}{w_i}$	$\frac{\pi_{ij} - \lambda_i w_j}{w_i}$	$\frac{\pi_{ij}}{w_i}$
CBS	$1 + \frac{\psi_i}{w_i}$	$\frac{\pi_{ij} - (\psi_i + w_i) w_j}{w_i}$	$\frac{\pi_{ij}}{w_i}$
NBR	$\frac{\lambda_i}{w_i}$	$-\lambda_i \frac{w_j}{w_i} + \frac{\gamma_{ij}}{w_i} + w_j - \delta_{ij}$	$\frac{\gamma_{ij}}{w_i} + w_j - \delta_{ij}$
GODDS	$1 + \varphi_1 + \frac{\beta_i}{w_i}$	$\frac{\theta_{ij} - \beta_i w_j}{w_i} + (\varphi_2 - 1)\delta_{ij} - (\varphi_2 + \varphi_1) w_i$	$\frac{\theta_{ij}}{w_i} + (w_j - \delta_{ij})(1 - \varphi_2)$

2.3 Restrictions derived from demand theory

Based on the set of preference axioms, some hypotheses can be derived in terms of consumer behavior. These can be imposed or tested when estimating demand responses. In other words, one can either restrict demand reactions to be in line with microeconomic theory or test whether theoretical assumptions are met. The most prominent theoretical restrictions derived from the preference axioms are the ones of adding-up, homogeneity and symmetry. These shall be briefly illustrated in the sequel.

Adding-up follows from the non-saturated preferences of consumers. In essence, adding-up ensures that the budget constraint is satisfied, so that all products' budget shares sum up to 1, and the equation $\sum_{i=1}^{N} p_i q_i = M$ holds. Related to this, consumers are considered to have homogeneous demand functions if an increase in all prices and expenditure by the same factor does not alter the demanded quantities of any good. This homogeneity property can be written as

$$\sum_{j=1}^{N} p_j \frac{\partial q_i(p_1,\ldots,p_N,M)}{\partial p_j} + M \frac{\partial q_i(p_1,\ldots,p_N,M)}{\partial M} = 0. \quad (17)$$

Symmetry is an empirically important feature, requiring that demand reactions for one good *i* related to a price change in good *j* are equivalent to demand reactions for good *j* when prices for *i* are changed:

$$s_{ij} = s_{ji} \quad (18)$$

When estimating a system of demand for several goods, the above restrictions can easily be integrated by restricting the respective parameters in the system directly. Beyond, some other theoretical foundations are often implicitly assumed to be met (Barten 1993), such as the negativity constraint, which requires the matrix of own- and cross-price effects in Hicksian demands to be symmetric and negative semidefinite. However, while the properties of symmetry, adding-up and homogeneity can usually be implemented rather smoothly, including the negativity condition can turn out more complicated.

2.4 Problems with household-level data: truncation, sample selection and censoring

Microdata, such as information on sociodemographic characteristics of individuals and households, have become increasingly important in recent times (Yen and Lin 2006). This type of data is used in E3. Alongside with additional insights, there can also be additional problems when microdata are used. Mainly, these problems may occur in the form of truncation, sample selection or censoring. All of these refer to cases in which values of dependent variables are limited in some sense. While censoring eventually refers to a non-normal distribution of the dependent variable, the general concern with truncation and sample selection is that missing values on the dependent variable do not occur randomly. In this case, using only the information available from a subpopulation may not allow for inferences regarding the total population of interest.

2.4.i Truncation and sample selection

With truncation, values of the independent variables are observed only if the dependent variable is observed (Judge et al. 1988). Sample selection, in a sense related to truncation and hence sometimes also termed incidental truncation, poses yet another very important case of missing data. The fundamental concern with sample selection is that those units for which the dependent variable is not observed may represent a subpopulation which differs from those for whom the dependent variable is observed. In contrast to truncation however, independent variables are observed even when the dependent variable is unobserved.

2.4.ii Heckman models for cases of sample selection

Heckman (1978) pointed out the potential for selection within a sample, and offered a correction which has been used extensively in applied studies of various fields. In his approach, Heckman suggests a selection equation to be estimated prior to estimation of the main equation. Applied to the context of demand analyses with different retail formats, the selection equation in the Heckman model can deal with the problem that not all retail formats are visited by all consumers.

In mathematical terms, the Heckman selection approach starts out by defining a main equation:

$$y_i = \boldsymbol{x}_i'\boldsymbol{\tau} + \varepsilon_i, \tag{19}$$

with y_i as the continuous dependent variable, $\boldsymbol{x}_i$ as the vector of explanatory variables, $\boldsymbol{\tau}$ as a vector of parameters and ε_i as the error term. Since y_i may not be observed for the full sample, another equation is introduced, which captures the selection process:

$$z_i^* = \boldsymbol{r}_i^{'}\boldsymbol{\varsigma} + \xi_i \tag{20}$$

The dependent variable z_i^* is defined to be binary, equaling zero if data on y_i is missing, and 1 otherwise. Explanatory factors are subsumed in the vector $\boldsymbol{r}_i$ with associated parameters $\boldsymbol{\varsigma}$, while ξ_i refers to the error term.

Problems with regard to selection mainly arise if the error terms ξ_i and ε_i in (19) and (20) are not independent, which would imply that the missing data on equation (19) was generated non-randomly (Heckman 1978). Allowing for the correlation between ξ_i and ε_i to be nonzero, and assuming that they both follow a bivariate normal distribution with zero means, the expected value of y_i in equation (19) can be written in the following way (Greene 2011):

$$\mathrm{E}[\mathrm{y} \mid \mathrm{x}, z_i^* > 0] = \boldsymbol{x}_i^{'}\boldsymbol{\tau} + E\left[\varepsilon_i \middle| \xi_i > -\boldsymbol{r}_i^{'}\boldsymbol{\varsigma}\right]$$

$$= \boldsymbol{x}_i^{'}\boldsymbol{\tau} + \rho_{\xi\varepsilon}\sigma_\varepsilon\kappa_i(\alpha_\xi) \tag{21}$$

with $\rho_{\xi\varepsilon}$as the correlation between ξ_i and ε_i, $\sigma_\varepsilon$as the standard deviation of ε_i, $\alpha_\xi = \frac{-r_i^{'}\varsigma}{\sigma_\xi}$ and $\kappa_i\left(\alpha_\xi\right) = \frac{\phi(\frac{r_i^{'}\varsigma}{\sigma_\xi})}{\Phi(\frac{r_i^{'}\varsigma}{\sigma_\xi})}$

Hence, omitting $\kappa_i\left(\alpha_\xi\right)$, a term sometimes referred to as the inverse Mills ratio, leads to biased estimates in equation (19) when ξ_i and ε_i are correlated. As a remedy, Heckman (1978) proposed a general procedure to allow for the correction of this potential bias:

1.) Estimate the parameters of equation (20) for the full sample with a probit model
2.) From these estimates, obtain $\phi(\frac{r_i^{'}\varsigma}{\sigma_\xi})$ and $\Phi(\frac{r_i^{'}\varsigma}{\sigma_\xi})$. Calculate $\kappa_i(\alpha_\xi)$ from these.
3.) Add $\kappa_i(\alpha_\xi)$ as an additional regressor to equation (19), and estimate equation (19) for $z_i^* > 0$.

4.) Calculate or bootstrap the correct standard errors for ε_i in equation (19)

Among others, Wooldridge (1995, 2002) extended this method to panel data models. The panel data model by Wooldridge (1995, 2002) is used in E3, where a probit model (20) for each time period is estimated to obtain $\kappa_i(\alpha_\xi)$. The basic rationale proposed by Heckman (1978), however, remains unchanged in this approach.

2.4.iii Censoring

Opposed to the case of sample selection, censoring refers to situations in which individuals with missing data on the dependent variable are not considered a distinct subgroup of the sample. Instead, censoring typically occurs in a situation with a set of interdependent equations, with missing values for only some of the dependent variables. For demand analyses based on household panel data, this is a usual case. Typically, the main equations of interest refer to a system of product groups, denoted in the following general form:

$$y_{it} = f(\boldsymbol{x}_{it}, \boldsymbol{\tau}_i), \tag{22}$$

with y_{it} as the dependent variable for product group i at time t, x_{it} as explanatory variables and τ_i as parameters associated with the explanatory factors.

Considering a range of products y_i, some may not be bought at all periods of time by all households. At this point, a distinction is typically made between the observed variable y_i^*, and the created variable y_i, with the following relationship between the two: y_i = 0 if $y_i^* \leq 0$; $y_i = y_i^*$ if $y_i^* \geq 0$. Hence, the dependent variable y is not normally distributed, but rather shows a left-hand side concentration of values at zero. In other words, the sample data distribution is a mixture of continuous and discrete distributions (Greene 2011). For $y_i^* \sim N[\mu, \sigma^2]$, the probability distribution is Prob $[y_i = 0] =$ Prob $[y_i^* \leq 0] = \Phi(-\mu/\sigma) = 1 - \Phi(\mu/\sigma)$, while for $y_i^* > 0$, y_i

has the density of y_i^*. As a consequence, it cannot be assumed that the values of y_i follow a regular continuous distribution. Instead, the observed values should be scaled in some way, to account for the discrete part of the distribution. Several ways exist to do so, such as the two-step method by Shonkwiler and Yen (1999), the generalized method of moments approach by Perali and Chavas (2000), the Amemiya-Tobin approach used by Dong et al. (2004b), quasi-maximum likelihood methods for panel data (Meyerhoefer et al. 2005), or one-step quasi and simulated-likelihood (ML) methods (Yen 2003, 2006).

2.4.iv Shonkwiler and Yen's (1999) method for cases of censoring

The two-step method by Shonkwiler and Yen (1999), called SY in what follows, shall be briefly described, as it is used in E3. The basic idea in the SY method is to include the probabilities of a positive outcome, P[y_{it} > 0], in the process. To do so, a binary variable, d_{it}, is created at first, taking on the value of one if y_{it} > 0, and zero otherwise. Thus, in cases of missing data on y_{it}^*, values of d_{it} are also replaced by values of zero. Accordingly, for any product i, there is a true underlying decision model $d_{it}^* = \boldsymbol{b}_{it}^{'}\boldsymbol{\zeta}_i + \eta_{it}$, with $\boldsymbol{b}_{it}^{'}$ as the vector of explanatory variables, $\boldsymbol{\zeta}_i$ as the corresponding parameter vector and η_{it} as the error term, but d_{it} replaces the underlying latent choice d_{it}^* in the estimation. As opposed to the Heckman procedure, the first step in the SY model can be considered a decision equation rather than a self-selection one, since individuals with $d_{it}^* = 0$ are not separated when estimating the main equations. In other words, the SY method addresses the problem of missing data on individual product groups, while people in this case are not deemed to belong to a particular subgroup of the sample just for not buying all available product groups.

In terms of the afore-mentioned scaling of y_{it}, SY show that the expectational values of y_{it} in the main equations can be derived as

$$E(y_{it}|\boldsymbol{x}_{it}, \boldsymbol{b}_{it}) = \Phi(\boldsymbol{b}_{it}^{'}\boldsymbol{\zeta}_i)\, f(\boldsymbol{x}_{it}, \boldsymbol{\tau}_i) + \delta_i \phi(\boldsymbol{b}_{it}^{'}\boldsymbol{\zeta}_i) \tag{23}$$

The SY procedure is fairly easily implemented. At first, a maximum likelihood (ML) probit model is estimated for each good in the system. From these, $\Phi(\boldsymbol{b}_{it}^{'}\boldsymbol{\zeta}_i)$ and $\phi(\boldsymbol{b}_{it}^{'}\boldsymbol{\zeta}_i)$ can be calculated, which are then inserted in the system of equations referred to by equation (23). Equations in (23) in turn can be estimated using Seemingly Unrelated Regression (SUR) or ML.

In the context of demand systems, the main assumption in the SY model is that the error terms in each good's binary selection equation and the respective demand equation are joint-normally distributed. In this case, the SY method yields consistent and unbiased estimates (Sam and Zheng 2010). As any model hinges on a number of requirements and assumptions, selecting a model includes choosing a set of assumptions which is deemed to be least troublesome. In this context, Akbay et al. (2008) state that there is no single perfect solution to incorporate a censoring mechanism into estimation of demand systems for household data. For example, the method developed by Yen (2005) is more efficient than the SY method. However, a multitude of probability integrals need to be evaluated with simulated ML when censoring occurs in various equations. In these cases the SY method avoids the computational burden of such methods and represents a useful alternative (Yen and Lin 2006).

3. Using a Generalized Ordinary Differenced Demand System to Estimate Price and Expenditure Elasticities for Milk and Meat in Austria (E1)

3.1 Extended abstract

The aim of this article is to estimate current price and expenditure elasticities in the Austrian food retail market. For this purpose, a nesting model is applied, in order to choose between different demand models. The model is sometimes referred to as the Generalized Ordinary Differenced Demand System (GODDS), with the main benefit that it allows for a statistical comparison between nested models, to identify the most suitable one for the data at hand. When applying the GODDS, potential endogeneity problems are taken into account by performing a Hausman-Wu test. Depending on the outcome of the Hausman-Wu test, estimations are either carried out using the method of Iterative Seemingly Unrelated Regression (ITSUR) or Iterative Three-Stage Least Squares (IT3SLS).

Beyond, the concept of multi-stage budgeting is incorporated, where the sensitivity of estimations with regard to different budgeting assumptions is also analyzed. Budget allocation in our case contains three stages, where the first one is constituted by the choice between food and non-food products. For the second stage, five broad groups of products are considered, namely milk, butter, fruits, meat and vegetables. The third and last stage includes milk and meat products on a more disaggregated level, e.g. pork, cheese etc.

The dataset used consists of monthly data on expenditures and quantities purchased during the time period 1997 to 2009. It is derived from the Austrian household panel RollAMA, whereas all purchase and expenditure data are aggregated on a monthly basis. Purchase information is included for several milk products, butter, fruits, vegetables, pork, poultry, and beef. Annual data from 1977 till 2010 on overall household expenditures and purchased quantities of food and non-food in Austria, which were obtained from the OECD, complement the data basis.

In terms of our estimation results, the strongest reactions to the disaggregated meat price changes at the third stage were found for pork and beef, while both drinking milk and cheese demand were also estimated to be highly elastic at the third stage. On

the more aggregate second stage, demand for butter turns out to be most elastic, whereas most other price elasticities end up with absolute values less or equal to one. Income elasticities at the second stage range from 0.30 (oils and fats) to 0.49 (meat). Thus, a ceteris paribus increase in real income of e.g. 20 percent, i.e. an increase in the order of magnitude as experienced by the average Austrian over the last 15 years (according to OECD statistics), would increase the consumption of meat in Austria by about 10 percent.

As compared to a study for Germany (Thiele 2008), differences in outcomes occur for the three types of meat at the third stage, where price reactions for Austria are throughout higher. In addition, while the propensity to substitute between different types of meat is not detected for Germany, the opposite is the case for Austria. In view of the significant positive cross-price elasticities for meat types at the disaggregate level, it seems likely that substitution of pork, poultry and beef is responsible for the slightly lower own-price elasticity of meat in Austria at the aggregate level. Looking at the disaggregated stage with regard to milk products, our results are quite in line with the ranges found in Bouamra-Mechemache (2008), who review 16 European studies on drinking milk and cheese. However, price reactions for milk and cheese in Austria are at the upper limit in absolute value.

In addition, our results indicate the importance of modeling a comprehensive budgeting process rather than isolated levels of product aggregation when deriving both price and expenditure elasticities of demand. With this regard, it is shown that differences across studies may vanish once the budgeting structures are brought in line.

3.2 The candidate's contribution to E1

The candidate is the main author of the paper.

3.3 Publication

Widenhorn, A. and Salhofer, K. (2014a). Using a Generalized Ordinary Differenced Demand System to Estimate Price and Expenditure Elasticities for Milk and Meat in Austria. German Journal of Agricultural Economics 63: 109-124.

4. Price Sensitivity Within and Across Retail Formats (E2)

4.1 Extended abstract

In this study, demand reactions of consumers are estimated and statistically compared for two different food retail formats, discount stores on the one hand, and conventional supermarkets on the other. In particular, elasticities of demand are analyzed for two scenarios. First, demand reactions are estimated for a scenario in which consumers only frequent either discounters or supermarkets, followed by an investigation of potential cross-format effects when consumers visit both types of stores.

As far as the underlying model is concerned, the Generalized Ordinary Differenced Demand System (GODDS) nesting model is applied, which allows for comparing several models' adequacy. In order to apply the correct estimation technique, Hausman-Wu tests are run to check for potential problems of endogeneity, leading to the use of either Seemingly Unrelated Regression (SUR) or Three-Stage Least Squares (3SLS). Following the estimation of parameters and the calculation of elasticities of demand, Welch tests, as well as Kolmogorov-Smirnov- and Wald tests are applied to check for statistical differences between elasticities of demand for both formats.

Monthly data on quantities and expenses for milk products in Austria, covering the time period between 1997 and 2009, serve as the basis for estimations. The dataset is part of the Austrian household panel RollAMA, containing information on consumption in 12 different retail chains in Austria. These retail chains are separated according to the RollAMA classification included in the dataset, into 4 discounters and 8 supermarkets. Milk products contain three categories, namely drinking milk, cheese and residual milk products.

Estimation results indicate that price elasticities in discount stores are higher for drinking milk and cheese, while for residual milk products the results vary depending on either isolated estimations for each format or conjoined estimation for both formats. Statistical tests for format-specific demand reactions largely support the hypothesis that consumers in discount stores and those in supermarkets respond differently to price changes. By tendency, discount store consumers seem to be more responsive to inner-

format milk price changes. Beyond this, demand reactions in supermarkets with respect to price changes in discounters also differ from the reverse case, i.e., from demand reactions in discounters when supermarket prices are changed. This is particularly true for the case of drinking milk, which confirms the strategic potential of drinking milk as a loss leader product.

4.2 The candidate's contribution to E2

The candidate is the main author of the paper.

4.3 Publication

Widenhorn, A. and Salhofer, K. (2014b). Price Sensitivity Within and Across Retail Formats. Agribusiness 30: 184–194.

5. Differentiation in Demand with Different Food Retail Formats (E3)

5.1 Extended abstract

In essence, this study investigates and compares various aspects of consumer behavior relating to discounters on the one side and supermarkets on the other. More precisely, the distinctiveness of discount consumers is analyzed both on an aggregate format- and on a disaggregate product level. On the format level, households' propensities to visit a discount store and overall portions of spending in discounters are analyzed. With regard to the product level, price and expenditure elasticities of demand for nine product groups in discounters and supermarkets are estimated and statistically compared.

As far as the format-level is concerned, a dynamic probit model by Wooldridge (2002) accounting for unobserved time-invariant heterogeneity of consumers and the initial bias is applied to identify determinants of consumers' choice of visiting a discounter or not. Hereafter, the factors influencing a household's budget portion spent in discounters are estimated applying a Heckman-type selection model, which takes into account that not all households have opted for visiting a discounter in all time periods. For the product level, the method developed by Shonkwiler and Yen (1999) is applied, which pays regard to the fact that not all households have consistently bought all the goods available in either format.

In terms of data, a RollAMA household-level panel dataset containing information on about 6500 households in Austria is used, including purchases for the time period between 2003 and 2007. Monthly quantities and overall expenditure on nine broad product groups (white milk, mixed milk, oils and fats, cheese, meat, sausages, fruits, vegetables, other products) are provided in this dataset, complemented by a number of household characteristics. With regard to different food retail formats, there are 40 food retail chains in the dataset, where 6 of these are defined as discount stores according to RollAMA classifications.

Results in terms of format choice indicate that income constraints represent a driving force behind households' decisions of visiting a discounter or not. Furthermore, differences in overall price levels in discounters and supermarkets also seem to play a major role when consumers choose between the formats. As the price gap between supermarkets and discounters widens, such that discounter products as a whole turn relatively cheaper, more people opt for discounters. In addition, people also spend a bigger portion of their budget on discount store products in the latter case. In terms of price elasticities of demand on the product level, results indicate that significant differences between price reactions in discounters and supermarkets exist. These differences are found for both inner- and cross-format price reactions. Interestingly, the results indicate that demand in supermarkets adjusts more strongly to inner-format price changes. However, this does not hold true for cross-format responses to price changes, where discount store demand turns out significantly more sensitive. In other words, while demand in supermarkets changes quite considerably when prices in supermarkets are changed, supermarket consumers are comparably less responsive to price changes in discounters.

5.2 The candidate's contribution to E3

The candidate is the main author of the paper.

5.3 Publication

Widenhorn, A. and Salhofer, K. (2014c). Differentiation in Demand with Different Food Retail Formats. Selected Paper for the 2014 EAAE Congress in Ljubljana, Slovenia, 26-29 August

6. Conclusions and discussion

Consumer reactions to price changes in food retailing were estimated in three different contexts. In the first essay (E1), which is based on a dataset with no separation by retail formats, general demand reactions for five broad product groups (milk, butter, fruits, meat and vegetables) were estimated, followed by an estimation of elasticities for sub-groups of milk (drinking milk, cheese and other milk products) and meat (beef, pork and poultry). As the results in this essay indicate, reactions to price and expenditure changes in Austria are fairly in conformity with the findings for neighboring markets, while price changes in some more disaggregated meat and milk types trigger a comparably strong reaction in Austrian consumers' demand. Further, I obtained that the premise of assumed budgeting stages can have a considerable impact on the results.

While estimates from this first part seem primarily useful for local policymakers, a topic of particular interest for retailers was raised in essay 2. More precisely, the question of differences in demand reactions across retail formats was addressed. Here, a more disaggregate viewpoint was adopted, separating food retailing by different formats and comparing reactions with regard to types of milk products in discounters on the one hand and more traditional retail types on the other. Many of the price elasticities were found to differ significantly across formats, implying that elasticities of demand in one single retail format do not necessarily apply to other formats. Hence, food retailers cannot expect aggregate demand estimates to be applicable for their particular type of store format. The results also suggest that discount store consumers tend to be more responsive to price changes of milk products. Beyond, there seems to be potential for drinking milk as a loss-leader product, since cross-format price elasticities for drinking milk are found to be significantly positive.

In the third essay, differences between consumers of discounters and supermarkets were further investigated. The essay is based on a household dataset including sociodemographic factors. Here, format and product choice determinants were considered. Furthermore, factors influencing the overall portion of budget spent on discounter products were analyzed, in addition to the estimation of elasticities of demand for nine product groups (white milk, mixed milk, oils and fats, cheese, meat, sausages, fruits, vegetables, other products). For empirical implementation, methods paying regard to the problems of censoring and sample selection were applied. In conformity with the previous indications in E2, E3 also concludes that demand reactions do differ significantly across formats. However, while results in E2 pointed at discount store consumers being rather more sensitive to inner-format price changes, the results in E3 indicate that supermarket consumers are more sensitive to inner-format price changes than discount store consumers. Hence, one may infer that the underlying data and method have the potential to alter the estimation results noticeably.

Differences in price responses for demand reactions across discounters and supermarkets, i.e. demand responses to price changes in another retail format, were also found in E3. These reactions are particularly interesting in terms of the strategic potential for enticement of customers from other formats. To this end, considering the results in E3 and E2, it seems that demand in discount stores responds more strongly to changes in supermarket prices than vice versa. Beyond, as far as format preferences are concerned, it appears that certain household factors such as low income and low education increase the probability that discount stores are chosen. However, further research is necessary to monitor the general validity of these results.

Looking at the overall findings of format-specific demand reactions, it has been shown that aggregate datasets are likely to represent averages of potentially diverse sets of consumers. As with studies of the type presented in E1, which are possibly most interesting for policymakers, an undistinguished viewpoint might suffice. However, considering the magnitude of product and format innovations in food retail markets worldwide, general validity of aggregate demand reactions for all interest groups seems questionable. Hence, the analyses presented in E2 and E3 should give food for thoughts for the numerous studies which observe different retail types or different store assortments in general.

Still, further investigations are necessary to identify the reasons behind the dissimilar demand reactions across formats. With this regard, data on consumer knowledge and expectations on quality would be desirable. It would also be interesting to know how consumers evaluate different format-product combinations, e.g. which level of quality consumers expect from organic product types in discounters, and how this affects their reactions to price changes. Altogether, it seems likely that developments on the food retail market will continue to raise questions on the homogeneity of demand responses, entailing a vast potential for future research.

7. References

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