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COMPETITIVE LOCATIONS OF GROCERY STORES IN THE LOCAL SUPPLY CONTEXT – THE CASE OF THE URBAN DISTRICT FREIBURG-HASLACH

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Abstract

The local supply function of grocery stores is threatened in rural areas as well as in urban districts. While "sufficient" or "qualified" local supply is defined normatively in terms of store accessibility and variety, the underlying assumptions on consumer behavior are not underpinned empirically. This article discusses the theoretical basics of spatial competition in grocery retailing from the perspective of retail location theory. The deduced assumptions on store choice are tested empirically regarding grocery stores in an urban district (Freiburg-Haslach), using an extended version of the Multiplicative Competitive Interaction (MCI) Model. As assumed by location theory and discussed in the local supply context, the most important aspect is store accessibility, which is operationalized in several ways. While store size has a positive impact, no clear results towards pricing can be found. There is empirical evidence on positive agglomeration effects with respect to different store formats.

Keywords: *Grocery stores, local supply, retail location theory, market area models*

1. INTRODUCTION

In several European countries, the structural change in the retail sector has left its mark in store location patterns: Coincident with business concentration and internationalization, the number of grocery stores has decreased substantially. The decline of (mostly small) grocery stores results in supply gaps, threatening the local supply function of grocery retailing, especially in rural areas (Küpper and Eberhardt, 2013). However, as grocery retail chains also relocate their stores from central and residential areas to more car-orientated locations (e.g. peripheral commercial areas), these problems also occur within cities on the urban district level (Baaser and Zehner, 2014; Baumgarten and Zehner, 2007; Wieland, 2011). In Germany, two simultaneous trends can be identified: 1) a decrease of grocery stores and increase of average store size (*scale-up*). 2) A shift of market importance from small supermarkets, formerly located in urban centers and residential areas, to larger supermarkets and discounters, both not bound to these location types (Krüger et al., 2013; Wieland 2011).

In the German context, *local supply* is a normative term which means the opportunity of neighborhood shopping. "Qualified" local supply is operationalized twofold: In a quantitative (or spatial) interpretation, a sufficient provision on the local level is measured by store accessibility, allowing grocery shopping without using a car, e.g. by a maximum accepted distance of 500 to 1,000 meters (airline or footway) or a walking time of ten minutes. The qualitative dimension of local supply addresses the sufficient provision with respect to the stores' assortment and the mixture of grocery store formats (Krüger et al., 2013). The claim of securing and/or establishing sufficient local supply is also addressed by German spatial planning, regional policy and urban development policy (BMVBS, 2013; Jakubowski and Koch, 2009). In several European countries, like Germany or the UK, a *retail impact assessment* is the main planning instrument with respect to the administrative authorization of new or the extension of existing retail locations, determining the impacts of new retail developments on existing locations using modeling techniques; in this context, an explicit purpose is to secure existing local supply locations (Khawaldah et al., 2012; Wolf, 2012).

Previous studies on local supply in Germany focus on the spatial accessibility of grocery stores (e.g. Baumgarten and Zehner, 2007; Baaser and Zehner, 2014; Neumeier, 2015; Wieland, 2011). This raises the question if accessibility is, in fact, the key element in grocery shopping. However, focusing accessibility ignores the stores' attraction to the consumers. The analysis of explanatory variables affecting *real* shopping behavior in the German grocery context has been considerably neglected: There are only two studies towards consumer behavior in grocery retailing, based on empirical store choice models (Lademann, 2007; Wieland, 2015), while the former is in an urban and the latter is in a rural context. One must conclude that 1) the normative definition of "qualified" or "sufficient" local supply is based on assumptions on consumer behavior which are not sufficiently empirically underpinned, 2) the qualitative dimension of local supply has been neglected in previous studies and 3) it lacks evidence on grocery shopping behavior on the small-scale level of urban districts.

This study attempts to answer the following research questions: 1) which competitive parameters of grocery stores are assumed to influence consumer behavior from the perspective of retail location theory? 2) Which explanatory variables representing these assumed key aspects of grocery store (spatial) competition affect real grocery shopping behavior on the small-scale level of an urban district? In particular, how important is accessibility for store choice? Furthermore, as in the local supply context, several measures of spatial accessibility are discussed, another question is: 3) Which accessibility measure best describes the (assumed) demand response to the distance to given grocery store locations?

In this paper, initially, a brief theoretical review is given about the characteristics of spatial competition in (grocery) retailing from the perspective of retail location theory and market area models. Based on these theoretical foundations, hypotheses towards explanatory variables influencing grocery shopping behavior are derived. The empirical test of these hypotheses is implemented by using a market area model approach based on empirically observed grocery shopping behavior from a customer survey in the urban district Haslach in the German city Freiburg. The results are discussed with respect to the research questions.

2. THEORETICAL BACKGROUND

2.1 Retail location theory

The first theories towards retail locations originate from microeconomics, focusing the aspect of spatial competition: A well-known model is the *principle of minimum differentiation* by Hotelling (1929), describing a duopoly with two firms selling the same good at the same selling price on a linear market. Both consumers and sellers possess perfect market information. The customers are uniformly distributed and have to pay the good's selling price and the transportation costs for reaching the sellers. As the latter is different between all consumers, they face different prices. While being utility-maximizers and cost-minimizers, respectively, consumers always choose the nearest seller. Being utility-maximizers as well, the two sellers relocate to maximize their profits. The best locational structure for the consumers (minimizing transportation costs) would occur if the sellers locate at the first and the third quarter of the linear market, respectively. In contrast, the best location for both sellers is a cluster in the middle of the market, each of them serving the left and the right side of the market, respectively.

In the *theory of monopolistic competition* by Chamberlin (1933), market interactions are regarded as a combination of monopoly and competition. Also outgoing from utility-maximization and perfect information of all market participants, the goods in a specific market are imperfect substitutes, as the consumers have preferences towards a specific product variant (*product differentiation*). Consequently, the sellers can increase product prices to a certain extent without any loss of demand, resulting in extra-profits. The degree of competition (monopoly) is as higher as the product variants are substitutable (unique). In the long run, the extra-profits motivate new sellers to enter the market, increasing competition until the extra-profits of all sellers are absent. Chamberlin explicitly discusses retail stores as an example of differentiation, as the individual location choice in proximity to the customers and apart from its competitors is a *spatial differentiation*, resulting in a *spatial monopoly* due to the consumers' convenience while traveling to the store. Consequently, retail competitors providing perfectly substitutable goods follow a strategy of competition avoidance (spatial dispersion) to secure their market areas. In contrast, retailers selling *different* goods tend to cluster, allowing customers to perform *multipurpose shopping* and/or *comparison shopping*.

Both Hotelling and Chamberlin show that spatial competition is a kind of imperfect competition: Because of different transportation costs, even identical goods offered by retailers with different locations are not perfect substitutes. Due to its proximity to its customers, a given store always profits from a spatial monopoly, whose extent is dependent on the proximity to its competitors (Biscaia and Mota, 2013; Eaton and Tweedle, 2012). Note that "transportation costs" in an economic sense is a hypernym for any kind of effort related to traveling.

The strategy of store clustering is another important aspect, as multipurpose and comparison shopping are the major sources of agglomeration economies in retailing, both also allowing customers to save transportation costs (Mulligan et al., 2012). This aspect is more strengthened when assuming consumers to have imperfect information: As Wolinsky (1983) shows, when the consumers wish to reduce search and transportation costs, they prefer retail agglomerations of imperfect competitors over isolated stores. Consequently, being profit-maximizers, competing sellers tend to build clusters.

The first explicit retail location theory is the *central place theory* (CPT) by Christaller (1933), while the work by Lösch (1940) is a related but more general spatial economic approach *including* the retail sector. It is presumed that the consumers are evenly distributed in an isotropic surface with identical transportation costs in all directions, while sellers as well as customers are utility-maximizers and possess perfect information. The consumers have to pay the selling price of a given good (*central good*) plus the related transportation costs to reach the supply locations (*central places*) which increase with distance. As the consumers have a budget constraint, their demand is elastic; thus, a central good's quantity demanded decreases with increasing transportation costs. Consequently, the customers visit the nearest central place when purchasing a single good. The maximum distance within the good is purchased is called *outer range*, and the corresponding price (including transportation costs) is the consumers' reservation price. To be economically viable, the seller of a good needs a demand threshold or, in the spatial context, a minimum market area, which is called *inner range*. Sellers providing the same good avoid competition. Due to the premise of an isotropic surface, the complete market is served on condition that the market areas have a hexagonal form. As shown by Lösch (1940), this solution for one good is the spatial equivalent of monopolistic competition. The central goods can be arranged hierarchically: The larger the inner and outer range, the higher the *order* of the good and the less the number of central places it is sold in. In the consequence, there is a hierarchy of central places of different order, resulting from the amount and order of central goods. Groceries are assumed to have a low inner and outer range due to a high distance sensitivity of consumers, thus, they are provided in many central places.

From an empirical-inductive perspective, Nelson (1958) derives *locational factors* in retailing from observed shopping behavior: Accordingly, a store's turnover can be traced back to 1) its *generative business* based on its own attraction, 2) its *shared business* resulting from the surrounding potential of multipurpose and comparison shopping and 3) its *suscipient business* due to external customer magnets. Nelsons *theory of cumulative attraction* states that clusters of competing retailers selling different product variants (e.g. shoe stores) generate more customer traffic as the sum of all stores if they were located solitary, because they allow comparison shopping, increasing the attraction perceived by the customers. Also including the opportunity of multipurpose shopping with respect to complementary goods, Nelson derives a mathematical *rule of retail compatibility* and empirical results in form of *compatibility tables*. Different types of groceries (e.g. supermarket and drugstore, bakery and butcher) are regarded as highly compatible.

The spatial competition models and central place theory paved the way for a new generation of mathematical models, especially in the context of the so-called "New Economic Geography" (Mulligan et al., 2012), all of them not differing in the key statements about consumer behavior mentioned above (Wieland, 2015). Retail location theories were also empirically tested with respect to grocery stores: Reigadinha et al. (2017) find support for both competition avoidance and clustering depending on store type and population density. In the German context, Stegner et al. (2010) document the trend of clustering of supermarkets and discounters, while Jürgens (2013) empirically proves the active formation of site cooperations by grocery stores of different formats (supermarkets and discounters).

2.2 Market area models

Market area models (or store choice models) are both a theoretical and empirical approach, originating from the work of Reilly (1929) and Converse (1949), both rather calculation formulas than theories and only considering two supply locations. Criticizing these approaches, Huff (1962) develops a model founded on microeconomic and behavioral-theoretic assumptions. The *Huff Model* is based on a multiplicative utility function representing the consumers' trade-off between two explanatory variables assuming to influence store choice (Huff, 1962; Huff and Batsell, 1975):

$$U_{ij} = A_j^{\gamma} d_{ij}^{-\lambda}$$

Where U_{ij} is the utility of the retail location j for the customers in origin i, A_j is the attraction of location j, d_{ij} contains the transportation costs from i to j, γ and λ are weighting parameters.

Huff (1962) translates "attraction" in terms of size: As the consumers are assumed to possess imperfect information, they decide for the destinations of their shopping trips on condition of uncertainty. The larger the assortment of a location, the more likely is to get the desired goods. However, as the consumers' search and decision costs rise with an increasing number of offered goods, size affects attraction under-proportionately, which means *diminishing marginal utility of size*, reflected by the weighting parameter ($0 < \gamma < 1$). To simplify the empirical application of the model, the selling floor space of retail locations is used as a proxy variable for assortment size. The transportation costs indicator in the model is explicitly regarded as travel *time*, attempting to reflect the *opportunity costs* of shopping trips; the related perceived disutility is expressed by an over-proportionate negative weighting of travel time ($|\lambda| > 1$).

Consumer behavior is regarded as *probabilistic*, which means that there is no prediction of a definite store choice. The probability to choose location *j* (*interaction probability*) is calculated as the quotient of its utility, U_{ij}, and the sum of the utilities of all alternatives:

$$p_{ij} = \frac{U_{ij}}{\sum_{j=1}^{n} U_{ij}} = \frac{A_j^{\gamma} d_{ij}^{-\lambda}}{\sum_{j=1}^{n} A_j^{\gamma} d_{ij}^{-\lambda}}$$

Where p_{ij} is the probability that customers from customer origin *i* choose retail location *j* and *n* is the total number of retail locations.

As the interaction probabilities ($0 < p_{ij} < 1$) can be interpreted as local market shares, the customer/expenditure flows from *i* to *j*, E_{ij}, result from multiplying p_{ij} by the customer/expenditure potential in customer origin *i*, C_i (Huff, 1962):

$$E_{ij} = p_{ij} C_i$$

The total market area of store *j*, T_j, equals the sum of all customer/expenditure flows over all *m* submarkets (Huff, 1964):

$$T_j = \sum_{i=1}^{m} E_{ij}$$

The local market shares and the resulting customer/expenditure flows represent a stable consumer equilibrium as the result of several store choices under uncertainty in the past (Huff and Batsell, 1975). Unlike CPT, the Huff Model assumes imperfect consumer information, overlapping market areas and real traffic conditions. However, the main problems of the model are 1) the values of the weighting parameters reflecting the consumer reaction on the retail locations' competitive parameters size (assortment) and transportation costs (accessibility) which are not equal over space and time, and 2) the models' limitation on two explanatory variables only (Huff and McCallum, 2008).

Both problems were solved by the *Multiplicative Competitive Interaction (MCI) Model* (Nakanishi and Cooper 1974; 1982), which is both a generalization and an econometric transformation of the Huff Model. The choice probability of an alternative *j* also depends on a multiplicative utility function, but including *h* (*h* = 1, … *H*) explanatory variables:

$$p_{ij} = \frac{\prod_{h=1}^{H} {A_{h}}_{j}^{\gamma_h}}{\sum_{j=1}^{n} \prod_{h=1}^{H} {A_{h}}_{j}^{\gamma_h}}$$

Where A_{hj} is the value of the *h*-th variable describing the alternative *j*, γ_h is the weighting parameter for the sensitivity of p_{ij} with respect to the variable *h*.

The MCI Model is a *revealed preference approach*, which means to infer store preferences from consumers' past behavior revealed (Tihi and Oruc, 2012). When real local market shares with respect to shopping trips or expenditures were observed in a survey, they become the dependent variable in a regression model and can be explained by the *H* independent variables. To allow the estimation of the weighting coefficients (γ_h) using common linear regression (OLS – Ordinary least squares), the model is transformed into an equation which is linear in parameters. The corresponding transformation is called *log-centering transformation* (Nakanishi and Cooper, 1974):

$$\log\left(\frac{p_{ij}}{\tilde{p}_i}\right) = \sum_{h=1}^{H} \gamma_h \log\left(\frac{A_{h_j}}{\tilde{A}_{h_j}}\right) + \log\left(\frac{\varepsilon_{ij}}{\tilde{\varepsilon}_i}\right)$$

Where all variables marked with a tilde ("~") reflect the geometric means of the corresponding variable and ε_{ij} is the stochastic disturbance term (residuum), reflecting the differences between observed and expected market shares. After the OLS estimation of the coefficients, they can be inserted into the probability equation above to calculate local market shares. If the utility function must be kept in its linear form, it can be expressed in terms of the so-called *inverse log-centering transformation* (Nakanishi and Cooper, 1982):

$$\hat{y}_{ij} = \sum_{h=1}^{H} \hat{\gamma}_h \log\left(\frac{A_{h_j}}{\tilde{A}_{h_j}}\right)$$

$$p_{ij} = \frac{e^{\hat{y}_{ij}}}{\sum_{j=1}^{n} e^{\hat{y}_{ij}}}$$

Where $\hat{y}_{ij}$ is the transformed utility of location j for customers in origin i and γ_h marked with a hat ("^") represents the estimated regression coefficients.

The MCI Model has already been used in the grocery context, mostly confirming the main statements of the Huff Model regarding store size and travel time or distance (e.g. Baviera-Puig et al., 2016; Suárez-Vega et al., 2011; Tihi and Oruc, 2012; Wieland, 2015). Regarding other aspects like store clustering or pricing, there is less evidence: Tihi and Oruc (2012) found the proximity to stores of the same store format (hypermarket) as a negative influence on local market shares. Wieland (2015) confirms this negative impact, but finds a positive influence of clustering with stores of another format (supermarket and discounter, and vice versa). With respect to grocery store pricing levels, Tihi and Oruc (2012) reject using a price variable due to multicollinearity problems, while Wieland (2015) finds a negative effect of price level on local market shares.

3. OWN STUDY

3.1 Research hypotheses

To answer the research questions, the central statements of retail location theory and market area models towards consumer behavior have to be translated into research hypotheses with respect to grocery retailing, which shall be tested in a real environment.

According to the Huff Model, the aspect of store size is assumed to have a positive influence on store choice (H_{1a}), while this influence should be under-proportionate due to diminishing marginal utility of size (H_{1b}). As most retail location theories assume that consumers response to price changes in a competitive environment, this can be transferred to the pricing level of grocery chains. Consequently, it is hypothesized that, the higher the price level, the less likely is store choice (H_2).

Store accessibility is identified as the key competitive parameter in spatial competition to achieve a spatial monopoly. As unanimously stated by retail location theories, it is expected that transportation costs (no matter how it is measured) have a negative influence on store choice (H_{3a}). Additionally, following the assumptions in the Huff Model, this negative influence is assumed as progressive (H_{3b}). A second locational aspect is the potential of multipurpose shopping and comparison shopping at the specific location, which is related to the qualitative definition of local supply (variety with respect to store formats). It is expected that spatial proximity to other grocery stores of a *different* store format increases store patronage (H_4).

3.2 Modeling framework

For empirically testing the research hypotheses, the MCI Model (see section 2.2) is used. According to both the Huff and the MCI Model, the dependent variable of the modified model used here must be the empirical local market shares (p_{ij}) of the grocery stores (j = 1, …, n) in the customer origins (i = 1, …, m). As there are different types of shopping trips which are performed more or less frequently and related to very different shopping budgets, one must distinguish between the shares of shopping *trips* (visits of the particular store) and of the related expenditures (money spent at the particular store). Thus, two models are built differing in their dependent variable, which is calculated separately for both empirically observed shopping trips and expenditures:

$$p_{ij_{st}} = \frac{O_{ij_{st}}}{\sum_{j=1}^{n} O_{ij_{st}}}$$

$$p_{ij_{ex}} = \frac{O_{ij_{ex}}}{\sum_{j=1}^{n} O_{ij_{ex}}}$$

Where $p_{ij\ st}$ and $p_{ij\ ex}$ equal the local market shares of grocery store j in customer origin i concerning shopping trips and expenditures, respectively, $O_{ij\ st}$ is the observed number of shopping trips from i to j, $O_{ij\ ex}$ is the sum of expenditures related to the shopping trips from i to j and n is the number of grocery stores in the study area.

According to the Huff Model, store size – measured as selling floor space in square meters (sqm) – is used as a proxy for the stores' assortment size, reflecting product range and variety and, thus, being an indicator related to the qualitative dimension of local supply. The pricing aspect cannot be included into the model as a continuous variable, as the available price level statistics (DISQ, 2015) do not cover all common grocery chains. Thus, these price patterns are represented using dummy variables for grocery chains referring to the observed price levels (standardized shopping cart) from DISQ (2015): Three dummy variables typifying the chains Netto (low price level), Aldi (middle) and Edeka (high) are included into the model.

The location aspect must be represented by two independent variables: None of the retail location theories declares a specific measuring unit of "transportation costs". While the Huff Model is originally formalized using car driving time as a proxy for spatial accessibility, in the local supply context, several measures of non-car traveling are discussed (Krüger et al., 2013). To identify the most meaningful accessibility indicator (third research question), six different measures are used: 1) the airline distance (in meters), 2) footway distance (meters), 3) footway time (minutes), 4) car driving time (minutes), 5) bike driving time (minutes) and 6) driving time with respect to public transport (bus, tramway). This results in six models each for both dependent variables (shopping trip and expenditure shares).

The second location aspect relates to clustering of stores of a different format and is calculated following the *Competing Destinations Model* by Fotheringham (1985). In the original concept, it measures the size-weighted spatial proximity to all competitors, which has already been used in MCI analyzes (Tihi and Oruc, 2012; Wieland 2015). In the present case, this approach is modified to model agglomeration with respect only to stores of a *different* format in one single variable:

$$C_j = \sum_{\substack{k \\ k \neq j}}^{K} D_{F_k \neq F_j} A_k d_{jk}^{-\lambda}$$

Where C_j is the spatial concentration indicator, $D_{Fk \neq Fj}$ is a dummy variable indicating if the store format of store *j* is *not* equal to the format of store *k*, A_k is the store size of store *k* (in sqm), d_{jk} is the airline distance between the stores *j* and *k*, λ is the weighting parameter of distance (equal to 2 in this case) and *K* is the number of all other grocery stores from the perspective of *j*.

As the model includes dummy variables, the underlying model structure has to be linear in parameters, leading to the MCI Model in the inverse log-centering transformation with a linear utility function in which the continuous variables are transformed:

$$\hat{y}_{ij} = \gamma \log\left(\frac{A_j}{\tilde{A}_j}\right) + \lambda \log\left(\frac{d_{ij}}{\tilde{d}_i}\right) + \theta_1 D_{Netto_j} + \theta_2 D_{Aldi_j} + \theta_3 D_{Edeka_j} + \varphi \log\left(\frac{C_j}{\tilde{C}_j}\right)$$

Where $\hat{y}_{ij}$ is the transformed utility of store *j* for customers in origin *i*, A_j is the size of store *j*, d_{ij} equals the transportation costs between *i* and *j*, $D_{Netto\ j}$, $D_{Aldi\ j}$ and $D_{Edeka\ j}$ indicate if store *j* belongs to the chain Netto, Aldi or Edeka, respectively, C_j is the spatial concentration indicator, all variables marked with a tilde ("~") reflect the geometric means of the continuous variables and γ, λ, Θ_1, Θ_2, Θ_3 and φ are the corresponding regression coefficients.

Table 1 presents an overview of the dependent variables in the MCI utility function, their corresponding grocery store competitive parameters and local supply dimensions as well as the related hypotheses which have to be tested.

Table 1. Independent variables in the MCI utility function

Indicator	Local supply dimension	Operationalization	Model variable(s)	Related hypotheses
Assortment size	Qualitative	Store size [sqm]	A_j	H_{1a}, H_{1b}
Pricing level	Qualitative	Dummy variables (1/0) for three pricing levels (low, middle, high)	$D_{Netto\ j}$, $D_{Aldi\ j}$, $D_{Edeka\ j}$	H_2
Accessibility	Quantitative	Distance: airline [m], footway [m]; travel time: Footway [min.], car [min.], bike [min.], public transport [min.]	d_{ij}	H_{3a}, H_{3b}
Multipurpose and comparison shopping potential	Qualitative	Concentration with respect to different formats [sqm/distance^2]	C_j	H_4

Source: own illustration

3.3 Empirical approach

3.3.1 Study area

The empirical modeling approach is applied to the local supply structures in the urban district Haslach of the German city Freiburg (state of Baden-Wuerttemberg). At an actual population of 19,730 (2016), the urban district covers an area of 3.42 km^2, resulting in a population density of 5,664 per km^2. Haslach is subdivided into four sub-districts (611-614; see figure 1), which are treated as customer origins in the model analysis.

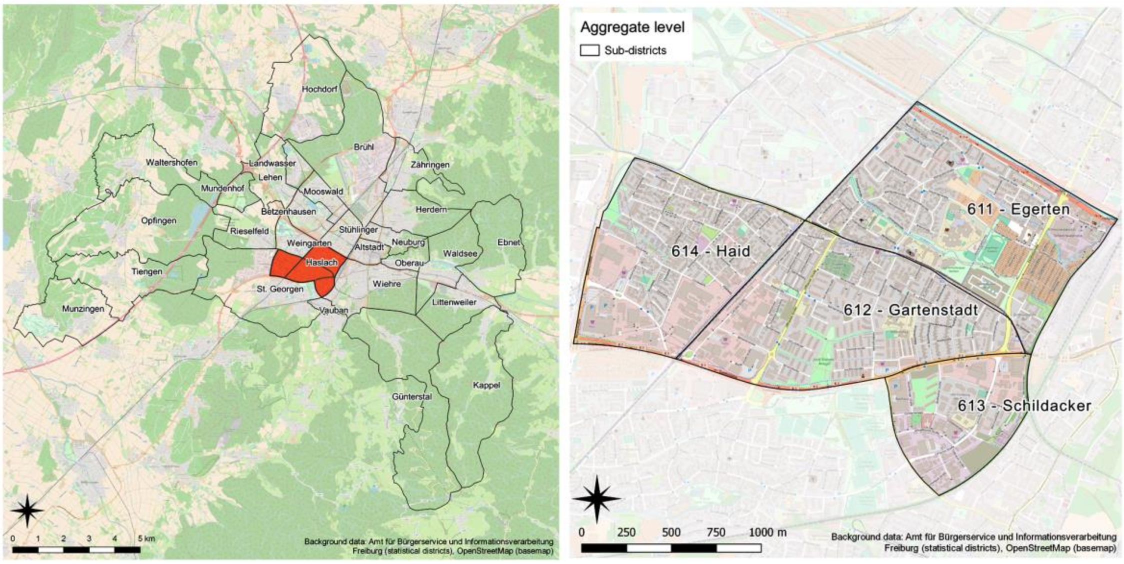

Figure 1. Study area.

3.3.2 Data collection

The first step of data collection was the identification of all relevant grocery stores (supermarkets, hypermarkets and discounters) in the study area and collecting their necessary attributes (name, chain, selling floor space and address). The resulting eight stores were gathered as geodata by storing them into a point shapefile. The stores' selling spaces were retrieved from chain websites or the associated land-use plans. The store format was identified according to the Nielsen typology (The Nielsen Company Germany, 2016).

To collect data about grocery shopping behavior, a consumer survey in Freiburg-Haslach was conducted. The oral survey took place at 13 highly frequented sample points (district center, public swimming pool, church, tram stations, residential areas, public park), due to the limited human resources in the study, in three of the four sub-districts (611, 612 and 614). To secure contacting different types of households, the survey was conducted between nine a.m. and six p.m. on Friday 11 and Saturday 12 May 2018. The respondents were drawn in form of a random sample, while the interviewers were instructed to contact any person crossing an imaginary line from the interviewers' perspective (Monheim, 1999).

A standardized questionnaire was used, concerning the residents' behavior patterns with respect to grocery retailing as well as their place of residence (assigned to the corresponding sub-district) and socio-demographic characteristics. To gather grocery shopping behavior, a revealed preference approach was used: Following the procedure in the only MCI study on German grocery retailing (Wieland, 2015), the respondents were asked about their two most recent grocery purchases and the expenditures related to each shopping trip. The eight grocery stores in Haslach were listed in the questionnaire, while providing a free text field for any other grocery stores, enabling the observation of purchases outside the urban district.

In the survey, 235 individuals, each one representing a household, were interviewed, distributed over the sub-districts as follows: 611: 71 (30.21%), 612: 144 (61.28%), 613: 1 (0.43%) and 614: 12 (5.11%). The remaining respondents without specification (2.98%) were excluded from the MCI analysis. The responders were 130 females (55.32%) and 95 males (40.43%) (not specified/survey drop-out: 10/4.26%). The age groups are represented as follows: Under 18: 8 (3.4%), 18 to 24: 26 (11.06%), 25 to 44: 54 (22.98%), 45 to 64: 76 (32.34%) and 65 and older: 68 (28.94%). The average household size in the sample is 2.31.

3.3.3 Data processing

The single purchases and expenditures were aggregated over the three customer origins. As only one respondent from sub-district 613 appeared in the sample, this person was assigned to the neighboring district 612. The m = 3 customer origins and n = 8 grocery stores result in a matrix containing $m*n$ = 24 entries. Four of these combinations (16.67 %) were equal to zero (no observed shopping trips from the specific origin i to a store j); as these values cannot be processed in the log-centering transformation, like in other MCI studies (e.g. Hartmann, 2005; Wieland, 2015), the observed purchases and expenditures ($O_{ij\ st}$ and $O_{ij\ ex}$, respectively) were increased by a small constant (equal to 0.1) before calculating p_{ij}.

What remains to be done was to calculate two of the independent variables for further processing in the MCI analysis: For each possible interaction between customer origin i and store j, the six measures of spatial accessibility (d_{ij}) were calculated using *Google Maps*. The concentration indicator was calculated using the selling floor space of the grocery stores and the airline distances (in meters) between them.

The analysis was made in *R* (R Core Team, 2017) using the package *MCI* (Wieland, 2017). *QGIS* (QGIS Development Team, 2018) was used for cartography and buffer analysis.

4. RESULTS

4.1 Descriptive analysis

4.1.1 Grocery stores and spatial coverage

Out of the eight grocery stores in Freiburg-Haslach, there are five discounters and one each of supermarkets, large supermarkets and hypermarkets, all of them with a total selling floor space of 15,644 sqm. As expected, the average expenditures per shopping trip differ between store formats with respect to the average store size (see table 2). Figure 2 shows the grocery store locations in Haslach, differentiated by store formats, and their spatial coverage in terms of a 500 meter buffer (which is the common operationalization of store accessibility from the quantitative dimension of local supply). Including three stores located in commercial areas (sub-districts 613 and 614), nearly the whole area is covered by at least one store, while most buffers overlap. Of course, buffers are not to be confused with real market areas, but with respect to the important aspect of spatial accessibility, this configuration suggests a high degree of spatial competition and a strong influence of accessibility on store choice.

Table 2. Grocery store characteristics

Store format	Small Supermarkets (400-999 sqm)	Large supermarkets (1,000-2,499 sqm)	Hypermarkets (>= 2,500 sqm)	Discounters	Total
No. of stores	1	1	1	5	8
Store size [sqm], sum	694	2,170	8,900	3,880	15,644
Store size [sqm], mean	694	2,170	8,900	776	1,955.5
No. of shopping trips	112	37	17	163	329
Expenditures [EUR], mean	19.96	40.59	53.69	27.56	27.79

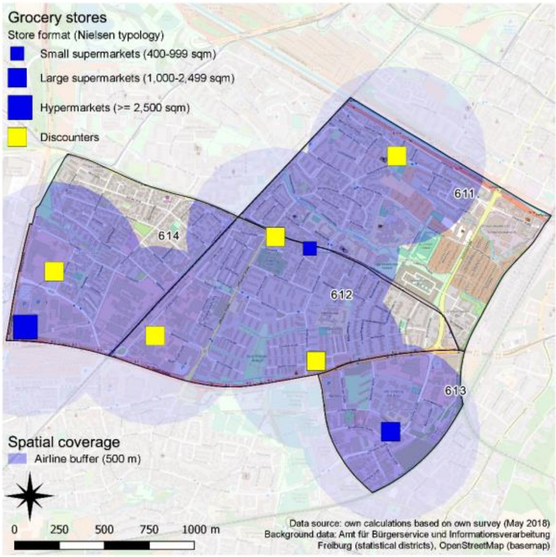

Figure 2. Spatial coverage of grocery stores.

4.1.2 Local market shares

Figure 3 shows the empirical local market shares of the grocery stores in the three customer origins (on the left: shares of shopping trips, on the right: shares of expenditures). The size of the circles indicates the absolute values the market shares refer to. In figure 4, the local market shares are plotted on the y axis, while the distance (here measured as airline distance in sqm) is represented on the x axis. The point size is equal to the logarithm of store size (in sqm), while the point color indicates the store format.

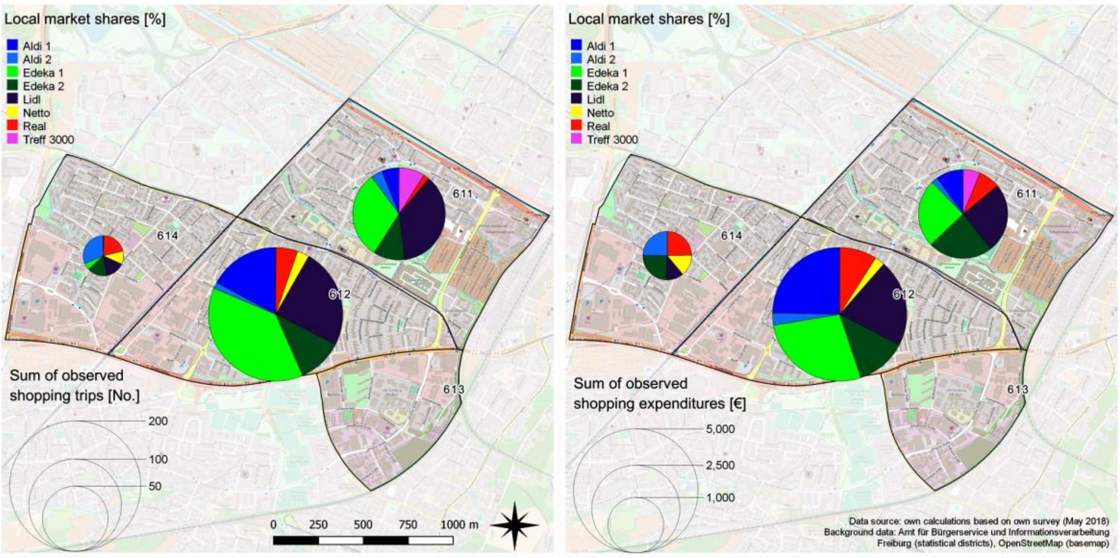

Figure 3. Local market shares of grocery stores.

This descriptive visualization reveals two interesting aspects: First, nearly any store is frequented from any sub-district, indicating a strong degree of spatial competition between the grocery stores. At least on this segmentation level of the market areas, there seems to be no full spatial monopoly. This is not surprising, taking into account the high store density in the study area and the spatial coverage (see section 4.1.1). Consequently, local market shares strongly decline with respect to distance, especially when looking at the shopping trip shares. As the plots below show, there are different distance decays for store formats: The larger (smaller) the store, the lower (higher) is the decline of market shares with respect to distance.

Second, it is obvious how shopping trip shares and expenditure shares differ with respect to store format and store size: The small supermarket tends to attract customers for smaller but more frequent purchases, while the large supermarket and the hypermarket offer the opportunity of less frequent major shopping trips. This aspect was already suggested by the format-specific differences in the average expenditures (see section 4.1.1), confirming the necessity of considering both shopping trips and expenditures in market area analysis.

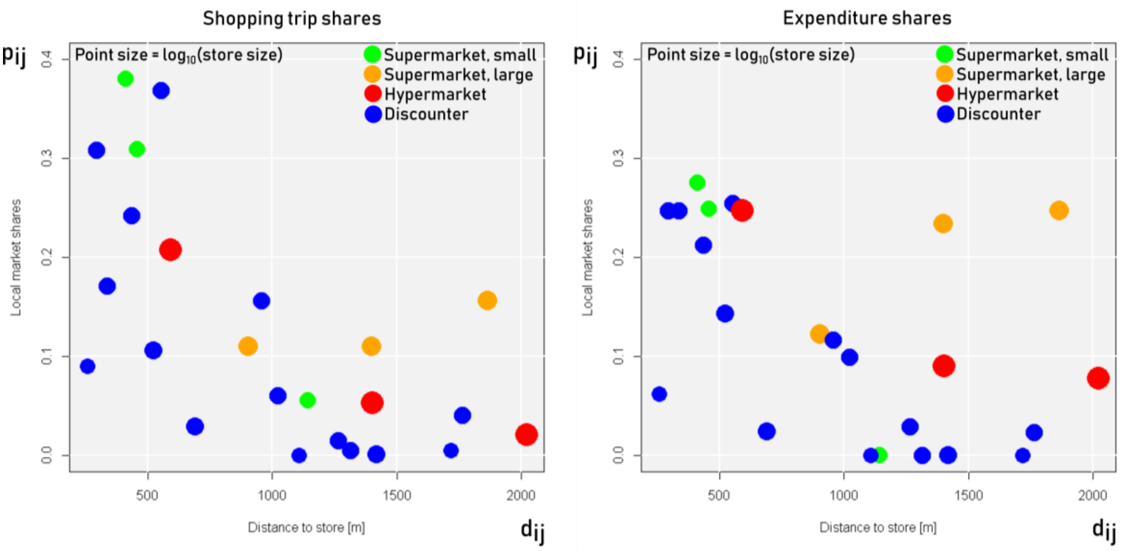

Figure 4. Local market shares of grocery stores with respect to distance, size and store format.

4.2 MCI Model findings

4.2.1 Modeling results

The MCI Model results are presented in tables 3 (shopping trip shares) and 4 (expenditure shares). In both cases, six models were estimated, only differing in their transportation costs indicator (d_{ij}). The table shows the regression coefficients and the relating standard errors (in parentheses). Out of all 12 models, eight are statistically significant at the 1% level ($p < 0.01$ with respect to the F Statistic), while three expenditure shares models (footway walk, footway time and bike driving time) are significant at the 10% level ($p < 0.1$) and one model (public transport) is not significant. All models were tested with respect to multicollinearity using the VIF (variance inflation indicators), which is always clearly below the critical value of five.

Table 3. MCI results – Shopping trip shares model

	Indicator for transportation costs$_{ij}$:					
Independent variables Coefficients (std. error in parentheses)	Airline [m]	Footway [m]	Footway [min.]	Car [min.]	Public transport [min.]	Bike [min.]
Store size$_j$	0.764** (0.287)	0.781** (0.333)	0.766** (0.327)	0.487* (0.251)	0.667* (0.384)	0.606* (0.332)
Transportation costs$_{ij}$	-1.967*** (0.406)	-1.827*** (0.489)	-1.934*** (0.504)	-3.483*** (0.620)	-1.510** (0.614)	-1.814*** (0.530)
Dummy Netto$_j$	-0.629** (0.283)	-0.560 (0.324)	-0.577* (0.319)	-1.092*** (0.271)	-0.622 (0.372)	-0.668* (0.335)
Dummy Aldi$_j$	-0.167 (0.223)	-0.133 (0.256)	-0.114 (0.253)	0.096 (0.214)	-0.157 (0.296)	-0.115 (0.267)
Dummy Edeka$_j$	0.598*** (0.204)	0.631** (0.233)	0.615** (0.230)	0.553*** (0.187)	0.621** (0.268)	0.613** (0.241)
Concentration$_j$	0.595* (0.290)	0.606* (0.331)	0.555 (0.330)	0.093 (0.293)	0.632 (0.384)	0.311 (0.371)
Observations	24	24	24	24	24	24
R^2	0.701	0.612	0.621	0.750	0.485	0.583
Adjusted R^2	0.601	0.483	0.495	0.667	0.313	0.444
Residual Std. Error (df = 18)	0.485	0.553	0.546	0.444	0.637	0.573
F Statistic (df = 6; 18)	7.035***	4.737***	4.924***	8.998***	2.822**	4.193***
Note: *p<0.1; **p<0.05; ***p<0.01						

Source: own calculations

Table 4. MCI results – Expenditure shares model

	Indicator for transportation costs$_{ij}$:					
Independent variables Coefficients (std. error in parentheses)	Airline [m]	Footway [m]	Footway [min.]	Car [min.]	Public transport [min.]	Bike [min.]
Store size$_j$	2.045*** (0.614)	2.039*** (0.690)	2.018*** (0.681)	1.614*** (0.544)	1.857** (0.750)	1.782** (0.671)
Transportation costs$_{ij}$	-3.128*** (0.870)	-2.772** (1.013)	-2.941** (1.048)	-5.710*** (1.345)	-2.253* (1.200)	-2.811** (1.071)
Dummy Netto$_j$	-0.703 (0.607)	-0.601 (0.670)	-0.627 (0.665)	-1.462** (0.587)	-0.695 (0.728)	-0.764 (0.676)
Dummy Aldi$_j$	0.100 (0.477)	0.143 (0.530)	0.172 (0.527)	0.537 (0.464)	0.104 (0.578)	0.175 (0.539)
Dummy Edeka$_j$	0.543 (0.437)	0.593 (0.482)	0.568 (0.478)	0.469 (0.406)	0.577 (0.525)	0.565 (0.488)
Concentration$_j$	0.650 (0.621)	0.685 (0.686)	0.607 (0.686)	-0.184 (0.636)	0.729 (0.751)	0.220 (0.750)
Observations	24	24	24	24	24	24
R^2	0.555	0.460	0.468	0.618	0.361	0.447
Adjusted R^2	0.407	0.281	0.291	0.491	0.148	0.263
Residual Std. Error (df = 18)	1.039	1.145	1.137	0.963	1.246	1.159
F Statistic (df = 6; 18)	3.748**	2.560*	2.643*	4.856***	1.694	2.428*
Note: *p<0.1; **p<0.05; ***p<0.01						

Source: own calculations

In each of the 12 models, transportation costs appear as statistically significant (mostly $p < 0.01$). As, due to the log-centering transformation, the MCI variables are standardized and the coefficient related to d_{ij} is the highest in each model, one can conclude that accessibility, no matter how measured, has the largest influence on local market shares in the present case. All λ coefficients are less than -1, which means an over-proportionately negative influence on store choice. Store size is always significant as well, but the positive influence differs between the shopping trips and the expenditure shares models: While the coefficient γ always ranges between zero and one in the former, indicating an under-proportionate effect, it is greater than one in the latter, which means an over-proportionate effect (Expenditure shares increase by a higher rate than store size increases).

The dummy variables, representing three different price levels, have the same signs in each model; however, not all of them are statistically significant. The dummy for the chain Netto (representing the lowest pricing level) is always negative and significant at least in all shopping trips models, while the Aldi dummy does not show any significant effect. The Edeka dummy affects local market shares of shopping trips significantly positive, but not the expenditure shares. The concentration variable is positive (except for the car driving time model of expenditure shares), but only significant ($p < 0.1$) in two of the shopping trip shares models. Comparing the shopping trip and expenditure shares models, the coefficients are within the same range, except for the models using car driving time as accessibility indicator.

4.2.2 Hypothesis discussion

The research hypotheses can be checked based on the statistical significance (which is the fundamental condition for further exploration) as well as the sign and value of the regression coefficients (see table 5).

Table 5. Hypothesis check

Indicator	Model variable(s)	Hypothesis	Shopping trip shares model	Expenditure shares model
Assortment size	A_j	H_{1a}	confirmed	confirmed
		H_{1b}	confirmed	rejected
Pricing level	$D_{Netto\ j}$, $D_{Aldi\ j}$, $D_{Edeka\ j}$	H_2	rejected	rejected
Accessibility	d_{ij}	H_{3a}	confirmed	confirmed
		H_{3b}	confirmed	confirmed
Multipurpose and comparison shopping potential	C_j	H_4	partially confirmed	rejected

Source: own illustration

According to the modeling results presented above, the first two hypotheses concerning store size are confirmed in the shopping trip shares model, as the influence on local market shares is positive (H_{1a}) and under-proportionate (H_{1b}). The former also applies for the expenditure shares, while, in the latter case, an over-proportionate influence was found. At least in the present case, a store's attraction concerning the choice if to visit or not is increased degressively by store size. This finding matches the assumptions in the Huff Model about the diminishing marginal utility of assortment size. However, the expenditures at the point of sale increase progressively with store size which can be explained by different types of grocery shopping trips: Large supermarkets and hypermarkets are visited less frequently, but they attract customers when they perform major shopping trips with large budgets.

With respect to the assumed negative effect of pricing level (H_2), no clear results were found, which leads to rejecting the price hypothesis. The coefficients are mostly insignificant, and, when significant, they show the reverse direction: As cheap as the grocery chain is, the less are the local market shares. There are at least three explanations for these findings, which are not mutually exclusive: 1) the pricing level does not matter anymore, as customers prefer quality-orientated stores over cheap stores. 2) The dummy variables do not reflect price levels correctly. 3) The dummy variables reflect rather the chain's image than the price level and the former masks the latter.

The hypotheses concerning the transportation costs are completely confirmed: In all cases, a negative (H_{3a}) and progressive (H_{3b}) effect on local market shares was found. Like in other studies (see section 2.2), transportation costs have an over-proportionate effect, indicating that accessibility is a major locational factor and stores benefit from the proximity to their customers.

The hypothesized positive effect of clustering with respect to stores of a different format (H_4) must be partially confirmed with respect to shopping trip shares, as the always positive effect is also significant in two cases. In the expenditures model, the relating coefficient is not significant in any case. Obviously, there is another competitive parameter switching its relevance whether shopping trips or the related expenditures are regarded: It is quite plausible to visit a store cluster (e.g. Real/Aldi in a commercial area) rather than a solitary store because this allows mixing the offers of two different store formats, but this does not imply higher expenditures: Customers could visit both stores and share their shopping budgets.

4.2.3 Accessibility indicators

As the dependent variable is the same in all six models of each case, the most meaningful accessibility indicator can be identified by comparing the explained variance of the models, measured as R^2 and adjusted R^2, respectively. Obviously, both models including car driving time as accessibility measure best meet this criterion. This might be due to two different reasons which are not mutually exclusive: 1) Most of the grocery shopping trips in the present case are, in fact, performed using a car, but this is rather unlikely when considering the high store density and the spatial coverage in the urban district (see section 4.1.1). 2) The car driving time is the best proxy of spatial accessibility, as it reflects the travel time regarding the specific traffic conditions better than other measures.

However, it is surprising that the second-best indicator is the airline distance, while all other models suffer from much less explained variance. In fact, the models including the airline distance as the transportation costs indicator are almost on the same level as the models using car driving time. As, in the local supply context, store accessibility is regarded as non-car-accessibility, frequently measured in terms of airline distance, the models using this indicator are to be preferred over the car driving time models.

5. CONCLUSIONS AND LIMITATIONS

Referring to the first research question, from a theoretical perspective, competition between grocery stores must be regarded as spatial competition: The aspect of spatial accessibility – translated as transportation costs in retail location theory – is a main competitive parameter of grocery suppliers allowing them to profit from a (limited) spatial monopoly when locating near to their customers. Exploiting this competitive advantage should result in spatial dispersion of stores, which would be a preferable outcome with respect to the quantitative dimension of the normative definition of local supply. However, clustering of grocery stores is also assumed to be a worthwhile strategy, on condition that they are not perfectly substitutable due to different store formats (supermarkets and discounters); the opportunity of multipurpose and comparison shopping increases the own attraction, which means profiting from agglomeration economies. As the consumers are assumed to possess imperfect information, making their decisions on condition of uncertainty, each store’s attraction can be expressed by its assortment, more precisely, its variety with respect to different products and product variants; however, due to rising search and decision costs, the generative business of a store does not grow proportionately to its size. The aspects of variety with respect to assortment and store formats refer to the qualitative dimension of local supply.

The key assumptions from retail location theory and market area models were tested by an example of grocery store locations in the urban district Haslach in Freiburg, Germany. The relating empirical results, which refer to the second research question, mostly confirm the hypotheses derived from the theories. As assumed by location theory and discussed in the local supply context, the most important influence on store choice is spatial accessibility of the stores, no matter how it is operationalized. This does not mean to choose the nearest store but within the consumers' trade-off, accessibility has the highest weighting. While store size has a clearly positive impact, no clear results towards the chains' pricing policy can be found. There is also empirical evidence on positive agglomeration effects with respect to the clustering of different store formats. With respect to the third research question, it is shown that, while the best indicator seems to be car driving time (which is opposed to the ideal of local supply), the second best is, surprisingly, the airline distance.

With respect to the normative local supply definition and the corresponding spatial planning instruments, three conclusions can be drawn: 1) As the quantitative dimension (easy accessibility) would be perfectly fulfilled when stores are dispersed but the qualitative dimension implies store clustering (greater variety with respect to different store formats), there might be a conflict of objectives between these two dimensions. Consequently, the best location pattern *would* be a spatial dispersion of grocery store *clusters* of a comparable size. 2) As the airline distance is obviously an acceptable operationalization of accessibility, it is appropriate to be used in local supply analysis or even preferred over other measures like street distances. This is advantageous, as the calculation of airline distance is much easier than network-based indicators which require an up-to-date road network. Furthermore, the airline distance is an objective measure, not assuming a specific travel mode choice. 3) The retail impact assessment in the spatial planning context, in which market area models are used frequently, should distinguish between shopping trip and expenditure shares; if there is an underlying survey about consumer shopping behavior, both aspects should be inquired.

However, the present study also faces some limitations: First, the transferability of the results is limited as the coefficients in econometric market area models are always linked to the specific competitive landscape, in which they were estimated. The present findings may be transferable to other urban districts with a similar store density, but not to e.g. rural areas. Second, a vulnerability of the present study is the underlying survey: Due to the nature of passer-by surveys, it cannot be fully representative as specific household types are more likely to be contacted outdoors than others. In the present case, a costly household survey was not possible as no financial funding was available. However, the study's methodical approach could be supplemented by replicating the hypothesis tests using a representative household survey in a future study.

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