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Chapter 1

Introduction and Summary

On the supply side, the German retail business is characterized by high consolidation and fierce competition. On the demand side, German consumers are extremely price-sensitive. Against this background, food retail pricing is of major importance for the retailers' marketing strategy. A key property of retail prices is the high level of price dispersion (VARIAN 1980): Retail prices for a given product vary not only over time but also across retailers. This price dispersion is predominantly caused by promotional prices¹. HOSKEN AND REIFFEN (2004) determine that 25% to 50% of the annual variation in retail prices is attributable to price promotions. Over time, the usage and importance of price promotions as a strategic marketing instrument has risen substantially, particularly in the German retailing business (HOFFMANN AND LOY 2010). Consequently, a wide range of theoretical models² aim to identify the rationales behind offering a product on promotion and to explain the pricing strategies as a whole. As these models result in contradictory hypotheses (BERCK ET AL. 2008), empirical research is essential in identifying the driving forces of particular pricing strategies. However, this type of study is particularly scarce for the German retail market (SCHMEDES

¹ Defined as temporal price reductions unrelated to cost changes.

² See HANSEN (2006) or BERCK ET AL. (2008) for a detailed overview.

2005). Thus, the central contribution of this dissertation is the empirical assessment of pricing patterns in the German retail business and the identification of the causes triggering the discovered pricing strategies.

Retail prices are the result of numerous influencing factors that might be related to either the demand or supply side or stem from governmental regulations. In order to contribute to the existing literature, the approach used in the six studies of this cumulative dissertation is to select one potential driver of retail prices and then conduct an in-depth study of whether and how that factor systematically affects retail prices. A special emphasis is placed on brand loyalty, product differentiation, temporal demand shifters, and the distribution channel.

Brand loyalty is a major characteristic of consumer behavior. Thus, several studies (RAJU ET AL. 1990; AGRAWAL 1996; ANDERSON AND KUMAR 2007; JING AND WEN 2008; KOCAS AND BOHLMANN 2008) theoretically analyze the impact of brand loyalty on retailers' optimal price setting. Small changes in the model's setup lead to fundamentally contradictive hypotheses: For example, AGRAWAL (1996) predicts that retailers will promote brands with strongly brand-loyal customers more often but with a smaller discount than weaker brands, while RAJU ET AL. (1990) arrive at the reverse conclusion. Overall, the empirical results of this dissertation indicate that brand loyalty is characterized by two dimensions: the number of loyal customers and the intensity of their loyalty. For example, brands might have a large share of loyal clients (large segment size) who would only accept a small amount of markup before switching to another alternative (low level of loyalty). The results indicate that these two dimensions of brand loyalty affect the promotional price strategy in opposite ways. An increased share of loyal customers leads to a more aggressive promotional price strategy. However, the higher the level of loyalty becomes, the less aggressive the pricing strategy will be. The rationale behind this finding might be that retailers seek to maximize the coverage of their promotional activities, while the potential loss from offering lower prices is minimized because brands whose loyal customers show a comparably high willingness to pay are given promotional prices less frequently.

Product differentiation is becoming increasingly important in the industrialized countries because food markets are considered to be saturated. For example, German consumers can choose between approximately 2,000 different yogurts. Thus, product differentiation has attracted growing attention in the literature. For instance, BONANNO (2012) developed a technique to account for product differentiation when estimating a demand model. This dissertation analyses the impact of product differentiation on prices levels and dynamic price

movements. A theoretical model is applied to the product differentiation context, and also, an empirical technique is presented to incorporate product differentiation into fitting error correction models. The results show that prices are not only dependent upon input costs but also follow the price movements of close substitutes.

At the retail level, demand is subject to seasonal fluctuations. Whether retailers respond to positive demand shocks by increasing or decreasing prices is a longstanding question within the marketing and economics literature. The standard model of competitive behavior predicts that firms will raise prices uniformly. More recently, CHEVALIER ET AL. (2003) discuss several theories as to why retail prices fall during periods of peak demand and present empirical evidence supporting their hypothesis. The studies in this dissertation contribute to the literature not by analyzing the price as an aggregate but by separating the price into the regular and the promotional price. Thus, more nuanced findings with respect to how retailers react to positive demand shocks are possible. Furthermore, the demand shocks are classified into overall demand shocks (e.g., Christmas), category demand shocks (beer during Ascension Day), and brand-level demand shocks (demand for a given beer whenever its sponsored soccer team plays). The findings support the idea that the effects differ greatly across the different types of demand shocks.

The impact of the distribution channel on retail prices is undisputed: While supermarkets generally choose to offer comparably higher prices connected with lower sales prices (“HILO”), discounters advertise everyday low prices (“EDLP”). This effect is highly significant in all of the studies presented here. However, research examining differences between these formats in terms of their speed of adjustment to input cost shocks is scarce. In times of volatile markets, this might be of interest for consumers. Thus, this dissertation analyzes how format influences the pass-through of input cost shocks. The analysis shows that discounters react more quickly to input cost shocks.

In the light of the competing theories regarding retail pricing strategies and the limited empirical research into the German market, this cumulative dissertation consists of six independent contributions that empirically analyze retail pricing in the German market. However, each article has its own research agenda and method.

The first two studies are devoted to the empirical validation of theories that assume brand loyalty plays a major role in determining promotional price strategies for brands in the breakfast cereal (Chapter 2) and beer (Chapter 3) markets. The study presented in Chapter 4

extends the analysis of the pricing mechanisms within the beer market by analyzing the effect of temporary demand shifts. Chapters 5 and 6 of this dissertation address how product differentiation affects the retail pricing strategy for yogurt. Chapter 5 documents how product attributes may explain the observed price differences for yogurt. Chapter 6 provides a theoretic model, as well as a new empirical approach, via which to test how product differentiation alters retailers' pricing in a dynamic way. Chapter 7 examines whether different retail outlets (supermarkets vs. discounters) react differently to input cost shocks. The methodological background for empirically determining the degree of brand loyalty is provided in Chapter 8.

Each article is summarized below. The summary includes the aim of the contributions, the data, the methods applied, and the main results. A critical assessment of each contribution, an outline for potential future research, and the managerial implications are presented in Chapter 9. Chapter 10 provides a German summary.

Price Promotions and Brand Loyalty: Empirical Evidence for the German Ready-to-Eat Cereal Market

Price promotions are the most important marketing instrument for German retailers. Brand loyalty is an essential driver of consumer behavior. Thus, several theoretical models have been created to address whether consumer brand loyalty influences retailers' promotional price strategy. However, the theories deliver contradictory hypotheses. Consequently, it is necessary to empirically determine which of the hypotheses derived from the theoretical models holds for the German breakfast cereal market. This market has been frequently studied in the economics and marketing literature for several reasons: high concentration ratios and price-cost margins, intense advertising activity, and frequent launches of new products. The data used in this study consist of two parts that are matched by the unique European Article Numbers (EANs). A household scanner data set is used to describe consumer brand loyalty, while a retail scanner data set is employed to determine retailers' pricing strategies.

In contrast to previous studies, this study accounts for two characteristics of brand loyalty (level of brand loyalty and segment size) in the review of the theoretical literature and in the empirical model. Theoretically, the level of brand loyalty is defined as the maximum price differential loyal consumers are willing to pay before switching to the cheapest alternative.

The segment size is a brand's share of loyal consumers. For example, Brand A might have few but deeply loyal clients, and Brand B might have a large share of loyal clients who prefer Brand B only slightly over Brand A. Thus, the segment size is higher for Brand B, while the level of brand loyalty is higher for Brand A. Empirically, a mixed logit model is estimated to assess both dimensions of brand loyalty. A household is labeled as loyal to a brand if that household's probability of purchasing that brand is higher than the probability of purchasing any other brand. The segment size is represented by the number of households loyal to each brand, and the level of brand loyalty is the average of the purchasing probabilities among the loyal households. Furthermore, the price promotional strategy is also characterized by two variables: the frequency of price promotions and the average price discount. The frequency is defined as the share of weeks in which a promotion occurs. The average discount is the percentage-based discount relative to the regular price.

The results of the mixed logit model show that brands vary substantially with respect to segment size and level of brand loyalty. For example, Kellogg's Frosties has the largest share of loyal clients. However, the estimate for the level of loyalty is higher for Kellogg's Toppas Classic and Kölln's Knusprige Haferfleks. The results of this model are used in the empirical model explaining retail pricing. Here, the dependent variables are the relative promotional discount (tobit model) and the promotional frequency (probit model). The exogenous variables of interest are the results of the mixed logit model, particularly the estimates of segment size and level of brand loyalty. The key result is that the level of brand loyalty exerts a negative influence on the relative promotional discount and promotional frequency. In contrast, segment size influences both dependent variables positively. Thus, more popular brands are chosen for promotion because they reach wider audiences. Because advertising is costly, the brands whose consumers show higher levels of loyalty are promoted less often and less intensively because the retailers seek to skim from the higher willingness of those loyal consumers to pay.

Spatial and Temporal Retail Pricing in the German Beer Market

Two essential characteristics describe demand for beer in the German market: First, Germans are particularly loyal to locally produced beer brands. Second, beer demand fluctuates temporally. Thus, the German beer market provides an ideal case study to test the theoretical models of the effect of brand loyalty and temporal demand shifters on retail pricing strategies.

With respect to the temporal demand shifters, standard models of competition predict rising prices during periods of higher demand. However, CHEVALIER ET AL. (2003) discuss three theoretical approaches that suggest why increasing demand in the retail business leads to falling prices. First, the demand becomes more elastic. Second, the incentives to leave a tacit cartel increase. Third, retailers might pursue a loss-leader pricing strategy. Theories regarding the impact of brand loyalty on pricing strategies deliver contradictory hypotheses.

To test these theories, weekly retail scanner data from the Madakom GmbH covering the years 2000 and 2001 are used. The top ten pilsner and wheat beers are selected on the basis of their revenue-based market share. Thus, the top ten pilsner beers are Becks, Bitburger, Hasseröder, Holsten, Jever, Krombacher, Radeberger, Rothaus, Veltins, and Warsteiner. The top ten wheat beers are Dinkel, Erdinger, Landskron, Löwenbräu, Maisel, Oettinger, Paulaner, Schneider, Schöfferhofer, and Spatenbräu. In order to describe the pricing strategies, regular prices must be separated from promotional prices. A price promotion is defined as a price cut of at least five percent with respect to the regular price. Additionally, a sale cannot last longer than four weeks. The regular price is defined as the last non-sale price that persisted for at least four weeks. On the basis of these definitions, three endogenous variables are determined. The frequency of price promotions equals one if there is a sale and zero if the regular price is applied. The promotional discount is the percentage-based discount of a sale relative to the regular price. Finally, the regular price is the price series in which the preceding regular prices have been substituted for the promotional price. This is an extension of the existing research because the effect on the regular price can be separated from the effect on the promotional strategy.

In the empirical model, the exogenous variable of interest is the distance of the retailer selling a beer from the main production facility that the beer stems from. As the brand loyalty is higher for locally produced beer brands, this distance indicates how high the level of brand loyalty is for a given brand in the region in which the beer is sold. Furthermore, special holidays and the average temperature are included in the model to capture the effects of demand shifters on pricing strategies.

In essence, it was found that with increasing distance between the retailer and the region of origin, the regular price rises significantly, while the promotional activity decreases. Thus, it can be concluded that it is preferred to promote well-known local brands. One reason might be that beer is used as a loss-leader product and that the efficiency of such a strategy increases with the popularity of the product on sale.

Regarding the temporal effects, various findings can be documented. While the regular price falls with higher temperatures, during Easter, and during the European Soccer Championship, it rises during Oktoberfest. Also, the effects of the temporal demand shifters on promotional strategies are mixed. One of the most pronounced effects can be documented for Ascension Day: The average discount and the frequency of promotions increase significantly.

How Do Retailers Price Beer During Periods of Peak Demand?

Evidence from Game Weeks of the German Bundesliga

This contribution also analyses the effect of temporary demand peaks on retail prices. In comparison to the preceding study, the match schedule of the Bundesliga is matched with the retail scanner data for several beer brands. Because Germans are very loyal to local beer brands and soccer teams and because those teams play nationwide, linking beer brands to the match schedule creates brand-level variation in beer demand. For example, if Werder Bremen plays against Bayern Munich in Munich, the demand for Becks (the sponsoring brand of Werder Bremen) in Munich should be higher during those weeks. The brand-level results show that the largest impact on the regular prices can indeed be documented for Bundesliga games. Interestingly, the sign of the effect varies across brands. Initial results show that retailers raise the price of beers for incoming teams and that the more successfully a team performs, the lower the prices of the beers connected to the team become. In essence, the results also document the importance of distinguishing the pricing strategy by separating regular prices from promotional prices. Furthermore, the findings indicate that brand-level demand shocks also influence retail prices.

Preissetzung auf dem deutschen Joghurtmarkt: eine hedonische Analyse

The yogurt market shows a high degree of differentiation, and innovations are launched on a frequent basis. Whereas most manufacturers offer a wide assortment of flavors, the production of specialties, e.g., probiotic or lactose-free yogurts, is concentrated within multinational food corporations and niche manufacturers. This study seeks to determine whether variations in yogurt prices can be attributed to product characteristics. Thus, a hedonic price model is estimated using retail scanner data that was collected from 2005 to 2008 in 536 retail stores throughout Germany. Using flavor, fat content, package type, brand name, and special variations (probiotic, lactose-free, and organic) as product characteristics, up to 74% of the observed price variation can be explained. Yogurts that are lactose-free

realize price premiums of up to 67% at the retail level, and yogurts being perceived as healthy (low-fat and probiotic) are more expensive than full-fat yogurts.

Product Differentiation and Cost Pass-Through: a Spatial Error Correction Approach

In the modern food retail business, most products are highly differentiated. Thus, this contribution focuses on the impact of product differentiation on pricing, particularly on the pass-through of input cost changes into final consumer prices. On the basis of a spatialized stock flow model, theoretical conclusions are derived. In this context, the degree of differentiation is translated into the distance among all products and is thus measured along a spatial dimension. In essence, the model predicts that the prices will be temporally and spatially correlated. The prices are dependent upon prices of alternative products and on the lagged prices of all alternatives. In addition, the more similar the products are, the closer the price movements will be to each other.

These hypotheses are empirically tested for the German yogurt market. The yogurt category is typically chosen for studies of product differentiation because this category is characterized by a very high level of differentiation. To measure the distance between the various yogurts, their key attributes are determined. The chosen attributes are the name of the manufacturer, nutritional information (fat content, calories, proteins, and carbohydrates), whether the yogurt is made using probiotic bacteria, flavor, and the length of the product line. First, distance matrices are determined for each characteristic. Then, these attributes are aggregated into a single distance matrix, which is plugged into a spatial panel error correction model (SPECM). This study presents the first application of a SPECM model to the product differentiation context. Using weekly retail scanner data from the SymphonyIRI Group collected from 2005 to 2011 in 536 retail stores, it can be shown that yogurt prices react to input cost changes for milk and to the price changes of similar products. More specifically, the vertical pass-through of input cost changes into consumer prices occurs at a rate of 41.6 %. The horizontal error correction effect amounts to 20.1%. Thus, there is a tendency for yogurt prices to be adjusted upwards if the prices of similar products increase.

Pass-through of Producer Price Changes in Various Retail Formats

Various sources of the incomplete pass-through of input cost changes into retail prices have been studied in the literature (e.g., the frequency of price adjustments, markup adjustments by firms, and local distribution costs). This study focuses on an additional explanation, the effect of retail format on pass-through rates. It is argued that supermarkets have higher local costs

than discounters, and thus, the pass-through of their input cost changes should be lower. Using a dataset that has frequently been chosen for pass-through studies (Madakom GmbH, weekly retail scanner data collected from 2000 to 2001 in 200 retail stores), it can be documented that discount retailers pass through 37% of a given producer price change, which is significantly more than the related 23% for supermarkets. Moreover, discounters react more quickly to input cost shocks.

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Chapter 2

Price Promotions and Brand Loyalty: Empirical Evidence for the German Ready-to-Eat Cereal Market

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Abstract

Price promotions are important marketing activities for food retailers; brand loyalty is a major requisite to foster brands' assets. Theoretical papers have analyzed the relationship between price promotions and brand loyalty, but only few empirical studies for grocery markets are available to test whether the models reflect actual pricing strategies of food retailers and manufacturers. In this analysis two detailed data sets for the German ready-to-eat breakfast cereal market are merged to investigate the relationship between price promotions and brand loyalty. The results support that brands with by a large segment of loyal clients are promoted more aggressively, while brands with higher levels of loyalty are put on sale less often at lower discounts.

2.1 Introduction

Promotional sales in various forms such as price promotions, coupons or displays are dominant features in the marketing mix of food retailers around the globe. In Germany price promotions are the most important instrument to lure customers into the store and to increase sales. In German supermarkets, breakfast cereals are on promotional sale every ten to twenty weeks and the average price reduction amounts to seven to fifteen percent of the regular price.³

Many theoretical studies suggest that the specific form of a promotional strategy is closely related to the nature of the consumers' brand loyalty for a product (NARASIMHAN 1988; RAJU, SRINIVASAN, AND LAL 1990; AGRAWAL 1996; KOÇAS AND BOHLMANN 2008). However, empirical research remains scarce. Thus, the central contribution of this paper is to provide a first study on the interrelationship between brand loyalty and price promotions for the European market. For the US, a similar study has been carried out by ALLENDER AND RICHARDS (2012). In contrast to ALLENDER AND RICHARDS (2012), we split the effect of brand loyalty into its two dimensions: the level and the strength of loyalty. The level of loyalty denotes the share of consumers being loyal towards a brand while the strength of loyalty describes the intensity of loyalty.⁴ This distinction is important as some brands might pursue a rather exclusive strategy with few but highly loyal customers, while other brands target at a larger audience.

The present study uses a unique combination of two data sets for breakfast cereals in Germany. We extend previous studies by matching both datasets by the unique European Article Number (EAN). To measure brand loyalty we employ a household panel data set which records the actual consumption behavior of 14.000 German households during the period 2000-2001. The price promotional strategy is derived from retail panel data for 108 German retailers for the same period⁵.

Estimating a mixed logit model, we find that there is substantial variation across the brands with respect to the two characteristics of brand loyalty. For example, Kellogg's Frosties has a

³ HOSKEN AND REIFFEN (2004: 137) and BERCK ET AL. (2008: 1261) show for the US that twenty to fifty percent of stores' product price variation can be attributed to variations due to sales' prices.

⁴ We use the terms "weak" and "strong" to describe the level of brand loyalty. We employ the terms "small" and "large" for the extent of brand loyalty. For example, a brand can have a few but very intensively loyal clients. Such a brand would be labeled as strong but small.

⁵ The dataset was discontinued in 2002. However, it is still used in the literature because of its detailed recordings of prices, quantities, characteristics of the included retailers and marketing activities (see e.g. EMPEN AND HAMILTON 2013).

very large loyal consumer segment, but the level of loyalty is comparably low, while only a few customers are loyal to Kellogg's Special K but these clients show higher levels of loyalty. Using these results, we find that in our model of the retailer's behavior, the retailers promote large brands more often and with a deeper discount. However, strong brands are promoted less often and less aggressively. The intuition behind the results is that those brands are chosen for promotions that reach a large audience while the loss of willingness to pay is minimized by choosing comparably weaker brands.

The paper is organized as follows. First, we review the existing theoretical literature on the relationship between price promotions and brand loyalty. In the following section, the theoretical models are translated into an empirical model. In the fourth section, the data sets and the matching procedure are presented. The fifth section entails the results of the brand loyalty estimates and relationship between price promotions and brand loyalty. Finally, we summarize our findings.

2.2 Theoretical Background

According to a widely used definition by JACOBY UND KYNER (1973) p. 2: "Brand loyalty is a biased (non random), behavioral response (buying), expressed over time, by some decision making unit, with respect to one or more alternative brands out of a set of such brands, and is a function of psychological (decision making, evaluative) processes."

While this general definition of brand loyalty is widely used in the literature (CHAUDHURI AND HOLBROOK 2001; DICK AND BASU 1994; OLIVER 2010), the implementation in theoretical and empirical models is less straightforward. To demonstrate the influence of brand loyalty on the retailers' optimal pricing strategy, at least two brands differing with respect to brand loyalty are generally introduced in the models. The asymmetry in brand loyalty is achieved by varying either the size or the level of loyalty. The size of brand loyalty is defined as the share of customers being loyal towards the brand. The level of loyalty captures the strength of the relationship between the brands and the loyal clients, e.g. a low level of loyalty indicates that customers only accept a small price differential between their favorite brand and the alternative while highly loyal customers would pay a large price differential before switching to a cheaper alternative.

The pricing strategy is characterized by the usage of price promotions, in particular, the firms differ with respect to the frequency of price promotions and the depth of price promotions:

Empirically, the frequency of price promotions is measured by the share of weeks in which a brand is offered on promotion. The promotional depth is characterized through the discount relative to the regular price levels.

The central idea of all models addressing the impact of brand loyalty on price promotions is that brand loyalty influences the consumers' purchase decisions which in turn determine the firm's optimal pricing strategies. The predominant feature of all models is the trade-off between either charging a higher price to the loyal customers or being the cheapest alternative on the market by offering high and frequent discounts. To show how either a variation in the level or the size of brand loyalty may alter the optimal promotional strategy, both aspects will be reviewed separately.

Level of loyalty

The basic set-up of the models are two manufacturers that sell their brands to the consumers. AGRAWAL (1996) extends earlier models (RAJU ET AL. 1990; RAO 1991) by including a monopoly retailer who sells both manufacturers' brands. The retailer seeks to maximize category profits and faces two options: Option one is to sell both brands at the consumers' reference price to the respective loyal segment. Option two is to offer either one of the brands on promotion to target the entire market in the respective period. To do so, the promotional depth needs to exceed the level of loyalty of the respective other brand. As the level of loyalty is higher for the stronger firm, the discounts for the weaker brand need to be higher. As this option is costly for the retailer because of the loss by the price reduction in the loyal segment, it is employed less often. In summary, AGRAWAL (1996) predicts that the stronger (weaker) brand will be promoted more (less) often but less (more) strongly.

*H₁: The level of brand loyalty is **negatively** related to the average price discount.*

*H₂: The level of brand loyalty is **positively** related to the frequency of price promotions.*

AGRAWAL's (1996) finding reverses the results obtained by RAJU ET AL. (1990). In RAJU ET AL. (1990) the manufacturers sell directly to the consumers. In this case, the stronger brand is promoted less often but offers bigger price reductions. The rationale behind this behavior is that the weaker brand uses price promotions for defensive purposes by giving incentives to its loyal customers to stay, while the stronger brand aggressively tries to attract customers that are loyal to the weaker brand.

*H₃: The level of brand loyalty is **positively** related to the average price discount.*

*H₄: The level of brand loyalty is **negatively** related to the frequency of price promotions.*

The major difference between both models lies in the inclusion of a retailer. Thus, empirically testing for the influence of the level of brand loyalty on the design of the pricing strategy may help to derive conclusions of the involvement of retailers in the pricing process.

Segment Size

The impact of the segment size on pricing corresponds to the finding that market shares also affect price promotional strategies. In the theoretical contribution of KOÇAS AND BOHLMAN (2008) brands differ with respect to the size of their loyal segment. The customers are divided into different groups: some customers are loyal towards one of the three brands, the remaining customers are called “switchers” as they always buy the cheapest alternative. The brand’s pricing strategy is driven by the relative share of loyal clients. The higher the share of loyal clients, the less profitable it is to offer promotions. Thus, the share of loyal clients is negatively related to the frequency of price promotions and to the average price discount.

*H₅: The size of the loyal segment is **negatively** related to the frequency of price promotions.*

*H₆: The size of the loyal segment is **negatively** related to the average price discount.*

HOSKEN AND REIFFEN (2004) develop a model in which retailers sell three products each and may choose which product goes on sale. The basis of the model is a Hotelling-type location game in which consumers maximize their expected utility by knowing which items have been advertised and will be on sale. Once consumers enter the store, they may buy more than one item. In this setting, retailers choose to promote popular items that appeal to a wider range of consumers more often because they want to attract consumers into their store.

*H₇: The size of the loyal segment is **positively** related to the frequency of price promotions.*

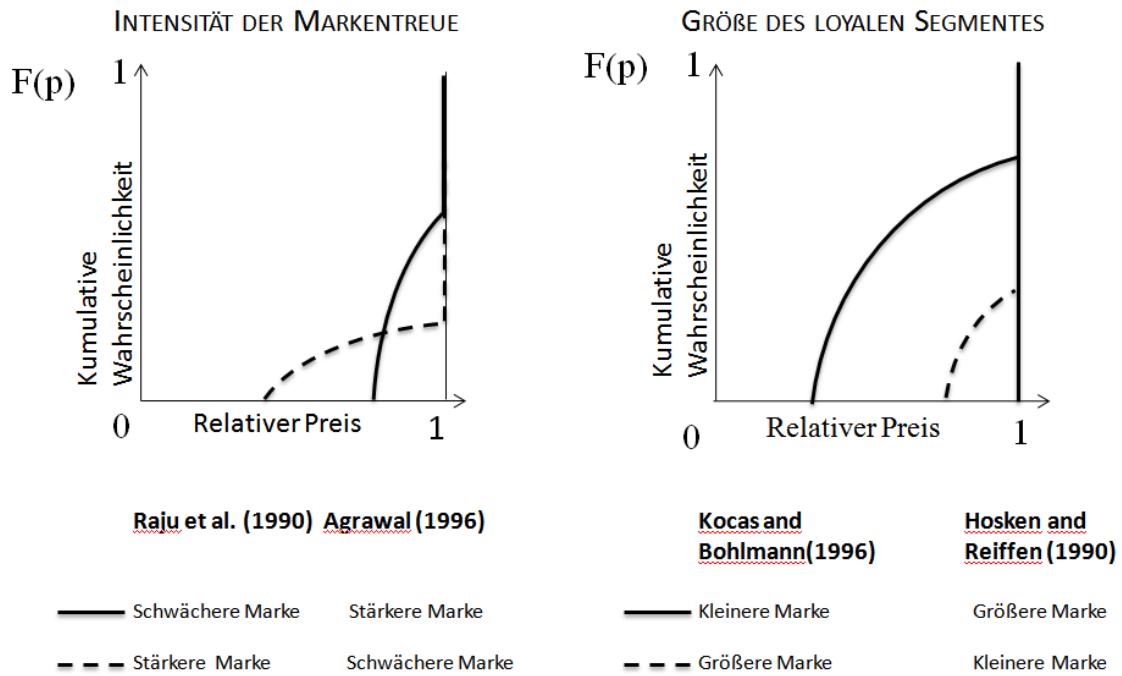
Summary of both effects

2. Brand Loyalty and Price Promotions

Summarizing the predictions of the theoretical models concerning the influence of the segment size and the level of brand loyalty on the retailer's price promotional strategy, we conclude that the theoretical literature remains inconclusive.

A visual summary of the hypotheses regarding the impact of brand loyalty on pricing strategies suggested in the literature is provided in Figure 1. The graph displays the relationship between the depth (the discounted price relative to the regular price) on the x-axis and the frequency of the price promotion (the cumulative probability of price promotions) on the y-axis for a strong or large and a weak or small brand. On the left hand, the relationship is pictured for brands differing with respect to the level of loyalty whereas the hypotheses with regard to the effect of the size of the loyal segment are illustrated on the right side.

In the left panel, the promotional frequency and depth are negatively related to each other: one brand is on sale more often (continuous line) but the average discount is smaller compared to the other brand (dotted line). Following AGRAWAL (1996), the continuous line represents the weaker brand while RAJU ET AL. (1990) conclude that this pricing behavior is optimal for the stronger brand. The right panel indicates that frequency and depth of promotion are positively related to each other: A brand that promotes more often will also provide deeper discounts. According to KOÇAS AND BOHLMANN (2008), the continuous line (dotted) represents the smaller (larger) brand while HOSKEN AND REIFFEN (2004) predict the reverse relationship.

Figure 1: Theoretical cumulative price distributions

Source: Own representation.

2.3 Econometric Model

To test the hypotheses outlined above, we proceed in two stages: First, the two characteristics of brand loyalty, the segment size and the level of loyalty, are identified for all brands. Therefore, we estimate a mixed logit demand model using household purchase information. Second, the estimates from the first stage are inserted into a model of retail pricing to extract the impact of brand loyalty on the design of pricing strategies.

Estimation of Brand Loyalty

In the theoretical models (e.g. AGRAWAL 1996) brand loyalty is defined as the maximum price differential consumers are willing to accept before switching to another brand. Measuring this price differential directly is infeasible as prices do not vary systematically. One solution would be to conduct experiments in a laboratory environment (PESSEMIEU 1959). However, results obtained from experiments are subject to a controversial discussion (LIST AND LEVITT 2005). Thus, the empirical brand loyalty literature turned to employ household panel data. In earlier applications, measures that are dependent upon the budget share were used, e.g. customers that devote more than 50% of the budget towards a brand were labeled as loyal

(RAJ 1982) or the proportion of times each brand was purchased on all preceding purchase occasions served as a measure for loyalty (KRISHNAMURTI AND RAJ 1991). However, these measures ignore potential influences of the marketing efforts. For example, if a brand is heavily advertised, the brand loyalty measures would increase even though consumers only respond to the advertising efforts. Thus, we adopt the approach outlined in AGRAWAL (1996) to estimate the level of brand loyalty. In particular, we estimate a random coefficients model, which is well suited for measuring brand loyalty for three reasons: First, it can be shown that the relative price differentials that are needed to make a consumer switch to another brand and the intercept values in the random coefficient models have perfect rank order correlation (AGRAWAL 1996). Thus, the empirical and theoretical approaches are consistent. Second, marketing mix variables can be incorporated into the model and the distorting effect of advertising efforts can be accounted for. Third, these models also capture the variation in demand for differentiated products and consumer heterogeneity by including random parameters.

In accordance with AGRAWAL (1996), we fit the following mixed logit model:

$$p_{hit} = \frac{\exp(u_{hit})}{\sum_j \exp(u_{hjt})} \quad (1)$$

$$u_{hit} = \sum_{b=1}^n \alpha_{1b} + \alpha_2 * price_{it} + \alpha_3 * promo + \alpha_4 * promo * price + \alpha_5 * prop + \varepsilon_{it} + \epsilon_{hit} \quad (2)$$

where p_{hit} stands for the probability that household h buys brand i at purchase occasion t , similarly the utility of household h of purchasing brand i at purchase occasion t is denoted by u_{hit} . The brand specific effects are captured by $\sum_{b=1}^n \alpha_{1b}$ and the influence of the prices on the household level utility for each decision is estimated by α_2 . The variable *promo* captures all types of advertising; it equals 1 whenever the product was on sale, was somehow featured in the store, e.g. on a special display, or was advertised in store specific communication channels. Thus, the effect of marketing activities on the utility is represented by α_3 . The interaction effect (α_4) between the retail price and promotional activities is represented by *promo*price*. This interaction effect was first employed by CHINTAGUNTA (2002) and is inserted to allow for a potential rotation of the demand curve, in case that the price elasticity is altered during promotional activities. Finally, the household's propensity (*prop*) towards a brand is measured according to GUADAGNI AND LITTLE (1983):

$$prop_{hit} = \theta * prop_{hit-1} + (1 - \theta)(y_{hit-1} - pr_{hi}^I) \quad (3)$$

The propensity is an exponentially weighted average of last purchases. θ represents a smoothing parameter that is generally set equal to 0.75, y_{hbt-1} is a binary variable that equals 1 if the brand was purchased during the last purchase occasion and pr_{hb}^I is the initial probability of a purchase of brand b of household h. Generally, the six initial purchase occasions are used to determine this probability. Consequently, $prop_{hbt}$ represents a exponentially weighted market share for each brand and each household where recent purchases are assigned a higher weight. The more often a household purchased a brand in the past, the closer the $prop_{hbt}$ becomes to 1, the less often a brand is bought by a household, the closer the measure approaches 0.

The parameters α_2 and α_5 are allowed to vary randomly over all households, so that different levels of price sensitivity and propensity are possible. The error term ε_{bt} captures the unobserved variation in household demand and the error term ϵ_{hbt} is assumed to follow an i.i.d. type I extreme value distribution. Consequently, the utility specification in equation 1 corresponds to a multinomial logit model.

The two features of brand loyalty, the level of brand loyalty and the size of the segment, are now determined using the first equation. A household is defined as loyal towards the brand the household shows the highest purchase probability for while the marketing mix variables as well as the propensity towards a brand are held constant. We will reevaluate the brand which a household is loyal to at each purchase occasion. The size of the loyal segment is defined as the number of loyal households, while the level of loyalty calculated by the average purchase probability estimated by equation (1) of the loyal households.

Measuring the influence of Brand Loyalty on Price Promotions

In the second stage, we use the brand loyalty estimates to test whether these parameters are influential in the pricing process. The first set of hypothesis relates to the effect of the degree of loyalty, the second set aims at the influence of the size of the loyal cohort on price promotional strategies. A price promotional strategy, in turn, is also defined by two features: the frequency of price promotions and the depth of price promotions. The frequency f_{br} is defined as the share of weeks that a certain brand is promoted during the observed period. Thus, the dependent variable is bound between 0 and 1, consequently a probit model is more appropriate than an OLS regression. The depth of a price promotion d_{br} is defined as the percentage based reduction of the regular price in the week before the promotion. As in our

data there are several price series that do not contain a promoted price (40 %), the dependent variable is bound at 0, thus, a tobit model with a lower bound at 0 will be estimated.

The retailers' promotional strategy is modeled as a function of the level of loyalty and the segment size and is formalized as follows:

$$f_{br} = \beta_1 + \beta_2 * \text{level } BL_b + \beta_3 * \text{size } BL_b + \sum_{i=1}^3 \beta_{4i} * \text{manufacturer} + \sum_{i=1}^5 \beta_{5i} * \text{retail chain} + \beta_6 * \text{discounter} + \mu_{1br} \quad (4)$$

$$d_{br}^* = \begin{cases} d_{br} & \text{if } d_{br}^* > 0 \\ 0 & \text{if } d_{br}^* \leq 0 \end{cases} \text{ with} \quad (5)$$

$$df_{br} = \gamma_1 + \gamma_2 * \text{level } BL_b + \gamma_3 * \text{size } BL_b + \sum_{i=1}^3 \gamma_{4i} * \text{manufacturer} + \sum_{i=1}^5 \gamma_{5i} * \text{retail chain} + \gamma_6 * \text{discounter} + \mu_{2br} \quad (6)$$

In addition, to the level of loyalty (*level BL_b*) and the size of the loyal segment (*size BL_b*), we control for manufacturer, retail chain and format specific effects. The first set of hypotheses following AGRAWAL (1996) implies that the level of brand loyalty is positively related to the frequency of price promotions ($\beta_2 > 0$) and negatively to the average discount ($\gamma_2 < 0$). The opposite findings match the theory of RAJU ET AL. (1990) ($\beta_2 < 0$ and $\gamma_2 > 0$). The second set of hypotheses predicts that both features of brand loyalty exert a positive influence on the two measures of the retailers' promotional strategy ($\beta_3 > 0, \gamma_3 > 0$).

2.4 Data and Matching Process

The empirical analysis focuses on the ready to eat breakfast cereals market which has been frequently studied in economics and marketing for several reasons. This market is characterized by high concentration ratios and price-cost margins, large advertising to sales ratios and frequent introductions of new products (NEVO 2001). Analyzing a market in which only few major companies compete is particularly suitable in the present context as the theoretical models typically assume an oligopolistic market structure where strategic price interactions need to be considered.

We employ data for the German ready-to-eat breakfast cereals market from two different sources: a consumer as well as a retailer scanner data set. Consumer household scanner data are provided by the ‘Gesellschaft für Konsumforschung’ (GFK) for the years 2000 and 2001 and include 14,000 households. Households scan their food purchases on a daily basis. Using ‘European Article Number’ (EAN) codes, each purchased product can clearly be identified. The panelists further add information about the point and date of purchase as well as whether or not the product was on sale. Among the households, we select only those households that purchased ten or more packages of breakfast cereals within the observation period of two years. In accordance with the literature (ALLENDER AND RICHARDS 2012), we furthermore choose those households that only purchase one brand at a time. If households buy more than one brand at one purchase event, we cannot distinguish between households that are variety seekers and households that consist of several members with diverging preferences. Furthermore, a prerequisite of the mixed logit model is that the choices are mutually exclusive. As a result, we exploit the purchase behavior of 1204 households.

The retail scanner data set is provided by MaDaKom GmbH (Markt-Daten-Kommunikation: Market Data Communication) and covers 104 weeks from January 2000 to December 2001. Individual product prices, volumes, and promotions are reported by EAN identification for 108 retailers located throughout Germany on a weekly basis. Stores are classified by size, number of checkouts, location, and affiliation to a retail chain. Retailers provide additional information on the usage of specific marketing instruments such as special packaging, display, feature, or price promotion of products.

In order to match the household and retail scanner data, we restrict our analysis to brands that are available in both data sets. We were successful in matching 129 identical products. From these we select only products with a market share greater than one percent based on the retail scanner data and with a significant number (at least twenty households) of consumers who bought the respective product over the entire period in the GfK sample. Our selected sample covers 85.84% of the retail scanner data and 36.57 % of the household scanner data. The coverage of the household scanner data is lower because the households report all their purchases but not all the retailers sell their data. This gap is predominantly caused by the two discounters Aldi and Lidl, who neither sell their data nor provide the data for scientific purposes. As Aldi and Lidl generally engage in an everyday low price (EDLP) strategy, the missing data will not impact the research question at hand because the two discounters would

2. Brand Loyalty and Price Promotions

never promote an item by putting it on sale. Instead, Aldi and Lidl would advertise a generally lower price level.⁶

The final sample includes 23 sub-brands belonging to four corporate brands: Kellogg's (14 brands), Nestlé (6 brands), Dr. Oetker (2 brands), and Kölln (1 brand). An overview over all brands and their revenue based market shares is provided in Table 1. On the right hand side, the market shares of the original data sets are displayed. The adjusted market shares within the selected data are reported on the right hand side. Overall, Kellogg's is the market leader in both data sets: In the retail scanner data, Kellogg's covers 65.97 % of the market. The market share in the consumer scanner data set is considerably lower as the two hard discounters that are not part of the dataset do not sell any national brands. However, the relative market shares within the selected brands (right hand side) are almost equal to each other- 76.57 % in the retail and 73.20 % in the consumer scanner data set. The most popular products are Kellogg's Frosties and Kellogg's Smacks with a market share within the adjusted data sets of around 12 %. Nestlé's products with the highest market shares are Nesquick and Cini Minis, each brand reaches a market share of around 4 to 5 % in the adjusted data sets. Dr. Oetker and Kölln have a smaller portfolio of brands, their brands have market shares of around 2 to 3 %. Also the remaining brands' market shares show highly consistent values across both data sets within the selected data, indicating that both data sets represent the German market of breakfast cereals well.

⁶ In addition, Aldi and Lidl are so-called “hard discounters” that are characterized through a limited assortment. Thus, each product variety is only offered once as a private label product and consumers do not have a choice between a potentially weaker/smaller or stronger/larger product (see COLLA 2003).

Table 1: Market Shares in the German Ready to Eat Breakfast Cereals Market

Manufacturer	Brand	Original Data		Selected Data	
		Retail Data	Consumer Data	Retail Data	Consumer Data
Kellogg's	Frosties	10.55 %	5.02 %	12.25 %	13.73 %
Kellogg's	Smacks	10.39 %	4.24 %	12.06 %	11.60 %
Kellogg's	Cornflakes	8.96 %	3.21 %	10.40 %	8.78 %
Kellogg's	Chocos	7.44 %	2.19 %	8.64 %	5.99 %
Kellogg's	Choco Krispies	6.30 %	2.62 %	7.31 %	7.17 %
Kellogg's	Crunchy Nut	4.85 %	2.04 %	5.63 %	5.58 %
Kellogg's	Toppas Classic	4.18 %	1.68 %	4.85 %	4.60 %
Kellogg's	Special K	3.31 %	1.73 %	3.84 %	4.73 %
Kellogg's	Froot Loops	3.19 %	1.47 %	3.70 %	4.02 %
Kellogg's	Smacks Choco	1.93 %	0.72 %	2.24 %	1.97 %
Kellogg's	Honey Loops	1.62 %	0.61 %	1.88 %	1.67 %
Kellogg's	Bran Flakes	1.22 %	0.24 %	1.42 %	0.66 %
Kellogg's	Chombos	1.02 %	0.59 %	1.18 %	1.61 %
Kellogg's	Toppas Traube	1.01 %	0.40 %	1.17 %	1.09 %
Subtotal Kellogg's		65.97 %	26.76 %	76.57 %	73.20 %
Nestlé	Nesquick	3.45 %	1.94 %	4.01 %	5.31 %
Nestlé	Cini Minis	3.42 %	2.00 %	3.97 %	5.47 %
Nestlé	Clusters Mandel	2.47 %	1.19 %	2.87 %	3.26 %
Nestlé	Trio	1.74 %	0.73 %	2.02 %	2.00 %
Nestlé	Aepple Minis	1.24 %	0.36 %	1.44 %	0.98 %
Nestlé	Clusters Banane	1.22 %	0.31 %	1.42 %	0.85 %
Subtotal Néstlé		13.54%	6.53%	15.73%	17.87%
Dr. Oetker	Knusper Schokos	2.37 %	1.25 %	2.75 %	3.42 %
Dr. Oetker	Knusper Honeys	2.24 %	0.88 %	2.60 %	2.41 %
Subtotal Dr. Oetker		4.61 %	5.35 %	2.13 %	5.35 %
Kölln	Haferfleks	2.02%	1.13%	2.35%	3.09%
Included brands		85.84 %	36.57 %	100 %	100 %
Other brands		14.16 %	63.43 %	0 %	0 %

Source: Own calculations based on data from MaDaKom (2001) and GfK (2001).

2.5 Results

Household Model

The results of the household-level demand model (equation 1) are summarized in table 2. To select between a mixed logit model and a random coefficient mixed logit model, we test first whether the results change if the model is estimated on a subset of the choices (HAUSMAN AND MCFADDEN 1984). We find that the assumption of independence of irrelevant alternatives (IIA) does not hold: the point estimates do significantly vary if we repeat the estimation on a subset of the choice options. Furthermore, testing for the joint significance of the random coefficients shows that the standard deviations are jointly different from zero, thus, we choose a random coefficient model over a multinomial logit model. To evaluate the overall goodness of fit, we follow BEN-AKIVA AND LERMAN (1985) and calculate the correct prediction rate; the model correctly forecasts 98.44% of all purchases.

The brand specific intercept terms in table 2 capture the effect of a particular brand on the probability of a household buying the brand. As all other brands combined form the outside option, the intercepts all being statistically significant different from zero and negative, does not reveal that the consumers prefer all other brands, instead, the relative intercepts have to be interpreted. Ceteris paribus, the most preferred brand is Kellogg's Frosties, while Kellogg's Toppas Traube is the least favored brand among the listed brands.

The results of the random coefficients models contain interesting results in addition to the brand loyalty estimates: The price coefficient is significantly negative, meaning that most consumers are price sensitive. However, we find a significant standard deviation of 0.034 showing that only 61.61 % of the consumers exhibit an negative own price elasticity. The remaining share of consumers tends to buy products that are relatively more expensive. Neither the promotion nor the interaction variable influences the households' purchase decision. A stronger effect is achieved by the purchase history. If a household purchased a brand in the recent past, the repurchase likelihood is significantly increased. The variation of this effect across households relative to the point estimate is rather limited.

Table 2: Results of the Random Coefficient Logit Model

Variable	Coefficient	T-Statistic
Price	-0.0101 ***	-6.09
Promotion	-0.0210	-0.09
Interaction Price * Promotion	0.0055	1.07
Propensity	5.7354 ***	136.11
Dr. Oetker		
Knusper Kissen Schoko	-1.5617 ***	-14.18
Knusper Honeyys	-1.2142 ***	-13.75
Kellogg's		
Bran Flakes	-2.1810 ***	-13.44
Choco Krispies	-0.6901 ***	-9.97
Chocos	-0.5429 ***	-8.32
Chombos	-1.7257 ***	-15.12
Cornflakes	-0.2966 ***	-5.51
Crunchy Nut	-0.6512 ***	-9.82
Froot Loop	-0.8983 ***	-11.10
Frosties	-0.2581 ***	-4.98
Honey Loops	-1.5119 ***	-14.35
Smacks	-0.3016 ***	-5.48
Smacks Choco	-1.1490 ***	-12.02
Special K	-1.1579 ***	-13.12
Toppas Classic	-1.2007 ***	-13.01
Toppas Traube	-2.7151 ***	-13.05
Kölln		
Knusprige Haferfleks	-1.0075 ***	-11.95
Nestlé		
Aepple Minis	-1.6315 ***	-13.59
Cini Minis	-0.7717 ***	-10.57
Clusters Banane Nuss	-1.7505 ***	-14.16
Clusters Mandel Nuss	-0.9744 ***	-11.64
Nequick	-0.6742 ***	-9.57
Trio	-1.4556 ***	-13.98
Distribution estimates:		
Price	0.0342 ***	21.32
Propensity	0.2098 *	2.11
N		603888
LR chi2(2)		410.12
LL		-18543.596

Legend: * p<0.05, ** p<0.01, *** p<0.001

Source: Own Estimations.

Table 3 contains the results of the estimation with respect to brand loyalty. In the column "Segment Size" it is indicated how many households are loyal towards the respective brand at

the respective purchase occasion. In total, we observed 25162 purchase occasions. Thus, the largest brand is Kellogg's with a segment size of 1468. As each household has on average carried out 21 purchases, a segment size of 1468 roughly corresponds to 71 loyal households. The results for the segment size are in perfect rank order correlation with the estimated brand specific intercepts in table 2. We measure the level of loyalty as the probability of buying the respective brand among the loyal households. Among the loyal households, the probability of buying Kellogg's Frosties is 65 %. Thus, while Kellogg's has the largest base of loyal households, the level of loyalty is not the highest among all brands. For example, Kellogg's Toppas Classic has a smaller loyal customer base, but the customers who are loyal towards that product show a very high level of loyalty: the purchase probability amounts to 78 %. This result manifests the importance of distinguishing between these two features of brand loyalty.

Retail Price Model

Table 4 entails the descriptive features of the price series that enter the model. The analysis builds upon 1,729 price series from 108 different retailers belonging to five different retail chains (Metro 470 price series, Markant 274 price series, Tengelmann 227 price series, Edeka 449 price series, and Rewe Group 219 price series).⁷ In the present context, we follow Hermann et al. (2005) and define a price promotion as a situation where the following three conditions are fulfilled: (a) the price of a particular product is at least 5 percent below the price during the previous four weeks, (b) the duration of this low-price period does not exceed four weeks, and (c) the price rises again after the promotion. Price promotions are calculated for each EAN code separately for products being sold over the entire period.

⁷ As we only considered price series with less than 20% missing observations, the number of observations is reduced from $108 \times 23 = 2,484$ potential observations to 1,729 observations.

Table 3: Brand loyalty estimates

Manufacturer	Brand	Segment Size	Level of Brand Loyalty
Kellogg's	Frosties	1468	0.65
	Smacks	792	0.60
	Cornflakes	1027	0.75
	Chocos	346	0.57
	Choco	259	0.55
	Krispies		
	Crunchy Nut	546	0.65
	Toppas Classic	145	0.78
	Special K	107	0.71
	Froot Loops	61	0.45
	Smacks Choco	0	0.00
	Honey Loops	39	0.70
	Bran Flakes	12	0.26
	Chombos	83	0.52
	Toppas Traube	0	0.00
Average Kellogg's		348.93	0.51
Nestlé	Nesquick	198	0.50
	Cini Minis	272	0.53
	Clusters	110	0.60
	Mandel		
	Trio	98	0.51
	Aepple Minis	27	0.42
	Clusters	40	0.41
	Banane Nuss		
Average Nestlé		124.17	0.49
Dr. Oetker	Knusper	82	0.55
	Schokos		
	Knusper	139	0.63
	Honeys		
Average Dr. Oetker		110.50	0.59
Kölln	Knusprige	178	0.76
Overall Average		262.13	0.53

Source: Own estimations.

Table 4: Summary Statistics Pricing

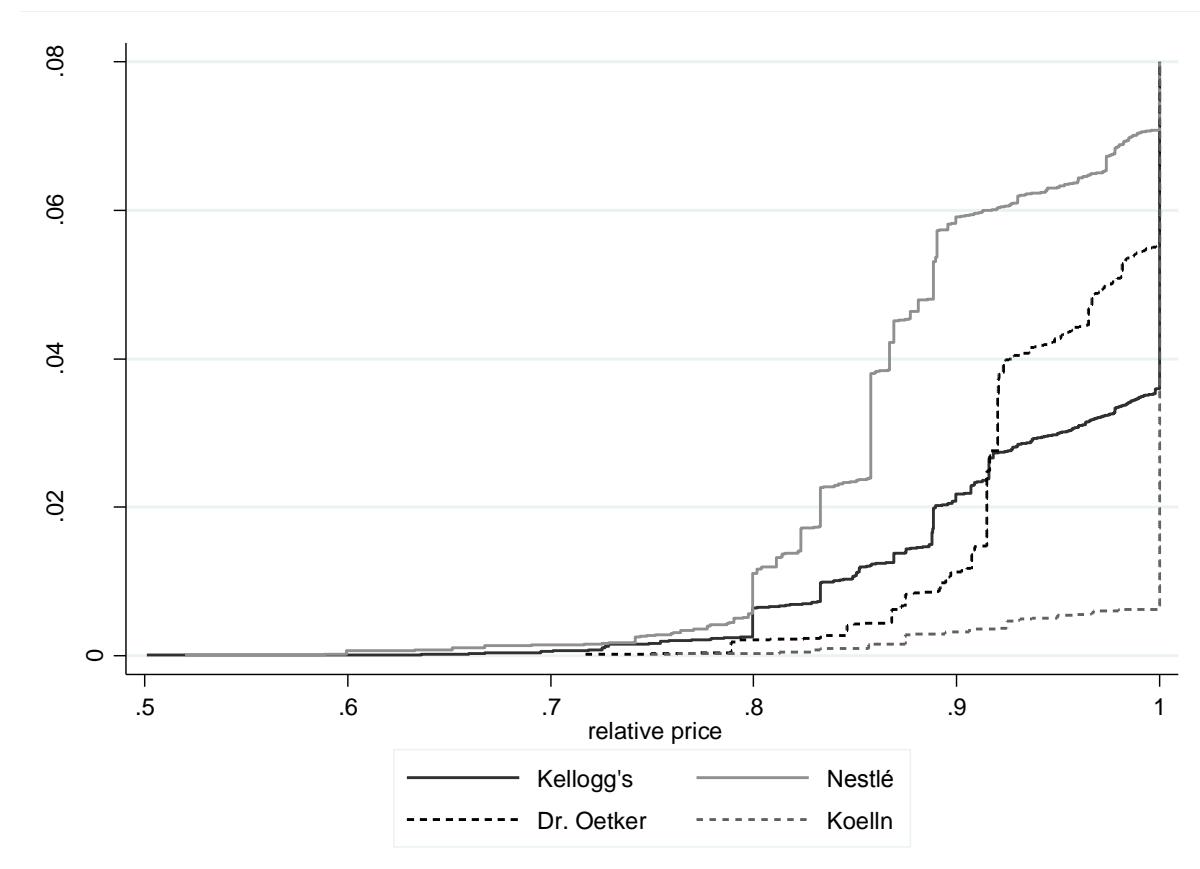
Manufacturer	Brand	Average Price in DM/100gr	Average Promotional Frequency	Average Promotional Depth
Dr. Oetker	Knusper Kissen			
	Schoko	0.81	5.34 %	9.27 %
	Knusper Honey's	0.93	3.73 %	10.34 %
Average Dr. Oetker		0.87	4.53 %	9.81 %
Kellogg's	Bran Flakes	1.15	1.13 %	8.54 %
	Choco Crispies	1.27	2.52 %	14.07 %
	Chocos	1.21	3.16 %	13.75 %
	Chombos	1.09	0.08 %	6.27 %
	Cornflakes	0.93	1.98 %	15.97 %
	Crunchy Nut	1.17	3.02 %	14.78 %
	Froot Loop	1.19	2.56 %	12.41 %
	Frosties	1.14	4.27 %	14.09 %
	Honey Loops	0.82	0.19 %	7.38 %
	Smacks	1.16	4.61 %	13.84 %
	Smacks Choco	1.12	5.29 %	13.33 %
	Special K	1.28	2.06 %	14.06 %
	Toppas Classic	1.25	3.20 %	13.32 %
	Toppas Traube	1.23	2.48 %	11.53 %
Average Kellogg's		1.14	2.61 %	12.38 %
Kölln	Knusprige Haferfleks	0.97	0.54 %	11.75 %
Nestlé	Aepple Minis	1.20	7.96 %	15.81 %
	Cini Minis	1.19	5.55 %	15.07 %
	Clusters Banane Nuss	1.20	7.81 %	15.55 %
	Clusters Mandel Nuss	1.22	7.42 %	15.07 %
	Nequick	1.17	4.60 %	14.97 %
	Trio	1.21	6.80 %	15.67 %
Average Nestlé		1.20	6.69 %	15.36 %
Overall Average		1.08	3.04 %	13.45 %

Source: Own Estimations.

The average price per brand in DM per 100gr ranges from 0.81 DM to 1.27 DM. Two features describe a price promotional strategy: the frequency and the depth of price promotions. The average promotional frequency equals 3.04 percent (i.e. on average one out of 23 brands is on sale) and the average depth of promotions amounts to 13.45 % percent. Nestlé's Aepple Minis show the highest promotional frequency, namely 7.96 %, which means that on average this brand is on sale 16.55 weeks within the observation period of two years. Kellogg's Chombos are far less often on sale, on average only 1.6 weeks over the observational period. If the

brands are on sale, the percentage based discount ranges from 6.27% (Kellogg's Chombos) to 15.81% (Nestlé Aapple Minis).

The empirical relationship between depth and frequency of price promotions aggregated at the manufacturer level is further illustrated in Figure 2. On average, Nestlé products are promoted most often and offered with the highest discounts. Kölln, on the other hand, is rarely promoted and if that is the case, the associated discounts are comparably small. Comparing depth and frequency of Kellogg's and Dr. Oetker, we find that the two sub-brands of Dr. Oetker are put on sale more often but offer smaller discounts: the two curves in Figure 2 intersect. Apart from Dr. Oetker, the cumulative probability functions are parallel to each other, implying a complementary relationship between the depth and frequency of sales. A brand is offered either frequently on sale at high discounts or infrequently at low discounts. Compared to the different cases illustrated in Figure 1 the empirical distribution rather matches the right panel. Note that these averages can be biased by several factors such as retail chain effects. In addition, the evaluation of the brand loyalty has to be connected to the pricing model. Thus, we turn to the estimation of the retail price model.

Figure 2: Empirical cumulative pricing distributions

Source: Own representation.

The parameter estimates of equation (4) and (5) are listed in table 5. We tested for overall significance and can reject the null hypotheses of no influence of the explaining variables for both models (p-value equals 0.00). We did not adopt a seemingly unrelated regression (SUR) approach as the set of explaining variables is identical in both models and thus, a SUR approach yields identical results compared to estimating the regressions separately. Additionally, we carried out a number of specification tests to evaluate the stability of our empirical results. The results reported remain nearly identical when modifying the definition of price promotions. Instead of requiring a price reduction of more than 5 percent for a maximum time span of four weeks, we experimented with 2.5 percent, 7.5 percent, 10 percent, and 15 percent thresholds for time spans of three and five consecutive weeks, respectively. The results are available from the authors upon request. Furthermore, Tobit models are extremely sensitive to heteroskedastic error terms. If heteroskedasticity is present in the data, the estimates will be biased and inconsistent. Thus, we repeated our estimations using Powell's 'Censored Least Absolute Deviations' (CLAD) estimator (KILIC ET AL. 2009),

which is robust to heteroskedasticity. The estimation results are very similar to those reported in Tables 5 and are available upon request.

Table 5: Determinants of the price promotional strategy

	Dependent variable: relative promotional discount (tobit model)		Dependent variable: Promotional frequency (probit model)		
	coefficient	t-value	coefficient	t-value	marginal effects
Level of BL	-0.075 ***	-3.63	-1.002 ***	-4.22	-0.0039
Size of BL	0.00006 ***	7.45	0.00066 ***	6.48	0.0003
Markant	-0.022 *	-2.35	-0.137	-1.35	-0.0535
Metro	0.001	0.13	0.526 ***	5.52	0.1947
Rewe	-0.173 ***	-14.36	-1.435 ***	-12.05	-0.5089
Tengelmann	-0.040 ***	-3.55	-0.672 ***	-5.65	-0.2630
Others	-0.016	-1.15	-0.141	-0.91	-0.0555
Discounter	-0.173 ***	-9.94	-1.322 ***	-7.63	-0.4678
Kellogg's	-0.025 *	-2.08	-0.745 ***	-5.18	-0.2714
Kölln	-0.091 ***	-4.43	-1.275 ***	-5.79	-0.4520
Nestlé	0.039 **	3.08	-0.070	-0.45	-0.0271
constant	0.116 ***	-6.82	1.356 ***	6.77	
Sigma	0.113 ***				
R ²			0.2251		
Chisquared	504.47		528.05		
p-value	0.00		0.00		
N	1729		1729		

Legend: * p<0.05, ** p<0.01, *** p<0.001, Own estimations. Base category is the manufacturer “Dr. Oetker” and the retail chain “Edeka”.

Source: Own estimations.

In both models the two characteristics of brand loyalty exert a statistically significant effect on the respective features of the pricing strategies. To complement the results of table 5, an overview of the results with regard to the hypothesis is provided in table 6. The level of brand loyalty is negatively related to the average price discount: If the loyalty increases by 1 %, the average discount drops by 0.075 %. Thus, we reject H₃ and accept H₁. The influence of the level of BL on the frequency of price promotions points into the same direction: our estimation results show that if the intensity of loyalty increases by 1 %, the brand is 1 % less

often on sale, which means that the number of promotions is cut by one week. Consequently, we reject AGRAWAL'S (1996) hypothesis regarding the effect on the frequency of price promotions (H_2) and do not reject the reverse hypothesis of RAJU ET AL. (1990) (H_4). Altogether, on the basis of the first four hypotheses we cannot draw conclusions with respect to the influence of the retailer because we cannot fully support the set of hypothesis for either one of the models. Instead, our results indicate the frequency and depth of price promotions are complementary to each other. Either a brand is promoted aggressively in terms of a high frequency or deep discounts or fewer and less pronounced price promotions are employed.

With respect to the hypotheses concerning the size effect, we reject the hypotheses stated by KOÇAS AND BOHLMANN (2008) and find empirical evidence for the model of HOSKEN AND REIFFEN (2004). On average, if a brand's segment size increases by one consumer, which equals a market share of 0.06% in the present context, the retailers promote the product c.p. on average half a week more often within two years and the discount decreases by 0.006%. The size effect also supports findings of adjacent research: Van OEST AND FRANSES (2005) find that larger brands promote more often and offer higher discounts. It also corresponds to the models by JING AND WEN (2008) and LAL AND MATUTES (1989, 1994). These authors investigate how differences in the 'popularity' of goods affect their probability of being on sale and argue that 'within groups of products that are close substitutes, more popular products are more likely to go on sales than less popular products' (HOSKEN AND REIFFEN 2004, p. 154).

Table 6: Overview of the results related to the original hypotheses

	Source	Type of BL	Hypothesis	Accepted or rejected
H₁	AGRAWAL (1996)	Level of BL	<i>negative</i> influence on the average price discount	✓
H₂	AGRAWAL (1996)	Level of BL	<i>positive</i> influence on the frequency of promotions	✗
H₃	RAJU ET AL. (1990)	Level of BL	<i>positive</i> influence on the average price discount.	✗
H₄	RAJU ET AL. (1990)	Level of BL	<i>negative</i> influence on the frequency of promotions	✓
H₅	KOÇAS AND BOHLMANN (2008)	Segment Size	<i>negative</i> influence on the average price discount.	✗
H₆	KOÇAS AND BOHLMANN (2008)	Segment Size	<i>negative</i> influence on the frequency of promotions	✗
H₇	HOSKEN AND REIFFEN (2004)	Segment Size	<i>positive</i> influence on the frequency of promotions	✓

Source: Own representation.

The coefficients of the retail chain and manufacturer dummies are also highly significant and consistent. The soft discounters⁸ in general promote less aggressively in terms of frequency and depth of sales which reflects their ‘everyday low price strategy’.

2.6 Conclusion

In this study we merge weekly retail scanner and daily consumer scan data for the German ready-to-eat breakfast cereals market to investigate the impact of brand loyalty on retailers’

⁸ Soft discounters offer, in comparison to hard discounters, a slightly wider assortment, including few national brands in addition to private label products (Colla 2003).

price promotional strategies. The key result of this study is that there is a strong relationship between brand loyalty and price promotional strategy even when we control for corporate brand and retail chain effects. We find strong empirical support for a negative impact of the ‘level of brand loyalty’ on the frequency and depth price promotions: Stronger corporate brands tend to be promoted less frequently by smaller discounts. This result partly supports the predictions of the theoretical model of AGRAWAL (1996). In addition, we also find a positive impact of the ‘size of loyalty’. The ‘size of loyalty’ (as well as the market share) of a particular brand is positively related to the frequency and depth of price reductions. These results would provide evidence for the model by HOSKEN AND REIFFEN (2004).

Although we have been able to explore the relationship between brand loyalty and price promotional strategies empirically on the basis of a unique data set, a few caveats pertain. First, pricing decisions of retailers typically are made in a multi-product environment which implies a complex set of interactions between different products and product categories. These interactions are not fully addressed in the current study due to the obvious dimensionality issue for a large equation system, but are worthy for further investigation. Second, theoretical and empirical studies typically investigate the relationship between brand loyalty and promotional strategies in a static context. Data permitting, it would be interesting to learn more about how price promotions dynamically influence consumer behavior and how changes in the degree of loyalty then feed back to pricing strategies. Analyzing the dynamics of the relationship between brand loyalty and promotional strategies is beyond the scope of the current study and is deferred to further investigations. Additionally, it is often argued that retailers use category managers who decide over the prices within a category independently of other categories (see e.g. ANDERSON AND VILCASSIM 2001).

Another interesting point for further research would be to theoretically analyze the interaction of umbrella brands and its sub-brands. Within the German market of breakfast cereals, Kellogg’s and Nestlé are the dominant players and offer several sub-brands in their assortment. This also applies for other markets, as for e.g. yoghurts (Danone (Aktivia, Fantasia), Müller Milch (Froop, Der Joghurt mit der Ecke)). Consequently, it would be interesting to develop a theoretical model that accounts for a more complex brand architecture and then to test this model in a second step.

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Chapter 3

Spatial and Temporal Retail Pricing in the German Beer Market

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Abstract

German consumers indicate a strong affection to locally produced beer brands. In addition, demand varies significantly throughout the year. Particularly, nationwide distributed brands need to consider consumer loyalty towards local brands (spatial pricing) and the seasonality of demand (temporal pricing) in their pricing strategy. ANDERSON AND KUMAR (2007) and CHEVALIER ET AL. (2003) develop models to derive hypotheses for the optimal spatial and temporal pricing strategies under these circumstances. Contrary to the neoclassical intuition, brands promote more aggressively on their home markets (strong brand loyalty) and in periods of peak demand. Employing retail scanner data for German beer, we find strong evidence for these hypotheses indicating that brand loyalty is a dynamic concept and consumer search is more intensive in periods of high demand.

3.1 Introduction

German consumers show a strong affection for locally produced beer brands. The use of regional specifics of landscape, culture or peoples' attitudes is widespread in marketing German beer (ZÜHLSDORF AND SPILLER 2012). Beer is a top ranked product with respect to consumers' association with regionally produced food categories (DLG 2011). Marketing managers therefore make use of the regional specifics to advertise brands. Web-sites, TV commercials or newspaper ads show well-known and appreciated characteristics of the region of origin to create a unique and favorable brand image. For example, the brand Jever always shows some quiet spots from beaches at the German North Sea, the brand Flensburger uses typical Northern German landscapes and specific human attitudes of people in the region of origin. In addition to the spatial aspect, beer consumption fluctuates seasonally due to holidays, special events (e.g. soccer championships) or hot weather. Beer consumption is up to 75 % higher in the summer (PRIVATE BRAUEREIEN 2011).

Therefore, the main research question of the paper is to what extent German beer brands employ spatially and temporally differentiated retail pricing and promotional strategies. Only a few studies have addressed issues of beer retail pricing. Recent examples are ROJAS (2008), ROJAS AND PETERSEN (2008) and SLADE (2004) who investigate the role of market power and the impact of advertisement on consumption on the US and UK beer market; they find no evidence of collusive behavior. ROJAS AND PETERSEN (2008) find predatory and cooperative effects for advertising. CULBERTSON AND BRADFORD (1991) show that beer prices vary substantially across US-States due to demand, excise taxes, exclusive territories and transportation costs. We add to the existing literature by analyzing spatial and temporal retail pricing and promotional strategies for the top ten beer brands in Germany at the level of individual retailers. The pricing and promotional strategies consist of three features, namely the regular price level, the frequency of promotions and the size of promotional discounts. For these features, we estimate the impact of the (regional) origin of brands, temporal shifters in demand and control for brand specific and retail chain specific variations of pricing strategies. The data under study are weekly retail scanner data for Germany.

We proceed as follows: First, we will describe the German beer market. Second, we develop the theoretical basis for spatially and temporally differentiated retail pricing strategies. In the following, we describe the data and explain the model specification. Fourth, we present the

estimation results for all characteristics of the retail pricing and promotional strategy. Finally, we summarize our findings.

3.2 The German Beer market

COLEN AND SWINNEN (2010) conclude that Germany, along with the US, UK, Czech Republic and Belgium, is one of the major “beer drinking nations” in the world. 53 percent of the total alcohol consumption in Germany comes from drinking beer. With an annual per capita consumption of about 100 liter, beer accounts for almost one seventh of the total per capita beverage consumption.

In a survey carried out in 2004 and 2005 EL CARTEL MEDIA (2005) investigated consumer preferences for beer in Germany. Results show that local brands have a strong position in the market. Every participant knows at least one local brand. For every second respondent the favorite beer is a locally produced brand. For 70 percent of the respondents, the brand is more important for the product choice in beer than the price. Thus, German consumers are highly loyal towards their favorite (regional) brand. The market shares of brands distributed nationwide shows that almost all of the top ten brands are market leaders in their (regional) home market. We define the home market as the region in which the main brewing facility of the brand is located. We define regions by the Federal States of Germany. For example, the brand Radeberger is brewed in Saxony. Table 1 shows the rankings of the regional market shares for the top ten pilsener brands in Germany for the years 2000 and 2001. Most of the brands have the highest market share in their region of origin and in adjoining regions.⁹ The shaded cells indicate the Federal State in which the respective brand is produced (region of origin).

⁹ A similar table that is available upon request emerges for wheat beers.

Table 1: Ranks of regional markets shares of beer brands in Germany 2000-2001

	Becks	Bitburger	Hasseröder	Holsten	Jever	Krombacher	Radeberger	Rothaus	Veltins	Warsteiner
Baden-Würt.	3	6	10	8	4	5	7	1	9	2
Bavaria	2	3	9	6	5	4	7	10	8	1
Berlin	2	8	5	4	7	6	3	10	9	1
Brandenburg	7	8	2	3	6	4	1	10	9	5
Bremen	1	7	9	3	5	4	8	10	6	2
Hamburg	4	6	8	1	3	5	8	8	7	2
Hessen	4	5	9	7	6	1	8	10	3	2
Mecklenburg Vorpommern	7	9	4	1	6	5	2	10	8	3
Lower Saxony	3	7	8	5	4	1	9	10	6	2
Northrhine-We.	5	3	9	7	6	1	8	10	2	4
Rhineland Pfalz	3	1	9	7	4	5	8	10	6	2
Saarland	5	1	7	9	4	3	6	10	8	2
Saxony	7	8	2	3	5	6	1	10	9	4
Saxony-Anhalt	8	9	1	2	6	4	3	10	7	5
Schleswig-Holstein	6	7	9	1	3	4	8	10	5	2
Thuringia	7	8	2	4	6	3	1	10	9	5
Mean Rank	5	6	6	4	5	4	6	9	7	3
Minium Rank	1	1	1	1	3	1	1	1	2	1
Maximum Rank	8	9	10	9	7	6	9	10	9	5
St. Dev.	2,2	2,7	3,2	2,6	1,2	1,6	3,1	2,3	2,2	1,4
Mean Market Share	7.7%	8.1%	5.8%	12.0%	5.0%	7.9%	7.9%	1.7%	3.2%	12.3%
Minium MS	0.4%	0.2%	0.0%	0.1%	0.5%	0.9%	0.0%	0.0%	0.0%	2.9%
Maximum MS	39.2%	47.2%	35.2%	66.7%	12.4%	21.5%	48.3%	26.5%	17.2%	20.7%
St. Dev.	9.5%	14.1%	9.5%	16.5%	3.3%	6.7%	12.6%	6.6%	4.7%	6.2%

Legend: Shaded fields highlight the regional origin of brands.

Source: Own calculations based on MaDaKom 2002.

Consumers can purchase beer in a variety of outlets, for example in specialized beverage shops (SBS), gas stations or in traditional food retail market. Hard discounters (e.g. Aldi, Lidl, Norma), co-operate discounters (e.g. Plus, Netto), small and big supermarkets (e.g. Edeka), and small, regional and national hypermarkets (e.g. Famila, Plaza, Real) belong to the traditional food retail market in Germany. The traditional food retail market outlets account for about 50 percent of the distribution of beer (GEWERKSCHAFT NAHRUNG-GENUSS-GASTSTÄTTEN 2009). The SBS make 35 percent of the market.

The top ten breweries produce 65 percent of the total beer output in Germany of 100 Mio. hl per year. The top ten pilsener brands have a cumulative market share of more than 50 percent.

In the sample period, the top ten brands are Becks, Bitburger, Hasseröder, Holsten, Jever, Krombacher, Radeberger, Rothaus, Veltins und Warsteiner. Though the top ten brands have a significant market share, the German market is fragmented compared to the US or other international markets (SLADE 2004; THE ECONOMIST 2010). In 2000, the top 4 breweries in the US covered 95 percent of the market, in Germany the top 4 make 30 percent of the market (ADAMS 2006). 75 percent of all European breweries are located in Germany. Import volumes are also less significant for the German market than for other European countries.

3.3 Theory

If consumers are loyal towards brands produced in the region, nationwide distributed brands are likely to consider this in their spatial pricing and promotional strategy. Brand loyalty implies that consumers accept price differentials before they switch from the preferred to another competing brand. Not all consumers in the market may be loyal to the regional brand. Some may be non-loyal or switchers who react more sensitive to price changes. Thus, it might be rational even for strong (regional) brands to compete for switchers or non-loyal consumers by putting the brand on sale. For example, the regional brand may increase its market share by underbidding its competitors to gain all switchers' demand. This is not a profit maximizing strategy for all periods; however, a mixed strategy can be rational. Several papers have analyzed the relationship between brand loyalty and promotional sales; the spatial aspect is to our knowledge not addressed in the literature yet. If we assume constant marginal costs of production for the brewers and restrictive transaction costs for consumers, we can solve the spatial pricing problem for each individual market separately and use the following models to obtain the impact of brand loyalty on (spatial) retail pricing.

AGRAWAL (1996), ANDERSON AND KUMAR (2007), JING AND WEN (2008) AND KOCAS AND BOHLMANN (2008) present models under various settings to determine the impact of brand loyalty on the retail pricing strategies of competitors. AGRAWAL (1996) models a retailer that sells a strong and a weak brand.¹⁰ Both brands have loyal customers, but the stronger brand's loyal customers are willing to accept a higher mark-up before switching to an alternative. The retailer faces two options: option one is to sell both brands at the consumers' reference price to the respective loyal segment. Option two is to offer either one of the brands on promotion to target the entire market in that period. Because the level of loyalty is higher for the stronger

¹⁰ The terms weak and strong indicate whether a brand few or many loyal customer or whether the loyalty is high or low.

brand, effective discounts for the weaker brand need to be higher. As this option is costly for the retailer (loss by price reduction in the loyal segment), it is used less often. Thus, regional (strong) brands may promote more often but at smaller discounts compared to other non-regional brands. JING AND WEN (2008) use a different composition of consumer segments and introduce a non-loyal price-sensitive switching segment. They assume loyal consumers only for the stronger (regional) brand and price sensitive consumers (switchers) else (non-regional brands). Depending on the level of brand loyalty and the relative size of respective consumer segments, six different outcomes are possible. With a relative increasing price sensitive consumer segment, brands offer deeper and more frequent promotions. Stronger brands will promote less (more) aggressively when the degree of brand loyalty is high (low) because it is more profitable to exploit the loyal segment instead of attracting price sensitive consumers. KOCAS AND BOHLMANN (2008) introduce three brands and define the power of brands in relative terms. For brands with a larger segment of switchers and a smaller segment of loyal customers it becomes profitable to offer higher discounts. Thus, stronger brands (more loyal customers) promote less often and offer smaller discounts. ANDERSON AND KUMAR (2007) present a dynamic model where brand loyalty is endogenously influenced by price promotions. If a brand is the cheapest in the first period, a fraction of switching consumers turns into loyal customers in the next period. Brands differ in the ability to turn switchers into loyal customers. Firms face the trade-off of either “harvesting” loyal clients by charging (high) regular prices or investing into future loyal customers. The stronger brand is more effective in turning switchers and thereby has a higher incentive to invest in future loyal customers. The strong brand offers more and higher price discounts.

In these models, the same regular price is assumed for all brands and periods. However, firms have some leeway in setting regular prices, which extends the choice set. If we set two discrete levels (high, low) for each characteristic (regular price, breadth and depth of price sales), we obtain six potential strategies. We briefly discuss four strategies. Strategy 1 consists of frequent promotions with high discounts and high regular prices in non-sale periods. This strategy is useful to attract shoppers and/or to generate new loyal customers who repay the costs of promotions in periods of high regular prices. This HiLo-pricing may also be part of a loss leader strategy. Strategy 2 indicates low frequency of price promotions, shallow discounts and low regular prices in non-sale periods. This strategy is close to an EDLP-

strategy and attracts shoppers and price sensitive variety seekers.¹¹ Strategy 3 focuses on exploiting loyal customers by setting high regular prices and a reserved use of promotional activities. Strategy 4 promotes aggressively and sets low regular prices in non-sale periods. This might be interesting for cost leaders or at least temporarily to enforce a higher market share or to drive competitors out of the market.

In a standard model of perfect competition, positive demand shifts lead to higher prices. CHEVALIER ET AL. (2003) discuss three different theories why the retailing business deviates from the standard model. First, consumers are more engaged in shopping during times of high demand. Thus, their demand becomes more elastic as they are more willing to search for low prices. Consequently, retailers are more inclined to lower prices and retail margins fall. If retailers have a higher incentive to deviate from tacit collusion during times of peak demand, then prices may also decrease. Costs of leaving a tacit cartel are equivalent to the sum of lower margins in future periods of which currently higher market shares have to be subtracted. If there is a peak demand, revenues of deviating from tacit collusion increase. Consequently, more retailers might lower their prices. Third, advertising is costly. Thus, retailers cannot advertise all their prices. According to the loss-leader strategy, retailers often promote items which consumers buy frequently, and which they find of particular importance for the store choice.

3.4 Model Specification and Data

The retail pricing strategy consists of three elements, namely the regular price level, the promotional frequency and the average promotional discount (BOLTON ET AL. 2007).

According to the theory, the composition of the consumer segment with regard to loyalty and the seasonal pattern of demand determine whether brands follow one of these strategies. In this paper, we presume that the brands are strong in the region of origin implying a high share of loyal consumers. Even though we do not directly measure the concept of brand loyalty, e.g. by consumer experiments or household scanner data, the market share of brands generally coincides with the level of brand loyalty (FADER AND SCHMITTLEIN 1993). We define the home market as the Federal State in which the brewery operates the main production

¹¹ EDLP: every day low price.

facilities. As shown in Table 1, most brands have the lead rank in the market share on their home market.

To test whether the location of markets and seasonal demand shifts affect the brands' pricing strategies on the German beer market, we separately estimate the following model specification for all three dimensions of pricing strategies (PS: frequency of price promotion, relative size of the discount or level of regular prices).

$$PS_{t,f,c,b,r} = \alpha + \beta Distance^{SP} + \mu Temperature + \sum_{i=1}^7 \gamma_i D_i^{TH} + \sum_{i=1}^2 \delta_i D_i^{FO} + \\ \sum_{i=1}^5 \varepsilon_i D_i^{CH} + \sum_{i=1}^{19} \vartheta_i D_i^{BR} + \varepsilon_{t,f,c,b,r} \quad (1)$$

The dependent variables PS are the average share of sales, the average relative discount or the average regular price level for a particular brand (b) (out of the top ten pilsner and top ten wheat beers) over all stores of the same format (f) and retail chain (c) in the same Federal State (r) in the same week (t). To calculate the dependent variables, we need to identify promotional and regular prices. We follow HOSKEN AND REIFFEN (2001) and define sales as significant temporary price reductions that are unrelated to cost changes. More specifically, a sale indicates a price cut by at least five percent with respect to the regular price. A sale does not last for more than four consecutive weeks. The regular or reference price is defined as the last non-sale price that persisted for at least four consecutive weeks. For generating time series of regular prices, sales' prices are replaced by preceding regular prices respectively.

Following the theoretical considerations, spatial consumer preferences affect spatial pricing strategies. Thus, the main variable is "distance", measuring the distance from the breweries to the federal state the retailers are located in.¹² The average daytime temperature for each federal state is captured in "temperature". To obtain dynamic adjustments in the pricing strategy, we include further dummies (D_i^{TH}). We account for nationwide school holidays, Father's Day, Easter and Pentecost. The Christmas dummy also captures the week before Christmas until New Year's Eve. A dummy "UEFA Euro 2000" captures the effects of the three weeks during the European soccer championship in 2000. An additional time-dependent dummy variables is "Oktoberfest", which equals 1 in the weeks of the Oktoberfest for retailers located in Bavaria. Retail chain (D_i^{CH}), retail format (D_i^F) and brand specific (D_i^{BR}) effects enter the model as well. For example, discounters may follow an EDLP-strategy with

¹² We take average distances between regional states.

fewer promotional sales and lower regular prices. Some retail chains may organize promotional activities nationwide while others pursue decentralized promotional strategies etc.

Essentially, the data at hand is panel data. Thus, panel-estimation techniques might be more appropriate than quasi-fixed effects OLS estimation. However, pretests showed that a fixed effects model should be chosen over a random effects model. But our main variable of interest is constant across the panels. Thus, a fixed effects model will not deliver the result of interest. Consequently, we decided to present the quasi-fixed effects model accompanied with the results of the random effects panel estimations. Here, pretests showed that we need to correct for heteroskedastic and serially correlated error terms, thus we adopt the estimation procedure outlined in BECK AND KATZ (1995). The two step estimator corrects the data first for serial correlation by using the Prais–Winsten regression. The second step is to apply OLS to the transformed dataset, here the standard errors are corrected for cross sectional correlation (CHEN ET AL. 2009).

We employ weekly retail scanner data provided by MaDaKom GmbH (2002) covering a two-year period from 2000 to 2001. The panel consists of about 200 retail stores. We select the top ten ranked beer brands in the sample by calculating the overall average market share for the category pilsener and wheat beers. The top ten pilsener brands are Becks, Bitburger, Hasseröder, Holsten, Jever, Krombacher, Radeberger, Rothaus, Veltins and Warsteiner and the top ten wheat beers are Dinkel, Erdinger, Landskron, Löwenbräu, Maisel, Oettinger, Paulaner, Schneider, Schöfferhofer and Spatenbräu. The data set includes all types of bottles and case sizes of which we use the most popular half-liter bottles. All stores belong to a retail chain, e.g. Metro, Edeka, Rewe, Markant and Tengelmann, and belong to a specific store format, e.g. discounters (DC), supermarkets (SM) and hypermarkets (HM).

Average regular prices range from 0,124 to 0,258 DM per 100 ml. Sales frequencies range from 0 to 5,03 percent. On average, every store puts beer on sale once a year. Average discounts range from 7,57 to 22,58 percent. Rothaus is a notable exemption offering no price promotions. Rothaus is the only beer brand in the sample which is exclusively sold on its home market Baden-Württemberg.

3.5 Results

We separately estimate the basic model specification shown in Equation 1 for all three dimensions of the pricing policy, namely for the average mean price, the share of promotional sales and the average level of discounts.¹³ To consider brand and outlet format specific effects, we estimate a quasi-fixed effect panel model. Because of the properties of the endogenous variables, we apply different estimation techniques. The frequency of sales is bound between 0 and 1; thus, a Probit-quasi-fixed effect model is estimated. The share of promotional sales indicates a lower bound at zero. We, therefore, use a Tobit-quasi-fixed-effect model. The model for the average regular prices indicates heteroscedasticity, which we account for by calculating robust standard errors. In Table 2, we present the results for all models. We will predominantly rely on the results of the quasi-fixed effects models as the Hausman test showed that a random effects model might deliver inconsistent results. However, the results of the random effects model are presented in parentheses.

¹³ Error terms of all three equations might indicate some interaction. Application of a SUR-estimation, however, is not necessary because the same exogenous variables enter the three equations.

Table 2: Estimation results for the brands' pricing characteristics

	Average Regional Price (OLS- Robust)	(Random Effects Model)	Average Discount (Tobit)	(Tobit Random Effects Model)	Average Frequency (Probit)	Average Frequency dF/dx (Probit)	(Probit-Random Effects Model)
Spatial Effects: Base category are home markets							
Distance	0,0054*** (0,0041***)		-0,0055*** (-0,0021***)		-0,0204 *** (-0,0020)	-0,0012** (-0,0020)	
Temporal Effects: Base category are all weeks in which none of these events took place							
Temperature	-0,0002 ** (0,0000*)		-0,0022*** (-0,0002***)		0,0085*** (0,0103***)	0,0005** (0,0128**)	
Father's Day	-0,0027 (-0,0001)		0,0487*** (0,0024*)		0,1875*** (0,1917***)	0,0128** (0,2299***)	
Pentecost	-0,0024 (0,0001)		-0,0384** (0,0017)		0,1613*** (0,0584)	0,0107** (0,0610***)	
Easter	-0,0042 * (-0,0004*)		0,0167 (-0,0004)		0,0582 (0,0282)	0,0035 (0,0370)	
Christmas	0,0015 (-0,0002)		-0,0528*** (-0,0005)		0,2083*** (0,2384***)	0,0143** (0,0193**)	
School	0,0019 ** (0,0004***)		-0,0147** (-0,0022***)		-0,0533** (-0,0010)	-0,0030** (-0,0088**)	
UEFA Euro	-0,0127 ** (-0,0003)		0,0105 (0,0003)		0,0166 (0,0193)	0,0010 (0,0128)	
Okttoberfest	0,0168 ** (0,0006)		0,0097*** (-0,0010)		-0,0421 (-0,0023)	-0,0023 (-0,0088**)	
Retailer Effects: Base category are discounters and retailers without affiliation to a retail chain							
Supermarket	0,0815*** (0,0892***)		0,0881*** (-0,0071***)		0,3089*** (0,3056***)	0,0193** (0,0170**)	
Hypermarke	0,0498*** (0,0590***)		0,0865*** (-0,0066***)		0,1234** (-0,0114***)	-0,0066** (-0,0103**)	
Edeka	0,0103*** (0,0131***)		0,0298** (-0,0114***)		-0,2084*** (-0,0149***)	-0,1567) (-0,1769)	
Markant	-0,0239*** (-0,0167***)		0,0481*** (-0,0114***)		0,1292*** (-0,0149***)	0,0078** (-0,0149**)	
Metro	-0,0557*** (-0,0602***)		-0,0308* (-0,0062***)		-0,3489*** (-0,0149***)	-0,6808*** (-0,6808***)	
Rewe	0,0038*** (0,0148***)		0,0861*** (-0,0149***)		-0,1726*** (-0,0131***)	-0,0088** (-0,0088**)	
Tengelmann	-0,0039** (-0,0026)		0,0367*** (-0,0131***)		-0,0088** (-0,0088**)	-0,2311)	
Brand Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1,2287*** (1,230236***)		-0,5428*** (-0,0098)		-2,0817*** (-2,9181***)	--	
Other							
N	124805	(124805)	125448	(125448)	124763	124763	(124763)
R-squared	0,6641	(0,9285)	(0,0753)		(0,0481)		sigma_u

Legend: * p<0.05, ** p<0.01, *** p<0.001, Results of the Panel specification in

Source: Own calculations based on MaDaKom 2002.

-0,5590

0,7562

0,3638

All specifications show high overall significance. The spatial effects are displayed in the first row of Table 2. Overall, the coefficients for the distance variable are highly significant. The regular price increases and the promotional activity decreases with rising distance from the home market. Thus, beer is on average cheaper and is promoted more intensively on the home market. The coefficient of 0,0054 implies that the regular price for 100 ml beer increases by 0,0054 DM (2,4 %) every 100 km the beer is sold further away from the brewery. The magnitude of the regular price effect appears to be economically important; average regular prices of brands range from 0,124 to 0,258 DM per 100 ml. The estimated decrease in the regular price on distant markets of 0,0054 DM per 100 ml corresponds to a relative change of two to four percent. Considering that percentage return on sales in German retailing is below one percent, price differences of two or four percent can be very relevant to business success. The average discount level in the sample is about 11 percent and the average frequency is about 2.9 percent. The estimators for the distance variable suggest that almost no sales are offered on distant markets and that discount levels on these markets are cut by half in comparison with the home market. These results clearly support the theory by ANDERSON AND KUMAR (2007) who theoretically derive that the stronger brand promote more aggressively using price promotions to generate new loyal customers. As brands are strong on their home market, price promotions are more frequently used. Regular prices are higher on the home market; thus, consumers pay even more in non-sale periods.

Temperature, dummies for national holidays during (Easter, Ascension Day, Christmas and Pentecost) and dummies for special events (UEFA Euro 2000, Oktoberfest) indicate the temporal differentiation of retail pricing strategies. CHEVALIER ET AL. (2003) shows that prices fall during peak demand. The price calculated in the study by CHEVALIER ET AL. (2003) is a weighted average over all brands including sales' and regular prices. We analyze regular and sales' prices separately to disentangle the substitution effects discussed in NEVO AND HATZITASKOS (2006). For example, particular events such as Ascension Day or Pentecost, which effects last for a (few) day(s), may affect the promotional strategy but not the regular price level. Near Ascension Day promotional discounts are 0,05 percent higher on average compared to other weeks. The likelihood of a promotion is also significantly higher for this event. In contrast, longer lasting events such as the soccer championship may rather impact the regular price than the promotional strategy. The majority of coefficients indicate the expected signs, regular prices decrease and promotional activity increases during times of peak demand. Only school holidays deviate from this pattern, regular prices increase and the

promotional activity slows down. One reason might be that school holidays do not indicate a close relationship to the consumption of beer.

One of the most pronounced effect on promotional discounts can be documented in the week before Ascension Day- average discounts are 5.6 percent higher. As the average discount equals 11 percent, this is 50 percent higher than in other weeks. In Germany, Ascension Day is also called “Father’s Day” which is used in particular by young men to hang out outdoors consuming beer and other alcoholic drinks. Ascension Day marks a peak in beer demand. On the contrary, during the European football championship, promotional measures are kept unchanged. However, regular prices are significantly lower in this period. Supermarkets and hypermarkets indicate higher regular prices of about 20 to 35 percent compared to discounters. Price discounts and the frequency of price promotions is also more pronounced for these outlets (HiLo-strategy). There is some evidence for chain specific pricing effects. Warsteiner, the control group, shows the highest regular price level. Oettinger is the cheapest brand in the market following an EDLP-strategy. Maisel offers most sales and the highest discounts.¹⁴

The main results of the quasi-fixed effects model are confirmed by the results of the panel estimation: the higher the distance between the retailer selling the brand and the brewery the beer originates from, the higher the average prices and the lower the average discount. However, the effect on the average frequency of price promotions has the same sign but is statistically insignificant. Also, the temporal and retailer effects hint into identical directions: For Father’s Day the regular price remains unaffected and both features of price promotions increase. During school holidays, the regular price increases while the promotional activities decrease. However, some other effects cannot be confirmed by the panel specifications. As the Hausman test showed, the panel specification may deliver inconsistent results and thus we rely on the quasi fixed effects specification.

3.6 Conclusion

Local beer brands can rely on more and higher brand loyal consumers. The spatial pricing strategy, thus, is to promote more aggressively on the home market and less on distant markets on the one hand. On distant markets, we find very few shallow promotions, and

¹⁴ Substituting brand dummies by category dummies for pilsner and wheat beer significantly reduced the model fit.

higher regular prices. For a non-local brand it is too costly to divert consumers that are loyal to local brands; their potential to generate new loyal customers is small. Breweries mainly drive the brand pricing policy. If the retailer is the main actor in setting prices, loss-leadership could serve as an alternative explanation for the results found. Beer is a fast moving consumer good and consumers are highly involved and well informed when buying beer. This would make beer an ideal candidate to act as a loss leader to attract customers to the store. Retailers use the strong (local) beer brand to attract a large number of customers. Similarly, the theory of CHEVALIER ET AL. (2003) is based on the retailers' response to more informed customers in periods of peak demand.

A managerial implication of these results may be that at least on the German beer market expanding breweries are better off taking over competing (local) brands to conquer distant markets instead of heavily discounting their product nationwide (on the distant markets). For past takeovers on the German beer market, we always find that new owners keep the taken over (local) brand's marketing concept almost as it was before. Thus, brewers leave the market by takeover, but their (local) brands' and marketing concepts do not die with it.

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Appendix

A1. Description of the Variables

Variable	Description	Mean Value	Min	Max
Dependent Variables: PS				
Average Regular Price	Average of prices of the same brand within the same week, federal state, retail chain and retail format	0.2256	0.1000	0.3200
Promotional Frequency	Share of promoted prices of one brand within one week, federal state, retail chain and retail format	0.0296	0.0000	1.0000
Promotional Discount	Average percentage-based price reduction among discounted prices of a brand within one week, federal state, retail chain and retail format	0.1111	0.0500	0.4747
Spatial Variable D_i^{SP}				
Distance	Distance between the retailers location approximated by state and the breweries location in 100 km.	3.3977	0.02	8.91
Temporal Variables D_i^{TH}, D_i^{CH}				
Temperature	Average weekly temperature during daytime for the state the retailer is located in.	10.3556	4.6858	24.5571
Father's Day	1 if the week preceding Father's Day, 0 otherwise	0.0195	0	1
Pentecost	1 if the week preceding Pentecost, 0 otherwise	0.0196	0	1
Easter	1 if the week preceding Easter, 0 otherwise	0.0193	0	1
Christmas	1 if the week preceding and following Christmas, 0 otherwise	0.0368	0	1
School Holidays	1 if for nation-wide school holidays, 0 otherwise	0.2488	0	1
Oktoberfest	1 during the Oktoberfest in Bavaria	0.0050	0	1
UEFA Euro 2000	1 if beer was sold during the European Football Championship in 2000	0.0264	0	1
Retailer Dummies D_i^{FO}				
Discounter	1 if beer was sold in a discounter, 0 otherwise	0.0816	0	1
Supermarket	1 if beer was sold in a retailer < 800 sqm not being a discounter, 0 otherwise	0.3625	0	1
Hypermarket	1 if beer was sold in a retailer > 800 sqm not being a discounter, 0 otherwise	0.5559	0	1
Chain dummies	1 if beer was sold in a retailer not affiliated with a retail chain, 0 otherwise	0.0503	0	1
	1 if beer was sold in Edeka, 0 otherwise	0.2572	0	1
	1 if beer was sold in Markant, 0 otherwise	0.1518	0	1
	1 if beer was sold in Metro, 0 otherwise	0.2863	0	1
	1 if beer was sold in Rewe, 0 otherwise	0.0752	0	1
	1 if beer was sold in Tengelmann, 0 otherwise	0.1790	0	1

A1. Description of Variables (continued)

Brand Dummies D_i^{BR}				
Brand dummies	1 if beer was produced by Becks, 0 otherwise	0.3015	0	1
	1 if beer was produced by Bitburger, 0 otherwise	0.0663	0	1
	1 if beer was produced by Dinkel, 0 otherwise	0.0105	0	1
	1 if beer was produced by Erdinger, 0 otherwise	0.0841	0	1
	1 if beer was produced by Hasseröder, 0 otherwise	0.0382	0	1
	1 if beer was produced by Holsten, 0 otherwise	0.0846	0	1
	1 if beer was produced by Jever, 0 otherwise	0.0529	0	1
	1 if beer was produced by Krombacher, 0 otherwise	0.0645	0	1
	1 if beer was produced by Landskron, 0 otherwise	0.0032	0	1
	1 if beer was produced by Löwenbräu, 0 otherwise	0.0270	0	1
	1 if beer was produced by Maisel, 0 otherwise	0.0103	0	1
	1 if beer was produced by Oettinger, 0 otherwise	0.0231	0	1
	1 if beer was produced by Paulaner , 0 otherwise	0.1096	0	1
	1 if beer was produced by Radeberger, 0 otherwise	0.0614	0	1
	1 if beer was produced by Rothaus, 0 otherwise	0.0054	0	1
	1 if beer was produced by Schneider, 0 otherwise	0.0085	0	1
	1 if beer was produced by Schoefferhofer, 0 otherwise	0.0374	0	1
	1 if beer was produced by Spatenbräu, 0 otherwise	0.0426	0	1
	1 if beer was produced by Veltins, 0 otherwise	0.0469	0	1
	1 if beer was produced by Warsteiner, 0 otherwise	0.1223	0	1

Source: Own calculation based on Madakom 2002.

Chapter 4

How Do Retailers Price Beer During Periods of Peak Demand? Evidence from Game Weeks of the German Bundesliga

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Abstract

The German Bundesliga is one of the most popular sports leagues in the world, ranking only behind the National Football League (NFL) in terms of game attendance. We use game weeks of Bundesliga teams to examine retailer beer pricing behavior in regions hosting games and exploit the regional brand-loyalty of German beer consumers to identify brand level demand shocks. We find retailer price adjustments at the category level in response to increased beer demand during game weeks mask considerably more nuanced pricing behavior at the brand level. Retailers significantly increase beer prices at the category level during Bundesliga game weeks; however, at the brand level retailers raise beer prices for some brands and discount beer prices for others during game weeks, offering significant price discounts for 10 of the top 30 beer brands in Germany but charging significant price premiums for 12 of the top 30 beer brands. By exploiting the regional brand loyalty of German beer consumers, we uncover an empirical regularity in retailer pricing behavior: Within regions hosting Bundesliga games, retailers selectively discount prices on beers preferred by consumers in the home team's region while raising prices on beers preferred by consumers in the visiting team's region. This finding provides evidence of retail price discrimination during periods of increased demand in the German beer market.

4.1 Introduction

A long-standing question in the bodies of literature from economics and marketing is whether retailers respond to positive demand shocks by raising or lowering consumer prices. In the standard model of competitive behavior, firms would uniformly respond to a positive demand shock by raising consumer prices. However, recent empirical evidence suggests that retail prices tend to fall during periods of peak demand (WARNER AND BARSKY 1995; CHEVALIER ET AL. 2003).

To date, much of the empirical evidence on retail price adjustments during peak demand periods has been conducted at the category level, for instance by examining cheese and snack cracker prices during Christmas, and canned seafood prices during Lent. But the use of category-level data can disguise other important forces that contribute to the observed trends in retail prices apart from the underlying demand shock. For example, it is possible that consumers simply substitute from high-priced brands to low-priced brands within a category during weekend and holiday periods of high demand, which can lead to spurious results by reducing category-level price indices, even when retailers do not alter prices for individual brands. Indeed, LEVY ET AL. (2010) provide evidence that supply-side forces increase the menu costs of retail price adjustment during the holidays, thereby making retail prices more rigid at the brand level during the holidays compared with the rest of the year.

In this paper, we empirically examine the pricing behavior of German supermarkets in response to demand shocks at the category level and brand level of the beer market. To identify demand shocks of each type, we exploit several features of the German beer market. First, German consumers have robust demand for beer, ranking only behind the Czech Republic, Austria and Ireland in per capita beer consumption (THE ECONOMIST 2010). Second, German consumers are extremely brand-loyal in their preference for regional beers, which moderates the potential for inter-brand substitution in response to relative price changes among individual brands. Third, Germans love football (soccer). We make use of these features to examine supermarket beer pricing behavior in German Federal States during game and non-game weeks of the German football Bundesliga. This allows us to link beer pricing behavior to brand-level demand shocks through the affiliation between sponsored beers and the fans of their regional football teams.

We frame our empirical work around three levels of market aggregation. We first examine beer demand at the category level, which accords with the approach followed by WARNER AND BARSKY (1995) and CHEVALIER ET AL. (2003), among others. Using this approach, we find support for the outcome that supermarkets increase their promotional activity during periods of peak demand, but we find only limited support for the outcome that supermarkets reduce beer prices (including during promotions). Beer promotions are more likely to be observed around Christmas, Pentecost, Father's Day, during Oktoberfest, during weeks when football games are hosted in the state, and during weeks of the European Championship. However, while retail beer prices indeed decline in our sample during the European Championship, retailers significantly increase beer prices during weeks when games are held within the state and during Oktoberfest.

Second, we examine beer pricing and promotional activity by retailers at the individual brand level among the 30 top-selling beers in Germany. Interestingly, although retailers significantly changed pricing and promotional behavior during game weeks for 22 out of 30 of the top-selling brands, we found the price responses to game weeks to be fairly equally divided between price reductions (10 of 22 cases) and price increases (12 of 22 cases). We link this finding to the performance of the football teams over our sample period, which includes the 1999/2000 and 2000/2001 seasons, and the first half of the 2001/2002 season. We show that retailers are more likely to selectively discount the price of a team's sponsored beer when the team is more successful in terms of league points.

4.2 Background and Theory

There are several theoretical explanations for why retail prices may decrease during periods of peak demand. One explanation put forth by ROTEMBERG AND SOLONER (1986) is that the incentive for retailers to defect from tacit price collusion is greater during periods of peak demand. The greater return to defection leads to more competitive conduct among retailers during high demand periods than during low demand periods, thus resulting in lower prices.

A related explanation is provided by Warner and Barsky in their model of consumer search. In WARNER AND BARSKY (1995), consumer search and travel costs are fixed, while the returns to searching increase in the average price level, so consumers search more intensively during periods of high demand than during periods of low demand due to greater expected returns

from their search. The increase in search intensity by consumers during peak demand periods makes demand more elastic, which provides retailers with an incentive to reduce prices.

A third explanation is based on the loss-leader advertising models of LAL AND MATUTES (1994) and HOSKEN AND REIFFEN (2001). The loss-leader explanation is that retailers place products that are highly demanded by consumers on sale, for instance turkeys at Thanksgiving, because selling a high-demand good at a low price, perhaps even below cost, can raise profits for multi-product retailers when consumers purchase more than one product at a time.

Another explanation that can explain the empirical observation of declining retail prices during periods of positive demand shocks is that a price decline at the category level can be driven by inter-brand substitution by consumers. As NEVO AND HATZITASKOS (2006) argue, consumers may simply purchase cheaper brands from retail product lines more often during periods of high demand than during periods of low demand. High demand periods may attract consumers into the product category who do not ordinarily purchase from the product line, so that a decrease in prices can be observed at the category level even if retailers do not change prices at the brand level. This would be true if periodic shoppers happen to prefer low-priced brands.

A major distinction in the testable hypotheses that arises from these explanations relies on whether or not the increase in demand occurs at the category level or brand level of the retail marketplace. For example, the prediction from search models is that retailers' incentive to promote a product is driven by a category-level shock in demand that raises the return from searching rival retailers, whereas the prediction from loss-leader models is that frequently-purchased products such as fluid milk are likely to be promoted more often than infrequently-purchased products. The implications from these models, which depend on category-level demand shocks, differ starkly from the implications of consumer brand-substitution that can occur within a given category in response to brand-specific demand shocks.

A novel element of our empirical approach is that our study of the German beer market allows us to distinguish between market-level, category-level, and brand-level demand shocks. Specifically, we control for periods of overall high consumer demand at the retail level, for instance during Christmas and holiday weeks, for periods of high beer demand at the category

level such as during Oktoberfest, and for periods of high beer demand at the individual brand level that occur during game weeks.

4.3 Are German Beer Consumers Brand-Loyal?

Brand loyalty in the German beer market is an important element of our identification strategy of brand-specific demand effects. EMPEN ET AL. (2012) examine brand-loyalty in the German beer market and find that consumers exhibit a high degree of brand loyalty in response to price changes among competing brands.

To examine brand-loyalty in the German beer market, we rely on retail prices collected by MaDaKom GmbH from 2000-2001 (MADAKOM 2002). This dataset, which contains scanner data from 125 retail stores in Germany, provides the most comprehensive data available on the German beer market. We group retail stores into 5 retail chains and include price series containing more than 92 out of 104 potential weekly observations. Among the 246 beer brands in our sample, our analysis encompasses 4,691 price series with approximately 470,000 price observations.

We match brand preferences for beer among German football fans by taking the sponsored beer for each football team as a proxy for the team beer. To identify the beer brand(s) associated with each football team, we e-mailed the manager of each football team and acquired information on the team's sponsored beer from 2000-2001. Table 1 contains an overview of all local football teams in Germany, their official beer sponsors in the 2000 and 2001 seasons, along with the federal state of origin (home state).

Table 1: Home States, Football Teams, and Sponsored Beers

Home State	Local Soccer teams	Sponsoring Beers
Baden-Württemberg	VfB Stuttgart	Dinckel
	SC Freiburg	Ganter
	SSV Ulm	Gold Ochsen
Bavaria	FC Bayern München	Erdinger
	TSV 1860 München	Löwenbräu
	1. FC Nürnberg	Kulmbacher
	SpVgg Unterhaching	Löwenbräu
Berlin	Hertha BSC	Berliner Kindl, Schultheiss
Brandenburg	Energie Cottbus	Lübzer; Landskrone
Bremen	Werder Bremen	Becks
Hamburg, Schleswig-Holstein	Hamburger SV	Holsten
	FC St. Pauli	Astra, Holsten
Hesse	Eintracht Frankfurt	Licher, Henninger
Mecklenburg Vorpommern	Hansa Rostock	Lübzer, Rostocker
Lower Saxony	VfL Wolfsburg	Hasseröder
North Rhine Westphalia	1. FC Köln	Küppers
	VfL Bochum	Fiege
	MSV Duisburg	König Pilsner
	FC Schalke 04	Veltins
	Borussia Dortmund	DAB (various)
	Arminia Bielefeld	Krombacher, Herforder
Rhineland-Palatinate	Bor. Mönchengladbach	Tuborg, Diebels
	Bayer Leverkusen	Bitburger, Gaffel
	1. FC Kaiserslautern	Karlsberg

Source: Own representation.

4.4 Empirical Methods

Our sample includes all football matches in the Bundesliga that took place in the 2000-2001 season. Altogether, 18 teams play in the Bundesliga, and each team plays against every other team twice per year-once at home and once away.¹⁵ Our sample thus contains 612 Bundesliga games across 16 states over the 104-week period of study. In addition, teams with winning records in each season advance to playoff games (DFB-Cup), and the top-performing teams

¹⁵ At the end of each season, the three lowest performing teams among the 18 teams are relegated to a lower league. Our observation period spans three seasons, and our analysis includes 24 teams.

advance to international games (Champions League and UEFA Cup).¹⁶ Using historical game schedules, we construct the variable “gameinstate”, which equals one if a football game took place in the respective federal state during that week and is otherwise zero. We also introduce a variable “EM2000” that captures weeks of the 11th UEFA European Football Championship, which was co-hosted by Belgium and the Netherlands from June 10 - July 2, 2000.

We supplement our data with information on weather and holiday dates. We obtain historical weather data from the German Weather Service and use this information to calculate the average temperature for each federal state in each week. Following CHEVALIER, KASHYAP, AND ROSSI (2003), we construct a “hot” weather variable, which equals one if the temperature exceeds 20° Celsius and zero otherwise. Variables for national holidays equal one in the weeks containing a holiday (or the week immediately preceding a holiday in the case of Sunday holidays). In constructing our Christmas variable, we also include the intervening week between Christmas and New Year’s Eve, and interpret this variable as capturing seasonal beer demand over the combined Christmas-New Year’s Eve holiday weeks.

4.5 Empirical Results

To examine the correspondence between regional beer demand and category-level and brand-level demand shocks, we follow NEVO AND HATZITASKOS (2006) in constructing two price indexes. Letting P_{jst} denote the logarithm of the price per 100 ml of product j at retail store s in week t, the price index P_t is the weighted average of all prices:

$$P_t = \sum_j \sum_s w_{jst} P_{jst} \quad . \quad (1)$$

We employ two different weights for P_{jst} . First, we weight beer prices according to the weekly share of revenue for product j at retail store s in week t. We refer to this index, which accords with the measure used by CHEVALIER ET AL. (2003), as the “variable price index”. Second, we weight beer prices by the share of the overall revenue normalized such that the weights add up to one each week. We refer to this index as the “fixed price index”.

¹⁶ We treat German teams playing in international games as if the games were taking place in Germany.

4.5.1 Category-Level Analysis

Table 2 summarizes our category-level results. The first two columns display the results of an OLS-regression of the prices on events that most likely influence beer demand while controlling for retail chain and retail format effects. Notice that our estimated coefficients are robust to the choice of variable price index or fixed price index. The third column presents the results of a Probit model on the likelihood of a retail price promotion.

Table 2: Category-Level Analysis of Retail Prices and Promotions

	p_var	p_fix	promotion	
Christmas	-0,000020	-0,000024	0,123000	***
Easter	-0,000006	-0,000009	-0,018300	
Pentecost	0,000053	0,000054	0,095200	***
Father's Day	0,000070	0,000073	0,127000	***
hot	0,000119 **	0,000121 ***	-0,019100	
em2000	-0,000189 *	-0,000185 **	0,084500 **	
gameinstate	0,000125 ***	0,000130 ***	0,005722 *	
Oktoberfest	0,000465 **	0,000430 ***	0,134000 ***	
Discounter	0,000078 ***	0,000089 *	-0,495000 ***	
chain1	-0,000876 ***	-0,000883 ***	0,157000 ***	
chain2	-0,000882 ***	-0,000877 ***	0,136000 ***	
chain3	-0,001430 ***	-0,001420 ***	0,320000 ***	
chain4	-0,000123 *	-0,000121 **	-0,113000 ***	
chain5	-0,000012	-0,000018	0,408000 ***	
trend	0,000001	0,000001	-0,001030	
trend ²	0,000000	0,000000	0,000009	
Constant	-0,000673 ***	-0,000675 ***	-2,179000 ***	
N	467250	467250	467250	

Note: * p<0.05, ** p<0.01, *** p<0.001

Source: Own representation.

The first four holiday coefficients (Christmas, Easter, Pentecost, and Father's Day) represent market-level demand effects that impact all product categories in the supermarkets. None of these coefficients are significantly different from zero in the first two columns; that is, retailers in our sample do not significantly reduce beer prices during holiday weeks. However, the likelihood of a price promotion significantly increases during Christmas and Father's Day, and decreases in the week before Easter.

The next four coefficients (hot, EM2000, gameinstate, and Oktoberfest) indicate events of anticipated high beer demand at the category level. Each of these coefficients exerts a statistically significant effect on beer prices in the case of both price indices. The coefficients indicate that beer prices rise at supermarkets during hot days, during Oktoberfest, and during game weeks within each state, whereas supermarkets throughout Germany discount beer prices during weeks of the European Championship (EM2000). In terms of promotions, beer is more likely to be put on sale during the European Championship, during in-state game weeks, and during Oktoberfest.

4.5.2 Brand-Level Analysis

Table 3 summarizes the results of our brand-level analysis. The beers listed in the table represent the top 30 selling beers in Germany, and the beers denoted with an asterisk refer to beers that also sponsor a regional football team. Notice that retailers significantly alter prices in response to game weeks for 22 of the 30 top-selling brands. Nevertheless, the “gameinstate” variable exhibits a markedly different effect across individual brands: for 12 of the 30 top-selling brands, retailers respond to game weeks by significantly raising the price of the sponsored brands, whereas retailers respond to game weeks by significantly reducing the price of the sponsored brands for 10 of the 30 top-selling brands.

Table 3: Product-Level Analysis of the Top 30 Beers

	Christmas	Easter	Pentecost	Father's Day	Hot	EM 2000	Gameinstate	Oktoberfest
Becks [†]	-0,000014	-0,000004	-0,000002	0,000019	0,000083	-0,000103	-0,000006	-0,000096
Berliner Kindel [†]	0,000003	0,000018	-0,000019	0,000088	0,000185 *	-0,000252	-0,000142 **	0,000000
Bitburger [†]	-0,000098	0,000043	-0,000111	-0,000129	-0,000098	-0,000147	-0,000287 ***	0,000350
Budweiser	-0,000350	-0,000031	0,000576	0,000460	-0,000369	-0,002680 **	0,001290 ***	0,000000
Clausthaler	-0,000011	0,000000	0,000009	0,000006	-0,000012	-0,000024	0,000002	0,000125 **
DAB [†]	-0,000064	0,000042	-0,000099	-0,000093	-0,000056	-0,000085	-0,000205 ***	0,000984 *
Diebels [†]	-0,000107	0,000080	-0,000184	-0,000183	-0,000099	-0,000176	-0,000446 ***	0,000983
Dinkel	-0,000038	0,000019	0,000029	0,000025	-0,000003	-0,000081	-0,000022	0,000000
Erdinger [†]	-0,000046	0,000013	-0,000045	-0,000044	-0,000097	-0,000060	-0,000163 ***	0,000095
Goldha	-0,000035	0,000007	0,000102	0,000094	0,000007	0,000070	0,000074	0,001590
Hasseröder	-0,000063	-0,000276	0,000473	0,000465	0,000517	-0,000245	0,002120 ***	-0,000844
Henninger [†]	-0,000005	-0,000003	0,000022	0,000019	0,000001	-0,000040	0,000030 **	0,000106 *
Holsten [†]	0,000009	-0,000289	0,000242	0,000258	0,000618 *	-0,000514	0,000820 ***	0,001040
Jever	0,000457	0,000165	0,000432	0,000859	0,002350 ***	-0,001500	0,001690 ***	0,000972 *
Karlsberg [†]	0,000148	-0,000080	0,000173	0,000198	0,000101	-0,000060	0,000562 ***	0,000000
Köstritzer	0,000033	-0,000047	0,000070	0,000064	0,000070	-0,000082	0,000254 ***	0,000036
Krombacher [†]	-0,000012	-0,000093	0,000091	0,000060	-0,000011	-0,000017	0,000194 ***	0,000254
Löwenbräu [†]	-0,000005	0,000017	0,000005	-0,000010	-0,000046	-0,000069	-0,000052 **	0,000027
Oettinger	-0,000059	0,000027	-0,000064	-0,000046	-0,000069	-0,000034	-0,000201 ***	0,000102
Paulaner	-0,000024	0,000006	0,000006	0,000007	-0,000019	-0,000064	-0,000019	0,000053
Radeberger	-0,000104	-0,000228	0,000258	0,000193	-0,000075	-0,000002	0,000994 ***	0,001110
Ratskrone	-0,000028	-0,000072	0,000111	0,000094	0,000009	-0,000151	0,000247 ***	0,000510
Rostocker [†]	-0,000037	-0,000055	0,000003	-0,000061	0,000680	-0,000777	-0,000157	0,000000
Rothaus [†]	-0,000973	-0,000156	0,000918	0,000285	-0,000358	-0,001910	0,000508	0,018900
Schloss	-0,000105	-0,000010	-0,000039	-0,000045	-0,000063	-0,000232 *	-0,000148 ***	-0,000100
Schultheiss [†]	-0,000051	0,000008	0,000007	0,000008	-0,000039	-0,000071	-0,000027	0,000000
Spatenbräu	-0,000676	0,000212	-0,000344	-0,000500	-0,001440 *	-0,000705	-0,001160 **	0,000466
Sternburg	-0,000106	-0,000150	-0,000181	-0,000199	-0,000393	-0,000133	-0,001890 ***	0,000000
Veltins [†]	0,000057	-0,000056	0,000257	0,000260	0,000273	-0,000047	0,000427 ***	0,000144
Warsteiner	-0,000011	-0,000031	0,000071	0,000081	0,000082	-0,000027	0,000138 ***	0,000245

Note: * p<0.05, ** p<0.01, *** p<0.001, †Sponsored beer for one or more regional football teams

Source: Own Representation.

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One factor that may influence the markedly different pricing behavior of retailers with respect to demand shocks for individual beer brands is the win-loss record of the teams. Indeed, the majority of brands that exhibit significant mark-down behavior in retail prices during game weeks are the sponsored brands of successful teams during the observation period.

To assess the correspondence between team success on the field and retailer pricing behavior for the team's beer sponsor, we sum the cumulative points collected by each team during the 1999/2000 and 2000/2001 seasons, and the first half of the 2001/2002 season. Teams in the Bundesliga receive three points for a win, one point for a tie.

Table 4 presents a summary of points for all teams that consistently played in the Bundesliga. The correlation between this indicator of the team's success and the coefficients of the "gameinstate" variable on the brand level (see table 4) amounts to $-0,41$, which is significantly different from zero at the 10% level. Winning teams may have a greater number of fans than teams with losing records, which suggests the demand shift may be larger for these sponsored brands relative to the beers sponsoring less successful teams.

Table 4: Performance of Selected Teams in 2000-2001

Soccer teams	Sponsoring Beers	Team Performance
FC Bayern München	Erdinger	169
Bayer Leverkusen	Bitburger, Gaffel	169
Borussia Dortmund	DAB (various)	153
FC Schalke 04	Veltins	150
Werder Bremen	Becks	133
VfL Wolfsburg	Hasseröder	118
Hamburger SV	Holsten	117
SC Freiburg	Ganter	113
VfB Stuttgart	Dinkel	110

Note: Includes all teams that consistently played in the first Bundesliga, Performance measured in achieved points (3- win, 1- tie) in season 1999/2000, 2000/2001 and the first half of 2001/2002

Source: Own representation.

4.6 Conclusion

This study exploits two features of the German consumer market: German consumers are loyal both to regional football teams and to regional beer brands. Our analysis reveals that the market shares of beer brands vary significantly across the federal states. We find that on average, beer prices do not respond to aggregated demand effects, but do respond to events influencing beer demand at the category level. Retailers set beer prices significantly lower during weeks of the European Championship, which is consistent with the use of beer as a loss-leader by supermarkets. Interestingly, we find that average beer prices rise in Bavaria during the Oktoberfest, although the likelihood of a price promotion is significantly higher during that period than in the remaining weeks of the year.

At the category level, we find that retailers set beer prices significantly higher during game weeks. However, at the level of individual brands, we find significant price increases for some beer brands and significant price decreases for other brands. Using data on the relative performance of teams during the observation period, we show that more successful teams are sponsored by beers that receive selective price discounts by retailers during game weeks.

The implications of this study for future research are threefold. First, future studies of retail pricing should carefully disentangle brand-level demand effects that influence the retailer's pricing decision, because observations at the category-level can mask countervailing effects that may significantly impact retail prices at the brand-level. More research is needed to extend our results from the German beer market to other consumer goods markets.

Second, how beer prices respond to demand shocks has also been empirically analyzed by CHEVALIER ET AL. (2003). Using data from the U.S. market, these authors find that beer prices rise significantly during Christmas and Memorial Day, and decrease during Labor Day, July 4th, and during weeks with above-average temperature. Our findings in the German market suggest that football games in a federal state have more important implications for supermarket beer pricing than holidays. It would be interesting to examine the implication of sporting events such as American football on beer prices in the United States.

Third, sporting events can provide a natural experiment for studying the consequences of regional brand-level demand shocks. Attending sporting events often involves traveling to regions where consumers have different local tastes, and this is particularly true for international events. The use of sporting events to identify brand-level demand shocks is a

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subject that merits further exploration and provides a natural step for further research. EMPEN AND HAMILTON (2012) provide some preliminary analysis of these effects by examining how retailers set prices for home team regional beers and away team regional beers during football games between teams from different federal states.

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Chapter 5

Preissetzung auf dem deutschen Joghurtmarkt: eine hedonische Analyse

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Zusammenfassung

Die Produktkategorie Joghurt gilt als hoch differenziert. In Deutschland sind über 2000 verschiedene Joghurts in mehr als 250 Produktlinien (z.B. „Almighurt“ von Ehrmann) auf dem Markt erhältlich. Während fast alle Hersteller über ein breites Geschmackssortiment verfügen, ist die Produktion speziellerer Varianten, wie z.B. probiotische oder laktosefreie Joghurts auf wenige, internationale Konzerne oder Nischenmolkereien konzentriert. In diesem Beitrag wird analysiert, inwieweit die Preisgestaltung bei Joghurt anhand der Produkteigenschaften erklärt werden kann und welche Produktattribute von den Marktteilnehmern mit besonders hohen Preisaufschlägen bewertet werden. Dazu wird ein hedonisches Preismodell auf der Basis von Einzelhandelsscannerdaten, welche von 2005 bis 2008 in über 500 Geschäften aus ganz Deutschland wöchentlich erhoben wurden, geschätzt. Als Produktcharakteristika werden sowohl Eigenschaften berücksichtigt, die innerhalb einer Produktlinie variieren (Geschmacksrichtungen), als auch solche, die Produktlinien untereinander abgrenzen (Fettstufen, Verpackungsarten, Markenzugehörigkeit, spezielle Eigenschaften). Insgesamt können 74 % der Preisvariation durch diese Produktattribute erklärt werden. Der Trend zu einer gesundheitsbewussteren Ernährung spiegelt sich in den Ergebnissen sehr deutlich wider. Probiotische (laktosefreie) Joghurts sind auf Einzelhandelsebene im Durchschnitt rund 15 % (67 %) teurer als naturbelassene Vollfettvarianten. Magerjoghurts (0,1 – 1,4 % Fett) können gegenüber den fettarmen Joghurts (1,5 – 3,4 % Fett) trotz niedrigerer Rohstoffkosten denselben impliziten Preis erzielen. Zudem spielt die Markenzugehörigkeit in der Preissetzung eine wichtige Rolle. Aus den Ergebnissen werden auch Implikationen für die milchverarbeitende Industrie abgeleitet.

5.1 Einleitung

Der deutsche Joghurtmarkt konnte in den vergangenen 15 Jahren ein starkes Wachstum erzielen. Obwohl der deutsche Lebensmittelmarkt im Allgemeinen als gesättigt gilt, ist der Pro-Kopf-Verzehr von Joghurts in Deutschland von 1995 mit 13,1 kg auf 17,8 kg in 2009 angewachsen (AMI, 2010). Diese Zahlen stehen im starken Kontrast zu den übrigen Produkten der weißen Linie (u.a. Milch, Buttermilch, Desserts, Sahne und Quark), welche einen Rückgang des Pro-Kopf-Verbrauches im selben Zeitraum zu verzeichnen hatten. Gründe für das Wachstum auf dem Joghurtmarkt sind angebotsseitig die vielfältigen Produktdifferenzierungsmöglichkeiten und Innovationen (vgl. GRUNERT UND VALLI 2001, sowie HERRMANN UND SCHRÖCK 2010); nachfrageseitig konnte von dem Gesundheitstrend profitiert werden (TRIVEDI 2011). Joghurts gelten bei den Konsumenten als gesund, deswegen eignet sich diese Warenguppe auch besonders gut als Träger für funktionelle Lebensmittelinhaltstoffe, wie z.B. probiotische Milchsäurekulturen oder prebiotische Pflanzeninhaltstoffe (DUSTMANN 2004). Seit Nestlé 1996 mit LC1 den ersten probiotischen Joghurt auf den deutschen Markt brachte, hat sich diese Produktkategorie längst von einer Nische zu einem Massenmarkt weiterentwickelt. Es wird sogar vermutet, dass der Joghurtmarkt von den derzeitigen Lebensmittelskandalen profitieren wird, da Joghurts als gesundheitsfördernd gelten (WIRTSCHAFTSWOCHE 2011).

Kaum eine Warenguppe bietet eine derartige Produktrvielfalt. In Deutschland konnten die Konsumenten von 2001 bis 2008 zwischen über 2000 unterschiedlichen Joghurts wählen (eigene Analyse, GfK ConsumerScan 2001-2008). Diese Angebotsbreite wird nicht nur durch die zahlreichen Markennamen erreicht, sondern auch durch die vielfältigen Differenzierungsmöglichkeiten. Von Himbeer-Maracuja bis Tiramisu, von Sahnejoghurt bis zu den „Light“ Produkten existiert für fast jeden Konsumentenwunsch das entsprechende Produkt. Die heterogene Preisgestaltung dieser Produktrvielfalt mit Preisen von 0,02 bis 1,03 € pro 100 g soll im Folgenden eingehender betrachtet werden. Welche Produktvarianten können einen höheren Aufpreis erzielen als andere? Zur Beantwortung dieser Frage wird ein hedonisches Preismodell formuliert und geschätzt. Als Datenbasis liegt ein Einzelhandelspanel der SymphonyIRI Group vor, welches die Jahre 2005-2008 umfasst.

Die vorliegende Studie erweitert die bisherige Literatur in verschiedenen Dimensionen. Anhand des aktuellen Datensatzes wird eine detaillierte Charakterisierung der Produktpalette vorgenommen, so dass auch der Einfluss gegenwärtiger Trends auf die Preisgestaltung untersucht werden kann. Die Vermarktung der Joghurts in Produktlinien findet explizit in der Analyse Berücksichtigung. In der hedonischen Preisanalyse werden ökonometrische

Erkenntnisse von verschiedenen Anwendungsbereichen dieser Methodik zusammengeführt.

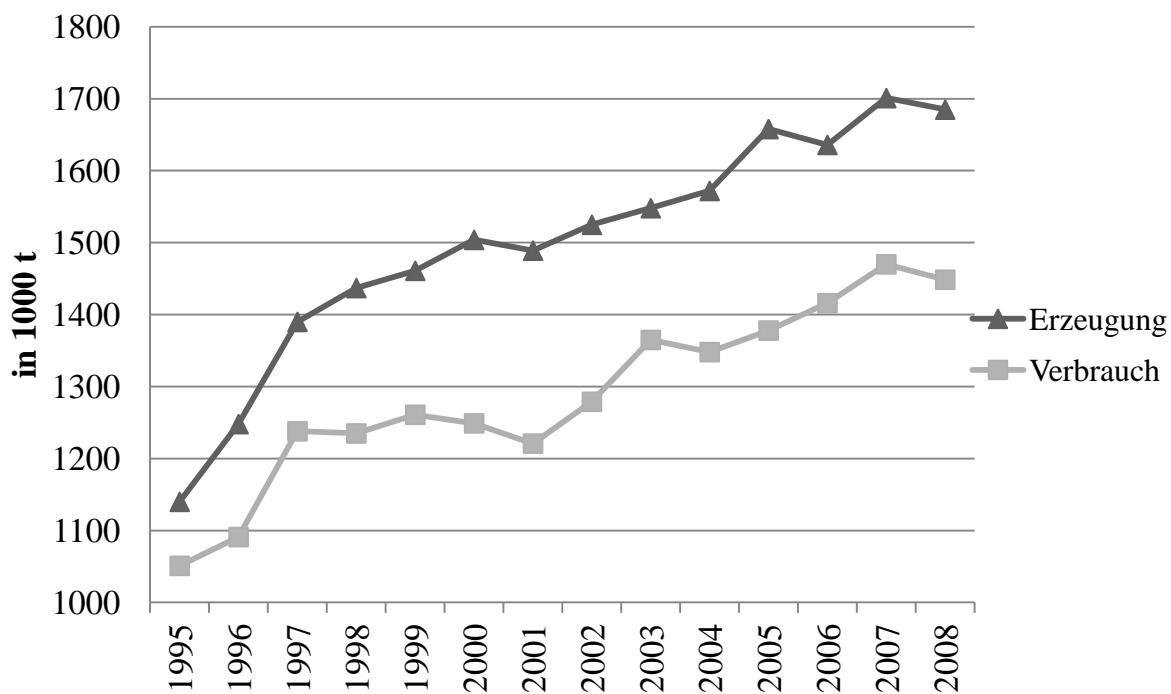
Im folgenden Kapitel wird der deutsche Joghurtmarkt kurz in Zahlen vorgestellt, sowie der bisherige Stand der Forschung aufgezeigt. Im dritten Kapitel wird die Datenbasis eingehender präsentiert und das empirische Modell spezifiziert und geschätzt. Die Ergebnisinterpretation erfolgt im vierten Kapitel. Abgerundet wird dieser Beitrag durch eine Diskussion der Ergebnisse im fünften Kapitel.

5.2 Hintergrund

5.2.1 Der deutsche Joghurtmarkt in Zahlen

Nach der Konsummilch ist Joghurt nicht nur die umsatzstärkste Warenguppe der weißen Linie, sondern hat auch als einzige dieser Kategorie seit Mitte der neunziger Jahre ein beträchtliches Wachstum erfahren. Im Jahr 2008 gingen 6 % der für Frischmilchprodukte benötigten Milch in die Joghurtproduktion, damit stellt diese Warenguppe für die Molkereien eine durchaus sehr relevante Produktkategorie dar. Die in Deutschland von 1995 bis 2008 erzeugte und verbrauchte Joghurtmenge ist in Abbildung 1 grafisch dargestellt. Insgesamt hat sich die Produktionsmenge im Zeitraum von 1995 bis 2008 von 1,1 Mio auf 1,7 Mio t ausgedehnt, gleichzeitig ist auch die nachgefragte Menge um 47 % angestiegen. Ungefähr ein Fünftel der in Deutschland hergestellten Menge wird ins Ausland exportiert, ca. 7 % des Verbrauches werden importiert. Gründe für das rasante Wachstum liegen neben dem Gesundheitstrend und den vielfältigen Produktinnovationen auch in den ausgeprägten Werbemaßnahmen der Branche. Die weiße Linie ist das Segment mit den zweithöchsten Werbeausgaben im deutschen Nahrungsmittelsektor. Im Jahr 2008 wurden 350 Mio. € für Werbung ausgegeben, dies entspricht 19 % der Gesamtausgaben für Nahrungsmittelwerbung (NIELSEN MEDIA RESEARCH 2008, zitiert nach BAUER MEDIA KG 2009).

Abbildung 1: Der deutsche Joghurtmarkt 1995-2008



Quelle: Eigene Darstellung auf Grundlage der ZMP Bilanzen (1999-2008).

Ein Pro-Kopf-Verbrauch von 17,8 kg Joghurt entspricht dem durchschnittlichen Verzehr von etwas mehr als zwei 150 g Bechern pro Woche. Joghurt ist ein regelmäßig konsumiertes Produkt, dementsprechend ist die Preiskenntnis der Konsumenten sehr hoch. Die Verbraucher zeigen für Joghurt sogar eine deutlich höhere Preissensitivität als für Milch, Joghurt ist das Produkt mit der vierthöchsten Preissensitivität in Deutschland (GfK, SAP 2010).

Hauptabsatzkanal für Milchprodukte ist der Discounter. Im Jahr 2008 wurden hier über 50 % des gesamten Umsatzes der Milchprodukte abgesetzt. Unter den Discountern erzielte Aldi mit 21 % und Lidl mit 14 % die höchsten Umsatzanteile (GfK, 2000-2008). Dabei hat jede Einzelhandelskette auch eine eigene Joghurthandelsmarke im Sortiment, mit der über ein Drittel des Joghurtumsatzes generiert wird (siehe Tabelle 1). Damit ist innerhalb der Warengruppe Joghurt der Handelsmarkenanteil deutlich geringer als in der gesamten weißen und gelben Linie (u.a. Butter und Käse). Dies könnte darin begründet sein, dass Joghurt ein deutlich differenzierteres Produkt als Butter oder Milch ist. Bei den Herstellermarken ist Müller Milch mit einem Marktanteil von fast 11 % über den Zeitraum 2001- 2008 der Marktführer. Neben Ehrmann, Campina, Bauer, Danone und Zott mit einem Marktanteil von über 5%, existieren ca. 61 weitere Herstellermarken in Deutschland (eigene Berechnungen, GfK ConsumerScan 2001-2008).

Tabelle 1: Umsatzmäßige Marktanteile auf dem Joghurtmarkt nach Hersteller- und Handelsmarken 2001-2008

Top 6 Anbieter der Herstellermarken	Marktanteil in %	Top 6 Anbieter der Handelsmarken	Marktanteil in %
Müller Milch	10,92	Aldi	17,80
Ehrmann	10,16	Lidl	7,75
Campina	7,52	Rewe	4,33
Bauer	6,70	Tengelmann	2,30
Danone	6,31	Edeka	1,54
Zott	5,14	Metro	0,95
Herstellermarken gesamt		Handelsmarken gesamt	
63,55 %		36,42 %	

Quelle: Eigene Berechnungen anhand GfK ConsumerScan, 2001-2008.

5.2.2 Stand der Forschung

Die besonderen Eigenschaften des Joghurtmarktes (hoher Innovationsgrad, breite Produktpalette, Gesundheitstrend) wurden durch verschiedene Studien bereits näher beleuchtet. HERRMANN und SCHRÖCK (2010) untersuchen die Determinanten des Innovationserfolges auf dem deutschen Joghurtmarkt anhand von 2000-2001 erhobenen Einzelhandelsscannerdaten. Die Erfolgswahrscheinlichkeit einer Innovation wird durch einen niedrigen Fettgehalt sowie einen hohen Distributions- und Innovationsgrad positiv beeinflusst. Fruchtjoghurts kosten 0,14 DM pro 100 g mehr und fettarme Joghurts sind um 0,25 DM pro 100 g günstiger als das Basisprodukt. Die Nachfrage nach Vielfalt auf dem Joghurtmarkt wird von KIM ET AL. (2002) analysiert. Die Joghurts werden nach Hersteller (Danone vs. Yoplait) und in fünf verschiedene, auf den nordamerikanischen Markt relevante Geschmacksrichtungen (Erdbeer, Piña Colada, gemischte Beeren, Blaubeeren und Natur) unterschieden. Auf der Basis von Einzelhandelsscannerdaten wird bestimmt, wie groß der monetäre Nutzenverlust der Konsumenten ist, wenn eine Geschmacksrichtung nicht im Sortiment gelistet ist. Erdbeerjoghurt stiftet den Konsumenten den höchsten Nutzen. BONNANO (2009) schätzt die Nachfrage nach funktionellen Joghurts und Joghurtdrinks auf dem italienischen Markt. Es kann die Hypothese bestätigt werden, dass gesundheitsorientierte Verbraucher eine höhere Wahrscheinlichkeit zeigen, probiotische Joghurts zu erwerben. Des

Weiteren zeigt BONNANO (2009), dass sich funktionelle Joghurtdrinks im Vergleich zu den klassischen festen funktionellen Joghurts, besser auf dem Markt durchsetzen konnten.

Einen Beitrag in Bezug auf die Preisgestaltung leisten DRAGANSKA und JAIN (2005). Sie beobachten, dass Unternehmen Joghurts meist in verschiedenen Produktlinien anbieten. Diese Produktlinien haben gemeinsame Eigenschaften (z.B. Fettgehalt oder probiotische Milchsäurebakterien) und innerhalb eines Geschäftes einen identischen Preis, es variieren jedoch die Geschmacksrichtungen. In der Praxis sind die Produktlinienattribute maßgeblich für die Preisgestaltung, nicht die einzelnen Sorten innerhalb der Linie. Daher wird untersucht, ob es tatsächlich für die Unternehmen optimal ist, je Produktlinie den gleichen Preis zu setzen oder ob zwischen den einzelnen Geschmacksrichtungen diskriminiert werden sollte. Die Autoren finden heraus, dass das beobachtete Preissetzungsverhalten tatsächlich optimal ist.

5.3 Material und Methoden

5.3.1 Die Datenbasis

Der Analyse liegen Einzelhandelsscannerdaten der SymphonyIRI Group für die Produktkategorie Joghurt¹⁷ zu Grunde. In 536 Geschäften¹⁸ wurden auf wöchentlicher Basis von 2005 bis einschließlich 2008 alle Joghurtverkäufe erfasst. Neben den erhobenen Preisen und abverkauften Mengen enthält der Datensatz auch produkt- und geschäftsspezifische Zusatzinformationen. Die Geschäfte werden durch Angaben zu der Größe der Verkaufsfläche, Lage und Geschäftstyp (z.B. Discounter oder Supermarkt) näher charakterisiert. Die Geschäfte lassen sich den jeweiligen Handelsunternehmen zuordnen, der Name der Kette ist jedoch aus Datenschutzgründen maskiert. Auch wurde den Produkten eine neue, maskierte EAN zugewiesen, da es sonst möglich ist, von den gelisteten Handelsmarken auf die Kettenzugehörigkeit eines Geschäftes zu schließen. Stattdessen gibt es eine Produktbeschreibung.

Der gesamte Datensatz enthält 536 Geschäfte, 2132 verschiedene Produkte und 208 Wochen, daraus resultieren 19,6 Mio. einzelne Preisbeobachtungen. Aus diesen werden diejenigen Preisreihen ausgewählt, welche eine 95 prozentige relative Vollständigkeit aufweisen.¹⁹

¹⁷ Joghurt enthaltende Getränke sind von der Analyse ausgeschlossen, diese Produktkategorie gehört zur Warengruppe der Milchmischgetränke.

¹⁸ Da Aldi und Lidl aufgrund ihrer Geschäftspolitik ihre Daten nicht verkaufen, sind sie nicht in dem Datensatz enthalten.

¹⁹ Wurde beispielsweise ein Produkt im betrachteten Zeitraum auf dem Markt eingeführt und im Folgenden regelmäßig dessen Preise erhoben, ist es auch Teil der Analyse.

Dadurch verkleinert sich der Datensatz auf 12,3 Mio. Datenpunkte. Die wöchentlichen Preise eines jeden Produktes werden über die Geschäfte gemittelt; daraus wird jeweils eine Preisreihe erzeugt. Dieses Vorgehen ist bei hedonischen Preisanalysen auf Basis von Einzelhandelsscannerdaten üblich (vgl. CHANG ET AL. 2010). Sonderangebote²⁰ bleiben in dieser Prozedur unberücksichtigt.

Abgesehen von Nischenprodukten und Naturjoghurts werden Joghurts vornehmlich in Produktlinien vertrieben. Deswegen können Produktattribute, die zwischen den Produktlinien (vertikale Produktdifferenzierung) und innerhalb der Linien (horizontale Produktdifferenzierung) variieren, unterschieden werden. Zur vertikalen Produktdifferenzierung tragen der Fettgehalt, die Verpackung, der Markenname und besondere Eigenschaften der gesamten Linie bei. Die horizontale Differenzierung erfolgt über Geschmacksvariationen. Beispielsweise vermarktet Ehrmann über 50 Joghurts unter „Almighurt“ und 5 Joghurts unter „FitVital“. Der Unterschied zwischen den Linien ist der Fettgehalt, innerhalb der Linien wechselt der geschmacksgebende Inhaltsstoff (z.B. Erdbeer oder Schokolade). Beide Arten von Produkteigenschaften sind entweder direkt im Datensatz enthalten oder können aus den Artikelnamen rekonstruiert werden. Da Produktlinien innerhalb eines Geschäftes zu einem identischen Preis angeboten werden, ist diese Unterteilung für Preisanalysen informativ.

In Tabelle 2 sind ausgewählte Kennzahlen sowohl für die gesamte Warengruppe als auch für einzelne Eigenschaften dargestellt. Nach Inflationsbereinigung mit dem Verbraucherpreisindex (2005=100) kosten die Joghurts im Durchschnitt über alle Beobachtungen 23 Cent pro 100 g. Abgesehen von dem Nischenprodukt Honigjoghurt²¹ variiert der Durchschnittspreis erwartungsgemäß stärker über die vertikalen als über die horizontalen Produkteigenschaften.

²⁰ Sonderangebote werden als Preisreduktion von mindestens fünf Prozent gegenüber einen mindestens vier Wochen gültigen Normalpreis definiert.

²¹ Die hedonische Analyse zeigt, dass der hohe Durchschnittspreis nicht auf die Eigenschaft des Honigjoghurts als solches, sondern auf Kombination mit anderen Merkmalen zurückzuführen ist.

Tabelle 2: Deskriptive Statistiken Produktcharakteristika und Preise

Produktattribute (Abk.)	Auftreten des Attributes				Preise des Attributes				Marktanteil ²² des Attributes von 2005-2008	
	Ø Auftreten Attribut	Min	Max	Stbw.	Ø Preis in € /100g	Min	Max	Stbw.		
Horizontale Produktdifferenzierung:										
Geschmacksvarianten:										
Natur	0,15	0	1		0,19	0,07	0,67	0,10	21,54	
Früchte	0,62	0	1		0,24	0,10	0,64	0,09	51,92	
Vanille	0,10	0	1		0,26	0,09	0,66	0,11	10,04	
Schokolade	0,05	0	1		0,27	0,14	0,66	0,12	10,06	
Kaffee	0,01	0	1		0,25	0,15	0,51	0,08	0,64	
Getreide	0,06	0	1		0,25	0,10	0,64	0,12	8,91	
Honig	0,01	0	1		0,43	0,19	1,05	0,30	0,27	
Nuss	0,02	0	1		0,27	0,14	1,05	0,15	1,96	
Vertikale Produktdifferenzierung:										
Besondere Eigenschaften:										
Probiotisch	0,07	0	1		0,26	0,09	0,52	0,11	14,40	
Laktosefrei	0,01	0	1		0,33	0,25	0,40	0,05	0,50	
Biologisch ²³	0,12	0	1		0,28	0,11	0,60	0,07	2,57	
Fettgehalt:										
Magerjoghurt (0,3-1,4 %)	0,16	0	1		0,21	0,08	0,67	0,08	13,61	
Fettarmer Joghurt (1,5- 3,4 %)	0,65	0	1		0,21	0,25	0,60	0,09	66,74	
Vollfettjoghurt (3,5 – 9,9 %)	0,14	0	1		0,30	0,16	1,05	0,13	17,39	
Sahnejoghurt (>10 %)	0,01	0	1		0,37	0,26	0,46	0,06	1,55	
Fettgehalt unbekannt	0,03	0	1		0,30	0,08	0,57	0,12	0,79	
Verpackung:										
Becher	0,84	0	1		0,23	0,03	0,67	0,10	77,25	
Zweikammerbecher	0,04	0	1		0,34	0,20	1,05	0,16	11,37	
Eimer	0,04	0	1		0,19	0,13	0,30	0,02	5,17	
Mehrwegverpackung	0,07	0	1		0,23	0,08	0,36	0,05	6,19	
Verpackungseinheiten	1,22	1	12	0,79						
Markenzugehörigkeit:										
Handelsmarke	0,20	0	1		0,18	0,07	0,44	0,07	12,15	
Ehrmann	0,07	0	1		0,23	0,15	0,48	0,05	10,51	
Campina	0,07	0	1		0,22	0,02	0,33	0,06	9,56	
Bauer	0,07	0	1		0,21	0,09	0,46	0,09	9,73	
Zott	0,04	0	1		0,24	0,13	0,39	0,05	6,81	
Müller Milch	0,04	0	1		0,30	0,20	0,63	0,09	15,26	
Danone	0,03	0	1		0,33	0,18	0,44	0,11	14,35	
Sonstige Herstellermarken	0,46	0	1		0,25	0,08	1,05	0,11	21,63	
Gesamt	2083 EANs				0,23	0,02	1,05	0,09		

Quelle: eigene Berechnungen anhand SymphonyIRIGroup 2005-2008.

Bei den Geschmacksrichtungen, welche die horizontale Produktdifferenzierung bewirken,

²² umsatzmäßig

²³ Produkte, welche die Europäischen Öko Verordnung Nr. 834/2007 erfüllen.

sind abgesehen von der Kategorie „Natur“ Mehrfachkombinationen möglich. Sowohl in Bezug auf die Anzahl der angebotenen Joghurts, als auch umsatzmäßig, dominiert auf dem deutschen Markt eindeutig der Fruchtjoghurt. 62 % der betrachteten Artikel enthalten eine Fruchtkomponente, womit die Hälfte des Umsatzes auf dem deutschen Markt erzielt wird. In diese Kategorie fallen sowohl nicht nur der klassische Erdbeerjoghurt, als auch moderne Kreationen wie der Maracuja- oder Kiwijoghurt. Den höchsten Durchschnittspreis zeigt der Honigjoghurt, welcher aber nur einen kleinen Marktanteil aufweist. Abgesehen von dem Naturjoghurt stellen der Vanille- und Schokoladejoghurt bedeutende Produktvarianten dar. Auch hat sich auf dem Markt der Zusatz von Getreide etabliert. Dabei kann es sich zum einen um sogenannte Knusperjoghurts handeln, welche mit cornflakesartigen Bestandteilen verkauft werden (z.B. „Knusper Banane mit Schokoflakes“ von Müller Milch), zum anderen fallen unter diese Kategorie auch prebiotische Joghurts, welche aufgrund von sekundären Pflanzeninhaltsstoffen die Wirkungsweise probiotischer Joghurts unterstützen (z.B. „Activia Pflaume mit Cerealien“ von Danone).²⁴

Joghurts mit besonderen Eigenschaften sind im Mittel teurer als der Durchschnitt. Bei 7 % der betrachteten Joghurts handelt es sich um probiotische Joghurts, dies entspricht 149 Produkten. Ca. 14 % des in der gesamten Produktkategorie erzielten Umsatzes wurden durch probiotische Joghurts erzielt. Im Vergleich dazu wird eine größere Anzahl an Biojoghurts auf dem deutschen Markt angeboten (255 Produkte). Diese können jedoch nur einen deutlich geringeren Umsatzanteil auf sich vereinen. Bei den laktosefreien Joghurtvarianten handelt es sich mit einem Marktanteil von 0,5 % um einen Nischenmarkt.

In Hinblick auf den Fettgehalt wird die fettarme Variante am häufigsten angeboten. Knapp 65 % aller Joghurts beinhalten 1,4 bis 3,4 % Fett. Mit diesen Produkten wird etwa 67 % des Umsatzes in dieser Warenguppe generiert. Zweitstärkste Kategorie ist der Magerjoghurt mit einem Marktanteil von 14 %. Sahnejoghurts sind durchschnittlich hochpreisiger und decken nur einen kleinen Marktanteil ab.

Die dominierende Verpackungsart ist der einfache Plastikbecher, nur jeweils 4 % der Joghurts werden als Zweikammerbecher oder als 500 g Eimer abgepackt. Mehrwegverpackungen werden für 7 % der Joghurts als Verpackungsmittel verwendet. Zweikammerbecher weisen mit 34 Cent pro 100 g den durchschnittlich höchsten Preis auf.

Handelsmarken sind im Durchschnitt am günstigsten. Während im Datensatz ca. 20 % der Produkte unter einer Handelsmarke vertrieben werden, machen diese nur ca. 12 % des

²⁴ Da bisher prebiotische Joghurts nicht eindeutig deklariert werden, konnte zwischen diesen beiden Varianten nicht unterschieden werden.

Umsatzes aus. Dieser Anteil liegt deutlich unter den in Tabelle 1 dargestellten Werten, da in dem ausgewerteten Einzelhandelsdatensatz Aldi und Lidl nicht vertreten sind. Die breitesten Produktpaletten bieten die Milchverarbeitungskonzerne Ehrmann, Bauer und Campina an. Danone und Müller Milch sind im Mittel die teuersten Hersteller und erreichen die höchsten Umsatzanteile.

5.3.2 Das hedonische Preismodell

Um die Preiseffekte der verschiedenen Produktattribute zu bestimmen, wird ein hedonisches Preismodell geschätzt. Bei dem hedonischen Ansatz werden Güter als Bündel bestimmter Attributen (z.B. Marke, Verpackung, Qualitätsmerkmale) verstanden, so dass ein Gut X innerhalb einer Warengruppe durch einen Vektor seiner Eigenschaften x_j ausgedrückt werden kann (vgl. DILLER, 2008):

$$X = (x_1, \dots, x_j). \quad (1)$$

Der Zusammenhang zwischen den Eigenschaften und den Produktpreisen wird durch die hedonische Preisfunktion modelliert:

$$p(X) = p(x_1, \dots, x_j). \quad (2)$$

Durch die Funktion in Gleichung (2) können hedonische Preise ermittelt werden, die den Wert der einzelnen Produkteigenschaften widerspiegeln. Diese Preise werden auch als implizite Preise bezeichnet, da kein getrennter Markt für die Eigenschaften besteht und sie nur im Bündel erhältlich sind (DILLER 2008). Die theoretische Fundierung der hedonischen Preisanalyse geht maßgeblich auf ROSEN (1974) zurück, welcher wiederum auf die Arbeit von LANCASTER (1966) aufbaut. ROSEN (1974) zeigt, dass bei Übereinstimmung von nachgefragter und angebotener Menge von einem Attribut (Markträumung) die hedonische Preisfunktion determiniert wird. Die impliziten, hedonischen Preise geben somit die marginale Wertschätzung aller Marktteilnehmer für die unterschiedlichen Charakteristika wider. Damit können signifikante, positive Koeffizienten sowohl die Wertschätzung der Konsumenten für diese Eigenschaften, als auch die hohen Kosten der Hersteller für diese Attribute darstellen (NERLOVE 1995).

Hedonische Preismodelle eignen sich für ein breites Anwendungsspektrum. In der Preisindexforschung werden hedonische Analysen genutzt, um Preisindizes von Qualitätsänderungen zu bereinigen (vgl. TRIPPLETT 2004). Aus diesem Anwendungsbereich

stammen verschiedene Weiterentwicklungen bezüglich der Modellspezifikation. So schlägt DIEWERT (2003) vor, die einzelnen Preisbeobachtungen mit den verkauften Mengen zu gewichten, um akkurate und homoskedastischere Preisschätzer zu erhalten. Im Agrar- und Ernährungswirtschaftlichen Bereich findet das hedonische Preismodell erstmals bei WAUGH (1928) Anwendung, um den Einfluss bestimmter Qualitätseigenschaften auf die Spargel-, Tomaten und Gurkenpreise zu bestimmen. Auch in der jüngeren Forschung werden hedonische Analysen durchgeführt, um die Auswirkung von Qualitätseigenschaften auf den Produktpreis von Lebensmitteln zu identifizieren (u.a. WENZEL 2001 sowie ROEBEN UND MÖSER 2010). Ein weiterer Schwerpunkt der Anwendung ist das Weinsegment. Wein eignet sich für die hedonische Analyse, da Wein, wie auch Joghurt, ein sehr differenziertes Produkt ist und objektiv Qualität nur schwer messbar ist (OCZKOWSKI 1994 und STEINER 2004).²⁵ Als weiterer Einsatzbereich ist neben den Lebensmittelpreisen auch der Immobilienmarkt hervorzuheben. Eine wesentliche Annahme des hedonischen Preismodells ist die Markträumung. Deswegen werden hedonische Analysen auch bevorzugt auf Märkten mit unelastischem Angebot wie auf dem Immobilienmarkt oder auf Märkten mit verderblichen Gütern durchgeführt (SHEPPARD 1999).

Unter der Standardannahme, dass die unbeobachteten Eigenschaften nicht mit den beobachteten Attributen korreliert sind, kann das empirische Modell wie folgt formuliert werden:

$$\begin{aligned}
 \ln(Preis_{it}) = & \alpha + \sum_{j=1}^3 \beta_j \text{ spezielle Eigenschaften}_{ij} + \sum_{j=1}^4 \delta_j \text{ Fettstufe}_{ij} \\
 & + \sum_{j=1}^3 \vartheta_j \text{ Verpackungsart}_{ij} + \vartheta_5 \text{ Gesamtmenge}_i + \vartheta_6 \text{ Packungen}_i \\
 & + \sum_{j=1}^7 \omega_j \text{ Marke}_{ij} + \sum_{j=1}^4 \tau_j \text{ Interaktionseffekte}_{ij} \\
 & + \theta \text{ Sonderangebotsfrequenz}_i + \theta \text{ Trendvariable} \\
 & + \sum_{j=1}^7 \gamma_j \text{ Geschmacksrichtungen}_{ij} + \epsilon_{it}
 \end{aligned} \tag{3}$$

Bei der abhängigen Variable $Preis_{it}$ handelt es sich um den inflationsbereinigten Preis eines

²⁵ Eine Darstellung über alle hedonischen Analysen für Lebensmittel ist in BÖCKER ET AL. (2004) aufgearbeitet.

Joghurts i in € pro 100 g Joghurt je Woche t , welcher über alle Geschäfte gemittelt wird. Die zu schätzenden Parameter sind $\alpha, \beta, \gamma, \delta, \vartheta, \omega, \tau$ und θ , der stochastische Fehlerterm ist ε_{it} und die Dummyvariablen sind die in Tabelle 2 dargestellten Produktattribute. Zusätzlich wird eine Trendvariable $t = 1, \dots, 208$ integriert, um mögliche Preissteigerungen der gesamten Kategorie, die z.B. aufgrund gestiegener Milchpreise über die Inflation hinausgehen, zu extrahieren. Als Basis dient ein naturbelassener Vollfettjoghurt ohne spezielle Eigenschaften, welcher in einem Plastikbecher abgepackt wird und weder unter einer Handelsmarke noch von einem der großen Unternehmen Ehrmann, Campina, Bauer, Danone, Zott oder Müller Milch vertrieben wird.²⁶ Die Gefahr der Multikollinearität muss besonders bei der Variablenauswahl für hedonische Preismodellen berücksichtigt werden, deswegen wird der Konditionsindex nach BELSLEY ET AL. (1980) berechnet.²⁷ Die Auswahl der Interaktionseffekte erfolgt nach STEINER (2004). Nur wenn die zusätzlichen Variablen einen ausreichenden ökonomischen Erklärungsgehalt beitragen, werden diese in das Modell aufgenommen. Die relevanten Interaktionseffekte stellen in dieser Studie probiotische Joghurts von Danone oder solche mit Getreidezusätzen, Zweikammerbecher von Müller Milch und Mehrweggläser der Produktlinie „Landliebe“ von Campina dar.

Zur der Auswahl einer geeigneten funktionellen Form schlagen MCCONNELL und STRAND (2000) vor, eine allgemeine Box-Cox Transformation vorzunehmen und anhand von Restriktionstests die geeignete Transformation zu wählen. Aufgrund der Testergebnisse wird hier die semi-logarithmische Form ausgewählt. Ein Vorteil dieser funktionellen Form sind die im Vergleich zu der rein linearen Spezifikation homoskedastischeren Fehlerterme. Nach DIEWERT (2003) eignet sich diese Methode auch besonders gut für Modelle mit mehreren Dummyvariablen. Die Interpretation der Schätzer erfolgt nach der Retransformation des Modells. Der mittlere prozentuale Preisaufschlag für z.B. probiotische Joghurts kann mit $(e^{\beta_1} - 1) * 100$ berechnet werden (HALVORSEN und PALMQUIST 1980). Sollten unberücksichtigte Eigenschaften mit den berücksichtigten korrelieren, kann ein Panelmodell mit festen Effekten, das die unbeobachtete Heterogenität absorbiert, geschätzt werden. Da dieses Modell zu qualitativ einheitlichen Aussagen führt, bleibt die Modellspezifikation in dieser Studie bei der in der Literatur gebräuchlichen, semi-logarithmischen Form. Wie in der Preisindexforschung üblich, werden die Beobachtungen mit den verkauften Mengen gewichtet, um möglichst genaue Schätzer zu erhalten.

²⁶ Unternehmen mit einem umsatzmäßigen Marktanteil von über 5 % sind mit einer Dummyvariablen versehen.

²⁷ Der Konditionsindex wird als Quotient des maximal auftretenden Eigenwertes und den Eigenwerten der einzelnen Schätzer bestimmt. Ein Index über 30 deutet auf Multikollinearität hin.

5.4 Ergebnisse

Die Schätzergebnisse des semi-logarithmischen hedonischen Preismodells sind in Tabelle 3 dargestellt. Mit dem Modell können 74 % der Preisvariation durch die Produktattribute erklärt werden. Alle Koeffizienten leisten auf dem 0,01 % Signifikanzniveau einen statistisch signifikanten Erklärungsbeitrag. Nach dem Test von BELSLEY ET AL. (1980) liegt keine Multikollinearität vor.

Einen ersten Indikator für die Plausibilität der Ergebnisse stellt der Vergleich der Preisaufschläge für horizontale und vertikale Eigenschaften dar. Die Variation der Preisaufschläge fällt innerhalb der vertikalen Produkteingeschaften deutlich stärker (-9 bis +17 Cent pro 100 g) als innerhalb der horizontalen Attributen (+2 bis +5 Cent pro 100 g) aus. Da Produktlinien innerhalb eines Geschäfts zu einem identischen Preis angeboten werden, entspricht dieses Ergebnis den Erwartungen.

Der in BLEIEL (2010) beschriebene Trend zu einem gesünderen Lebensstil lässt sich in den Ergebnissen zum einen an den Preisaufschlägen für probiotische und laktosefreie Joghurts und zum anderen an den impliziten Preisen für die unterschiedlichen Fettstufen ablesen. Der zu probiotischen Joghurts gehörende Koeffizient ist 0,14, dies impliziert einen prozentualen Preisaufschlag von $100 * (e^{0,14} - 1) = 15,03\%$ im Vergleich zu dem Basisjoghurt. Dies entspricht einen Aufpreis von 3 Cent pro 100 g. Auf dem Markt für Probiotika gibt es die Tendenz, diese mit prebiotischen Pflanzeninhaltsstoffen („Synbiotika“) zu kombinieren, da Prebiotika die Wirkung von Probiotika verstärken. Die Preisaufschläge für solche Joghurts sind mit 5 % vergleichsweise niedrig. Diese Produkte sind seit ca. 2006 auf dem Markt und werden bisher nicht explizit als solche beworben. Für laktosefreie Joghurts liegt der Aufpreis sogar bei 67 %. Es wird geschätzt, dass ca. 15- 20 % aller Deutschen unter Laktoseintoleranz leiden. Durch das gestiegerte Gesundheitsbewusstsein lassen immer mehr Konsumenten entsprechende Tests durchführen und richten ihre Ernährung neu aus (LEITZMANN ET AL. 2005). Auch die Fettgehalte beeinflussen die Joghurtpreise signifikant. Von der Kostenseite her betrachtet müsste eigentlich gelten, dass Fettgehalt und Preis positiv korreliert sind, da sich der Rohstoffwert von Milch aus dem Fett und Eiweißgehalt zusammensetzt. So ist Sahnejoghurt auch 62 % teurer und fettarmer Joghurt 25 % günstiger als Vollfettjoghurt. Jedoch unterscheidet sich der implizite Preis von Magerjoghurt nicht signifikant von fettarmen Joghurts, obwohl dieser weniger Fett enthält. Dies könnte darin begründet sein, dass immer mehr gesundheitsbewusste Konsumenten die „Light“ Joghurts vorziehen.

Auch die Marken spielen eine wichtige Rolle in der Preisgestaltung. Handelsmarken sind pro 100 g durchschnittlich 9 Cent günstiger. Unter den explizit berücksichtigten Herstellermarken kosten nur Bauer Joghurts weniger als der Durchschnitt der übrigen Herstellermarken. Ehrmann, Zott und Danone erzielen mit 3 Cent pro 100 g die höchsten Preisaufschläge. Hierbei ist jedoch zu beachten, dass ca. die Hälfte der 64 Danone Joghurts probiotische Milchsäurekulturen enthält und unter der Produktlinie „Activia“ vermarktet wird. Diese Joghurts können mit 73% den höchsten Preisaufschlag auf sich vereinen, der Effekt geht weit über die Kombination der einzelnen Merkmale hinaus und ist das Ergebnis einer intensiven Werbestrategie: „Danone hat über einen sehr langen Zeitraum seine bekannten probiotischen Produkte sehr stark beworben. ... [Danone hat es geschafft], sich über massiven Werbedruck in den vergangenen Jahren deutlich von seinen Mitbewerbern abzusetzen.“ (NIELSEN MEDIA RESEARCH 2011). In 2006 beliefen sich die Bruttowerbeausgaben für Activia auf 22 Mio. €. Das sind 10 Mio. € mehr als Coca Cola im selben Jahr in Werbung investierte.

Bei den verschiedenen Verpackungsarten sticht u.a. der Zweikammerbecher mit einem deutlichen Preisaufschlag gegenüber einem einfachen Becher hervor. Diese Becherart wurde 1974 von Müller Milch erfunden und wird seitdem auch stark beworben („Der Joghurt mit der Ecke“). Dennoch sind Zweikammerbecher von Müller Milch günstiger als andere. Dies könnte darin begründet sein, dass Müller Milch im Vergleich zu anderen Molkereien relativ

Tabelle 3: Ergebnisse semi-logarithmische hedonische Preisanalyse

Produktattribute (Abk.)	Koeffizient	t-Statistik	Impliziter Preis in € pro 100g [†]	Preisaufschlag in % [†]
Konstante	-1,444***	-748,23		
Horizontale Produktdifferenzierung:				
Geschmacksvarianten: Basis Naturjoghurt				
Früchte	0,139***	150,85	0,03	14,91
Vanille	0,201***	124,03	0,05	22,26
Schokolade	0,0782***	50,08	0,02	8,13
Kaffee	0,205***	44,16	0,05	22,75
Getreide	0,0740***	39,51	0,02	7,68
Honig	0,151***	13,72	0,04	16,30
Nuss	0,215***	76,94	0,05	23,99
Vertikale Produktdifferenzierung:				
Besondere Eigenschaften: Basis Joghurt ohne diese Eigenschaften				
Probiotisch	0,140***	46,84	0,03	15,03
Laktosefrei	0,513***	57,51	0,15	67,03
Biologisch	0,477***	162,59	0,14	61,12
Fettgehalt: Basis Vollfettjoghurt (3,5 – 9,9 %)				
Magerjoghurt (0,3-1,4 %)	-0,298***	-190,55	-0,06	-25,77
Fettarmer Joghurt (1,5- 3,4 %)	-0,288***	-211,87	-0,06	-25,02
Sahnejoghurt (>10 %)	0,487***	122,82	0,14	62,74
Fettgehalt unbekannt	-0,102***	-18,12	-0,02	-9,70
Verpackung: Basis Plastikbecher				
Zweikammerbecher	0,320***	94,53	0,09	37,71
Eimer	-0,152***	-44,84	-0,03	-14,10
Mehrwegverpackung	-0,148***	-41,59	-0,03	-13,76
Verpackungseinheiten	-0,0514***	65,38		
Markenzugehörigkeit: Basis sonstige Herstellermarken				
Handelsmarke	-0,491***	356,03	-0,09	-38,80
Ehrmann	0,110***	68,57	0,03	11,63
Campina	0,0637***	32,12	0,01	6,58
Bauer	-0,114***	-66,60	-0,02	-10,77
Zott	0,116***	65,23	0,03	12,30
Müller Milch	0,0421***	18,30	0,01	4,30
Danone	0,115***	30,48	0,03	12,19
Interaktionseffekte:				
Danone-Probiotisch	0,550***	111,33	0,17	73,33
Probiotisch-Getreide	0,0505***	9,85	0,01	5,18
Müller Milch – 2 Kammerbecher	-0,171***	-43,94	-0,04	-15,72
Landliebe-Mehrwegglas	0,102***	20,58	0,02	10,74
Dynamische Aspekte:				
Trend	0,000579***	85,26	0,00001	0,06
Sonderangebotsfrequenz	0,0240***	17,52		

Legende: N= 286 104, R²=0,74, * p < 0,05, ** p < 0,01, *** p < 0,001, † relativ zur Basiskategorie, welchen einen Durchschnittspreis von 0,19 € aufweist, Korrekturen nach HALVORSEN UND PALMQUIST (1980)

Quelle: Eigene Berechnungen.

spät fettreduzierte und probiotische Produktlinien ins Programm aufnahm und nun die klassischen Produkte wie „der Joghurt mit der Ecke“ im betrachteten Zeitraum aggressiver zu vermarkten versuchte (WIRTSCHAFTSWOCHE, 2006). Während Mehrwegverpackungen allgemein mit einem Preisabschlag (-14 %) gegenüber dem Plastikbecher einhergehen, können die Mehrweggläser der „Landliebe“ Joghurts deutliche Preisaufschläge (+10 %) erreichen. Landliebe wird von den Konsumenten als Qualitäts- und Traditionsmarke wahrgenommen.

Sonderangebote werden auf dem Joghurtmarkt regelmäßig genutzt. Im Durchschnitt wird jeder Artikel dreimal pro Jahr um 20 % reduziert, die Sonderangebotsstrategien variieren jedoch erheblich. Je mehr Sonderangebote für einen Joghurt angeboten werden, desto höher ist auch der durchschnittliche Normalpreis. Obwohl der Preis inflationsbereinigt ist, übt auch die Trendvariable einen signifikant positiven Einfluss aus. Es ist denkbar, dass die Milchpreishausse um den Jahreswechsel 2007/2008 auf die Joghurtpreise durchschlug. Da keine Informationen über die Kostenstruktur der einzelnen Unternehmen (z.B. für die Patentierung einer probiotischen Joghurtkultur oder das Entfernen von Lactose) vorliegen, können keine fundierten Rückschlüsse über die jeweiligen Margen der Unternehmen und der einzelnen Marktsegmente gezogen werden.

5.5 Diskussion und Ausblick

Die Resultate zeigen, dass sich die Unternehmen durch Produktdifferenzierung auch mit der Preisgestaltung von der Masse absetzen können. Einzelne Submärkte wie z.B. der für probiotische Joghurts sind hoch konzentriert. Auch kleinere Molkereien sollten in Erwägung ziehen auf den Gesundheitstrend aufzusteigen und probiotische Produktlinien auf den Markt zu bringen. Ein gewisses „Aufpreispotential“ ist möglicherweise bei den synbiotischen Joghurts noch zu realisieren, da die Kombination von Probiotika mit prebiotischen Inhaltsstoffen bisher kaum beworben wird.

Die Ergebnisse bestätigen und erweitern bisherige Studien. In einer schriftlichen Befragung von DUSTMANN (2004) stimmt ein Viertel der Teilnehmer der Frage, ob ein Aufpreis von 15% für funktionelle Produkte gerechtfertigt sei, uneingeschränkt zu. Dies entspricht genau dem in dieser Studie empirisch bestimmten Aufpreis für probiotische Joghurts. HERRMANN und SCHRÖCK (2010) verwenden einen Datensatz von 2000-2001, diese Studie beruht auf einem Datensatz von 2005 – 2008. Im Verhältnis werden in dieser Studie ein kleinerer Preisaufschlag für Fruchtjoghurts und ein kleinerer Preisabschlag für fettarme Varianten identifiziert. Dieser Vergleich verdeutlicht die Verlagerung der Präferenzen der Konsumenten

über die vergangenen Jahre. „Light“ Joghurts sind zunehmend gefragter und neben dem klassischen Fruchtjoghurt liegen auch ausgefallenere Joghurts mit Getreide, Honig oder Nüssen im Trend. Auch KIM ET AL. (2002) fanden noch, dass Erdbeerjoghurts den Konsumenten den größten Nutzen stiften. Diese Studie zeigt, dass inzwischen eine höhere Anzahl unterschiedlicher Produktcharakteristika berücksichtigt werden sollte.

Bisher wurden alle dokumentierten Preise eines Produktes über alle Einzelhandelsketten und Geschäftstypen (z.B. Discounter vs. Verbrauchermärkte) gemittelt. In einem nächsten Schritt soll getestet werden, ob Ketten- oder Formatabhängige Effekte vorliegen. In dieser Hinsicht sind zwei verschiedene Einflüsse denkbar: Erstens könnte der implizite Preis eines einzelnen Produktattributes von der verkaufenden Einzelhandelskette oder von dem Geschäftstyp abhängig sein. Zweitens könnten Konsumenten die Listung eines Joghurts in den verschiedenen Geschäftstypen auch als Produkteigenschaft wahrnehmen. So ist es geplant, das Set der betrachteten Produktattribute um den Distributionsgrad zu erweitern.

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Chapter 6

Product Differentiation and Cost Pass-Through: a Spatial Error Correction Approach

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Abstract

In the saturated food market of developed countries, most food categories are highly differentiated. In this article, we theoretically and empirically assess the influence of product differentiation cost pass-through for the German yoghurt market. Adopting a spatialized stock flow model, it is shown that theoretically prices depend on prices of differentiated products and lagged prices. Using weekly retail scanner data from 2008 to 2010 covering 536 retailers and estimating a spatial panel error correction model (SPECM), we also find empirical evidence that prices are vertically and horizontally connected. Our results indicate that the vertical cost pass-through from the price of raw milk to the consumer price of yoghurt is comparably high (41.6% per week) as well as spatial spillovers in error correction (20.1% per week). If similar products are priced above the long-run equilibrium, there exists a tendency to follow those prices and adjust prices upwards. Thus, according to BEENSTOCK and FELSENSTEIN (2010) we find global and spatial error correction processes within the German yoghurt market.

6.1 Introduction

Theoretically, the degree of product differentiation has been linked to the magnitude of industry-wide cost shock pass-through rates (FROEB ET AL. 2005; ZIMMERMAN and CARLSON 2010). Empirical evidence, however, is scarce. KIM and COTTERILL (2008) estimate the cost pass-through for a differentiated product, processed cheese, adopting a structural model. The degree of differentiation within the market plays only a minor role; the product attributes are employed to set up a demand model. Another exemption is RICHARDS ET AL. (2012), who study pass-through rates of a differentiated product (milk) in comparison with an undifferentiated product category (potatoes). They find that pass-through rates tend to be lower for milk. Besides the level of product differentiation, this difference in pass-through rates can be attributed to several other factors such as market power or loss-leader pricing strategies. To extract the influence of product differentiation on pass-through rates, this study goes one step further. Instead of determining the degree of differentiation for a category as a whole, we determine the degree of differentiation within a category in a multidimensional attribute space and use this information to estimate a spatial panel error correction model (SPECM) for the German yoghurt market. The “spatial” aspect in the model will be the degree of product differentiation, thus we can directly determine the influence on product similarity on pass-through rates. By estimating a SPECM we can simultaneously determine how retail yoghurt prices adjust to cost shocks of the price of raw milk (vertical pass-through) and to price changes of close substitutes (horizontal pass-through). Typically, studies focus on horizontal (LISTORTI AND ESPOSTI 2012) or vertical (BESANKO ET AL. 2005) price adjustment only. As there is evidence for both forms of pass-through, the study provides valuable insight into how these different price dynamics influence each other.

As a theoretical basis for the empirical application of this paper, we adopt a spatialized stock flow model to the yoghurt market. The basic idea is that in each period yoghurts are produced, some yoghurts are still existing from the previous period and some yoghurts leave the stock as they are either consumed or discarded. Using this framework, we can show that yoghurt prices depend on prices of similar yoghurt types and lagged prices of all yoghurts.

From a methodological standpoint, this article is the first application of a SPECM to a product differentiation setting. Standard error correction models quantify the dynamic relationship between two non-stationary variables that are related in the long run (ENGLE AND GRANGER 1987). The standard method has been extended to panel applications. The major advantage is that by accounting for the cross-sectional as well as for the time dimension, the estimation

power increases significantly (PERSYN AND WESTERLUND 2008). In this paper, we apply a “spatialized” version of a panel error correction model which was first proposed by BEENSTOCK AND FELSENSTEIN (2010). In the original application, the authors find that housing prices in Israel are locally and spatially integrated and show evidence for spatial error correction in the short run. We translate this model into a setting of product attribution. The key advantage of a SPECM is that it allows for simultaneously determining the adjustment process of prices to the costs of a common input factor and the influence of price changes of close substitutes. We choose a reduced form instead of a structural approach because it allows for identifying a pass-through rate without imposing specific assumptions of the functional form of the consumer demand and the conduct of the category-pricing manager (BESANKO ET AL 2005).

Recently, in the literature of retail pricing product differentiation received more attention. Due to increasingly saturated food markets, that are typical for developed countries, product differentiation is a promising strategy to stimulate the consumers’ demand (WIRTHGEN 2005). RICHARDS ET AL. (2013) find that manufacturers have an incentive to create similar products because those products show wider price-cost margins. BONANNO (2012) estimates a linear AIDS model for the Italian yoghurt market, in which a multidimensional measure of product differentiation is explicitly integrated. Contrary to RICHARDS ET AL. (2013), this study highlights the importance of product differentiation as a tool to increase profits. A unique feature of both studies is to integrate a multidimensional measure of product differentiation, based on PINSKE and SLADE (2004), into two different empirical demand models. We follow along those lines and incorporate a multidimensional measure of the product attribute space into a SPECM.

In this paper, we chose to analyze the yoghurt category because it is highly differentiated and thus often chosen in a product differentiation context (BONANNO 2012; DRAGANSKA and JAIN 2006; EMPEN 2011; RICHARDS ET AL. 2013). Yoghurts are generally sold in product lines that cover yoghurts of several flavors and are uniformly priced. Product lines are differentiated by quality attributes such as fat content, additional ingredients and dairy. Our dataset stems from the SymphonyIRI Group GmbH (SIG: SymphonyIRI Group 2011) and consists of weekly observations of yoghurt sales and prices collected weekly in over 500 retailers located throughout Germany. We analyze the pricing behavior of all product lines exceeding a market share of 0.3%, thus, our data spans over 19 lines produced by eight dairies complemented by three private label lines. Hence, we consider 22 different product lines.

We find that industry wide cost shocks are passed through by 41.6%. This measure is significantly influenced by accounting for product differentiation: Without incorporating the distance matrix, the long-run adjustment drops significantly. The reason is that the disturbances from the long-run equilibrium of the “neighbor” yoghurts positively influence the prices’ differences, e.g. if a yoghurt is priced above the long-run equilibrium close substitutes show the tendency to follow and also adjust prices upwards. If that effect is left unaccounted for, the vertical pass-through rate will be underestimated.

The paper contributes to the literature in several ways: Methodologically, we develop a new framework in which horizontal and vertical pass-through can be estimated simultaneously. Furthermore, we provide evidence for the impact of the extent of product differentiation on pass-through rates. From a managerial perspective, the results show that product differentiation can be a useful tool to set a product apart from competition: the further differentiated a product is, the less integrated its prices will be with the overall market.

The remainder of the article is organized as follows. In the next section, we provide a brief theoretical model that links product differentiation to pass-through. In chapter three, we present the obligatory pretests as well as our SPECM and the definition of space in the present context. Then, we show our data complemented by a short descriptive overview of the German yoghurt market. In chapter five, we present and interpret the estimation results. Finally, we conclude with the implications of our study and suggest directions for further research.

6.2 Theoretical Model

To assess the impact of product differentiation on pass-through rates, we employ a spatialized version of a stock-flow model. The spatial aspect is covered by two different yoghurt alternatives A and B that are sold in the supermarket. The stock flow model incorporates that yoghurts are produced in each period and delivered to the supermarket, at the supermarket there is a stock of yoghurts and in each period, some yoghurts are disposed as they have not been sold. An application for the housing market is presented in BEENSTOCK and FELSENSTEIN (2010).

We assume that there are two different yoghurts on the market and there is a positive demand for each of the alternatives. The quantity of yoghurts sold for each alternative is identified by the following migration model:

$$Q_{At} = \varphi_{A0} - \varphi_{A1}P_{At} + \varphi_2 P_{Bt} \quad (1)$$

$$Q_{Bt} = \varphi_{B0} - \varphi_{B1}P_{Bt} + \varphi_2 P_{At} \quad (2)$$

Consequently, the demand for product type A is dependent upon the autonomous demand φ_{A0} , the price for product type A P_{At} , and the price for the other product P_{Bt} . The parameter φ_2 defines the nature of the relationship between the alternatives, if they are perfect substitutes φ_2 converges to infinity, if the products are totally unrelated φ_2 becomes 0. φ_{A1} and φ_{B1} determine the degree of price sensitivity of the demand to own- price changes.

Furthermore, we suppose that production costs are the same for both types of yoghurts. But there is imperfect substitution between producing type A or B. The producers decide to manufacture the type that is currently more profitable. Thus, supply is determined by the following equations:

$$S_{At} = \mu_{A0} + \mu_{A1}P_{At} - \mu_{A2}P_{Bt} \quad (3)$$

$$S_{Bt} = \mu_{B0} + \mu_{B1}P_{Bt} - \mu_{B2}P_{At} \quad (4)$$

Here, the parameters μ_{A0} and μ_{B0} reflect the general production of yoghurts for both types. Similar to the demand function, μ_{A1} expresses the reaction to own price changes while μ_{A2} captures reactions to cross price changes.

The yoghurt stocks (H_{At}, H_{Bt}) at the retail level in period t are determined as follows:

$$H_{At} = S_{At-1} + \varepsilon H_{At-1} - \psi H_{At-1} \quad (5)$$

$$H_{Bt} = S_{Bt-1} + \varepsilon H_{Bt-1} - \psi H_{Bt-1} \quad (6)$$

Consequently, the yoghurt stocks for type A (B) are composed of three parts: Firstly, the production S_{At-1} (S_{Bt-1}) of the period before. Secondly, a certain share of the yoghurt stocks of type A εH_{At-1} (εH_{Bt-1}) of the period before is still being sold at the retailer or has been purchased by the consumer but has not been consumed yet. Finally, a certain share of the yoghurts ψH_{At-1} (ψH_{Bt-1}) leaves the stock of yoghurts because it is either consumed or discarded.

Now, the yoghurt market is in equilibrium if $Q_{At} = S_{At}$ and $Q_{Bt} = S_{Bt}$. The solution for the prices is given in equations 7 and 8.

$$P_{At} = \frac{1}{\varphi_{A1}} [\varphi_{A0} - \mu_{A0} - \mu_{A1}P_{At-1} + \mu_{A2}P_{Bt-1} - (\varepsilon - \psi)H_{At-1}] \quad (7)$$

$$P_{Bt} = \frac{1}{\varphi_{B1}} [\varphi_{B0} - \mu_{B0} - \mu_{B1}P_{Bt-1} + \mu_{B2}P_{At-1} - (\varepsilon - \psi)H_{Bt-1}] \quad (8)$$

In essence, the prices are spatially and temporally correlated to each other. The prices are dependent upon the price of the other alternative (spatial aspect) and upon lagged prices of both types (temporal aspect). Furthermore, it is possible to derive long-term solutions to the pricing problem by setting variables at time t equal to their value at $t-1$.

$$P_{At} = \frac{\varphi_{A0} - \mu_{A0}}{\varphi_{A1} + \mu_{A1}} + \frac{\varphi_2 - \mu_{A2}}{\varphi_{A1} + \mu_{A1}} P_B - \frac{\varepsilon - \psi}{\varphi_{A1} + \mu_{A1}} H_A \quad (9)$$

$$P_{Bt} = \frac{\varphi_{B0} - \mu_{B0}}{\varphi_{B1} + \mu_{B1}} + \frac{\varphi_2 - \mu_{B2}}{\varphi_{B1} + \mu_{B1}} P_A - \frac{\varepsilon - \psi}{\varphi_{B1} + \mu_{B1}} H_B \quad (10)$$

Equations 9 and 10 show the spatial long-term relationship between the prices of both types. The closer the types, the higher the degree of substitution φ_2 , the closer the prices are correlated with each other.

6.3 Empirical Model

6.3.1 Measuring Distance

In the present context, we do not use “distance” in the literal case but as a measure of closeness between two product lines. This procedure is adopted from PINSKE and SLADE (2004), who originally implemented the method in demand analysis. Based on LANCASTER (1966) demand is estimated for product characteristics instead of determining the demand for the product as a whole. Similarly, we define “close neighbors” as product lines that share a lot of product attributes. In our data, we have three different types of product attributes: continuous, count and discrete attributes. First, we create a distance measure for each characteristic separately. In a second step, we combine those matrices into one final measure of distance among all product lines. All measures are scaled and transformed so that they range between zero and one while measures closer to one (zero) imply that the two products lines are very similar (dissimilar).

To determine the distance among continuous product attributes, we employ an inverse measure of the Euclidian distance comparable to ROJAS (2008). By using the inverse, instead of measuring how far apart two products are, we measure how close together two products are:

$$d_{ij}^C = \frac{1}{(1+2\sqrt{\sum_{k=1}^n (z_{ik}-z_{jk})^2})}, \text{ with } i \neq j \text{ product lines and } k (k=1,2,\dots,N) \text{ product attributes .}$$

To measure the effect of discrete attributes, we create a zero-one matrix whose elements are defined as follows:

$$d_{ij}^D = \begin{cases} 1, & \text{if products } i \text{ and } j \text{ are identical with respect to attribute } D \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

Lastly, we have one count data attribute (number of flavors a product line offers). To measure distance of count data, we employ the BRAY and CURTIS (1957) dissimilarity measure, which usually originates from ecology to compare the variety of species in a defined environment.

$$d_{ij}^{Count} = 1 - \frac{\sum_{k=1}^n |z_{ik} - z_{jk}|}{\sum_{k=1}^n (z_{ik} + z_{jk})} \quad (12)$$

All the distances d_{ij} will be collected in an NxN matrix. The row-standardized elements of the distance matrix will be labeled as w_{ij} .

6.3.2 Pretests

A prerequisite of cointegration between two variables is that both variables contain a unit root. Thus, we determine for the order of integration before we proceed to test for panel cointegration. As a unit root test, we employ the IPS-test (IM ET AL. 2003), which is particularly suited for dynamic heterogeneous panels. The test is based on the mean individual unit root statistics and proposes a standardized t-bar test statistic based on the ADF (augmented Dickey-Fuller) statistics averaged across the different groups. For a sample of N cross sections over T time periods, the t-bar statistic is constructed to test the null hypothesis that all individual units contain a unit root. IM ET AL. (2003) suppose a stochastic process, y_{it} , which is generated by the following first-order autoregressive process:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \varepsilon_{it}, \quad (13)$$

Then, the null hypothesis of unit roots becomes

$$H_0: \rho_i = 0 \text{ for all } i,$$

against the alternative

$$H_1: \begin{cases} \rho_i < 0 \text{ for } i = 1, 2, \dots, N_1 \\ \rho_i = 0 \text{ for } i = N_1, N_2, \dots, N \end{cases} \quad \text{with } 0 < N_1 < N$$

This specification of the alternative hypothesis allows ρ_i to differ across groups. Consequently, the test enables some (but not all) of the individual series to have unit roots under the alternative hypothesis (IM ET AL. 2003). More specifically, IM ET AL. (2003) assume that under the alternative hypothesis the fraction δ of the individual processes that are stationary is non-zero, namely if

$$\lim_{N \rightarrow \infty} \left(\frac{N_1}{N} \right) = \delta, \quad 0 < \delta \leq 1. \quad (14)$$

This condition is necessary for the consistency of the panel unit root tests.

In the case of cross sectional dependences the IPS-test might be biased. In order to avoid this potential failure we additionally run a unit root test developed by HADRI (2000). This test is a residual-based Lagrange Multiplier test which is explicitly unbiased in the case of cross

sectional dependences in the panel data (RICHARDS ET AL. 2012). HADRI (2000) considers the following model:

$$p_{it} = r_{it} + \varepsilon_{it}, \quad (15)$$

Where r_{it} is a random walk

$$r_{it} = r_{it-1} + u_{it}. \quad (16)$$

where the ε_{it} and u_{it} are mutually independent normals and *i.i.d.* across i ($i = 1, 2, \dots, N$) panels over t ($t = 1, 2, \dots, T$) time periods. The initial values r_{i0} are treated as fixed unknowns and play the role of heterogeneous intercepts. The stationary hypothesis is $\sigma_u^2 = 0$. Since the ε_{it} 's are assumed to be *i.i.d.*, then under the null hypothesis p_{it} is stationary (HADRI 2000).

If two variables are particular I(1), but their linear combination is I(0), the linear combination cancels out the stochastic trend in the two non-stationary time series. In this case it is generally said that the two time series are cointegrated. Cointegration means that two variables have a long-run relationship between each other. Two major approaches to test for cointegration may be used: residual-based tests and error correction tests. The idea behind the residual-based tests is to run a regression and test the estimated residuals for stationarity. If these residuals are stationary, there exists a long-run relationship between the two variables, thus the variables are cointegrated. The design of the error correction test is to construct an error correction model and investigate whether the error correction term is significant. A significant error correction term implies that deviations from the long run relationship between two time series are corrected towards the long run relationship.

Having panel data at hand, testing for cointegration becomes more complex because it is not only necessary to account for the time series dimension T but also for the cross sectional dimension N . WESTERLUND (2007) developed four error-correction-based panel cointegration tests to determine whether the panel is cointegrated. The main motivation to use this test is to overcome the so called common factor restriction which applies in most residual based tests. A common factor restriction is in place whenever the long-run parameters for the variables in their levels are restricted to equal the short-run parameters for the variables in their differences. As the tests proposed by WESTERLUND (2007) are based on structural rather than residual dynamics, they do not impose any common factor restrictions. WESTERLUND (2007) considers the following data generating process for the error-correction process:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i (y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it} \quad (17)$$

where $t=1,2,\dots,T$ is an index of the time-series units and $i=1,2,\dots,N$ an index of the cross-sectional units. The parameter d_t contains the deterministic components. α_i determines the speed at which the system corrects back to the long-run relationship after a sudden shock. If α_i is negative, the data generating process shows error-correction behavior, which implies that y_{it} and x_{it} are cointegrated. Two of the four Westerlund-tests can be further classified as group mean tests while the remaining two tests are panel tests. The group mean statistics are commonly known as “between” dimension tests and they are similar to a panel unit root statistic against heterogeneous alternatives (RICHARDS ET AL. 2012). For the group mean test statistics it is not necessary that the α_i s are equal, thus the error correction coefficient is estimated for each cross-section unit individually. Thus, the null hypothesis of no cointegration is tested versus the alternative hypothesis $\alpha_i < 0$ for at least one i . The two test statistics are G_t and G_a (G_a is normalized by T)²⁸. The second group of tests is based on panel statistics. Panel statistics, often referred to as the “within” dimension test, are analogous to panel unit root statistics against homogeneous alternatives (RICHARDS ET AL. 2012). These tests suppose that the α_i s for all cross-sectional units i are equal, which implies to test the null of no cointegration against the alternative hypothesis $H_1: \alpha_i = \alpha < 0$. The two test statistics of the panel test are called P_t and P_a ²⁸.

In addition to test for the time series properties of the data, we will also conduct a pretest with respect to the validity of the model’s assumption that the prices of similar products are more connected compared to prices of more heterogeneous products. Thus, before fitting a full spatial panel error correction model, we will estimate a bivariate error correction model for all product lines. The long run equilibrium of the bivariate relationships are represented as follows:

$$CP_{it} = \alpha_i + \theta CP_{jt} + u_{it} \quad (18)$$

for all $i \neq j$ with CP_i denoting the retail price of yoghurt line i . The error correction representation of this relationship becomes:

$$\Delta CP_{it} = \pi_{0i} + \pi_{1ij} u_{it-1} + \sum_{l=1}^L \pi_{2il} \Delta CP_{it-l} + \sum_{l=1}^L \pi_{3il} \Delta CP_{jt-l} + v_{it} \quad (19)$$

In equation 19, π_{1ij} captures the extent of the adjustment to the long-term equilibrium. Thus, we will extract that coefficient and we will run an auxiliary regression to check whether the adjustment process is influenced by the degree of differentiation of the products.

²⁸ For more detailed information on the test-statistics and their derivation see Persyn and Westerlund (2008).

$$\pi_{1ij} = \sigma_0 + \sigma_1 w_{ij} + \varepsilon_{ij} \quad (20)$$

As the pass-through is higher, the lower π_{1ij} is and the degree of homogeneity increases in w_{ij} , $\sigma_1 < 0$ indicates that the pass-through increases for more similar products. If $\sigma_1 < 0$ does not hold, that could be either a signal for misspecification of the distance matrix or it signalizes that the degree of similarity does not affect horizontal pass-through rates.

6.3.3 Spatial Error Correction Model

Supposed that both variables are I(1) and the cointegration tests confirm a cointegrated relationship, the long run equilibrium in this market is given through:

$$CP_{it} = \alpha_i + \gamma PP_{it} + \delta CP_{it}^* + u_{it} \quad (21)$$

Let CP_{it} , PP_{it} and CP^*_{it} denote spatial panel data where i indicates the spatial cross-sections ($i=1,2,\dots,N$) and t the time period ($t=1,2,\dots,T$). CP represents the endogenous variables, which are the consumer prices of yoghurt in our setting, and PP the exogenous variables, which is the producer prices of raw milk. Asterisked variables denote spatial lags defined as:

$$CP_{it}^* = \sum_{j \neq i}^N w_{ij} CP_{jt} \quad (22)$$

where w_{ij} are row-summed spatial weights with $\sum_i w_{ij} = 1$. This integration of a spatial dimension into the model allows for an expansion of the range of our analysis from a within panel perspective to a simultaneous account for between panel relationships.

In spatial panels the spatially lagged variables are linear combinations of the underlying data, thus spatially lagged variables must have the same order of integration as the data which they are derived from. Consequently, if CP is difference stationary, CP^* has to be difference stationary as well (BEENSTOCK and FELSENSTEIN 2010). Following ENGLE and GRANGER (1987), cointegration and error correction are mutually dependent, hence we modify the long-run relationship in equation (18) to a dynamic specification in first differences, which nevertheless keeps the information of the long-run relationship. The residuals u_{it} of equation (18) represent the deviations from the long run equilibrium and are incorporated as error correction terms (ECT) into our spatial error correction model. This spatial error correction model describes the dynamic adjustment process of cointegrated variables to their long-run equilibrium.

In the long-run, the spatial error correction representation of equation 19 becomes:

$$\Delta CP_{it} = \gamma_0 i + \gamma_1 u_{it-1} + \gamma_2 u_{it-1}^* + \sum_{l=1}^L \gamma_{3_l} \Delta CP_{it-l} + \sum_{l=1}^L \gamma_{4_l} \Delta CP_{it-l}^* + v_{it} \quad (23)$$

The coefficient γ_1 represents the local error correction and is expected to be negative; otherwise there would be no error correction process. γ_2 is the spatial error correction coefficient with

$$u_{it-1}^* = \sum_{j \neq i}^N w_{ij} u_{jt-1}. \quad (24)$$

u_{it-1}^* corresponds to the weighted error correction processes of the spatial neighbors, thus in cases of spatial spillovers in error correction, the dynamics of CP will be affected by u^* among neighbors. Following BEENSTOCK and FELSENSTEIN (2010) we define ***local error correction*** in the situation that γ_1 is negative but γ_2 is not significantly different from 0. In this case, consumer prices of the product lines react on price changes of raw milk but do not respond to changes of the consumer prices of similar product lines. In the reverse case that γ_2 is nonzero but γ_1 equals zero, the situation is defined as ***spatial error correction***. When both types of error correction occur, the finding is defined as ***global error correction*** (BEENSTOCK and FELSENSTEIN 2010). The autoregressive dynamics are shown by γ_{3_l} (autoregressive coefficient) and γ_{4_l} (spatial autoregressive coefficient) with l indicates the respective lag ($l = 1, 2, \dots, N$).

6.4 Data and Variables

For this study we use German consumer prices of yoghurt as well as raw-milk prices at the producer level. The retail prices for yoghurts are collected weekly starting in the first week of 2005 through the last week in 2010 ($T=312$) by the SymphonyIRI Group GmbH (SIG: SymphonyIRI Group 2011). Yoghurts are generally sold in product lines (DRAGANSKA and JAIN 2006). Typically, product lines differ in quality and price, but within each line the manufacturer offers an assortment of several flavors.²⁹ Usually, the different yoghurts belonging to one product line are placed next to each other in the supermarket and are sold at the same price. We select the product lines having a sales based market share above 0.01%. Thus, we analyze the top 22 product lines and cover 58% of the overall market. A further description of the product lines with respect to their attributes and prices is presented in table 1. For example, the dairy Bauer offers yoghurts in the product lines “Der große Bauer” (rank

²⁹ The information which yoghurts belong to the same product line is not part of the original dataset. Thus, we grouped the yoghurts over the following variables: dairy, brand, fat content, probiotic, submarket (natural or flavored) and volume. Thus, these variables contain identical values within each product line and differ with respect to at least one variable across product lines.

2), “Mövenpick” (rank 13) and “Extra Leicht” (rank 21). The distinction between those lines is predominantly the fat content: “Der Große Bauer” contains around 3.5% fat, the yoghurts in the “Mövenpick” line are branded as a dessert option and show a higher fat content and the “Extra Leicht” are fat-reduced yoghurts. Each product line comprises several different flavors as e.g. strawberry or vanilla.

Table 1 provides an overview of the important two types of variables that will enter our model: product attributes and prices. We use the product attributes to characterize the similarity of the product lines. Comparable to “real” spatial analyses, the definition of a neighbor matrix is subject to the researcher’s evaluation and it is hard to find objective criteria. Our final neighbor matrix consists of four different criteria: the dairy the yoghurt is branded with, the nutritional content, whether it is a probiotic yoghurt or not and the flavor. Each criterion is equally weighted and within each criterion each variable also obtains identical weights.³⁰ The first criterion is the dairy manufacturing the product line. In addition to the name of the product line, yoghurts are also branded with the name of the diary. As manufacturer specific costs might also influence pass-through among product lines, thus, the manufacturer is a criterion by itself. In our data, we have eight different diaries offering one to five different product lines within the top 22. Three out of the 22 product lines are private labels. The actual brand name is masked by the IRI for these products as by contract the retailers should remain anonymous and as each retailer offers a specific private label, unmasking the brand name would reveal the retailer. However, we also have the additional information on the product lines such as fat level and volume.³¹ Next, we combined four variables on nutritional information about the variable into one criterion. The fat content is part of the IRI data and we added information on the calories, proteins and carbohydrates per 100gr. The fat content is grouped into four groups. Twelve product lines show fat contents ranging from 3.5% to less than 10%, the fat content in four lines exceeds 10%, five yoghurts are classified as non-fat (fat content < 1.5%) and one product line has a fat content between 1.5% and 3.5%. The average yoghurt contains 104 calories per 100gr., 4 gr. protein and 13 gr. carbohydrates. The level of fat content, calories and carbohydrates is positively correlated to each other while the protein content is negatively correlated with the other nutritional variables. We decided to separate the information whether a yoghurt contains probiotic

³⁰ Our results are robust to alternative specifications of the neighbor matrix.

³¹ Further nutritional variables had to be collected via an online page on which such information is collected (“Kalorientabelle, kostenloses Ernährungstagebuch, Lebensmittel Datenbank - Fddb,” n.d.). To approximate the nutritional values for these products, we averaged over the nutritional contents of the most similar national brands.

yoghurt cultures or not from the other nutritional variables because from the producers' and consumers' perspective this product attribute is found to be viewed as quite important for pricing and purchasing decisions (EMPEN 2011). The fourth criterion is a combination of flavor-related variables. We measure how big the assortment within each product lines is. On average, each line is made up by 6.9 different flavors. The two top selling brands offer substantially more flavors (35 and 20), but these are not always available as these two product lines include seasonal products such as for example a special winter or summer yoghurt. In addition, we determined whether each product lines also offers the seven top selling flavors (strawberry, chocolate, vanilla, cherry, coffee, nature, cereals). The resulting neighboring matrix in which the criterions manufacturer, nutrition, probiotic and flavor obtained equal weights is presented in the appendix (A1). The values may theoretically vary between 0 and 1. As we row-standardized the matrix, the values add up to 1. Thus, a weight above 0.05 (1/21) indicates that product lines are close matches and values below 0.05 are a sign for dissimilarity. Overall, product lines produced by the same dairy score higher similarity values. Across dairies, for example private label 2 and 3 are quite similar, as they contain similar nutritional values. As there is only one probiotic product line in our sample ("LC1", rang 6), it is the most differentiated product line in our sample.

The second part in table 1 summarizes information on the prices. With an average price of 0.09 to 0.16 €/100gr, the private labels are generally the cheapest products. The highest priced product line is "Smarties", on average the price is 0.62€/100gr. The special feature of this line is that it contains sugar-coated chocolate pieces. Thus, the spread between the cheapest and the most expensive product line is 0.53 €/100g. The standard deviation of the prices ranges from 0.01 to 0.05. The lowest and highest observed price for each product line is also shown in table 1. For some product lines, the spread between the prices is quite high (e.g. "Mit der Ecke Knusper" rank 3). Lower price observations can be explained by periodic sales. The high observations stem from high-priced hypermarkets. Finally, table 1 provides the average neighbor price for each product line. This average is calculated by all other prices weighted by the neighbor matrix, thus the variance among the neighbor prices is considerably lower. Again, the private label products are connected with lower neighbor prices because the other private labels are close substitutes for each other; consequently, they get higher weights for each other.

We complement the retail scanner data with raw-milk prices at the producer level. The milk prices are sampled by the German Ministry of Food, Agriculture and Consumer Protection

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(BMELV different volumes) who undertake extensive surveys of the German dairy industry. The prices reflect an average price per kilogram milk which the dairies pay to their milk producers. We use the milk prices as a proxy for the input price changes because yoghurt is predominantly made of milk.

Table 1: Descriptive statistics for the 25 most significant yoghurt product lines over the period 2005 to 2010

Rank	Market Share	Product Line	Product Attributes								Prices				
			Dairy	Nutrition			Probiotic	Flavor		Price (in €/100g)			Average Neighbor Prices (in €/100g)		
				fat content ¹	calories (in kcal/100g)	proteins (in g/100g)		number of types	Strawberry ²	mean	Std. Dev.	Min.	Max.		
1	9.89%	Almighurt	Ehrmann	normal	102	3.1	16	No	35	Yes	0.25	0.04	0.11	0.57	0.24
2	9.84%	Der große Bauer	Bauer	normal	88	3.2	13.3	No	20	Yes	0.2	0.02	0.09	0.3	0.24
3	7.21%	Mit der Ecke Knusper	Müller	normal	147	4.3	20.1	No	6	Yes	0.29	0.04	0.16	0.95	0.24
4	4.41%	Mit der Ecke	Müller	normal	103	4.1	14.9	No	5	Yes	0.29	0.04	0.08	0.43	0.26
5	4.14%	Sahnejoghurt	Zott	cream	141	2.3	15.5	No	9	Yes	0.29	0.04	0.15	0.45	0.23
6	3.31%	LC1	Müller	normal	90	3.7	10.1	Yes	2	No	0.25	0.04	0.11	0.32	0.23
7	3.18%	Froop	Müller	normal	103	3.9	16.1	No	5	Yes	0.28	0.04	0.11	0.84	0.26
8	2.66%	Family Fruit	Danone	normal	116	3.5	16.9	No	7	Yes	0.2	0.02	0.09	0.62	0.25
9	1.86%	Lünebest	Hochwald	normal	92	3.9	14.1	No	14	Yes	0.24	0.03	0.11	0.39	0.19
10	1.81%	Private Label 1	Private Label 1	low-fat	93	4	16.8	No	6	Yes	0.11	0.02	0.04	0.2	0.13
11	1.77%	Rahmjoghurt	Weihenstephan	cream	166	3	15.2	No	10	Yes	0.38	0.04	0.12	0.51	0.24
12	1.26%	Smarties	Müller	normal	164	3.5	23.9	No	2	No	0.62	0.03	0.32	0.71	0.23
13	1.18%	Mövenpick	Bauer	cream	183	3	16.6	No	9	Yes	0.4	0.05	0.14	0.53	0.23
14	1.13%	Campina	Campina	non-fat	47	4.4	7.1	No	3	Yes	0.18	0.02	0.1	0.22	0.21
15	0.94%	Landliebe	Campina	normal	100	3.9	15	No	8	Yes	0.31	0.03	0.12	0.6	0.22
16	0.86%	Jogole	Zott	non-fat	49	3.9	8	No	4	Yes	0.26	0.03	0.15	0.46	0.21
17	0.84%	Bighurt	Ehrmann	normal	65	3.9	4.5	No	1	No	0.19	0.02	0.09	0.24	0.19
18	0.57%	Mark Brandenburg	Campina	normal	146	2.7	16.8	No	10	Yes	0.19	0.03	0.12	0.29	0.21
19	0.42%	Private Label 2	Private Label 2	non-fat	46	4.4	6.9	No	4	Yes	0.16	0.02	0.11	0.29	0.13
20	0.31%	Private Label 3	Private Label 3	non-fat	78	4.5	6	No	1	No	0.09	0.01	0.03	0.1	0.24
21	0.25%	Extra Leicht	Bauer	non-fat	50	4	7.1	No	6	Yes	0.19	0.02	0.09	0.24	0.18
22	0.14%	Cremighurt	Ehrmann	cream	149	2.9	18.5	No	3	Yes	0.34	0.04	0.16	0.42	0.19

Legend: 1. fat level is defined by the fat content. We employ the European fat content classification: non-fat: max. 0.5% fat; low-fat: 1.5-1.8% fat; normal: min. 3.5% fat; cream: min. 10% fat. 2. Flavor is made up by the additional binary variables chocolate, cherry, vanilla, coffee, nature and cereals..

Source: Own calculations.

6.5 Results

6.5.1 Pretests

The results of the unit root tests are displayed in table 2. While the IPS and Hadri test is used for the panel data (retail and neighbor prices), we employ a standard Augmented Dickey Fuller test (ADF-test) for the raw milk prices. Following the Akaike information Criterion, the optimal lag structure is 6. The IPS-test results indicate that all retail prices series contain a unit root. The test suggests that at least one of the neighbor prices is stationary. This might be due to the fact that the IPS test is not applicable in the case of cross sectional dependences. The neighbor prices, however, are weighted averages of the retail prices and are consequently strongly related to each other. Thus, the Hadri test seems to be more appropriate in this case and it confirms that the retail prices as well as the neighbor prices contain a unit root and are I(1). According to the results of the ADF-test, in which the null hypothesis is that the price series contains a unit root, the raw milk prices are also I(1).

Table 2: Results of the Unit Roots Tests

	Retail Prices		Neighbor Retail Prices		Raw Milk Prices	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
IPS-test	-79.7869	0.000	9.6763	1.0000		
Hadri-test	1.9*e03	0.000	5.7*e03	0.0000		
ADF Test					-0.932	0.77

Source: Own calculations.

To test for cointegration between the retail prices and the raw milk price, we apply the test after WESTERLUND (2007). The results are presented in table 3. Each of the four cointegration-tests supposed by WESTERLUND (2007) strongly rejects the null hypothesis that the series are not cointegrated, i.e. there is a long-run relationship with error-correction behavior between the producer prices of raw milk and the consumer prices of yoghurt. Thus, the preconditions to estimate an error correction model are fulfilled.

Table 3: Results of the Westerlund Panel Cointegration Test

Statistic	Value	Z-value	P-value
<i>group mean tests</i>			
Gt	-4.041	-85.922	0.000
Ga	-78.623	-410.907	0.000
<i>panel tests</i>			
Pt	-147.15	-70.597	0.000
Pa	-67.273	-399.940	0.000

Source: Own calculations.

Our analysis builds upon the assumption that we expect yoghurt prices to be connected horizontally and that the more similar the products are, the closer the connection among the prices. Before turning to estimate the full model, we determined the bilateral error correction models for the average price of each product line in each week. From these regressions (equation 18), we extracted the coefficients for the adjustment to the long-run equilibriums. If there is error correction, this coefficient has to be ranging between 0 and -1. This is the case for almost all combinations, only the product line “Campina” has no significant feedback with five other product lines. To determine whether the distance between the product lines influences the magnitude of the error correction process, we regressed the distance on the long-term adjustment parameter (ECT). The closer the products are, the higher the distance measure. Consequently, our auxiliary regression supports the hypotheses that the yoghurt prices react stronger to price changes of similar product lines.

Table 4: Results of auxiliary regression

Dependent variable: ECT	Coefficient	t-statistic
Distance	-0.553**	-2.56
Intercept	-0.237***	-19.38

Legend: ***/**/* indicate statistical significance at the 1%/5%/10% significance level

Source: Own calculations.

6.5.2 The Econometric Model

The pretests concluded that all price series are I(1), have a cointegrated relationship and the horizontal relationship of the prices is influenced by the similarity of the yoghurts. Thus, we proceed to fit a panel error correction model with a spatial dimension as presented in equation 23. The results are reported in table 5. ECT denotes the error correction term, which is equal to the lagged residuals from equation 23 and captures the adjustment process to deviations from the long-run equilibrium. The coefficient is -0.416, meaning that if the producer price for milk changes, the deviation is on average cut back by 41.6% each week. The second coefficient, ECT* shows how prices react to spatially lagged deviations. Unlike the original ECT, this parameter of spillovers is not economically restricted to be either negative or positive. Positive spatial spillovers indicate that if e.g. the price of similar yoghurt is too high, there is a significant tendency that prices also adjust upwards. In our model the spatial spillover effect of error correction amounts to 0.201, which means that 20.1% of the neighboring error spillover onto the local yoghurts. According to the classification provided in the original application of spatial error correction models (BEENSTOCK and FELSENSTEIN 2010), we find significant local (ECT) and spatial error correction (ECT*) mechanisms, which is labeled as global error correction.

Furthermore, table 5 also incorporates 6 lags of the producer price, 6 lags of the autoregressive price and also 6 spatial lags of the autoregressive component. The lag order is determined using the AIC. All coefficients are statistical significant. Thus, we can conclude that the current changes in local yoghurt prices depends on the lagged changes of the producer prices for raw milk and on the lagged changes in prices of neighboring yoghurts as well as on lagged changes in prices of the local yoghurt. Overall, the model is statistically different from 0 and explains 45.21% of the observed variance.

Table 5: Spatial fixed-effects panel error correction model

Spatial-ECM			ECM	
Dependent variable: ΔCP_{it}	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
<i>error-correction-terms</i>				
ECT _{it-1}	-0.416***	-161.9	-0.398***	-163.3
ECT* _{it-1}	0.201***	8.7		
<i>lags of the autoregressive consumer prices</i>				
ΔCP_{it-1}	-0.502***	-194.5	-0.520***	-213.5
ΔCP_{it-2}	-0.467***	-182.0	-0.474***	-194.5
ΔCP_{it-3}	-0.386***	-155.8	-0.387***	-163.5
ΔCP_{it-4}	-0.268***	-117.7	-0.271***	-123.4
ΔCP_{it-5}	-0.150***	-77.2	-0.148***	-78.4
ΔCP_{it-6}	-0.065***	-44.9	-0.063***	-44.6
<i>lags of the spatial-autoregressive consumer prices</i>				
ΔCP^*_{it-1}	-0.250***	-24.0		
ΔCP^*_{it-2}	0.056***	4.5		
ΔCP^*_{it-3}	0.201***	15.5		
ΔCP^*_{it-4}	0.084***	6.4		
ΔCP^*_{it-5}	0.143***	11.6		
ΔCP^*_{it-6}	0.119***	11.8		
<i>lags of the producer prices</i>				
ΔPP_{it-1}	0.157**	2.14	-0.168**	-2.3
ΔPP_{it-2}	-0.613***	-9.2	-0.870***	-13.2
ΔPP_{it-3}	0.113**	2.1	0.306***	5.7
ΔPP_{it-4}	0.0674	1.0	-0.087	-1.3
ΔPP_{it-5}	0.162**	2.2	0.254***	3.5
ΔPP_{it-6}	0.326***	4.6	0.607***	8.6
Intercept	0.000231***	7.8	0.0001***	9.0
<i>model fit</i>				
F-Test (p-value)	21045.05 (0.00)		32147.51 (0.00)	
R ²	0.4521		0.4503	
<i>Specification tests</i>				
likelihood ratio test	LR chi2 (7) = 1645.83		Prob > chi2 = 0.00	
Wald test	F (7, 510092) = 234.72		Prob > F = 0.00	
Hausmann test	Chi2(13) = 1702.21		Prob > chi2 = 0.00	

Source: Own calculations.

To further analyze the value of the new approach instead of estimating an error correction model, we report the results for comparison on the right hand in table 4. The ECT term in the restricted model is 1.8% larger compared to the spatial version of the model and the coefficient of determination drops by 0.18%. Even though the differences in absolute values seem to be rather small, different additional tests show that the corresponding spatial model fits the data significantly better: First, a likelihood ratio test allows us to conclude that the added spatial variables together result in statistically significant improvement in the model's fit. Moreover, a Wald-Test further shows that all spatial variables are jointly statistically different from zero. Finally, we can reject the null hypothesis of a Hausman-test that the differences across the model are not systematically different from zero.

6.6 Conclusion

In this article, we theoretically and empirically analyze the spatial and temporal price relationships on the German yoghurt market. We adopt a spatialized version of the stock flow model in which producers may decide which of the two varieties they want to offer while consumers may choose between the alternatives. Thus, the relative prices are the decisive factor that determines which yoghurt is produced and sold. In essence, the model shows that prices of one product type are dependent on the prices of other varieties and on lagged prices. The closer substitutes the products are, the higher the correlation of the prices in the long run. To empirically confirm this finding, we simultaneously estimate the effect of a commodity price change and the price change of close substitutes on retail prices by modeling a SPECM. Our results indicate that the vertical cost pass-through from the price of raw milk to the consumer price of yoghurt is comparably high (41.6% per week) as well as spatial spillovers in error correction (20.1% per week). If similar products are priced above the long-run equilibrium, there exists a tendency to follow those prices and adjust prices upwards. Thus, regarding to BEENSTOCK and FELSENSTEIN (2010) we find global error correction processes within the German yoghurt market. Furthermore we detect that the estimate for the adjustment to the long-run equilibrium is significantly higher when the current price levels of close substitutes are accounted for in the panel error correction model. Furthermore, we can show that the closer two products are, the closer are their price movements. Consequently, our results highlight the importance for accounting for within category product differentiation.

From a managerial perspective, spatial spillovers in error correction could be used as a strategic tool by the retailer. Assume a retailer offers strong brands, maybe even so-called “must haves” for which the degree of market power lies on the wholesale and weaker brands that are potentially interchangeable. If the retailer seeks to adjust those prices downward, the manager could identify close substitutes; renegotiate lower wholesale prices for those products and wait for the stronger brand to follow the lead.

In further research, the procedure introduced in the present context of product differentiation can also be applied to a literal spatial setting: what is the influence of a retailer’s location on price pass-through? Moreover, the proposed techniques could be useful in competition analysis: using a SPECM it is possible to simultaneously test for the relevant market with respect to product substitutability and in a geographical sense.

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Appendix

A1. Neighbor Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	Sum	
1	Almighurt	0	0.06	0.05	0.05	0.05	0.01	0.05	0.03	0.05	0.05	0.03	0.04	0.06	0.04	0.05	0.05	0.06	0.05	0.05	0.03	0.05	0.07	1	
2	Der große Bauer	0.06	0	0.05	0.05	0.05	0.01	0.05	0.04	0.05	0.05	0.03	0.05	0.07	0.04	0.05	0.05	0.04	0.05	0.05	0.03	0.07	0.05	1	
3	Mit der Ecke Knusper	0.05	0.05	0	0.07	0.04	0.04	0.07	0.04	0.04	0.05	0.03	0.07	0.04	0.04	0.05	0.04	0.04	0.05	0.05	0.04	0.05	0.05	1	
4	Mit der Ecke	0.05	0.05	0.07	0	0.05	0.04	0.08	0.04	0.05	0.05	0.03	0.06	0.05	0.04	0.05	0.04	0.04	0.05	0.04	0.03	0.04	0.05	1	
5	Sahnejoghurt	0.05	0.05	0.05	0.06	0	0.01	0.05	0.04	0.05	0.05	0.04	0.04	0.06	0.05	0.05	0.07	0.04	0.05	0.05	0.04	0.05	0.06	1	
6	LC1	0.02	0.03	0.08	0.09	0.02	0	0.10	0.08	0.03	0.03	0.06	0.11	0.02	0.03	0.03	0.02	0.07	0.03	0.02	0.07	0.03	0.03	1	
7	Froop	0.05	0.04	0.06	0.08	0.04	0.04	0	0.04	0.05	0.05	0.04	0.06	0.04	0.04	0.05	0.04	0.05	0.05	0.04	0.04	0.04	0.04	1	
8	Family Fruit	0.04	0.04	0.05	0.05	0.04	0.04	0.05	0	0.05	0.04	0.06	0.05	0.04	0.05	0.05	0.04	0.07	0.04	0.05	0.07	0.04	0.04	1	
9	Lünebest	0.05	0.05	0.05	0.06	0.05	0.02	0.06	0.04	0	0.05	0.03	0.04	0.05	0.05	0.06	0.05	0.04	0.05	0.05	0.04	0.05	0.05	1	
10	Private Label 1	0.05	0.05	0.05	0.05	0.05	0.01	0.05	0.04	0.05	0	0.03	0.04	0.05	0.05	0.06	0.05	0.05	0.04	0.06	0.08	0.06	0.06	0.04	1
11	Rahmjoghurt	0.04	0.04	0.04	0.04	0.05	0.04	0.05	0.07	0.04	0.04	0	0.05	0.04	0.05	0.04	0.04	0.07	0.04	0.05	0.07	0.05	0.05	1	
12	Smarties	0.04	0.05	0.07	0.07	0.04	0.05	0.07	0.05	0.04	0.05	0.04	0	0.04	0.04	0.05	0.04	0.05	0.05	0.04	0.04	0.04	0.04	1	
13	Mövenpick	0.06	0.08	0.05	0.05	0.06	0.01	0.05	0.03	0.05	0.05	0.04	0.04	0	0.05	0.05	0.05	0.03	0.05	0.04	0.03	0.07	0.06	1	
14	Campina	0.04	0.04	0.04	0.05	0.05	0.01	0.05	0.04	0.05	0.05	0.04	0.04	0.05	0	0.07	0.06	0.04	0.07	0.06	0.05	0.06	0.05	1	
15	Landliebe	0.05	0.05	0.05	0.06	0.05	0.02	0.05	0.04	0.05	0.05	0.03	0.05	0.04	0.07	0	0.05	0.04	0.08	0.05	0.03	0.05	0.04	1	
16	Jogole	0.05	0.05	0.05	0.05	0.07	0.01	0.05	0.04	0.05	0.05	0.03	0.04	0.05	0.06	0.06	0	0.04	0.05	0.06	0.04	0.06	0.04	1	
17	Bighurt	0.06	0.04	0.04	0.05	0.04	0.04	0.05	0.07	0.05	0.04	0.06	0.05	0.04	0.04	0.05	0.04	0	0.04	0.04	0.06	0.04	0.07	1	
18	Mark Brandenburg	0.05	0.05	0.05	0.05	0.05	0.02	0.05	0.04	0.05	0.06	0.03	0.05	0.05	0.07	0.08	0.05	0.04	0	0.05	0.03	0.05	0.05	1	
19	Private Label 2	0.04	0.05	0.05	0.05	0.04	0.01	0.05	0.04	0.05	0.08	0.04	0.04	0.04	0.06	0.05	0.06	0.04	0.05	0	0.07	0.06	0.04	1	
20	Private Label 3	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.07	0.04	0.07	0.06	0.05	0.04	0.05	0.04	0.04	0.06	0.04	0.08	0	0.05	0.04	1	
21	Extra Leicht	0.04	0.07	0.05	0.05	0.04	0.01	0.05	0.04	0.05	0.05	0.04	0.04	0.06	0.06	0.05	0.06	0.04	0.05	0.06	0.04	0	0.04	1	
22	Cremihurt	0.07	0.05	0.05	0.05	0.06	0.01	0.05	0.04	0.05	0.05	0.04	0.04	0.06	0.05	0.05	0.04	0.06	0.05	0.05	0.03	0.05	0	1	
Sum		1.00	1.03	1.10	1.16	0.97	0.49	1.17	0.93	1.01	1.05	0.83	1.08	0.98	1.01	1.10	0.99	0.98	1.07	1.05	0.92	1.06	1.01		

Source: Own calculations.

Chapter 7

Pass-Through of Producer Price Changes in Different Retail Formats

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Abstract

In this paper, we use product-level data for Germany to estimate the pass-through of producer price changes to final consumer prices. In particular, we are interested in different reactions across retailer formats. Therefore, we distinguish between two retail formats: discounters and supermarkets. We analyze the German ground coffee market and show that supermarkets have a higher price level and change their prices more often compared with discounters. We find that discount retailers pass-through 37% of a producer price change, significantly more than the 23% for supermarkets.

7.1 Introduction

In this paper, we use detailed product-level data for Germany to estimate the pass-through of producer price changes to final consumer prices. We consider as a new explanation for the degree of pass-through the respective retail format of a retailer. The choice of retail format implies different local costs, which in turn mitigate producer price shocks. Therefore, we distinguish between two retail formats, discounters and supermarkets, and analyze the German ground coffee market in the years 2000 to 2001.

The pass-through into consumer prices has substantial consequences for the price volatility, the frequency of price adjustment, and the prices paid by different income groups. Recently, producer prices for coffee fell by about 32% from their peak in the second quarter in 2011 to their value of USD 1.65 per pound in the first quarter 2012. Likewise, the price of cocoa decreased in the same period by about 34%. Sugar prices, finally, first increased in the first quarter 2011 by 15% and then dropped by 23% in the first quarter of 2012.³² Public concerns about how these price changes transmit into consumer prices make it crucial to estimate the magnitude of pass-through and determine possible forces that mitigate the price volatility (RICHARDS AND HAMILTON 2011). The frequency of price adjustments can also be affected by the retail format. Due to their retail concept discount retailers generally change prices less often compared to supermarkets. In this sense, the presence of discount retailers implies an increase in the price rigidity at the consumer level. This is essential for the discussion on nominal price rigidities in macroeconomics (see, EICHENBAUM ET AL. 2011). Finally, differences in pass-through rates across retail formats need to be accounted for in the ongoing debate on inequality and the prices paid by low-income households (SEE, E.G. BRODA ET AL. 2009 OR LEIBTAG AND KAUFMANN 2003). A recent study by the German market research institute GfK (2008) shows that in Germany low-income households, such as students or unemployed people, have much higher expenditure shares at discounters. As a consequence, these households are affected relatively more if discounters pass-through price changes to a higher degree.

The literature provides substantial evidence for incomplete pass-through of cost shocks, such as import or producer price changes, into consumer prices across countries and sectors (Campa and Goldberg 2005, 2010). While the estimated coefficients differ in size across countries, for Germany, Campa and Goldberg (2010) provide an aggregate estimate of around 21%. In other words, a 10% decrease in producer prices leads to a 2.1% decrease in consumer prices. This leaves a considerable part of the price change that is not passed through and needs to be explained. Using detailed product data some sources for incomplete pass-through rates have been determined. The most important ones are the frequency of price adjustment (Gopinath and Itskhoki 2010), mark-up adjustments by firms

³² Sources: International Coffee Organization, International Cocoa Organization and Public Ledger via Datastream.

(HELLERSTEIN 2008), and local distribution costs (NAKAMURA AND ZEROM 2010). Especially local cost components can explain up to 50% of the incomplete pass-through of cost shocks to final consumer prices (NAKAMURA AND ZEROM 2010 or HELLERSTEIN, 2008).³³

The current paper considers retailers that obtain their products from the specific producers. Then, they add their own local costs and set their retail price for consumers.³⁴ We emphasize one crucial part of local cost components that retailers have to cover. That is, we consider retailers differing in the amount of additional services they supply. In the food retailing sector, possible services can be additional shop assistants, a broader product assortment, more cash points in order to reduce the waiting time for customers, or a sales area that is more ample. Indeed, service quality of retailers is frequently stated as influencing consumers' choices of their shopping stores.³⁵ All these factors add to the producer price and are locally supplied. Thus, they drive a wedge between the final consumer price of a retailer and the producer price. As a consequence, a 10% change of the producer price will imply a change of less than 10% of the consumer price which is generally named incomplete pass-through. An identical change in the producer price is thus passed through differently to consumer prices depending on the degree of services provided in the specific retail format.

In Germany the two dominant retail formats in the grocery market are supermarkets and discounters. These two retail formats pursue different strategies to attract customers. In contrast to supermarkets the concept of discounters can be summarized as providing low prices, reducing the interior of the shopping outlets to a minimum and serving a clearly defined small number of products (GFK 2008; CLEEREN ET AL. 2010). In this paper, we think of these factors as services. If such services are attached to an otherwise identical product the final consumer price is higher. The discounter phenomenon originated in Germany and, here, discounters increased their market share from about 32% in 2001 up to 43% in 2007 (GFK 2008). Discounters have become an important part of the grocery sector in other countries as well. In the last years the number of discount stores in Europe has increased by approximately 30% to reach a number of 45,000 in 2010. Discounters now have market shares in the grocery sector ranging from 10% in Belgium, 19% in Austria to about 35% in Norway (see PLANET RETAIL 2006 AS CITED IN CLEEREN ET AL. 2010). It is, thus, important to analyze the effect of discounters on consumer price pass-through and price changes, and Germany provides the adequate environment for such a study.

³³ Another interesting line of research considers the type of pricing contract between the manufacturer and the retailer. In a number of papers, Bonnet and Dubois, for instance, introduce vertical contracts between manufacturers and retailers (BONNET AND DUBOIS 2010A, 2010B). An empirical test then reveals that, for instance, resale price maintenance increases pass-through rates substantially (see Bonnet et al. 2011).

³⁴ In this paper, the retail price is the price the consumer has to pay. So the terms "retail price" and "consumer price" have identical meanings.

³⁵ For instance, TANG ET AL. (2001) consider service quality as "fixed benefit of shopping" and CLEEREN ET AL. (2010) see it as one possibility for supermarkets to differentiate themselves from discounters.

We employ a data set of the MADAKOM GMBH (2001), a former market research institute in Germany, at the Universal Product Code (UPC)-level for a sample of German retailers covering the years 2000 and 2001. We consider the category of ground coffee so we can use raw coffee bean prices as approximation of producer prices. Ground coffee is an appropriate category as it provides a relatively homogeneous product and the main ingredient, raw coffee beans, is internationally traded, not produced in Germany and thus needs to be imported by all producers. We assume that price differences across retail formats are induced by service differences. For example, in the first week in the year 2000 a 500gr package of “Jacobs Krönung Mild” was sold for DM 7.49 at a discounter belonging to the key account Edeka and for DM 7.99 at a supermarket of Rewe’s retail network, another large German key account. Thus, this difference of DM 0.50 is attributed to the costs of additional services occurring in the supermarket.

We find that supermarket retailers have a broader product assortment, a higher price level and change prices more often compared to discounters. We then apply an error correction model (ECM) to account for a possible cointegration relation between the producer price and the specific retail price series. Only half of the retail price series we analyze are cointegrated with the producer price. Therefore, we also use a reduced-form approach to include all price series in the analysis. The pass-through of producer price changes to final consumer prices is incomplete and the retail format is indeed an important factor. We show that stores belonging to the discount retail format have a significantly larger pass-through rate of 37% compared to 23% for supermarkets.

Closely related papers to ours are BONNET ET AL. (2011) and LEIBTAG ET AL. (2007). BONNET ET AL. (2011) employ the same data set as this paper but differ in two major aspects. First, they aggregate the data and do not use the UPC-level. More precisely, they define a product as one brand (e.g. Melitta) sold at one key account (e.g. Rewe). By contrast, we make use of the UPC-level and define products by UPC-codes and consider the specific store that sells this product. Second, they use a structural model. In a reduced-form approach BONNET ET AL. (2011) estimate a pass-through rate of about 18%, comparable to the 25% we obtain if we do not distinguish retail formats. In their structural model, however, the pass-through rate increases to about 50 to 60%. The structural model allows considering the effects of non-linear pricing strategies and two-part tariffs between wholesalers and retailers on pass-through. They conclude that pass-through rates increase, for instance, with resale price maintenance by 10% by reducing the double-marginalization problem. While their structural model provides valuable insights it is not feasible with the number of products we obtain at the UPC-level. Therefore, following CAMPA AND GOLDBERG (2005) we apply an error correction model and a reduced-form approach while emphasizing the role of different retail formats. LEIBTAG ET AL. (2007) focus on the ground coffee sector in the US at the commodity, wholesale and retail price level. Using quarterly data from 2000 to 2004 they estimate pass-through to be 22% after 6 quarters for wholesale and retail prices. We carry out a similar analysis for Germany but consider a much more disaggregated

level - we use weekly data. This is of particular importance when analyzing retail data, as promotional sales frequently occur on a weekly basis (VON CRAMON-TAUBADEL ET AL. 2006). Furthermore, our panel variable is more disaggregated: a single good sold in a specific store in one week. In contrast to LEIBTAG ET AL. (2007), we do not have wholesale prices at our disposal. Instead, we chose ground coffee as the product category for which approximations of the producer price can be made using the price of raw coffee beans.

Our contribution to the literature is the following: First, studies on cost pass-through such AS BONNET ET AL. (2011), LEIBTAG ET AL. (2007), NAKAMURA (2008), KIM AND COTTERILL (2008), and BERCK ET AL. (2009) perform their analysis without considering discount retail formats.³⁶ We differ from these papers in that we carry out the analysis at a more disaggregated level, as we are able to distinguish a single product at a single store. We show the substantial price and pass-through rate differences for discounters compared to supermarkets.³⁷ Second, we add to the growing literature on the interaction of discounters and supermarkets (CLEEREN ET AL. 2010; GIJSBRECHTS ET AL. 2008; GONZÁLEZ-BENITO ET AL. 2005).³⁸ These studies generally consider the intensity of competition between discounters and supermarkets. Our paper, however, considers one of the consequences of this competition, i.e. price adjustment. Fiercer competition among supermarkets would suggest that they adjust prices faster and to a higher degree. We show the contrary. Discounters are the ones that react more given a change in the producer price. We attribute that to additional services provided in supermarkets that reduce the price decreasing effect of lower producer prices. Finally, BRODA ET AL. (2009) show that about one third of the price differences between low- and high-income households in the U.S. is explained by the choice of the store. High-income households prefer stores with a nicer ambiance that charge higher prices. We provide a comparable picture for Germany. The prices of

³⁶ NAKAMURA (2008) employs a wide US sample of products on the UPC-level. She finds that 65% of price variation is common within one key account and concludes that the pass-through of manufacturer costs changes to retail prices is not the most important explanation for price variability. KIM AND COTTERILL (2008) find that cost pass-through rates for processed cheese are lower under collusion compared to Nash-Bertrand price competition. BERCK ET AL. (2009) analyze the pass-through of corn, wheat and gasoline prices to retail prices of chicken and cereals in the US for 2003-2005. They find significant differences in the pass-through rates depending on sales. The estimated pass-through rates are 17% for corn price changes and 30% for feed price changes to the net price of chicken. These estimates are about 50% larger compared to the ones using gross shelf prices. This again indicates the importance of accounting for sales.

³⁷ Other studies on a more aggregated level, such as Bettendorf and Verboven (2000), use price indices for their analysis. The authors study the Dutch market and find incomplete pass-through of the price of green beans to consumer prices. They conclude that costs other than coffee beans, such as labor costs and packaging costs are the dominant reasons for incomplete pass-through. Since additional service costs include, for instance, wages their finding supports our line of argumentation that these service costs induce incomplete pass-through rates.

³⁸ CLEEREN ET AL. (2010) classify competition within a format as intraformat competition and competition between supermarkets and discounters as interformat competition. They find it to be intense in both dimensions but fiercer among supermarkets. The appearance of discounters only affects a supermarket's profitability from two discount stores onwards. GIJSBRECHTS ET AL. (2008) provide an alternative explanation for multiple stop grocery shopping. Consumers not only take into account price differences but also other shopping benefits, including "in-store benefits" such as a store's service level. GONZÁLEZ-BENITO ET AL. (2005) find higher intra- compared to interformat competition, too. They derive a two-step consumer shopping decision. First it is based on the retail format and in a second step on the specific store, e.g. a consumer decides to shop at a discounter and then chooses to go to Penny.

discount retailers include a lower amount of local cost components such as services, and, thus, the pass-through rates of producer price changes are higher. As a consequence, low-income households are affected relatively more by price changes, of otherwise identical products. This intensifies existing price differences and needs to be taken into account when measuring price differences and inequality.

The remaining paper is structured as follows: In the next section, we present our data in greater detail and deduce stylized facts on retail chains and their average prices in Germany. Section 3 then presents the empirical strategy and the results. Potential limitations of our approach are discussed in section 4. Finally, section 5 concludes.

7.2 Data and Stylized Facts

In this section, we start with a short description of the ground coffee market in Germany. Then, based upon a thorough introduction of the data at hand, we will show basic characteristics of the prices observed across retail formats, particularly to what extent prices were altered during the period under observation and how long prices remained unchanged.

7.2.1 German Ground Coffee Market

When a consumer buys a package of coffee at a retailer it generally has passed through the two production steps growing and roasting (RICHARDSON AND STÄHLER 2007). First, coffee beans are grown in the southern hemisphere and the four major producers of coffee in 2000 to 2001 are Brazil, Vietnam, Colombia and Indonesia.³⁹ These coffee beans are internationally traded and the two largest importing countries in 2000 are the U.S. and Germany, with about 24 million and 14 million imported 60kg bags, respectively. This implies a market share of 16% for Germany.⁴⁰ The second production step is roasting the coffee beans. The German roasting market is dominated by a few firms with Jacobs and Tchibo/Eduscho⁴¹ having the highest market shares in 1999 of 27% and 24%, respectively (LIENING 2000 as cited in KOERNER 2002). Finally, the roasted coffee is sold to retailers and then to consumers.⁴² In Germany, average coffee consumption was about 6.79kg per capita in 2010.⁴³ While there are a couple of other factors determining the price of ground coffee, such as wages or transportation costs, DRAGANSKA AND KLAPPER (2007) pointed out, that green beans are the major

³⁹ Source: ICO (a), online database.

⁴⁰ Source: ICO (b), online database.

⁴¹ The producers Tchibo and Eduscho merged in 1997 but still their products are sold with the two distinct brand names. We, thus, follow other studies of the German ground coffee market (DRAGANSKA AND KLAPPER, 2007; BONNET ET AL. 2011) and consider these brands as being different.

⁴² Note, that some firms, for instance Tchibo, use own stores to sell their coffee (see, FEUERSTEIN 2002), which reduces the dependency of roasting firms to retailers. However, the data does not cover sales for these stores, so we are not able to analyze potential price differences at own stores and other retailers.

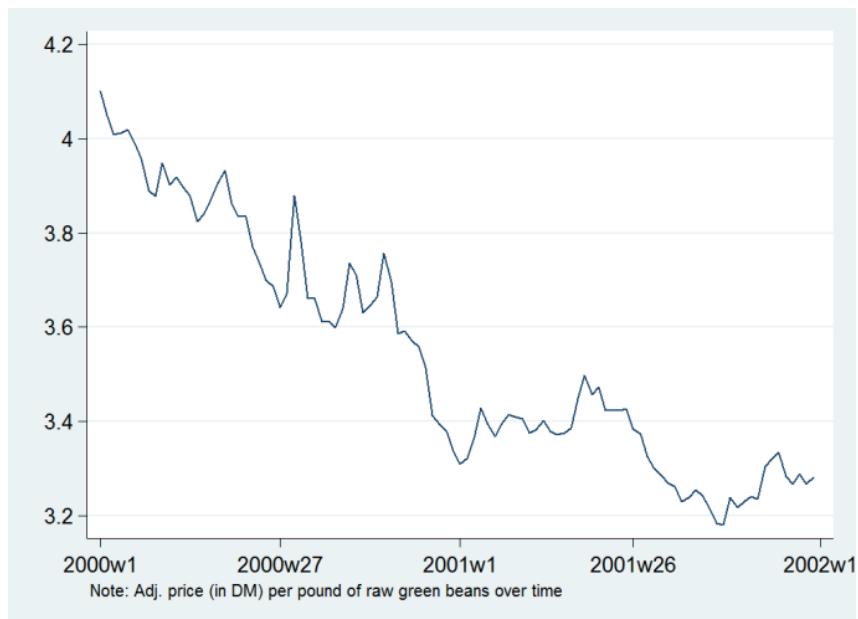
⁴³ Source: ICO (c), online database.

force for driving marginal costs. We follow their argumentation and thus assume that green bean prices approximate producer prices and we abstract from any other potential factors that might influence producer prices.

7.2.2 Data Set and Data Processing

In order to show how producer price changes are passed through to consumer prices, we need to adjust green bean prices carefully. More precisely, we use the composite daily price in cents per pound of raw green beans obtained from the International Coffee Organization (ICO) via Datastream. We then follow DRAGANSKA AND KLAPPER (2007) and adjust this price with the Dollar-Deutsche Mark exchange rate, deduct a 15% loss in volume due to roasting of the raw beans und add the German coffee tax of 2.16 DM per pound.⁴⁴ As can be seen from Figure 1, despite the large fraction of taxes, we observe a substantial decrease in the adjusted price of raw green beans from over DM 4 in the first weeks of 2000 to roughly DM 3.20 in late 2001. So, within two years the approximated producer price is reduced by roughly 20% and the question is to what extent and how rapidly these cost savings were passed through to final consumer prices.

Figure 1: Adjusted price (in DM/pound) of raw green beans



Source: Own representation.

Consumer prices at the UPC-level were collected by the Madakom GmbH on a weekly basis from 2000 to 2001 in 200 retailers located throughout Germany, the world's second largest coffee market (Koerner, 2002). Within this sample, we concentrate on the five biggest key accounts: Edeka,

⁴⁴ Throughout the analysis we keep the notation of Deutsche Mark (DM). Recall, however, that in 2000 and 2001 the exchange rate between DM and Euro was fixed at 1.9558 DM/Euro.

Markant, Metro, Rewe, and Tengelmann.⁴⁵ These key accounts capture about 93% of the sales in our data. Besides Rewe, all these key accounts maintain supermarket and discount stores. Edeka, for instance, has stores named Edeka that represent the supermarket segment. Netto, on the other hand, is the name of Edeka's discounter stores.⁴⁶ On the brand side, we focus on Tchibo, Eduscho, Melitta, Jacobs, Onko, Dallmayr, and Idee. Altogether, these brands account for about 88% of all sales in each key account. As shown by BONNET ET AL. (2011), the interaction of producers or wholesalers and retailers influences the pricing strategies, but this is not the focus of the current paper. Therefore, the producer price for all these brands is identical and is approximated by the adjusted green beans price. Nevertheless, we include brand dummies in our empirical analysis to take into account brand-specific effects on the pass-through rate.

In the following, we restrict our data set to packages of 500gr. With a share of 80.76% of the sales this packaging type is by far the most common one on the German market. It also enables us to focus on ground coffee only, and we have thus not included other products, such as instant coffee or espresso which are sold in smaller packages and differ substantially in terms of prices.

Promotional activities, such as price discounts, are frequently used at the retail level. By the often applied definition of HOSKEN AND REIFFEN (2004) promotional prices are “temporary reductions in retail prices that are unrelated to cost changes”. In other words, we need to define a real or regular price and its deviations in order to exclude promotional prices from the analysis.⁴⁷ We define regular prices as prices not having been altered for four consecutive weeks. Promotional prices are price reductions exceeding 5%. Promotional prices can only last for four weeks, otherwise we define them as long-term price reductions. We obtain our adjusted price series by replacing promotional prices by the regular prices that were valid the week before the item was on sale. Figure 2 provides an example for the product “Onko Naturmild, 500gr” across retailers and formats. Each of the nine graphs represents the price series at a specific store of a key account. For instance, “(1) Edeka DC” in the top left corner stands for one discount store belonging to the key account Edeka. The brighter dashed line shows the original price series including all discounts. The black solid line represents the adjusted “regular” price at a store. We see that promotional activities are seldom used in discount stores in

⁴⁵ Unfortunately, ALDI and Lidl, with 4200 and 2900 stores, respectively, in 2007 the largest discounters in Germany (GfK, 2008), are not included in our data set. We share this shortcoming with all other studies (e.g. BONNET ET AL. 2011 and DRAGANSKA ET AL. 2010). However, this is not a major concern. As ALDI and Lidl generally do not sell branded products but rather own or no-name brands, we would not be able to compare identical products across different key accounts.

⁴⁶ This restriction is important. Price differences across retailers might stem from other factors as well. Models with heterogeneous retailers imply price differences which are based on productivity differences (RAFF AND SCHMITT 2011). Retailers that distribute products more efficiently will have lower costs. Compared to single retailers these efficiency gains are more pronounced for larger retail chains as they invest more in technology (e.g. BASKER 2007 OR FOSTER ET AL. 2006). However, in this study we only consider supermarkets and discounters which are actually part of larger key accounts such as Rewe or Tengelmann and do not include single shop retailers. Thus, the effect of single store retailers does not influence our results.

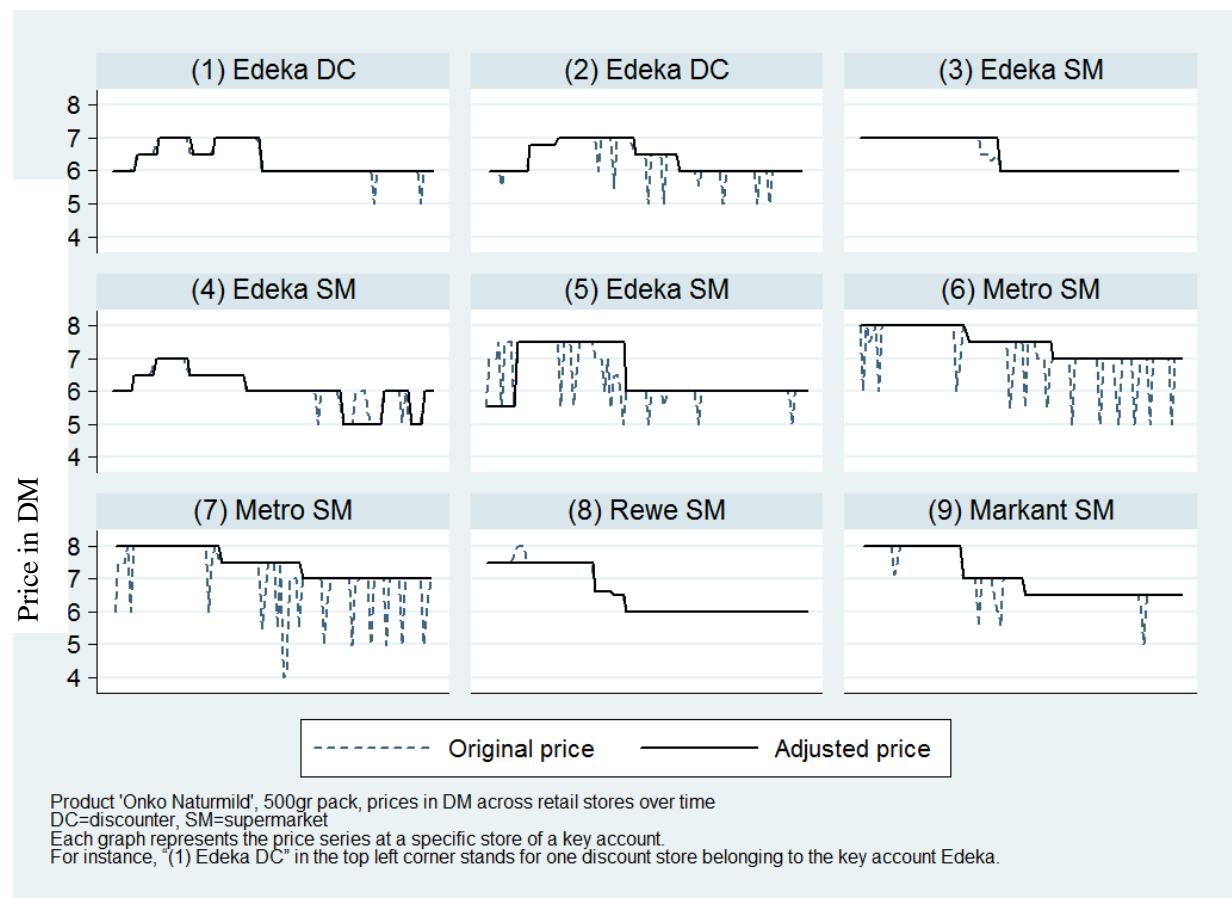
⁴⁷ Retailers might use price discounts strategically in response to a producer price change. We further discuss this aspect in section 4.

contrast to supermarkets. Furthermore, the adjusted prices are relatively stable and do change less frequently. For instance, as we see in the bottom right corner of Figure 2, “(9) Markant SM” a supermarket store of the key account “Markant” changes prices twelve times in the original price series.⁴⁸ If we calculate the regular price this reduces to two adjustments of the regular price. In addition, we observe that promotional price reductions do not need to be uniform across stores of the same retail format of one key account. For instance, “(4) Edeka SM” and “(5) Edeka SM” are both supermarket stores of the key account Edeka. The original price moves almost one to one with the adjusted price in the store represented by “(4) Edeka SM”. By contrast, the original price series shown in the store “(5) Edeka SM” exhibits several price promotions that are filtered out for the adjusted price series. One possible explanation for differences in promotional price reductions and price levels for retail stores of the same format within the same key account might be the geographical region of a retailer. Our data set includes a variable that defines a relatively heterogeneous geographical region.⁴⁹ However, it covers only a small number of retailers within the same region. For instance, about 63% of all observations belong to stores that share a region with two or less other retail stores. Therefore, we do not focus on price differences within one region. In the empirical analysis, however, we account for this and include regional dummies.

⁴⁸ Note, that a promotional price reduction is counted twice as a price change. First, when the price is reduced to its promotional level, and second, when the price switches back to its old price level. Counting promotional price reductions as one price change still results in six price changes in this example.

⁴⁹ That is cities (e.g. Freiburg) as well as districts (e.g. Unterfranken) and federal states (e.g. Thüringen) are included in one variable.

Figure 2: Original and adjusted retail prices for a selection of stores



Source: Own Representation.

7.2.3 Stylized facts of price formation across retail formats

First, we turn to the description of prices observed in the dataset. In order to describe retail prices over time, we distinguish between two major characteristics: current price levels and price movements. Table shows that the average price, the sales area and the number of products sold by discounters are smaller compared to supermarkets. For instance, the discounters operated by Edeka have an average price of DM 7.15 per 500gr package of coffee, sell 25 different UPCs, the average store is equipped with two cash points, and its sales area is 437 m² large. Edeka's supermarkets, on the other hand, charge higher prices, DM 7.80 on average, and with 56 UPCs they offer a broader set of products. In addition, if we calculate the average price for goods excluding sales with promotional prices the gap between prices across retail formats increases. Comparing the average prices with and without promotional prices (columns 3 and 4), we see that discounter prices only slightly increase by DM 0.05 in the case of Edeka in contrast to its supermarkets' prices that are raised by DM 0.21. Overall, supermarkets price their coffee products DM 1.08 higher than discounters and the price gap increases if the promotional prices are excluded.

Table 1: Average prices, sales area, number of cash points, UPCs, stores and observations

chain	format	Average of					Number of	
		all prices	prices	sales	cash	UPCs	stores	obs.
		no PA*	area	points				
Edeka	Discounter	7.15	7.20	437	2.0	25	5	8,851
	Supermarket	7.80	8.01	793	2.8	56	24	73,112
Markant	Discounter	6.15	6.18	250	4.0	9	1	581
	Supermarket	8.09	8.31	807	3.4	51	8	21,967
Metro	Discounter	6.94	7.05	500	2.0	15	1	1,117
	Supermarket	7.76	7.96	1,092	4.2	50	9	28,662
Rewe	Supermarket	7.77	7.83	863	3.3	43	12	30,368
Tengelmann	Discounter	6.59	6.67	587	2.9	21	16	20,403
	Supermarket	8.01	8.20	831	3.3	52	24	58,370
Others	Discounter	7.08	7.10	583	3.0	31	5	7,491
	Supermarket	7.98	8.11	947	3.6	55	14	37,779
<hr/>								
All	Discounter	6.82	6.89	544	2.8	23	28	38,443
	Supermarket	7.90	8.07	867	3.3	52	91	250,258
Average	All retailers	7.75	7.91	791	3.2	45		

*PA = promotional activity

Source: Own Representation.

Table shows the evolution of the average prices and their differences. The producer price of coffee dropped by 18%, from DM 3.97 in the first quarter of 2000 to DM 3.27 in the last quarter of 2001. In the same period, final consumer prices were reduced by less - on average by 3.8 %. The reduction differs substantially across retailers. Discounters generally lowered prices by more. For Tengelmann, for instance, prices in the discounter section dropped on average from DM 6.85 to DM 6.50, implying a decrease by 5.14% relative to 0.72% in its supermarket section, and for Edeka it is 4.65% relative to 3.76%. The last two columns of table 2 indicate that in all key accounts the relative difference between prices paid at supermarkets compared to discounters increased. In the first quarter in 2000 prices at discounters were on average 13.7% lower. In the last quarter of 2001 this gap increased to 15.25%. Besides the producer price, final consumer prices include markups, transportation costs, and additional local cost components such as services. Given a decrease of the producer price, the share of other components in the consumer price rises, pronouncing existing price differences. The observed

7. Pass-through of producer price changes in different retail formats

increasing gap between prices paid at discounters relative to supermarkets thus supports the argument that consumer prices at supermarkets include other cost components to a higher degree compared to discounters.

Table 2: Average prices and relative price differences over time

Consumer Prices							
chain	format	Average price			Relative price difference		
		1. quarter	4. quarter	Δ	discounters vs. supermarkets		
					2000	2001	
Edeka	Discounter	7.42	7.07	-4.65%	-9.05%		-9.90%
	Supermarket	8.15	7.85	-3.76%			
Markant	Discounter	6.22	5.98	-3.85%	-25.38%		-26.85%
	Supermarket	8.33	8.17	-1.91%			
Metro	Discounter	7.71	6.66	-13.66%	-4.16%		-15.38%
	Supermarket	8.04	7.86	-2.20%			
Rewe	Supermarket	7.95	7.60	-4.35%			
Tengelmann	Discounter	6.85	6.50	-5.14%	-17.04%		-20.73%
	Supermarket	8.26	8.20	-0.72%			
Others	Discounter	7.16	6.95	-3.01%	-12.23%		-11.00%
	Supermarket	8.16	7.81	-4.35%			
All		7.04	6.72	-4.54%	-13.71%		-15.25%
		8.16	7.93	-2.80%			
Average		7.87	7.58	-3.78%			
Producer Price							
Adj. price of coffee beans [†]		3.97	3.27	-17.62%			

[†] including tax and adjusted for exchange rates and losses due to roasting

Source: Own Representation.

Besides the actual price level, the frequency of price adjustments is another important channel for price transmissions (GOPINATH AND ITSKHOKI 2010). Table shows that discounters change prices

less often than supermarkets. Here, we calculated the average number of price changes and the duration of a price spell in each store with and without promotional activities. On average Edeka's discounter section has 8.2 price changes per product within the time period of our sample. Its supermarkets exhibit 12.4 price changes. Not surprisingly, if we exclude changes due to promotional activities, the numbers decrease substantially to 2.1 and 2.4, respectively, for Edeka. In other words, if a product was sold in a store in each week within the two years covered by our data, its price has been changed only 2.1 times, slightly more than once a year.⁵⁰ Stores belonging to the discounter section of the key account Tengelmann change prices 2.7 times and thus more often than supermarket stores of the same key account that have a frequency of 1.4. This also holds for Markant but the pattern is reversed for Edeka and Metro. On average across retail formats, discounters change prices less often than supermarkets if we include promotional price changes. Given that supermarkets generally pursue a more distinct HILO pricing strategy, excluding promotional prices results in an almost equal number of price changes across the two retail formats.

⁵⁰ These values generally fit into other studies' findings. NAKAMURA AND STEINSSON (2008) report that excluding promotional activities the duration of consumer prices in the US is in between 8 to 11 months. For France, BAUDRY ET AL. (2004) find average price durations for food of 5 months and prices being less often changed in discounters. The same pattern holds for Italy, with an average price duration of 5 months for unprocessed food goods and larger retailers changing prices more often (Veronese et al., 2005). For Germany, HOFFMANN AND KURZ-KIM (2006) find a much longer duration and large heterogeneity for processed food ranging from 6 to up to 48 months. The discrepancy to our results might be explained in that we focus on one product group only, coffee, while the other studies consider a wider range of goods. The large heterogeneity across goods found by Hoffmann and KURZ-KIM (2006) supports this view.

Table 3: Average number of price changes and duration of price spells per store

		Average number of price changes		Average duration of a price spell		Obs. indicating PA*	
		including PA*		excluding PA*		including PA*	excluding PA*
		total	ratio				
Edeka	Discounter	8.2	2.1	7.7	18.9	300	0.16
	Supermarket	12.4	2.4	4.0	11.5	874	0.29
Markant	Discounter	6.1	2.2	9.1	18.3	49	0.08
	Supermarket	12.0	2.1	4.2	12.9	714	0.25
Metro	Discounter	1.2	0.9	33.8	26.8	340	0.30
	Supermarket	16.3	2.8	3.7	12.5	789	0.24
Rewe	Supermarket	10.0	2.9	5.4	11.9	537	0.20
Tengelmann	Discounter	9.3	2.7	6.0	12.8	313	0.25
	Supermarket	6.9	1.4	5.9	15.6	537	0.22
Others	Discounter	4.5	1.8	9.0	15.8	191	0.13
	Supermarket	10.6	2.2	4.2	11.6	666	0.25
All	Discounter	7.7	2.3	7.0	14.8	280	0.21
	Supermarket	10.7	2.2	4.5	12.6	686	0.25
Average	All retailers	10.4	2.2	4.7	12.9	591	0.24

*PA = promotional activity

Source: Own Representation.

However, the duration of unchanged prices is generally larger for discounter stores, even if price promotions are accounted for. In the case of Edeka it is 18.9 consecutive observations for discounters compared to 11.5 for supermarkets if we exclude price changes due to promotional activities. The last column of Table 3 shows the ratio of all observations indicating any promotional activity per store. We see that promotional activities are intensively used by supermarkets but rather seldom occur for discounters in the key accounts Edeka and Markant. An average store of Edeka's discounter format

has 16% of its observations indicating some promotional activity in contrast to 29% for the average supermarket.⁵¹

Based on the stylized facts presented above, there are two competing hypotheses as to why pass-through rates of producer price changes might be higher or lower in discounters and supermarkets. Table shows that discounters carry fewer products, have smaller sales areas, and fewer cash points. Table 2 and Table indicate that discounters offer lower prices and prices hold for a longer time period. Given a producer price change, two effects emerge. First, supermarkets' higher final consumer prices contain a local cost component such as costs for a larger product assortment range that should reduce the pass-through rate. On the other hand, supermarkets seem to change prices more often, even though we adjusted for promotional price changes, compared to discounters, which try to maintain the same price for a longer time. For the U.S. GOPINATH AND ITSKHOKI (2010) report that the frequency of price adjustment is positively correlated to the pass-through rate. So, this second effect should increase the pass-through rate for supermarkets. Depending on which effect dominates, pass-through rates of producer price changes can be larger or smaller for discounters which we will analyze empirically in the next section.

7.3 Empirical Analysis

In order to empirically determine the pass-through rate of producer price changes into retail prices with respect to the retail formats, we follow the approach outlined in CAMPA AND GOLDBERG (2005): First, we test whether the price series are stationary. Given that the price series are nonstationary, the next step is to test whether a cointegrated relationship exists. If the price series are cointegrated, we adapt the ECM. If the hypothesis of a cointegrated relationship is rejected, we continue estimating a reduced-form approach as motivated in CAMPA AND GOLDBERG (2005) as well as in GOPINATH AND ITSKHOKI (2010). In fact, only half of the retail price series we analyze are cointegrated with the producer price. Whether or not two variables are cointegrated also depends on the time horizon. So one possible reason as to why some retail price series do not show a cointegrated relationship with the producer price can be attributed to the restricted time period of two years in our data set. Therefore, we adopt both approaches in our analysis.

⁵¹ One outlier in Table is Metro's discounter section. Not only is the duration of prices higher than in any other format, it also decreases when we exclude promotional activities. In the data several of its prices are indicated as being sold in combination with a promotional activity although the price remains unchanged. Of these promotional activities, a high percentage is "display" and not price reductions. "Display" is unrelated to price reductions. So this marketing instrument simply shows products at an exposed place to increase sales. Furthermore, although the observations are marked as belonging to the discounter format we are not aware of any discounter in the Metro network. Therefore, we exclude these observations from our empirical analysis.

7.3.1 Error Correction Model

As described in the previous section, we use consumer price data for the German ground coffee sector and approximate producer prices using the adjusted price of raw green beans. We investigate whether the retail format influences the pass-through of price changes of the producer price into the retail prices in two stages: In the first stage, we estimate an ECM to obtain the adjustment coefficients. Second, the estimates of the individual dynamic cost-price adjustment enter an estimated dependent variable regression in which we can test whether retail format influences the adjustment process using dummy variables (HOLM ET AL. 2012). Here, the effect of the specific retail format on the extent of price pass-through is of particular interest.

Fitting an ECM, in turn, involves four steps. First, we evaluate the nonstationarity of the price series. If the price series are integrated of order one ($I(1)$), we can proceed to the second step, which is to estimate the long-run relationship to obtain the residuals. Third, we test whether the residuals are stationary, implying that a cointegrated relationship exists (ENGLE AND GRANGER 1987). Finally, we adapt the ECM. The data set contains 712 different retail price series, thus, the steps one through four have to be repeated 712 times. Out of all retail price series, 47 do not contain any price changes. Consequently, these price series are not $I(1)$. All but four of the remaining retail price series, as well as the producer price series are $I(1)$. A cointegrated relationship exists in 50% of the price series. The non-cointegrated retail price series show only minor or no price changes. Thus, they do not share a cointegrated relationship with the producer price. Finally, the coefficients are estimated using equation (1).⁵² Here, Δp_{jt}^r denotes the first difference of the logarithm of the retail price of retailer r for product j in period t , Δp_t^w is the first difference of the logarithm of the producer price. If no cointegrated relationship exists, equation (1) is estimated without the long-term adjustment ($\lambda_j^r ecm_{t-1}$) (Bahmani-Oskooee and Payesteh, 1993), in order to obtain the contemporaneous price adjustments.

$$\Delta p_{jt}^r = \delta + \lambda_j^r ecm_{j,t-1} + \sum_{i=0}^5 \alpha_{ij}^r \Delta p_{t-i}^w + \varepsilon_{jt}^r \quad (1)$$

Two coefficients are of particular interest, the long-term adaption to distortions of the equilibrium (λ_j^r) and the short term or contemporaneous pass-through rate (α_{ij}^r).⁵³ The short-term reactions α_{ij}^r are predominantly insignificant (94%), indicating that there is almost no significant reaction of retail price changes to changes of the producer price within the same week and four weeks following the change of the producer price. The long-term reaction on the other hand is significant on a 5% significance level in 86% of the cointegrated price series. On average, the estimated λ_j^r from the

⁵² We tested for asymmetric price transmission. Those effects were statistically insignificant.

⁵³ In the reduced-form approach in equation (3) we need to include lagged values of the producer price in order to account for a possible sluggish adjustment of the retail price. We estimated the pass-through rates for 1 up to 11 lags, respectively. As the main part of the adjustment occurred up to the fifth lag we included five lagged values in this regression. To provide comparison, we decided to also include five lags of the producer price in the ECM.

cointegrated price series equals -0.206. In other words, in all following weeks the distortions between the producer and the retail prices are reduced each week by 20.6 %.

Next, we consider whether this long term pass-through rate differs with respect to retail formats. As a long term price adjustment process can only be assessed if a cointegrated relationship exists and equals zero if there is no such relationship, we first analyze whether the existence of a cointegration is influenced by the retail format. As shown in Table 4, out of 582 price series originating from a supermarket, 310 price series are cointegrated with the producer price series. The share of cointegrated price series is higher for the supermarkets than for the discounters.

Table 4: Existence of cointegration by retail format

	Supermarkets	Discounters	Total
Cointegration	310 (53 %)	46 (35 %)	356
No Cointegration	272 (47 %)	84 (65 %)	356
Total	582	130	712

Source: Own Representation.

If no cointegrated relationship can be determined, the long term adoption rate equals zero. Generally, the coefficients for the long term adoption rate are negative, as distortions from the long term equilibrium are reduced in the following weeks. Thus, we adopt a Tobit model with an upper bound at zero to determine whether the retail format significantly influences the pass-through rates. The model can be expressed in terms of the latent, non-observable variable $\lambda_j^{r^*}$ (BAUM 2006):

$$\begin{aligned}
 \lambda_j^{r^*} = & \rho + \theta * \text{Discounter} + \sum_{c=2}^5 \delta_c * \text{key account}_i + \sum_{b=2}^7 \tau_b * \text{Brand}_i \\
 (2) \quad & + \sigma_1 * \text{big city} + \sigma_2 * \text{medium city} \\
 \lambda_j^{r^*} = & \begin{cases} 0 & \text{if } \lambda_j^{r^*} \geq 0 \\ \lambda_j^{r^*} & \text{if } \lambda_j^{r^*} < 0 \end{cases}
 \end{aligned}$$

The parameter of interest in equation (2) is θ . If it is statistically significant it can be concluded that the pass-through process varies across retail formats. To single out this effect from other variables potentially influencing the adjustment process, we include further variables. LEVY ET AL. (1998) analyze the actual workflows of the price pass-through process in different retail chains. The authors find evidence for varying pass-through processes across retailers. Thus, we introduce key account dummies to the model. In addition, we add brand dummies as the different manufacturers might also react differently. In our case with a predominantly decreasing producer price, for example, the retail prices of brands produced by manufacturers holding large inventories might be adjusted to a lesser

extent. Furthermore, we also include dummies for retail stores located in cities exceeding 100,000 inhabitants (“big city”) and in cities with at least 20,000 to 100,000 inhabitants (“medium cities”). Retailers located in areas with less than 20,000 inhabitants (“small cities”) serve as reference category to avoid the dummy variable trap. Here the intuition is that the larger the city, the more retailers are located within a certain area. Thus, the pressure to adjust prices might be higher in these areas.

The results are presented in Table . The negative sign of the coefficient θ suggests that discounters adjust prices to a larger extent than supermarkets. However, the effect is statistically insignificant. The price adjustment process is much more influenced by brands and retail chains. Although we approximate producer prices by the identical adjusted green beans prices, we observe differences across producers. For example, the positive coefficient of the variable for the brand Eduscho indicates that price series of Eduscho UPCs are generally adjusted less than price series stemming from the brand Tchibo. Retail prices of coffee packages of the brand Melitta react most strongly to producer price changes: on average, price series observed from Melitta adjust 6.0% stronger compared to the predicted price adjustment process of Tchibo’s products. The effects of the affiliation to a key account are in general less pronounced compared to the brand effects, only the key account Tengelmann shows a significantly stronger reaction compared with Edeka. Retailers located in urban surroundings adjust their consumer prices significantly less than other retailers.

Table 5: Results of the estimated dependent variable regression

Tobit – Model	
Discounter	-0.016
Base: Tchibo	
Eduscho	0.003
Melitta	-0.060*
Jacobs	0.028*
Onko	0.012
Dallmayr	0.042*
Idee	-0.016
Base: Edeka	
Markant	-0.018
Metro	-0.002
Rewe	-0.013
Tengelmann	-0.030*
Base: Small city	
Big city	0.013*
Medium city	0.023*
Constant	-0.158*
Regional Dummies	Yes
N	712

* $p < 0.05$

Source: Own Representation.

7.3.2 Reduced Form Approach

Only half of the price series are cointegrated, so we complement our analysis employing a reduced-form estimation equation motivated by several other pass-through studies (E.G. CAMPA AND GOLDBERG 2005; GOPINATH AND ITSKHOKI 2010). More precisely, we estimate

$$\Delta p_{jt}^r = \sum_{i=0}^5 \alpha_i \Delta p_{t-i}^w + \sum_{i=0}^5 \beta_i (\Delta p_{t-i}^w * discouter) + \gamma_{discouter} discouter + \gamma' \mathbf{D} + \varepsilon_{jt}^r. \quad (3)$$

Here, Δp_{jt}^r is the first difference of the logarithm of the price of product j at retailer r at time t , Δp_t^w denotes the first difference of the logarithm of the producer price, which is identical across retailers. The dummy variable *discountr* equals 1 if retailer r is classified as a discountr. We add five lags in order to account for a possibly slow adjustment of final consumer prices. We performed unit root tests for all variables.⁵⁴ The producer price is a non-stationary time series. We therefore write our estimation equation in first differences. The total pass-through of producer price changes for a supermarket is, thus, given by $\sum_{i=0}^5 \alpha_i$ and for a discountr it amounts to $\sum_{i=0}^5 (\alpha_i + \beta_i)$. If $\sum \beta_i > 0$, then the pass-through rate is larger for discountrs. As in the previous section additional control variables are regional dummies, retailer and brand fixed effects and a dummy variable for the location of a store in cities exceeding 100,000 inhabitants. These variables are included in the vector \mathbf{D} , and ε_{jt}^r represents the error term. Store, key account, and brand fixed effects control for time invariant characteristics such as the location of a store or different pricing strategies for a key account or brand. Brand-key account fixed effects take into account specific arrangements or differences in market power in price negotiations between a brand producer and a specific key account. As illustrated in the example in Figure 2 above, the weekly scanner data for the time period under observation does not show any obvious sign of a seasonal pattern. However, there might be an impact of some weeks due to holidays or other time specific influences, but these should most reasonably be considered as uniform across products. So we decided to include weekly dummies in our regression and do not seasonally adjust each price series

Table summarizes our results. In the first two columns we exclude the interaction term in order to calculate an average pass-through rate across all retailers. The remaining specifications differ with respect to whether we include additional fixed effects (3 and 4), cluster the error terms by key account (5) or by key account and its specific format (6) or if we use different estimators (7 and 8). The rows “All” and “Supermarket” then show the cumulative effect of the α_i 's, the row “Discountr” gives the cumulative effect of the α_i 's and β_i 's. The respective columns below provide the result of an F-test of the joint significance of the coefficients.⁵⁵

Column 2 shows, that for all retailers together the pass-through of producer price changes to final consumer prices is incomplete and the sum of the α_i 's amounts to 0.25. In other words, a 10% decrease of the producer price leads to a corresponding decrease of the consumer price of 2.5%, implying a pass-through rate of 25%. The F-test shows that these coefficients are jointly significantly different from zero. If we distinguish retail formats, we see in column 3 that supermarkets pass-through 23% compared to 37% for discountrs. The sum of the β_i 's amounts to about 0.14 and

⁵⁴ Results are presented in the Appendix in Table A1 and A2.

⁵⁵ More detailed results on the respective coefficients are presented in Table A3.

captures the influence from the interaction of the producer price and the retailer being a discounter. Thus, discount retailers pass-through a significantly larger amount of producer price changes to their final consumer prices. Changing the estimator, clustering the error term, adding more fixed effects to capture brand or store specific effects does not alter the coefficients. The fixed effects for the key accounts and brands do not show any consistent differences across key accounts or brands and neither does the dummy variable for cities exceeding 100,000 inhabitants.

Table 6: Pass-through estimation by retail format

	1	2	3	4	5	6	7	8
Dependent variable	Δp_t^r							
Observations	55,437	55,437	55,437	55,437	55,437	55,437	55,437	55,437
Adj. R2	0.002	0.015	0.016	0.016	0.016	0.016	0.016	0.018
F-Statistic	3.42	7.23	7.49	6.55				
Root MSE	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
All	0.125*	0.254*						
All: Prob > F	0.000	0.000						
Supermarket ($\sum \alpha_i$)			0.226*	0.227*	0.227	0.227	0.225	0.226*
SM: Prob > F			0.000	0.000	0.060	0.051	0.051	0.019
Discounter ($\sum \alpha_i + \beta_i$)			0.374*	0.374*	0.374*	0.374*	0.374*	0.374*
DC: Prob > F			0.000	0.000	0.009	0.002	0.002	0.000
F-Test interactions (joined)			13.1	13.1	13.2	173.2	169.0	1038.2
Prob > F			0.000	0.000	0.014	0.000	0.000	0.000
Number of groups						712	712	

Included:

regional dummies	yes	yes	yes	yes	yes	yes	yes	yes
weekly dummies		yes	yes	yes	yes	yes	yes	yes
key account FE		yes	yes	yes	yes	yes		yes
brand FE		yes	yes	yes	yes	yes		yes
store FE		yes	yes	yes	yes	yes		yes
key account-brand FE				yes	yes	yes		
clustered					yes [#]	yes'	yes'	yes'
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	FE	RE

[#]clustered by key account

'clustered by key account and its specific format (discounter and supermarket)

* $p < 0.05$, SM = Supermarket, DC = Discounter**Source:** Own Representation.

We also performed several other robustness checks. The results are presented in the Appendix in Table A4. In particular, the magnitude of our results seems to be sensitive to the seasonal adjustment method applied. If we seasonally adjust each price series separately with weekly time dummies (column 1), we do not measure a significant pass-through rate for discounters. Nevertheless, their point estimate is still

larger compared with supermarkets. On the other hand, if we do not seasonally adjust at all (column 2), the pass-through rate of the discounters is significantly larger again and amounts to about 24%. As pointed out before, though, the individual price series do not show a seasonal pattern, so we decided to include weekly dummies to capture seasonal influences. Adding a full set of monthly time dummies (column 3) increases the magnitude of pass-through rates to 33% for supermarkets and 47% for discounters but does not affect the ranking. Incorporating a lagged value of the dependent variable (column 4) leaves our results unaltered. If we exclude all price series that do not have any price change within our time period (column 5 thus excludes 47 out of the total of 712 price series), the results again remain almost unchanged: discounters still pass-through a higher percentage than supermarkets. We also checked whether our adjustment of the coffee price affects the results (column 6). While the magnitude of the pass-through rate seems to be sensitive to this adjustment, the ranking is not. In our final check, we perform the regression in levels and include a lagged value of the dependent variable to correct for autocorrelation in the error terms (column 7). We obtain the same picture: Supermarket prices react less to changes in the producer price compared to discounters.

7.4 Discussion

Our results are generally in line with previous studies on the pass-through of producer price changes but underline how important it is to account for retail formats. BONNET ET AL. (2011) point out that the relationship between producers and retailers matters. Using the identical data set we show that a distinction between retail formats also significantly affects the pass-through rates. BRODA ET AL. (2009) demonstrate that about one third of the price differences between low- and high-income households are explained by the choice of the store. High-income households prefer stores with a nicer ambiance and service levels that charge higher prices. In Germany, households with a relatively low income purchase relatively more at discount retailers (GFK 2008). Our data covers a period of price decreases. Periods of increasing producer prices, however, would reduce the price differences between different income groups due to the higher pass-through rate for discounters.

In this paper, we analyze the effect of producer price changes for ground coffee. However, the implications of our study go beyond that and are important for measuring the magnitude of other imported goods' prices on domestic consumer prices, too. As mentioned in the introduction, from the second quarter in 2011 to the first quarter 2012 the price of cocoa decreased by about 34%. Sugar prices first increased in the first quarter 2011 by 15% and then dropped by 23% in the first quarter of 2012.⁵⁶ Retail format specific pass-through rates thus reveal that these price changes are transmitted to consumer prices to a significantly higher degree if the share of discounters is larger in a market.

⁵⁶ Sources: International Coffee Organization, International Cocoa Organization and Public Ledger via Datastream.

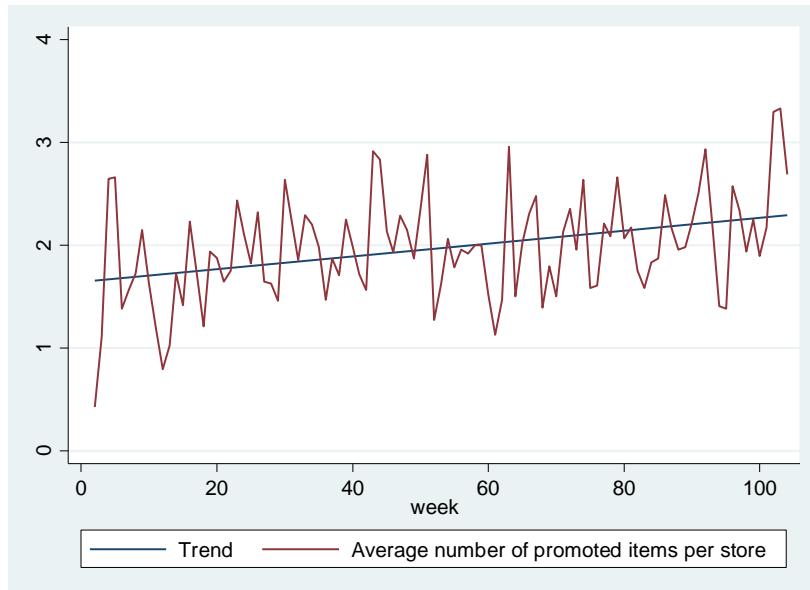
The concept of discount retailers originates from Germany, for that reason we chose this market for the empirical study. In many countries, however, discounters are only starting to expand their activities and the consequences of a larger discounter presence will become visible. For instance, in October 2005 ALDI opened its first affiliate in Switzerland. A recent study by the Swiss Institute for Retail Management (WEBER AND RUDOLPH 2011) exhibits that within three years the percentage of managers expecting intensified price competition rose from 59% in 2008 to 89% in 2011. Based on our findings of increased price pass-through by discount stores, increased price competition can be expected if more discount stores enter the market. Furthermore, the distinction between retail formats in empirical analyses should be carefully considered in markets in which discounters intensify their activity.

The degree of competition among supermarkets and discounters is part of a lively debate among researchers (CLEEREN ET AL. 2010). While we do not directly consider competition among retailers, we do observe that the frequency of price adjustment as one implication of competition differs across retail formats. Discounters pursue a strategy of rarely using promotional activities such as price discounts compared to supermarkets. Instead, they try to maintain lower prices and hold prices constant for a longer time. Consequently, one potential limitation of our findings is that we excluded promotional prices because in the literature on price promotions, these are defined as being unrelated to cost changes (HOSKEN AND REIFFEN 2004). However, it could be the case that supermarkets, which generally pursue a HILO pricing strategy in Germany, use price promotions strategically to react to producer price changes. Translated to our setting of falling producer prices that could imply that supermarkets might have reacted to the falling producer price by promoting ground coffee products more frequently or offering higher discounts and thus lowering their average price.

Figure 3 depicts the average number of promoted items per week and supermarket. On average, a supermarket in our sample carries 16 distinct ground coffee products and promotes averaged over both years each week 2.33 items. Figure 3 shows that the average number of items on sale varies over time. The promotional frequency increases slightly and comparing the two years under study shows that in 2001 on average 2.49 items were on sale and in 2000 only 2.16. Thus, the promotional frequency increased by 0.33 items per week. Or expressed differently, in 2001 each retailer offered an additional sale on one out of 16 items every three weeks compared to 2000. Figure 4 shows that also the average promotional discount increased over time and was particularly high in weeks 40 to 60, when producer prices decreased significantly. Overall, the average promotional discount in the supermarket equals 16.2%. In 2000 it is 15.2% comparing to 17.2% in 2001. It becomes evident that supermarkets also elevated the average discount by 2%. Carrying out a paired t-test for the weekly average number of promotions and the respective average discounts shows that both are significantly higher in 2001 compared to 2000 (p -value < 0.001). Both effects taken together, supermarkets decreased their overall average prices by intensified promotional activity. The question is whether the increased promotional

activity can compensate for lower price adjustments of falling producer prices. Again comparing 2000 and 2001, a rough calculation shows that considering the increased promotional activity in 2001 leads to a pass-through rate of 32% instead of 25%.⁵⁷ This is still considerably smaller compared to the pass-through rate of the discount retailers (37%), but provides some evidence that retailers use price promotions strategically.

Figure 3: Average number of price promotions per week and supermarket 2000-2001

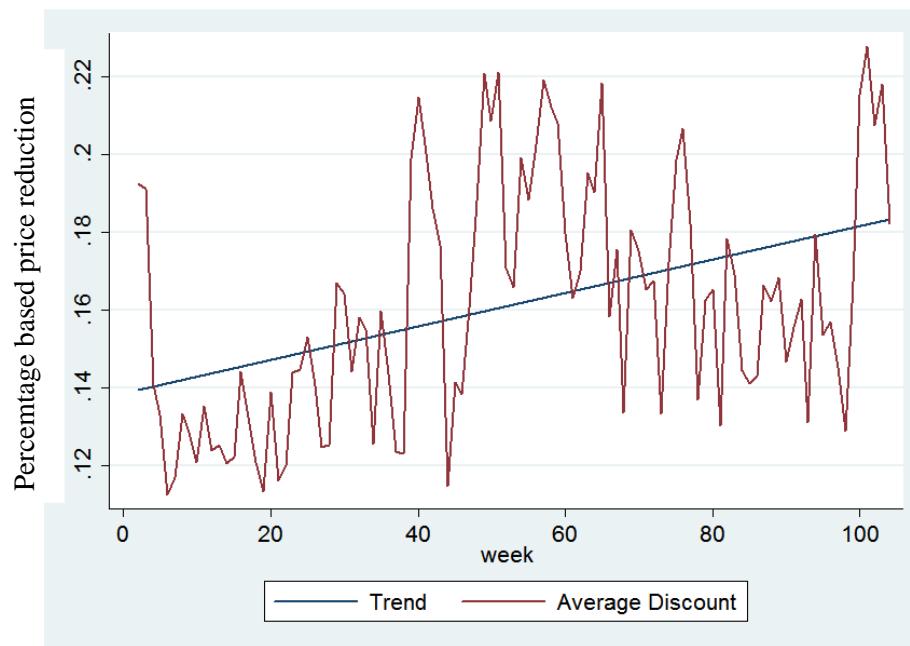


Source: Own Representation.

However, supermarkets and discounters offer a large variety of products and the promotional pricing strategy for one product is not independent of other products' prices. That is, price discounts on coffee products do not need to be correlated to producer price changes. Instead, they might be used as a loss leader to generally attract customers to a retail store (HOSKEN AND REIFFEN 2004). Since our data set only covers coffee products, we are not able to observe the full promotional pricing strategy of a retailer. Therefore, we decided to follow the literature and considered the regular price of products in our main analysis.

⁵⁷ The average regular price for 500gr coffee is DM 7.93 in 2000 and DM 7.67 in 2001, and thus falls by 3%. The producer price for coffee decreased by 12%, which implies a pass-through rate of approximately 25%. An additional discount of 2% in 2001 relates to an additional nominal discount of DM 0.15. This discount is on average additionally applied to 2.49 out of 16 items, thus the average price decreased by DM 0.02. Thus, also considering the increased promotional activity, the average price was DM 7.65 in 2001. Calculating the percentage decrease from 2000 to 2001 leads to a pass-through rate of 32%.

Figure 4: Average promotional discount per week and supermarket in 2000 and 2001



Source: Own Representation.

7.5 Conclusion

The current paper studies the pass-through of producer price changes into consumer prices at the product-store level and explicitly distinguishes discount and supermarket retail formats. While the literature on retail competition starts to analyze the impact of these specific retail formats, pass-through studies generally have neglected this aspect. We demonstrate that the differences in the two retail strategies are reflected in lower average prices, a longer duration of price spells and less frequent price changes for discounters. Estimating a reduced-form pass-through model we find that discounters pass-through 37% of producer price changes, a rate significantly higher compared to supermarkets' 23%. We attribute the difference in pass-through rates to additional service costs. These are part of the final consumer prices and are much higher in the case of supermarkets. In addition, service costs provide one explanation as to why local costs components affect pass-through rates. This result is only partly obtained in the ECM model, presumably due to the fact that for approximately half of the retail price series, no cointegrated relationship exists. In the estimated dependent variable regression, we find that discounters pass through price changes to a larger extent than supermarkets. In this model, however, the effect is not statistically significant.

Our study provides further evidence that consumer price reactions to an identical producer price change differ across retailers. Pass-through studies using more aggregated data are not able to capture these differences across retail formats. Furthermore, as has been shown in other surveys, households

differing in income do not purchase their goods with the same intensity across stores (GFK 2008; BRODA ET AL. 2009). Retail discounters are much more frequently visited by lower income households. This, in turn, implies that pass-through rates are higher for households purchasing more intensively at discount retailers. That is, in times of producer price decreases they benefit relatively more but the contrary may hold for periods of price increases. This intensifies existing price differences and needs to be taken into account when measuring price differences and inequality. Finally, we present evidence that the frequency of price adjustments differs across retail formats. In the food retail sector, price rigidities depend on the retail strategy. Prices at discount retailers are more rigid compared to prices at supermarket retailers.

We chose ground coffee to be able to directly compare our results to previous studies on pass-through using the same dataset that did not account for retail formats. However, RICHARDS ET AL. (2010) argue that the level of pass-through of input cost changes depends upon the level of product differentiation. The higher the degree of differentiation is the lower is the expected degree of pass-through. Thus, a natural step for future research would be to validate our results for additional product categories.

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Appendix

A1. Unit root test

We tested the adjusted price series for coffee for the existence of a unit root using the Dickey-Fuller test. We included three lags and a trend and Table A 1 indicates that the null hypothesis of non-stationarity cannot be rejected. The retail price series were tested with Fisher's unit root test for unbalanced panels. In this case, the null-hypothesis is non-stationarity for all series which clearly is rejected as shown in Table A 2. Due to the non-stationarity of the coffee price series we generally apply first differences of the variables in our regressions.

Table A 1. Unit root test

Variable	no. of lags*	test statistic	cr. values			order of integration
			1%	5%	10%	
Adj. coffee price	3	-2.20	-4.04	-3.45	-3.15	I(1)

*according to information criteria in Stata

Source: Own Estimations.

Table A 2. Panel unit root test

Variable	ADF-Test		Phillips-Perron		order of integration
	p-value	Inv. Chi-squared	p-value	Inv. Chi-squared	
Retail price*	0.00	3332	0.00	3288	I(0)

*Number of panels: 712

Source: Own Estimations.

A3. Additional regression results

	1	2	3	4	5	6	7	8
Dependent variable:	Δp_t^r							
Δp_t^w	0.060*	0.02	0.026	0.026	0.026	0.026	0.027	0.026
	(0.009)	(0.013)	(0.014)	(0.014)	(0.026)	(0.026)	(0.026)	(0.026)
Δp_{t-1}^w	0.013	0.077*	0.092*	0.093*	0.093*	0.093*	0.092*	0.092*
	(0.009)	(0.014)	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)	(0.014)
Δp_{t-2}^w	0.060*	0.066*	0.043*	0.043*	0.043	0.043*	0.043*	0.043*
	(0.009)	(0.015)	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)	(0.014)
Δp_{t-3}^w	0.000	0.040*	0.048*	0.048*	0.048	0.048	0.048	0.048
	(0.009)	(0.014)	(0.015)	(0.015)	(0.035)	(0.037)	(0.037)	(0.037)
Δp_{t-4}^w	0.022*	0.061*	0.050*	0.050*	0.05	0.05	0.05	0.05
	(0.009)	(0.014)	(0.014)	(0.014)	(0.036)	(0.031)	(0.031)	(0.031)
Δp_{t-5}^w	-0.030*	-0.011	-0.034*	-0.034*	-0.034	-0.034	-0.035	-0.034
	(0.009)	(0.013)	(0.014)	(0.014)	(0.067)	(0.062)	(0.062)	(0.063)
$\Delta p_t^w * discouter$			-0.031	-0.031	-0.031	-0.031	-0.031	-0.031
			(0.023)	(0.023)	(0.046)	(0.040)	(0.040)	(0.040)
$\Delta p_{t-1}^w * discouter$			-0.075*	-0.075*	-0.075*	-0.075*	-0.075*	-0.075*
			(0.022)	(0.022)	(0.022)	(0.030)	(0.030)	(0.031)
$\Delta p_{t-2}^w * discouter$			0.112*	0.111*	0.111	0.111	0.112	0.112
			(0.023)	(0.023)	(0.070)	(0.064)	(0.064)	(0.064)
$\Delta p_{t-3}^w * discouter$			-0.041	-0.041	-0.041	-0.041	-0.041	-0.041
			(0.023)	(0.023)	(0.044)	(0.048)	(0.048)	(0.048)
$\Delta p_{t-4}^w * discouter$			0.061*	0.061*	0.061	0.061	0.062	0.061
			(0.022)	(0.022)	(0.068)	(0.075)	(0.075)	(0.075)
$\Delta p_{t-5}^w * discouter$			0.121*	0.121*	0.121*	0.121*	0.122*	0.121*
			(0.023)	(0.023)	(0.031)	(0.031)	(0.031)	(0.031)
Observations	55,437	55,437	55,437	55,437	55,437	55,437	55,437	55,437,000
Adj. R2	0.002	0.015	0.016	0.016	0.016	0.016	0.016	0.018
F-Statistic	3.42	7.23	7.49	6.55				
Root MSE	0.024	0.024	0.024	0.024	0.024	0.024	0.024	
All	0.125	0.254						
All: Prob > F	0.000	0.000						
Supermarket ($\sum \alpha_i$)			0.226	0.227	0.227	0.227	0.225	0.226
SM: Prob > F			0.000	0.000	0.060	0.051	0.051	0.019
Discouter ($\sum \alpha_i + \beta_i$)			0.374	0.374	0.374	0.374	0.374	0.374
DC: Prob > F			0.000	0.000	0.009	0.002	0.002	0.000
F-Test interactions (joined)			13.10	13.08	13.24	173.20	169.00	1038.22
Prob > F			0.000	0.000	0.014	0.000	0.000	0.000
Number of groups							712	712

A3. Additional regression results (continued)

	Included:							
	yes	yes	yes	yes	yes	yes	yes	yes
regional dummies								
weekly dummies		yes	yes	yes	yes	yes	yes	yes
key account FE		yes	yes	yes	yes	yes		yes
brand FE		yes	yes	yes	yes	yes		yes
store FE		yes	yes	yes	yes	yes		yes
key account-brand FE				yes	yes	yes		
clustered					yes#	yes'	yes'	yes'
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	FE	RE

#clustered by key account

'clustered by key account and its specific format (discounter and supermarket)

* $p < 0.05$, SM = Supermarket, DC = Discounter

Source: Own Estimations.

A 4. Pass-through estimates: robustness checks

	1	2	3	4	5	6	7
Variation:	Each price series seas. adj.	No seas. adj.	Add monthly time dummies	Include Δp_{t-1}^r	Drop price series w/o changes	Unadj. Coffee price	Levels and p_{t-1}^r
Dependent variabel			Δp_t^r				p_t^r
Observations	55,437	55,437	55,437	55,437	51,625	55,437	57,685
Adj. R2	0.002	0.002	0.020	0.016	0.017	0.016	0.968
Root MSE	0.021	0.024	0.024	0.024	0.025	0.024	0.025
Supermarket	0.130*	0.096	0.326*	0.227	0.244*	0.093*	0.024*
SM: Prob > F	0.002	0.174	0.018	0.051	0.046	0.047	0.001
Discounter	0.158	0.226*	0.474*	0.374*	0.387*	0.137*	0.033*
DC: Prob > F	0.130	0.000	0.014	0.002	0.002	0.001	0.000
Interactions							
F-Test (joined)	125.0	57.7	74.9	172.5	201.9	247.5	1031
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Included:							
regional dummies	yes	yes	yes	yes	yes	yes	yes
weekly dummies			yes	yes	yes	yes	yes
key account FE	yes	yes	yes	yes	yes	yes	yes
brand FE	yes	yes	yes	yes	yes	yes	yes
store FE	yes	yes	yes	yes	yes	yes	yes
key account-brand FE	yes	yes	yes	yes	yes	yes	yes
clustered	yes'	yes'	yes'	yes'	yes'	yes'	yes'
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS

'clustered by key account and its specific format (discounter and supermarket)

* $p < 0.05$, SM = Supermarket, DC = Discounter

Source: Own Estimations.

Chapter 8

Mixed Logit Models

8.1 Introduction

Mixed logit models belong to the class of discrete choice models that analyze which variables systemically influence a choice. One major strength of mixed logit models is that they can approximate any random utility model and are, thus, well embedded into economic theory (MCFADDEN AND TRAIN 2000). With the rise of appropriate simulation techniques and their implementation into software packages, mixed logit models became increasingly popular in the mid-1990s. In early 2000, HENSHER AND GREENE (2003) even state that mixed logit models are “*the most promising state of the art discrete choice model currently available*”; this statement has recently been reconfirmed by HOLE AND KOLSTAD (2012). The main difference between mixed logit models and standard logit models is that the researcher may specify a distribution according to which preferences are distributed over the population. For example, the degree of price sensitivity⁵⁸ can be assumed to follow a normal distribution. Then, the researcher estimates the parameters of the distribution, as e.g. the mean and the standard deviation of the price sensitivity, instead of obtaining a point estimate. Furthermore, the mixed logit approach overcomes two additional limitations of standard logit models: Firstly, mixed logit models do not impose any restrictions on the substitution patterns. This is particularly important if the alternatives show varying degrees of similarity. Then, the assumption of independence of irrelevant alternatives (IIA)⁵⁹, which is empirically often

⁵⁸ In this context, price sensitivity is defined as the influence of the price on the purchase decision.

⁵⁹ The IIA assumption fixes the substitution patterns. The standard example where the IIA assumption is inappropriate is known as the “red bus-blue bus problem”: A discrete choice model of transportation choice is

rejected, has not to be imposed. Secondly, the unobserved factors can be correlated over time (TRAIN 2009) that becomes important whenever repeated choices of the same individual are analyzed.

Mixed logit models can be applied for a wide range of research questions and data sources. In chapter 2 of this dissertation, consumer scanner data are used to obtain information about the level of brand loyalty of the consumers. Thus, in this methodological contribution the focus lies on the application of the mixed logit models to describe the households' brand loyalty. Furthermore, mixed logit models can also be applied with retail scanner data sets. Using retail scanner data, aggregated demand models can be estimated using the mixed logit technique ("BLP-Model", see BERRY ET AL. 1995). In fact, mixed logit models are the "*workhorse of demand estimations*" (RICHARDS ET AL. 2012). Additionally, several applications include choice experiments in which the participants stated which alternative they would prefer given the information at hand (e.g. GREBITUS ET AL. 2013; HOLE AND KOLSTAD 2012; MENAPACE ET AL. 2011).

This methodological chapter is structured as follows: First, the theoretical background is presented. Afterwards, a basic choice model, a logit model, is presented in order to highlight the advancements of the mixed logit approach against the standard logit model in the following chapter. Finally, it will be shown how the methodology can be applied to estimate brand loyalty using consumer scanner data.

8.2 Random Utility Models

The basis of discrete choice models is the assumption of utility maximizing behavior. All decision makers are assumed to choose the alternative that provides the maximum level of utility. Random choice models add the assumption that individual choice behavior is intrinsically probabilistic and can be formalized as follows (TRAIN 2009):

The decision maker n can choose among a set of alternatives J . Each alternative is associated with a distinct level of utility U_{nj} with $j=1, \dots, J$. Now, the decision maker chooses the alternative with the highest level of utility. The researcher observes only the attributes of the alternatives, the attributes of the decision maker and the final choice. It is important to note

estimated for a red bus and a car. Then, a blue bus is introduced that is functionally like the red bus (identical route, timing and pricing). If IIA is assumed, the model predicts that an identical share of car drivers and red bus users will switch to the blue bus while in reality, the introduction of the blue bus will attract relatively more bus takers than former car drivers. The IIA assumption is a rather strong assumption and is often empirically rejected.

that the decision maker is aware of all his levels of utility for all alternatives while the researcher generally only observes the outcome and thus only knows which alternative provides the maximum level of utility for the decision maker. Thus, the behavioral model for the decision maker is: choose i if and only if $U_{ni} > U_{nj}$ for all $j \neq i$. Furthermore, the utility is decomposed into two parts: a deterministic (explainable) component V_{nj} and a random (unexplainable) component ε_{nj} . Thus, the following equation holds:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad (1)$$

The characteristics of the unexplained part ε_{nj} depend upon the researcher's specification of V_{nj} . As the researcher does not know ε_{nj} , this term is treated as random. Its joint density vector $\varepsilon_n = (\varepsilon_{n1}, \dots, \varepsilon_{nj})$ is labeled as $f(\varepsilon_{nj})$. Now, the researcher is able to make probabilistic statements regarding the decision maker's choice (TRAIN 2009):

$$P_{ni} = Prob(U_{ni} > U_{nj} \text{ for all } i \neq j) \quad (2)$$

Equation 2 expresses that the probability that decision maker n chooses alternative i equals the probability that alternative i causes the highest utility among all alternatives j for decision maker n . Consequently, using equation 1, the sum of observed and unobserved components of the utility have to be the highest among all alternatives:

$$= Prob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \text{ for all } i \neq j) \quad (3)$$

In equation 4, the terms are rearranged: if the difference between the random terms $\varepsilon_{nj} - \varepsilon_{ni}$ is smaller than the difference of the observed utility components $V_{nj} - V_{ni}$, the decision maker chooses i .

$$= Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \text{ for all } i \neq j) \quad (4)$$

As the probability is a cumulative distribution, equation 4 can be rewritten to equation 5, in which $I(\cdot)$ is an indicator function that equals 1 whenever the expression in the parentheses holds:

$$= \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \text{ for all } i \neq j) f(\varepsilon_n) d\varepsilon_n \quad (5)$$

Thus, equation 5 is an integral with several dimensions over the density of the unobserved component of the utility (compare TRAIN 2009, p. 19). Now, the different choice models as for example the logit, probit or mixed logit models are derived from varying assumptions concerning the distribution of the unobserved portion of the utility. Not all the potential

distributions of $f(\cdot)$ take closed form solution for the integral. If it is assumed that the unobserved part of the utility follows the iid extreme value distribution, the model is called a logit model. The probit model builds upon the assumption that $f(\cdot)$ follows a multivariate normal distribution. In mixed logit models it is assumed that the unobserved portion of the utility follows two different distributions: one part is a iid extreme value distribution, the other part can be specified by the researcher (TRAIN 2009).

8.3 Logit Models

Logit models are the most popular choice models (TRAIN 2009) primarily because of two reasons: Firstly, the integral in equation 5 takes a closed form solution and can thus be calculated without simulation. Consequently, the estimation process is not very computer-intensive. Secondly, the results of the logit model are easier to interpret compared to other choice models.

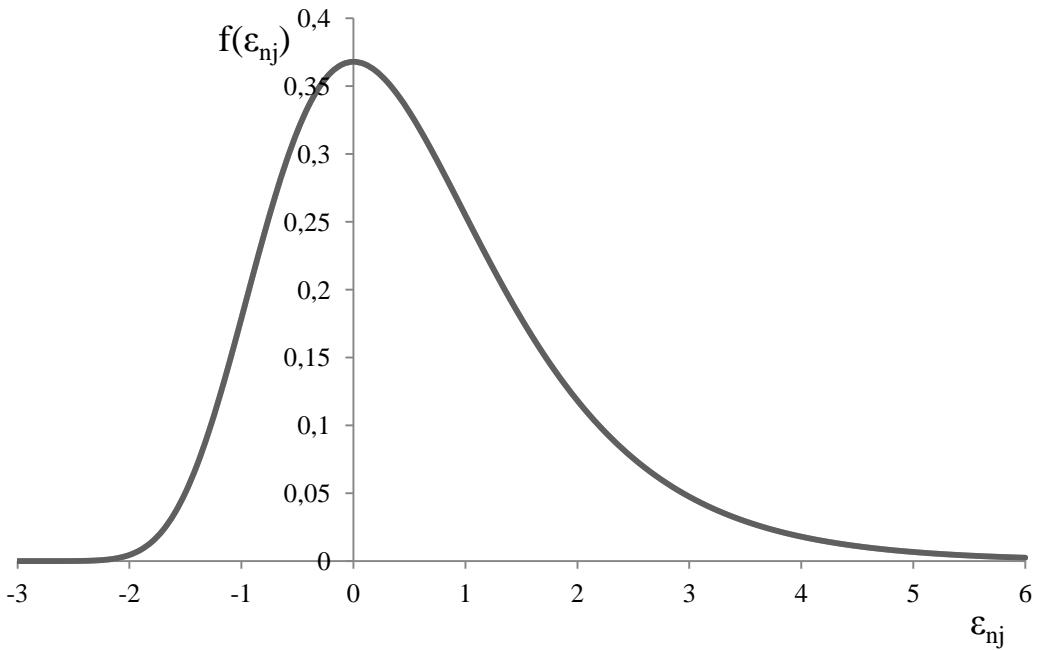
As proven in MCFADDEN (1973), the logit model is obtained by assuming that the distribution of the unobserved utility in equation 5 follows an extreme value distribution⁶⁰. This distribution is characterized by the density function presented in equation 6 and the cumulative density function in equation 7.

$$f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} \quad (6)$$

$$F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}}. \quad (7)$$

A visual characterization of an exemplary extreme value distribution is represented in figure 1. The variance of the distribution is $\pi^2/6$. The mean of this distribution is not necessarily zero. Unlike the normal distribution, the extreme value distribution is slightly positively skewed. Moreover, the tails are “fatter” compared to a normal distribution. However, the extreme value and the normal distribution are often empirically indistinguishable (TRAIN 2009).

⁶⁰ The extreme value distribution is also called Gumbel distribution or type I extreme value distribution.

Figure 1: density function of the extreme value distribution

Source: Own representation.

The major advantage of this distribution is that the difference between two random variables ε_{nj} and ε_{ni} that are distributed according to the extreme value distribution follows a logistic distribution (compare equation 8 and 9).

$$\varepsilon_{nij}^* = \varepsilon_{nj} - \varepsilon_{ni} \quad (8)$$

$$F(\varepsilon_{nij}^*) = \frac{e^{\varepsilon_{nij}^*}}{1+e^{\varepsilon_{nij}^*}} \quad (9)$$

This relationship between the extreme value and the logistic distribution becomes important for the derivation of the logit choice probabilities. Rearranging equation 4 results in the following expression:

$$P_{ni} = \text{Prob}(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj}) \text{ for all } i \neq j \quad (10)$$

Taking ε_{ni} as given, equation 10 becomes the cumulative distribution for each ε_{nj} evaluated at $\varepsilon_{ni} + V_{ni} - V_{nj}$ (compare equation 7). As all the unobserved parts of the utility are assumed to be distributed independently, the cumulative distribution for all $i \neq j$ becomes the product of the individual cumulative distributions:

$$P_{ni|\varepsilon_{ni}} = \prod_{i \neq j} e^{-e^{(\varepsilon_{ni} + v_{ni} - v_{nj})}} \quad (11)$$

In equation 11 it is assumed that ε_{ni} is given to simplify the derivation of the final choice probabilities. However, ε_{ni} is unknown and the researcher only knows that it follows the extreme value distribution. Consequently, the choice probability becomes the integral over all potential values of ε_{ni} each weighted with its density. Thus, in equation 12 the product of all individual cumulative distributions is multiplied by the density of the extreme value distribution and integrated over the unobserved part of the utility:

$$P_{ni} = \int (\prod_{i \neq j} e^{-e^{(\varepsilon_{ni} + v_{ni} - v_{nj})}}) e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} d\varepsilon_{ni} \quad (12)$$

The main reason that the logit model became so popular is that the integral in equation 12 has a closed form solution. Using basic algebra transformation⁶¹, equation 12 can be transformed to equation 13:

$$P_{ni} = \frac{e^{v_{ni}}}{\sum_j e^{v_{nj}}} \quad (13)$$

Now, the representative observed part of the utility is assumed to be linear in parameters:

$$v_{nj} = \beta' x_{nj}. \quad (14)$$

The vector β represents the coefficients to be estimated and x_{nj} is a vector of variables describing the alternatives j . Then, the logit choice probabilities are:

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \quad (15)$$

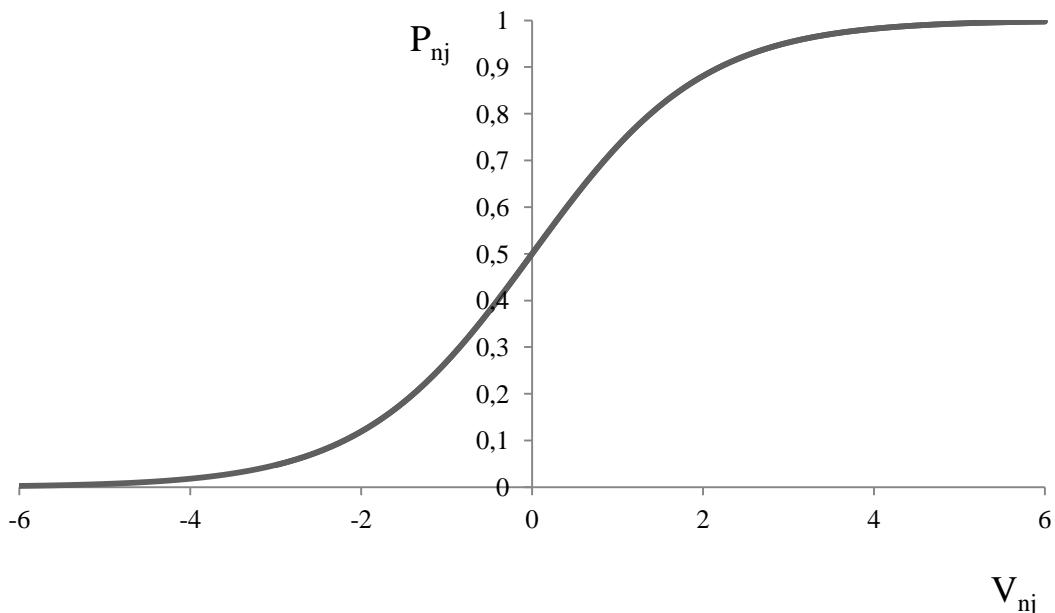
Logit models are solved using the maximum likelihood technique.⁶² The standard logistic function is depicted in figure 2. It shows several interesting properties (TRAIN 2009). First of all, it is bound between 0 and 1, which is well suited for estimating probabilities. Secondly, it never becomes exactly 0. Consequently each alternative has some probability of being chosen. If an alternative is assumed to have a probability of 0 of being chosen it has to be excluded from the set of alternatives. Thirdly, the probabilities of all alternatives add up to 1. Fourthly, the curve is S-shaped. Thus, marginal changes in the observed part of the utility lead

⁶¹ The interested reader is deferred to TRAIN (2009), chapter 3.10.

⁶² A detailed description of the derivation of the maximum likelihood function and its optimization is presented in GREENE (2002 p. 670-673).

to varying marginal effects on the probability of being chosen. This aspect is of great importance for the interpretation of the estimated coefficients.

Figure 2: Standard logistic function



Source: Own representation.

Following TRAIN (2009, p. 46), there are three major limitations of logit models that cannot be modeled: random taste variation, flexible substitution patterns and correlation of unobserved factors over time.

A logit model is able to account for variation in tastes as long as they are connected to an observed variable. For example, the extent of price sensitivity might vary with the available income. Rich households might be less price sensitive compared with poorer households. However, in reality tastes vary randomly or are related to demographic characteristics that are unknown to the researcher. Then, the logit model would be a misspecification.

Another important disadvantage of logit models is the IIA assumption that fixes the substitution patterns. The relative odds of choosing an alternative i instead of j is fixed regardless what other options are available. The most famous example to further explain how restricting this assumption is, is the red bus-blue bus problem. The participants are given the choice to take the red bus or the car. Assume that each alternative is chosen with a probability of 50%. Thus, the ratio of probabilities becomes 1. Now, a second blue bus is introduced which drives on exactly the same route and times as the red bus. Given the IIA assumption, the logit model would predict that now, the participants choose each alternative with a probability of one third

as the ratio of the probabilities of the red bus and the car has to be one and the probability of taking either bus should be identical. However, in real life one would expect that the probability of taking the car remains 50% while using either bus is connected with a probability of 25%. In empirical applications of the logit model, it has to be tested whether the IIA assumption holds. A popular test is to reestimate the model excluding one alternative and testing whether the coefficients change significantly. If the IIA does not hold, the logit model represents a misspecification (TRAIN 2009).

Finally, the logit model cannot account for the correlation of unobserved factors over time. In discrete choice settings, researchers often analyze repeated choices over time. For example in household panel data, the same household chooses among the same product category several times. Also in choice experiments the participants have to choose several times. Thus, the researcher most often analyzes a sequence of choices. A logit model can only accommodate dynamics related to observed variables. However, unobserved variables are often also correlated over time. E.g. a household might be brand loyal towards a brand and chooses to buy that brand several times. If there are no variables available that may explain why a certain household is loyal towards a certain brand, a logit model fails to take that state dependence into account.

Despite the disadvantages, logit models present an adequate solution for a wide range of empirical applications. The main advantage is the closed form solution of the integral in equation 12. Thus, researchers have been able to estimate logit models even with limited computer power.

8.4 Mixed Logit Models

In sum, mixed logit models with random parameters across decision makers show the relevant advantage of allowing for taste heterogeneity unconditional on socioeconomic covariates (GREBITUS ET AL. 2013; MENAPACE ET AL. 2008). The mixed logit approach solves all three limitations of standard logit models: this model relaxes the IIA assumption, allows for random taste variation and the correlation of unobserved factors over time. However, mixed logit models require more programming skills and higher computer power. The main goal for the coefficients that have been selected to vary randomly is to estimate the moments of the distribution (e.g. the mean and the variance of the normal distribution) instead of only estimating a point estimate. Similar to the logit model, the mixed logit model can also be derived using the random utility approach. The only difference is that some parameters are

allowed to vary over the individuals. Thus, the only difference regarding the random utility model arises in the explained part of the utility (compare equation 14 and 16): the subscript n is added and indicates that the parameter β_n is individual specific:

$$V_{nj} = \beta_n' x_{nj} \quad (16)$$

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_n' x_{nj} + \varepsilon_{nj} \quad (17)$$

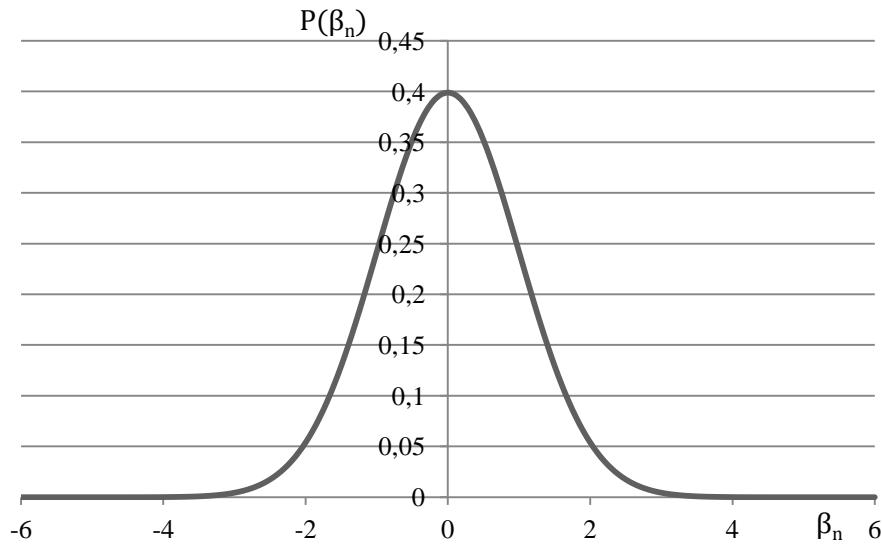
V_{nj} represents the observed part of the utility. x_{nj} are the observed variables and β_n are the coefficients which are now specific to the decision maker. For example if the price is observed for each alternative, the degree of price sensitivity might vary over the decision makers. Assuming that the researcher knows β_n , the choice probabilities are identical to the case of standard logit models. Given β_n , the probability of choosing alternative i is:

$$L_{ni}(\beta_{ni}) = \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{nj}}} \quad (18)$$

Of course, β_n is unknown. Then, the choice probability becomes the integral over all possible values of β_n , which are described by the distribution that is assumed for β_n (compare BONNET AND SIMIONI 2001):

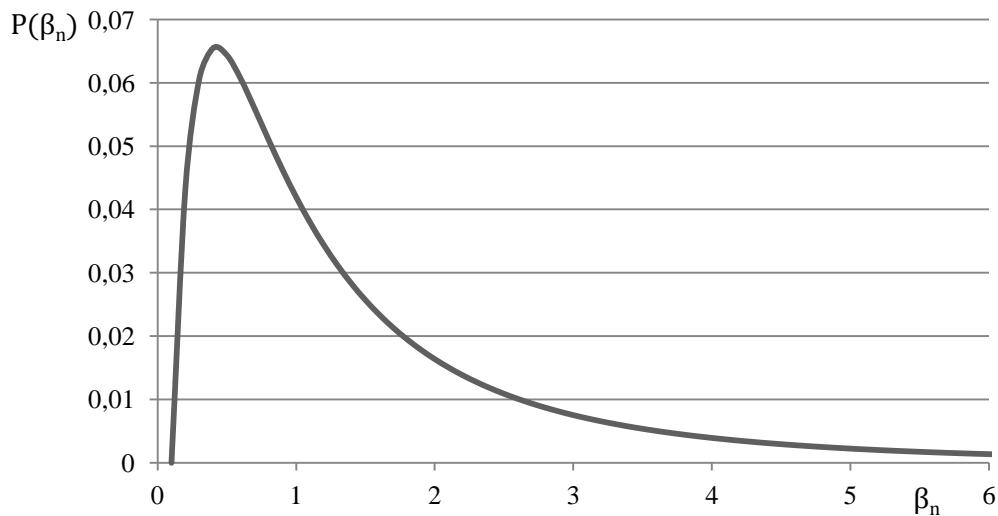
$$P_n = \int \left(\frac{e^{\beta' x_n}}{\sum_j e^{\beta' x_n}} \right) f(\beta | \theta) d\beta. \quad (19)$$

θ are the population parameters for the distribution of β_n . The researcher must choose a distribution for β_n . Potential distributions include the normal distribution, the lognormal distribution, the triangular distribution or the uniform distribution. An example of normal distribution is depicted in figure 3. During the estimation process, the mean and the standard deviation will be determined so that it becomes the best fit for the data. As the distribution is unbound, extreme values are also possible. Furthermore, it is possible that the decision makers can be split into two groups: one segment that shows a positive coefficient while the other segment dislikes a certain attribute. For example in figure 3 the population is split in half. An exemplary application of this type of distribution can be found in BROWNSTONE ET AL. (2000).

Figure 3: Normal distribution

Source: Own representation.

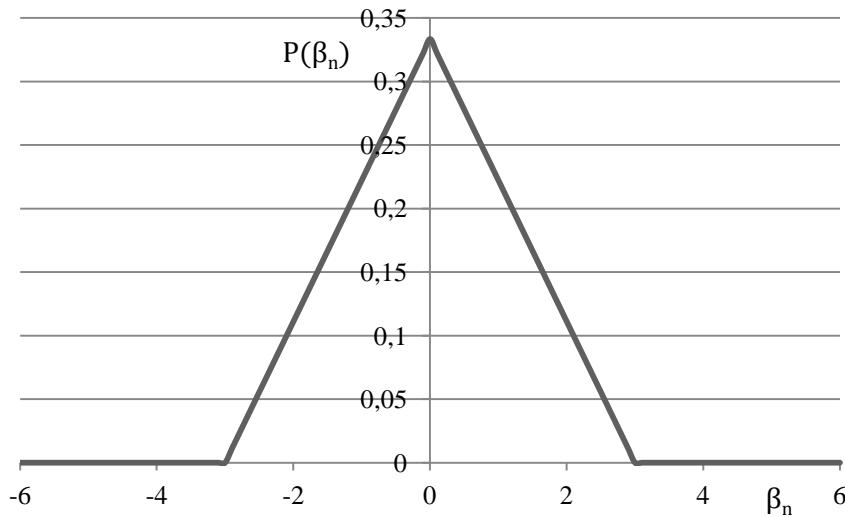
The lognormal distribution is pictured in figure 4. The lognormal distribution is often applied when the researcher expects or seeks to force the coefficients to be either negative or positive for all decision makers. For example, it is often assumed that all decision makers have a preference for lower prices. If the researcher intends to impose a negative coefficient, the variable is multiplied by -1. But even if a lognormal distribution assures the correct sign, several studies have found the lognormal distribution to be problematic because of two reasons: they can be difficult to estimate and because of the unbounded upper support very high values are also potentially possible (REVELT AND TRAIN 2000).

Figure 4: Lognormal distribution

Source: Own representation.

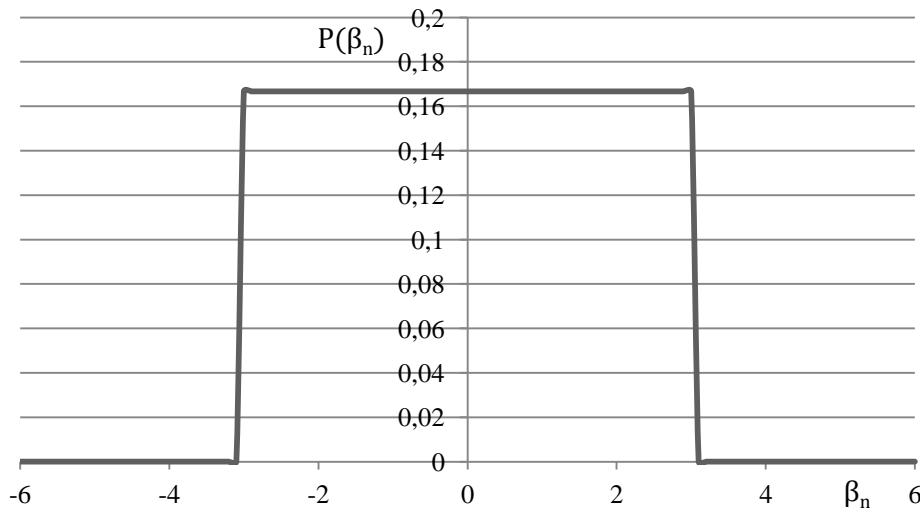
An empirical application of the triangular (figure 5) and uniform distribution (figure 6) can be found in REVELT AND TRAIN (2000). The advantage of both distributions is that they have bounded supports on both sides. Consequently, unrealistically low or high coefficients become impossible. However, standard statistical packages often do not contain the option of triangular or uniform distributions of the random coefficients as in practice those distributions are rarely chosen.

Figure 5: Triangular distribution



Source: Own representation.

Figure 6: Uniform distribution



Source: Own representation.

After the researcher specified a certain distribution for the random parameters, the log-likelihood function needs to be maximized. The log-likelihood function is shown in equation 20.

$$LL(\theta) = \sum_{n=1}^N \ln[P_n(\theta)] \quad (20)$$

The integral in equation 19 does not have a closed form, thus, it has to be approximated via simulation (REVELT AND TRAIN, 2000). Then, the distribution parameters θ (mean and variance) can be recovered maximizing the simulated log-likelihood function. More precisely, the following steps are carried out (BONNET AND SIMIONI 2001):

- (1) A starting value for the distribution parameters θ is chosen.
- (2) β is drawn from $f(\beta)$.
- (3) The choice parameters $L_{ni}(\beta_{ni})$ are calculated.
- (4) These steps are repeated and saved.
- (5) Then, the results are averaged.
- (6) Finally, the log-likelihood function is maximized dependent upon θ .

Recently, the simulation process has been improved by employing Halton sequences instead of random numbers (TRAIN 2000). A programmed syntax for STATA is presented by HOLE (2007).

To decide whether a multinomial logit model⁶³ or a mixed logit model is the better fit for the data, it has to be tested if the IIA assumption holds (ALLENDER AND RICHARDS 2012). A commonly executed test was proposed by HAUSMAN AND McFADDEN (1984), who suggest to restrict the alternatives by excluding one of the alternatives. Then, the restricted and unrestricted models are compared using a Lagrange multiplier test. Under the null hypothesis, the data is conform with the IIA assumption. Furthermore, it is often tested whether the standard deviation of the estimated distribution of β_n is statistically significantly different from 0 using a t-test or an F-test in the case of multiple varying parameters. Another option to compare the fit for two models is to evaluate measures of the goodness of fit. Following BEN-BEN-AKIVA AND LERMAN (1985) the average probability of correct predictions can be compared across different specifications.

8.5 Brand Loyalty in Choice Models

Brand loyalty is commonly defined as “*a biased (non random), behavioral response (buying), expressed over time, by some decision making unit, with respect to one or more alternative brands out of a set of such brands, and is a function of psychological (decision making, evaluative) processes*” (JACOBY AND KYNER 1973). Thus, brand loyal consumers have a special bond with a certain brand and they repeatedly buy that brand. Empirically, we

⁶³ Multinomial logit models are basically logit models with multiple choice options.

differentiate between two aspects to evaluate a brands performance regarding brand loyalty: Firstly, the segment size is important. The segment size represents the number of loyal clients. Secondly, the level of loyalty is an important aspect of characterizing brand loyalty. The level of loyalty measures the intensity of the loyalty of the clients. While some customers might be deeply connected to a brand, others might only prefer a certain brand to a limited degree over other brands.

In order to measure brand loyalty using a mixed logit model, a meaningful random utility model has to be specified. Then, the probabilities of buying a certain brand for each decision maker and purchase occasion are calculated. Following AGRAWAL (1996) as well as ALLENDER AND RICHARDS (2012), a decision maker is loyal towards the brand he shows the highest purchase probability for. The segment size is then the number of decision makers being loyal towards a brand. The average purchase probability of the loyal households serves as a proxy for the level of loyalty.

The most important advancement in specifying random utility models applied to the choice among brands is the incorporation of “purchase event feedback”. To account for the effect of last purchases on current choices in empirical choice models has attracted wide attention in the marketing literature. It has been named as one of the most important advancements in choice modeling (AILAWADI ET AL. 1999). The seminal contribution of GUADAGNI AND LITTLE (1983) shows a way to account for purchase event feedback. In essence, a variable is included that captures an exponentially smoothed measure of previous purchases. This methodology notably improves the fit of choice models in the context of households choosing between a set of food brands as households are often brand loyal. AILAWADI ET AL. (1999) compared different potential ways to include purchase event feedback in choice models and found that the methodology of GUADAGNI AND LITTLE (1983) contributes very strongly to a good statistical model fit and an overall good prediction rate. The disadvantage of this approach is that it is a rather “ad hoc” specification that lacks a theoretical background. However, this method has been widely applied in the literature (e.g. AGWARAL 1996; ALLENDER AND RICHARDS, 2012) and has thus been the chosen method in chapter 2 of this dissertation.

The parameter that captures the effect of past purchase decisions on current purchase decisions (*prop*) is added to the theoretical random utility model. An empirical application of this specification of the random utility model is presented in chapter 2 of this dissertation as well as in RICHARDS AND ALLENDER (2012).

$$U_{nbt} = \sum_{b=1}^n \beta_{1b} + \beta_2 * price_{bt} + \beta_3 * promo_{bt} + \beta_4 * promo_{bt} * price_{bt} + \beta_5 * prop + \varepsilon_{bt} + \epsilon_{hbt}. \quad (21)$$

The variable “*prop*” measures the propensity towards a brand for each household. This measure goes back to GUADAGNI AND LITTLE (1983):

$$prop_{nit} = \vartheta * prop_{nit-1} + (1 - \vartheta)(y_{nit-1} - pr_{ni}^I) \quad (22)$$

This propensity represents an exponentially weighted average of last choices. ϑ stands for a smoothing parameter that is generally set equal to 0.75, while y_{nit-1} is a binary variable that becomes 1 if the brand was chosen during the last purchase occasion and pr_{ni}^I represents the initial probability of a purchase of brand b of household h. Thus, altogether $prop_{nit}$ is an exponentially weighted market share for each brand and each household where recent purchases are assigned a higher weight. If a household exclusively purchases one brand, the measure becomes 1, the less often a household buys a certain brand, the measure approaches 0. By including this variable in the specification of the random utility model, the statistical fit of the empirical choice model generally improves significantly. Furthermore, the state dependence of households can be accounted for.

The remaining coefficients are usually brand specific constants ($\sum_{b=1}^n \beta_{1b}$) and coefficients to capture the effect of the price (β_2) and the promotional activities (β_4) of the alternatives. In the exemplary specification presented in equation 21, an additional variable is inserted to measure the interaction effect of the price and the promotional activities. This procedure is first proposed in CHINTAGUNTA (2002). If the price elasticity is changed during the promotional activity, the demand curve is allowed to rotate due to this interaction effect.

The specification of which coefficients are assumed to vary randomly over the decision makers is up to the researcher. Also the form of the distribution has to be defined. Following ALLENDER AND RICHARDS (2012), the coefficients for the price effect and the propensity effect are assumed to vary over the households. The coefficient for the price is regularly chosen by researchers as it is known that different persons show different levels of price sensitivity. As some people have been found to be variety seekers and thus have a negative purchase event feedback while others show positive purchase event feedback because they like to repurchase the same brand, the coefficient for the propensity effect is also assumed to be distributed differently over the population. If for example a normal distribution is chosen for the random effects, it can be tested whether the standard deviation is statistically

significant from zero. If this hypothesis can be rejected, assuming random coefficients is appropriate.

As noted above, a decision maker is labeled as brand loyal towards the brand he has the highest purchase probability for. The purchase probabilities are estimated following the outline presented in precedent subchapter. The level of loyalty (*level of BL_b*) is the average of the probabilities ($P_{nt}(b)$) of the loyal decision makers (Ln_b):

$$\text{level of } BL_b = \frac{1}{Ln_b} \sum_n P_{nt}(b) \quad (23)$$

A potential further extension of this method includes the possibility to capture additional alternative-specific unobserved variations (see GREENE AND HENSHER 2007).

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Chapter 9

Conclusion

This dissertation consists of six studies that empirically examine the pricing patterns of the German retail market. Linkages between consumer behavior, brand and product attributes, distribution channels and pricing strategies are uncovered. Depending upon the specific research questions, all studies not only contribute to the existing research, but also entail economic implications and recommendations for marketing practitioners and consumers. In addition, promising future research opportunities can be identified. However, the studies and the interpretation of the results are also subject to some limitations. Thus, a final conclusion is presented in this chapter. As all studies are based upon the same type of data, retail scanner data, this conclusion begins with a critical assessment of the data. Afterwards, each study is discussed separately.

Retail Scanner Data: a Critical Assessment

All studies presented in this dissertation employ retail scanner data matched with further data sources (e.g. product attributes collected in the retail outlets and on the internet, household scanner data, input costs, information on weather, dates of soccer games or other special events). The main advantage of this type of data is that it provides detailed, highly disaggregated weekly information on prices and sold quantities of a wide range of products within one category. Thus, the pricing patterns can be analyzed on a detailed level and due to the large number of participating retailers (Madakom GmbH: 200 retailers, SymphonyIRI Group: 536 retailers) and households (GfK: 20.000-40.000 households) the conclusions can be drawn based upon a large sample.

However, retail panel data generally suffer from several disadvantages. First, the leading hard discounters, Aldi and Lidl, do not disclose their data. However, a comparison between the

prices of private label products from Aldi and Lidl, which can be extracted from the household scanner data, and the prices of private label products of reporting discounters shows that the price levels and movements are very similar to each other. Furthermore, in several studies of this dissertation the prices of identical products are compared across retail outlets on the basis of EAN-codes. As hard discounters hardly sell nationwide brands during the observation period (2000-2010), comparisons on the brand level with other retailers are impossible anyways.

Another limitation is the inseparability between the influence of the manufacturers' and retailers' impact on pricing strategies if studies are exclusively based upon retail scanner data. For the US, there are retail scanner datasets available that are complemented by wholesale prices. Then, researchers are able to identify the retail margins and can directly measure the retailer's control over the prices. However, similar datasets are unavailable for Germany. Inquiries at the providers of the national retail scanner data sets and at local retail chains were unsuccessful as German retailers are very reluctant to implicitly disclose their margins. Thus, this issue cannot fully be dissolved. In some studies (Chapter 6 and 7), input cost data were gathered to approximate wholesale prices and empirical evidence suggests that retailers rather than manufacturers determine the pricing strategies within the stores (BERCK ET AL. 2008).

In conclusion, the pricing patterns in the retail store can still be documented on a very detailed level using retail scanner data. However, conclusions with regard to the initiator of the pricing strategies have to be discussed carefully.

Price Promotions and Brand Loyalty:

Empirical Evidence for the German Ready-to-Eat Cereal Market

In this study, the linkage between brand loyalty and price promotional strategies is empirically tested. A central contribution of this study is distinguishing between the two dimensions of brand loyalty: the level of loyalty and the segment size.⁶⁴ Indeed, reverse effects for both dimensions are identified. While brands with a higher level of loyalty are promoted less aggressively, brands with more loyal customers (higher segment size) are promoted more aggressively. This finding offers an interesting insight into how brands are selected for promotion. Brands that reach a broader audience have a higher probability of being on sale. Furthermore, the potential loss by offering a sale is minimized as brands whose

⁶⁴ The level of brand loyalty is defined as the maximum price differential loyal consumers are willing to accept for their favorite brand before switching to the cheaper alternative. The segment size captures the number of consumers being loyal towards a certain brand.

clients show a high level of loyalty are less often selected for a sale. Additional results even show that these results also hold on the manufacturer level, meaning that the same pattern applies within the brands of one manufacturer.

Usually, the procedure to empirically test theoretical models is to find the model that matches best with the existing market conditions and to verify whether the predictions obtained from the theory apply in the real world. However, this approach cannot be pursued in this context. First, all models are built upon a specific set of assumptions and these are very similar to each other; small differences in the set up lead to conflicting results. The brand architecture of the market for breakfast cereals is reflected in none of the models. In reality, there are four leading manufacturers producing several brands each. However, the theoretical models are built around two or three brands at maximum. Consequently, it is impossible to identify one single model that reflects the German market for breakfast cereals best. Second, the models generally do not acknowledge the two dimensions of brand loyalty, namely level and segment size. Instead, one dimension is selected in each model. Thus, the approach adopted in our paper is to extract hypotheses from each model and test these hypotheses separately. Taken both aspects together, a natural extension of the empirical research presented here is to create a theoretical model that also incorporates the two dimensions of brand loyalty and, in addition, allows for more complex brand architecture: multiple manufacturers that produce several brands each.

Spatial and Temporal Retail Pricing in the German Beer Market

This study contributes to the literature by recognizing the regional brand loyalty of the German consumers for beer and translating the models linking brand loyalty and pricing strategies into a spatial context: How is an identical product priced across regions? Are prices systematically different if the product is sold in the region it originates from compared to all other regions?

From an economic point of view, it can be shown that the “law of one price” does not hold on the German beer market. National brands pursue diverging pricing strategies across different regions in Germany. In particular, promotions are more likely to occur in the regions the brands originate from.

In Germany, beer represents a product category with a longstanding tradition of using the regional aspect in advertising the product. For example, Flensburger features Nordic landscapes in their TV advertisements. Nowadays, selling regional products is a key

marketing trend. Thus, it might be worthwhile for marketing practitioners who are about to launch a regional brand nationwide to have a look at the pricing patterns of the German beer market. Furthermore, it might be rewarding for the consumers to know that prices differ regionally. Potentially, traveling consumers might take advantage by trying new beers when they are on holiday or, if they are extremely brand loyal, taking their own regional brand along.

An interesting extension of this study might be to account for mergers. The German beer industry consolidated massively in the last decade and studying the effects on the pricing patterns of the brands might unravel interesting insights into the effects of mergers. However, the limited time frame of the data at hand impeded taking this effect into account.

How Do Retailers Price Beer During Periods of Peak Demand?

Evidence from Game Weeks of the German Bundesliga

The impact of major sport events on demand and pricing has not been addressed in the literature before. The chosen market is particularly interesting as Germans tend to be loyal to regional beer brands and regional soccer teams. Furthermore, watching a soccer game is a major occasion for beer consumption. Then, regional teams playing all over Germany creates brand-level demand shocks that allow for a more nuanced analysis of the pricing strategies on the German beer market. This approach can easily be applied to other product categories and sport leagues.

Existing literature concentrated on analyzing market-level demand shocks that apply to a wide range of products (e.g. week before Christmas) and category-level demand shocks (e.g. tuna/Lent, avocado/Super Bowl, beer/Ascension Day). The results presented in this study highlight that the effects of brand-, market- and category-level demand shocks on pricing strategies vary significantly. Moreover, the impact of those shocks can be measured at the category-level or for each brand separately. The level of aggregation will also influence the obtained results because inter-brand substitution might take place.

The results presented in the paper hint to a story of price discrimination: On the brand-level the schedule of the Bundesliga games exerts the largest impact on the prices. However, the sign of the coefficients varies significantly. In this paper, it can be documented that the prices of the beers connected to more successful teams tend to fall. A potential underlying reason might be that retailers choose to promote those beers that reach the largest audience and the

success might be positively correlated to the number of fans. In a follow-up study, a brand-level regression should analyze the separate effects of game weeks on beer prices of beers connected with the home team opposite to beers of the guest team. First results indicate that prices for the home team fall, while prices for the beers of the guest team rise during game weeks. Thus, there is some evidence for retail price discrimination that has to be explored in future research.

Preissetzung auf dem deutschen Joghurtmarkt: eine hedonische Analyse

The aim of this study is the documentation of the influence of product attributes on retail prices. The hedonic price analysis delivers interesting results. Overall the trend towards a healthier lifestyle in connection with strong brand effects can be shown: First, brand affiliation exerts an important influence on the yoghurt prices. Second, special yoghurts such as lactose-free, probiotic, organic or synbiotic⁶⁵ yoghurts realize significant price mark-ups. Third, interaction effects between brands and special attributes may result in additional mark-ups. For example, a probiotic yoghurt from Danon (German: Danone) achieves 73,33% higher prices compared to the base category (natural yoghurt with a fat content of 3,5%). Fourth, yoghurts with lower fat contents are not necessarily cheaper than yoghurts containing more fat even though the ingredients should be less expensive.

The study also entails interesting information for marketing practitioners. Numerous new yoghurts are launched on the German market each year. Using the regression results presented in this study, marketing managers may obtain a realistic estimate of the final consumer prices a certain product may reach. For consumers it might be interesting to see that even though the absolute price differentials across products are small, the relative price differences are comparably large. Additionally, a large share of the price differences is caused by brand effects. Thus, reconsidering the chosen yoghurt (in particular the brand) might pay off.

The advantage of hedonic price analysis is that this method is a good starting point for analyzing pricing patterns associated with product attributes. However, a general limitation of this method is that it cannot be examined whether the observed price effects result from the supply side or the demand side. The following questions remain unanswered: Are probiotic yoghurts more expensive because the associated production process is more complex and costly, or because firms spend more on advertising those yoghurts? Or do the retailers or manufacturers seek to achieve higher margins? Or do consumers have a higher willingness to

⁶⁵ A synbiotic yoghurts contains probiotics and prebiotics.

pay for those yoghurts and that is skimmed by the manufacturers or retailers. Consequently, further research is needed to clarify the underlying reasons of the documented price differentials for certain attributes.

Product Differentiation and Cost Pass-Through: a Spatial Error Correction Approach

In more and more saturated food markets product differentiation becomes increasingly important. Instead of offering totally new products, manufacturers often launch new products that are only slightly different from existing alternatives. For example, on the yoghurt market the manufacturers offer flavors that are specific to the season (e.g. baked apple for Christmas time). This study contributes to the growing theoretical and empirical research on product differentiation and is focused on the effect on cost pass-through. To theoretically study the impact of product differentiation on cost pass-through, a spatialized stock flow model originally applied to the housing market is translated to the product differentiation context. Even if the predictions stemming from this model- prices are dependent on input costs and lagged prices of similar products- seem straightforward, building and solving such a model is less straightforward. From an economic perspective, the theoretical model provides insight into how following a competitor's lead in adjusting prices upward or downward even though the input prices remain constant may also be the result of non-collusive behavior.

The empirical application of the model, which is to estimate a spatialized version of a panel error correction model, also represents a valuable extension of the existing empirical literature on cost pass-through. The attributes of the products are defined and measured in a multidimensional spatial context and are organized into a spatial distance matrix which is then incorporated into a panel error correction model. Using this approach, horizontal and vertical error correction processes can be measured simultaneously. In this study, we find significant evidence for both types of price alignments: Consumer prices are not only changed if input costs vary (vertical pass-through) but also if the consumer prices of similar products change (horizontal pass-through).

Marketing practitioners might use these findings if they wish to exert influence on prices of the “must-stock” products that are generally very strong brands. Then, adjusting the prices of similar products might lead to the desired price effects because the manufacturers of the stronger brands will follow the price lead of those similar products.

Pass-Through of Producer Price Changes in Different Retail Formats

Several factors leading to incomplete pass-through of cost changes have already been identified in the literature, e.g. the frequency of price adjustments, mark-up adjustments by firms and local distribution costs. Thus, this study contributes to the ongoing search for reasons for the incomplete pass-through by focusing on the impact of the retail format on pass-through rates. Using a dataset that has already been employed for similar research questions, it can be shown that the retail format also influences the input cost pass-through for identical products. We find that discount retailers have a significantly larger pass-through rate. This finding might be caused by the lower services provided by the discounters.

In times of volatile commodity markets this finding might be of interest for the consumers because the study predicts that closely following the prices in the different retail outlets might pay off: If input prices fall, discounters are more likely to adapt more quickly and grocery shopping at the discounter might be even cheaper. If commodity prices rise, discounters will pass through that price change faster and the relative price differential between the two outlet types becomes smaller. From the research perspective, it is highly recommended that future studies should simply include retail format dummies in their analysis because differences in the pricing strategies of the two formats are clearly revealed in this study.

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Chapter 10

Zusammenfassung

Der deutsche Lebensmitteleinzelhandel (LEH) ist angebotsseitig durch intensiven Wettbewerb und nachfrageseitig durch preissensitive Konsumenten gekennzeichnet. Folglich spielt die Preissetzung eine wichtige Rolle für das Marketing. Die Preise im LEH weisen eine erhebliche Dispersion auf, sowohl innerhalb der Geschäfte über die Zeit als auch zwischen den Geschäften. Sonderangebote tragen im besonderen Maße dazu bei. Eine Vielzahl theoretischer Ansätze zielt auf die Erklärung dieser Preisdispersion. Der Kernbeitrag der vorliegenden Dissertation besteht in der empirischen Prüfung und Weiterentwicklung dieser Ansätze am Beispiel des deutschen LEH unter Verwendung von Scannerkassendaten. Insbesondere wird in dieser Arbeit aufgezeigt, wie die Markentreue der Konsumenten, die Produktdifferenzierung, temporäre Nachfrageschocks und die Absatzkanäle die Preissetzung systematisch beeinflussen und somit einen Teil der beobachteten Preisdispersion erklären.

Viele Konsumenten sind ausgewählten Marken gegenüber treu. Deswegen untersuchen mehrere theoretische Modelle den Zusammenhang zwischen Markentreue und Preissetzung. Aufgrund gegensätzlicher Hypothesen aus den theoretischen Modellen kommt der empirischen Überprüfung der Modelle eine besondere Bedeutung zu. In dieser Dissertation wird dieser Zusammenhang sowohl auf dem Markt für Frühstückscerealien (Kapitel 2) als auch auf dem Biermarkt (Kapitel 3) getestet.

Die dritte Studie konzentriert sich auf die Auswirkung von temporären Nachfrageschocks auf die Preissetzung am Beispiel des Einflusses des Bundesligaspielplans auf die Bierpreise (Kapitel 4).

Produktdifferenzierung gewinnt in den Industrieländern zunehmend an Bedeutung, da die Lebensmittelmarkte als gesättigt gelten. Beispielsweise können die Konsumenten in Deutschland zwischen ca. 2000 verschiedenen Joghurts wählen. Für diesen Markt wird in der Dissertation untersucht, wie sich die Produktdifferenzierung auf das Niveau der Preise (Kapitel 5) und auf die dynamischen Preisanpassungsprozesse (Kapitel 6) auswirkt. In der letzten Studie wird der Einfluss des Absatzkanals auf die Weitergabe von Inputkostenänderungen untersucht (Kapitel 7).

Price Promotions and Brand Loyalty:

Empirical Evidence for the German Ready-to-Eat Cereal Market

Sonderangebote sind ein bedeutendes preisliches Marketinginstrument im deutschen LEH. Markentreue ist eine wichtige Determinante des Konsumentenverhaltens. Deswegen untersuchen mehrere theoretische Beiträge den Einfluss von Markentreue auf die Preissetzung. Da die theoretischen Modelle unterschiedliche und teilweise sogar widersprüchliche optimale Verhaltensweisen prognostizieren, ist eine empirische Untersuchung nötig, um zu testen welches Modell die Preissetzung auf dem deutschen LEH am besten beschreibt. Diese Studie konzentriert sich auf den deutschen Markt für Frühstückserealien. Dieser Markt ist aus folgenden Gründen besonders für derartige Untersuchungen geeignet: Die Branche ist hoch konzentriert auf wenige Unternehmen, die Margen und die Werbeintensität sind verhältnismäßig hoch und es werden häufig neue Produkte eingeführt. Zur Messung der Markentreue werden Haushaltsscannerdaten (GfK, 2000-2004) verwendet. Um die Preissetzungsstrategie zu charakterisieren werden Einzelhandelsscannerdaten (Madakom GmbH, 2000-2001) genutzt. Diese beiden Datenquellen werden anhand der Produktcodes zusammengeführt.

Markentreue wird in den theoretischen Modellen allgemein so definiert, dass treue Kunden einen Aufpreis für ihre Lieblingsmarke zahlen würden. Die Intensität der Markentreue wird dann durch die Höhe des maximal akzeptierten Aufpreises bestimmt. Die Größe des treuen Segmentes entspricht der Anzahl der treuen Kunden. Somit kann es Marken geben, die zwar nur wenige treue Kunden aufweisen, aber deren Intensität der Markentreue verhältnismäßig hoch ist. Andersherum es ist auch möglich, dass eine Marke eine große Schar treuer Kunden hinter sich hat, deren Markentreue jedoch nicht so stark ausgeprägt ist. Im Unterschied zu bisherigen empirischen Arbeiten wird in dieser Studie explizit berücksichtigt, dass Markentreue in diesen zwei Dimensionen gemessen werden kann. Zur empirischen

Bestimmung dieser beiden Dimensionen wird ein Mixed Logit Modell geschätzt. Die Haushalte werden der Marke gegenüber als treu bewertet, für die sie die höchste Kaufwahrscheinlichkeit zeigen. Die durchschnittliche Kaufwahrscheinlichkeit der treuen Kunden wird dann als Maß für die Intensität der Markentreue verwendet. Auch die Preissetzungsstrategie wird anhand von zwei Maßen empirisch beschrieben. Die Frequenz der Sonderangebote ist die Wahrscheinlichkeit, dass ein Produkt zu einem Sonderangebotspreis angeboten wird. Die Höhe der Sonderangebote ist der prozentuale Preisnachlass gegenüber dem regulären Preis. Sonderangebote sind in Anlehnung an die Literatur als Preise definiert, die nicht länger als vier Wochen gelten, mindestens 5% unter dem regulären Preis liegen und nach der Sonderangebotszeit wieder angehoben werden. Der reguläre Preis ist als letzter Preis definiert, der mindestens vier Wochen galt und kein Sonderangebot war.

Die Ergebnisse des Mixed Logit Modells zeigen, dass die Marken sehr unterschiedliche Strukturen in der Markentreue ihrer Kunden aufweisen. Beispielsweise verfügt Kellogg's Frosties über die größte treue Kundengruppe. Die Intensität der Markentreue ist jedoch für andere Marken wie beispielsweise Kellogg's Toppas Classic höher. Diese Ergebnisse fließen jeweils als exogene Variable in das Modell zur Schätzung des Einflusses der Markentreue auf die Preissetzung ein. Die abhängigen Variablen sind die Frequenz der Markentreue (Probit Model) und die Höhe der Sonderangebote (Tobit Model). Das Hauptergebnis der Studie ist, dass die Intensität der Markentreue beide Parameter der Preissetzungsstrategie negativ beeinflusst, während die Größe des markentreuen Segmentes einen positiven Einfluss ausübt. Die Begründung hinter dieser Strategie könnte sein, dass so die Reichweite der Sonderangebote maximiert wird und dass gleichzeitig die Kosten eingedämmt werden, da weiterhin die hohe Zahlungsbereitschaft der intensiv treuen Kunden abgeschöpft wird.

Spatial and Temporal Retail Pricing in the German Beer Market

Der deutsche Biermarkt zeichnet sich durch zwei Merkmale aus: Die Konsumenten sind gegenüber regionalen Marken besonders treu und die Biernachfrage fluktuiert saisonal. Deswegen ist diese Warengruppe besonders geeignet, um empirisch den Einfluss von Markentreue und temporär schwankender Nachfrage auf die Preissetzung zu testen. Der Einfluss von Markentreue auf die Preissetzung wird in den theoretischen Modellen konträr diskutiert. Bezüglich der Nachfrageschocks besagt die neoklassische Theorie, dass die Preise bei steigender Nachfrage steigen sollten. Neuere Ansätze prognostizieren jedoch fallende Preise in Zeiten von temporär steigender Nachfrage aufgrund verschiedener

Erklärungsansätze, beispielsweise könnten die Lebensmitteleinzelhändler Bier als Lockartikel⁶⁶ („loss leader“) nutzen.

Auf der Basis von wöchentlichen Einzelhandelscannerdaten (Madakom, 2000-2001) wird die Preissetzung der jeweils zehn umsatzstärksten Pils- und Weizenbiere bestimmt. Die Sonderangebote werden dann durch die prozentuale Höhe des Preisnachlasses und durch ihre Einsatzhäufigkeit beschrieben. Durch die Zerlegung der Preisstrategie in die drei exogenen Variablen regulärer Preis, Sonderangebotshöhe und –breite sind im Vergleich zur bestehenden Literatur differenziertere Aussagen möglich, da bisher nur der Preis als Ganzes untersucht wurde. Um den räumlichen Einfluss auf die Preissetzung zu bestimmen, wird als exogene Variable die Distanz zwischen der Herkunft der verkauften Biere und dem Einzelhändler verwendet. Da die deutschen Konsumenten der regionalen Marke gegenüber treu sind, wird anhand dieser Variablen der Effekt von Markentreue auf die Preissetzung gemessen. Zur Bestimmung des Einflusses temporär ansteigender Nachfrage werden folgende Variablen im Modell berücksichtigt: nationale Feiertage (Weihnachten, Ostern, Christi Himmelfahrt und Pfingsten), die Schulferien, die Temperatur und besondere Ereignisse, welche die Biernachfrage beeinflussen (UEFA-Cup und das Oktoberfest). Des Weiteren werden anhand von Dummyvariablen die Effekte von Marken, Distributionskanälen und Lebensmitteleinzelhandelsketten berücksichtigt.

Das zentrale Ergebnis der Studie ist, dass die Sonderangebotshöhe und –frequenz steigt, je näher die Herkunft und Verkaufsstätte der Biere aneinander liegen. Die Beweggründe dieser Strategie könnten in dem höheren Bekanntheitsgrad der regionalen Marken und somit in einer höheren Reichweite der Sonderangebote liegen. Im Hinblick auf die Effekte der temporalen Variablen kann festgestellt werden, dass der reguläre Preis tendenziell mit höheren Temperaturen, vor Ostern und den Europameisterschaften steigt, jedoch während des Oktoberfestes fällt. Auch die Effekte dieser Variablen auf die Parameter der Sonderangebotsstrategie sind gemischt. Der deutlichste Effekt wird in der Woche vor Christi Himmelfahrt gemessen; dann werden Biere deutlich aggressiver beworben. Die Ursache für dieses Ergebnis liegt wahrscheinlich darin, dass während Christi Himmelfahrt die Biernachfrage deutlich steigt und die Lebensmitteleinzelhändler dann Biersonderangebote nutzen, um die Konsumenten in die Geschäfte zu locken.

How Do Retailers Price Beer During Periods of Peak Demand?

⁶⁶ Das sind Produkte, welche deutlich günstiger und teilweise sogar unter dem Einstandspreis angeboten werden um Kunden in das Geschäft zu locken. Die Marge auf die nicht beworbenen Artikel ist dann in der Regel höher.

Evidence from Game Weeks of the German Bundesliga

Dieser Beitrag ergänzt die vorangegangene Studie um den Einfluss von markenspezifischen Nachfrageschwankungen auf die Preissetzung in der Warengruppe Bier im deutschen LEH. Als zusätzliche Effekte werden hier die Bundesligaspielepläne der Teams der 1. Bundesliga mit erfasst. Da die Fans zum größten Teil der regionalen Biermarke oder dem Biersponsor gegenüber treu sind, wird durch die bundesweit stattfindenden Spiele eine erhebliche Varianz in der markenspezifischen Nachfrage ausgelöst.

Die Ergebnisse variieren je nachdem, ob der Datensatz auf aggregierter Ebene ausgewertet wird (Warengroupenebene) oder ob die Analyse nach Marken getrennt erfolgt (Markenebene). Auf Warengroupenebene kann gezeigt werden, dass Ereignisse, welche die gesamte Nachfrage nach Lebensmitteln beeinflussen, wie beispielsweise Weihnachten oder Pfingsten, keinen signifikanten Einfluss auf den Preis ausüben. Jedoch steigt die Wahrscheinlichkeit, dass ein Bier zum Sonderangebotspreis angeboten wird, während dieser Wochen signifikant an. Diese Wahrscheinlichkeit steigt auch während Wochen, in denen ein Event stattfindet, welches speziell die Biernachfrage betrifft, wie zum Beispiel Bundesligaspiele. Auf Markenebene werden divergierende Ergebnisse gemessen. Hier haben Bundesligaspiele gegenüber allen anderen Variablen den größten Einfluss auf die Preissetzung. Interessanterweise variiert das Vorzeichen des Effektes jedoch erheblich. Erste nähere Untersuchungen zeigen, dass die Preise von Bieren, die mit erfolgreicheren Teams assoziiert werden, während der Spielwochen tendenziell eher fallen.

Preissetzung auf dem deutschen Joghurtmarkt: eine hedonische Analyse

Der Joghurtmarkt ist durch eine sehr hohe Produktdifferenzierung gekennzeichnet; neue Produkte werden regelmäßig auf dem Markt eingeführt. Während die meisten Hersteller viele verschiedene Geschmacksrichtungen und Fettstufen anbieten, ist die Produktion von Joghurts mit besonderen Eigenschaften wie probiotische Milchsäurebakterien, biologisch erzeugten Zutaten oder laktosefreien Joghurts entweder auf sehr große multinationale Konzerne oder Nischenhersteller konzentriert. In diesem Beitrag wird empirisch untersucht, ob und wie die verschiedenen Produktattribute den Preis beeinflussen. Dazu wird ein hedonisches Preismodell mit Einzelhandelsscannerdaten (IRISymphony Group) geschätzt. Die Daten sind wöchentlich in über 500 Lebensmitteleinzelhandelsgeschäften in ganz Deutschland von 2005 bis 2008 gesammelt worden. Es fließen ca. 19 Mio. Preisbeobachtungen in die Studie mit ein. Als Produktattribute werden die Geschmacksrichtung, Fettgehalt, Verpackungsart,

Markenname, besondere Eigenschaften (probiotisch, biologisch, synbiotisch und laktosefrei) und Interaktionseffekte berücksichtigt. Mit diesen Produktattributen können 74% der Preisvariation erklärt werden. Insgesamt kann in den Ergebnissen der Trend zu einer gesünderen Ernährung abgelesen werden. Beispielsweise erreichen laktosefreie Joghurts einen Preisaufschlag von 67% gegenüber dem Vergleichsjoghurt (Naturjoghurt, 3,5% Fettgehalt, Markenprodukt). Auch probiotische Joghurts und Joghurts mit geringerem Fettgehalt sind verhältnismäßig teuer. Es ist jedoch zu beachten, dass bei hedonischen Preisanalysen nicht geklärt werden kann, ob die Preisaufschläge angebots- oder nachfrageinduziert sind.

Product Differentiation and Cost Pass-Through: a Spatial Error Correction Approach

In gesättigten Lebensmittelmärkten versuchen Hersteller zunehmend durch Produktdifferenzierung sich von der Konkurrenz abzusetzen. In dieser Studie wird die Auswirkung von Produktdifferenzierung auf dynamische Preissetzungsprozesse analysiert. Es wird sowohl theoretisch als auch empirisch beleuchtet, wie sich die Ähnlichkeit der Produkte auf die Weitergabe von Inputkostenänderungen auswirkt. In einem theoretischen Modell wird gezeigt, dass die Produktpreise nicht nur auf Inputkostenänderungen reagieren, sondern auch auf Preisänderungen ähnlicher Produkte. Empirisch wird die Ähnlichkeit von 22 Joghurtproduktlinien in einer räumlichen Distanzmatrix anhand eines multidimensionalen Maßes, welches die entscheidenden Produktattribute berücksichtigt, gemessen. Somit kann dann ein räumliches Panelfehlerkorrekturmodell erstmals auf eine Fragestellung in der Produktdifferenzierung übertragen werden. Im Endeffekt kann gezeigt werden, dass langfristige Ungleichgewichte aufgrund einer Änderung der Rohstoffkosten von Milch wöchentlich mit 41,6% abgebaut werden. Aber auch die horizontale Preisanpassung an ähnliche Produkte spielt eine wichtige Rolle: hier werden Ungleichgewichte in jeder Periode mit 20,1% abgebaut. Wenn der Preis für ein Produkt erhöht wird und somit eine höhere Marge erzielt wird, dann werden die Preise ähnlicher Produkte in dieselbe Richtung folgen.

Pass-through of Producer Price Changes in Different Retail Formats

In empirischen Untersuchungen wird wiederholt festgestellt, dass Inputpreisänderungen nicht vollständig in die Preise, welche die Konsumenten letztendlich im LEH bezahlen, durchgereicht werden. Dieser Beitrag erweitert die Literatur über die Sammlung von Gründen für die unvollständige Weitergabe von Inputkostenänderungen um den Einfluss des Distributionskanals. Es wird anhand des Marktes für abgepackten gemahlenen Kaffee

empirisch gezeigt, dass Discounter schneller auf Inputkostenänderungen reagieren als Supermärkte. Eine Ursache könnte in den höheren allgemeinen Servicekosten der Supermärkte liegen.

Dieses Ergebnis ist in Zeiten von volatilen Märkten für die Konsumenten sehr interessant. Die Studie prognostiziert, dass sich der Preisunterschied zwischen Discountern und Supermärkten bei sich ändernden Inputkosten verschiebt. So wird vorhergesagt, dass bei fallenden Inputkosten die Preise im Discounter schneller angepasst werden und somit der Preisunterschied zwischen den Formaten zunimmt. In diesem Fall nimmt die relative Attraktivität der Discounter kurzfristig zu. Wenn die Inputpreise jedoch steigen, dann reichen die Discounter auch diese Preisänderung schneller weiter und der Preisunterschied zwischen den Formaten wird kurzfristig kleiner. Dieses Resultat sollte auch zukünftig in der Analyse der Auswirkungen von Inputkostenänderungen auf die Preise im LEH berücksichtigt werden – beispielsweise in Form einer Dummyvariablen.

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