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A Micro-Econometric Store Choice Model Incorporating Multi- and Omni-Channel Shopping: The Case of Furniture Retailing in Germany

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Online retailing and multi-/omni-channel shopping are gaining in importance. However, there is a significant lack of research focused on incorporating online shopping into models of spatial shopping behavior. The present study aims (1) to construct a store choice model which includes both physical and online stores as well as the opportunity for omni-channel shopping, and (2) to identify the main drivers of spatial shopping behavior given the availability of both channels. Based on a representative survey, this study employs a revealed-preference approach toward store choice and expenditures in furniture retailing. The statistical analysis is performed using a hurdle model approach, with the expenditures of individual consumers at (online or physical) furniture stores serving as the dependent variable. Results show that channel choice (online vs. offline) is mainly influenced by psychographic characteristics, place of residence, and age of the consumers. Store choice and expenditures are primarily explained by store features such as assortment size, omni-channel integration, and accessibility. This study demonstrates that e-shopping can be integrated into a store choice model and that both the modeling approach and the subsequent findings are of significance for retail companies and spatial planning.

Introduction

Online shopping is gaining in importance, with the European market share equaling 12.0% in 2019—although marked country variability exists, e.g., Germany: 15.9%, UK: 19.4%, France: 10.9% (Statista 2020). In this context, e-shopping may be regarded as a key driver of competition for physical retail stores, especially in the context of a decreasing share of private consumption spent in retail (GfK 2020). Therefore, it is not surprising that spatial impacts of online shopping are a key issue in retail geography, whereby online-offline competition impacts established retail locations. Decreasing customer numbers and expenditure levels in physical retailing may lead to falling demand for retail properties and rising vacancy rates in town centers, shopping

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malls, and other retail agglomerations (Doherty and Ellis-Chadwick 2010; Singleton, Dolega and Riddlesden 2016; Stepper 2016).

However, this evolution of e-shopping cannot be simply understood as a contrast between single-channel retailers. Competition between physical retail stores and "internet pure players" such as *Amazon* is, in fact, the exception rather than the rule. Consideration must be also given to the influence of multi-channel shopping and omni-channel shopping. In multi-channel shopping products are sold via at least two shopping channels which operate independently from each other, example, via physical stores and online separately. An omni-channel (sometimes also referred to as cross-channel) retailer allows different channels to be combined within the same purchasing process. These combinations may include the provision of information about products online before customers buy in-store, so-called "Research online, buy offline", or another variant, "Buy online, pick up in store", or in the case of returns, "Buy online, return offline". Omni-channel shopping might even be regarded as a supporting benefit for physical retailers, as customers increasingly engage in omni-channel shopping (Cao and Li 2015; Flávian, Gurrea, and Orus 2020; Heinemann 2015). Surveys show the commonness of channel-switching during the same purchasing process, such as browsing in one channel before buying in the other, or using the "Buy online, pick up in store" service (ECC and Hybris 2013; Boniversum 2018; Handelsverband Deutschland and IFH Köln 2019; McKinsey 2019).

Emerging from these significant developments is the important question as to how spatial shopping behavior is affected by multi- and omni-channel shopping. Spatial shopping behavior includes consumer store choice and the related spatial interactions from consumer origins to retail locations and as such, this behavior constitutes a key issue in retail geography (Timmermans 2004). Research literature on multi-channel shopping behavior tends to focus on (aggregated) channel choices rather than store choices, and furthermore, fails to incorporate the opportunity for omni-channel shopping (Suel and Polak 2018). Classical retail location theory is only designed for physical retail locations (Brown 1993; Reigadinha, Godinho, and Dias 2017), and previous empirical studies toward store choice have only incorporated physical stores (Rauh, Schenk, and Schrödl 2012; Wieland 2015).

The present study aims (1) to construct a store choice model which includes both physical and online stores as well as the opportunity for omni-channel shopping, and (2) to identify the main drivers of spatial shopping behavior given the availability of both channels. This empirical analysis focuses on furniture retailing in Germany as an appropriate example. Based on a representative consumer survey conducted in two German regions—one urban, one rural —, a micro-econometric store choice model has been formulated. This model is based on a specific type of count data model for excess zeros—the hurdle model. The dependent variable in the model equals an individual consumer's expenditure at a specific (online or physical) store. The independent variables in the model include shopping transaction costs, store assortment size, objective consumer characteristics, and finally, shopping attitudes.

The following sections of the paper are structured as follows. Section "Spatial shopping behavior and multi-channel shopping" contains a literature review on (1) store choice behavior with respect to physical stores, (2) multi-channel shopping behavior in terms of channel choice, and (3) the integration of multi- and omni-channel shopping into store choice models, a factor which has been widely neglected in the literature thus far. Section "Methodology" presents (1) the modeling approach including the explanatory variables and their expected impact, and (2) the data collection methodology. In Section "Results and discussion", the empirical findings are discussed in terms of (1) intermediate and descriptive results, and (2) hurdle model results for both survey areas. Section “Conclusions and limitations” contains the main conclusions of this study and a discussion of related limitations.

Spatial shopping behavior and multi-channel shopping

Two research fields are considered as highly relevant for the present study, (1) the investigation of spatial shopping behavior with respect to physical retailing, and (2) multi- and omni-channel shopping behavior. Theoretical and empirical studies on spatial shopping behavior investigate consumer store choice within a system of physical shopping locations. This approach represents a core focus of several perspectives emerging from retail location theory, where store choice and customer volume are taken as key determinants of economic success in retailing (Brown 1993; Reigadinha, Godinho, and Dias 2017).

Although designed for several types of services, central place theory (CPT) (Christaller 1933), and its successors (e.g., Lange 1973; Ghosh 1986), have maintained a critical role in explaining store choice for decades. This family of theories emphasizes the respective roles of accessibility and transport costs on the choice of a shopping location. Two key messages emerging for these theories is that consumer demand decreases with increasing transport costs (distance-dependent demand), and consumer sensitivity toward transport costs reduces with decreasing purchasing frequency of the desired good. Moreover, the potential for buying several central goods during one trip (multipurpose shopping) is regarded as an attraction factor of supply locations, which may therefore be regarded as a positive agglomeration effect with respect to suppliers of different sectors (urbanization economies). However, localization economies, that is, the cumulative attraction of competing stores, are not considered in CPT.

In Anglo-American retail science, the construction of several quantitative market area models comprising similar theoretical assumptions toward spatial consumer behavior has been attempted. Originating from deterministic models for two supply locations (Reilly 1931; Converse 1949), Huff (1962) created a probabilistic store choice model based on micro-economic assumptions. Store choices are assumed to be impacted by (1) travel time, and (2) the shopping location’s respective assortment and store size. Travel time is assumed to have an overproportionate negative influence on store choice due to the opportunity costs involved in traveling to shopping locations. Store size is assumed to increase consumer utility of visiting a store because consumers decide for a shopping location based on imperfect information, whereby, the larger the store’s assortment, the more likely it is that a consumer will obtain the desired goods. However, as consumer search and decision costs increase with increasing assortment, a larger assortment is assumed to be affected by diminishing marginal utility. In the Huff model, the probability that a consumer chooses a store for a shopping trip is equal to the store’s utility relative to the sum of the utilities of all shopping locations. Thus, unlike CPT, the Huff model does not predict a shopping decision exactly, but rather estimates the probability of a decision based on the assumption of utility maximization and incorporating imperfect information. Probabilistic store choice of utility-maximizing consumers, as introduced in the prominent Huff model, is the basic principle of both aggregated and individual store choice models (Rauh, Schenk, and Schrödl 2012; Wieland 2015).

Although developed independently, CPT and the Huff model are similar with respect to their assumptions concerning shopping location utility, especially with respect to distance-dependent demand, which differs between shopping goods (Güssefeldt 2002). However, the concepts differ in the way in which store choice is regarded (deterministic vs. probabilistic). The assumptions with respect to assortment and accessibility have been frequently confirmed in empirical model-based store choice studies (e.g., González-Benito, Greatorex, and Muños-Gallego 2000; Orpana and Lampinen 2003; Popkowski Leszczyc, Sinha, and Sahgal 2004; Lademann 2007; Briesch, Chintagunta, and Fox 2009; Tihi and Oruc 2012; Suárez-Vega, Gutiérrez-Acuña, and Rodríguez-Díaz 2015; Wieland 2015, 2018; Baviera-Puig, Buitrago-Vera, and Escriba-Perez 2016; Hillier, Smith and Whiteman 2017).

Another theoretical perspective emphasizes the role of positive agglomeration effects in retailing. For example, in his classical microeconomic model ("*principle of minimum differentiation*"), Hotelling (1929) describes a duopoly in a linear market, where suppliers relocate to maximize their profits. The best location for both suppliers is a cluster in the middle of the market, where each of them serves one half of the market. Stemming from an inductive perspective and based on empirical observations on shopping behavior, Nelson (1958) formulated the "*theory of cumulative attraction*" and the "*rule of retail compatibility*". The theory of cumulative attraction relates to competing retailers selling different product variants (e.g., shoe stores). In several retail sectors, if such stores cluster together, they enable comparison shopping, and thus, generate more customer traffic as compared to the sum of all these retailers when located in solitary locations. However, stores from different sectors may increase their joint demand if they build an agglomeration provided that such stores are compatible with respect to multipurpose shopping. This retail compatibility is represented by Nelson in a formula for customer exchange between two stores and is additionally demonstrated in compatibility tables for combinations of retail sectors.

Positive agglomeration effects have only been examined in a few store choice studies, and the related findings were not congruent. An early implementation of agglomeration effects into the popular Huff model was conceptualized by Fotheringham (1985) in his *competing destinations model*. Clustering of competing retailers from the same store format was found to increase competition in grocery retailing (e.g., Orpana and Lampinen 2003; Li and Liu 2012; Tihi and Oruc 2012; Wieland 2015). However, Wieland (2015) found a positive effect of spatial proximity with respect to stores of other store formats for grocery retailing, and also demonstrated evidence of cumulative attraction with respect to consumer electronics stores.

Unlike investigation into spatial shopping behavior, research on multi- and omni-channel shopping includes at least two shopping channels, in particular, physical and online shopping. However, these studies typically investigate channel choice rather than store choice, and thus, the shopping alternatives under examination are aggregated over the corresponding channels (Suel and Polak 2018). One focus is on channel-specific shopping transaction costs. These costs include aspects such as travel time to physical stores, or delivery charges and delivery time in online retailing, and thus, there is an obvious connecting point between retail location theory and channel choice studies. Several studies have shown that better accessibility to physical shopping locations and increasing delivery charges and delivery time decrease the likelihood of online shopping (e.g., Hsiao 2009; Chintagunta, Chu, and Cebollada 2012; Marino, Zotteri, and Montagna 2018; Schmid and Axhausen 2019).

Other studies have found socio-demographic and/or spatial attributes of the consumers to be explanatory variables of channel choice. One obvious tendency emerging from the literature is that consumers of a younger age tend to buy more online than elder consumers, which may be attributed to their experience with information and communication technology. Furthermore, the likelihood of e-shopping is higher for consumers with higher education and/or income, male consumers, and consumers in employment (Farag et al. 2006; Burkolter and Kluge 2011; Clarke, Thompson, and Birkin 2015; Beckers, Cárdenas, and Verhetsel 2018; Wiegandt et al. 2018).

With respect to spatial differences in channel choice, there are two competing hypotheses: firstly, the *innovation-diffusion hypothesis* assumes that the inhabitants of *urban* areas are more likely to buy online due to a greater openness to new technologies; whereas, the *efficiency hypothesis* states that consumers in *rural* areas tend to buy more online because of the lower accessibility of physical shopping locations (Cao, Chen, and Choo 2013). In particular, older studies have produced evidence supporting the first hypothesis (e.g., Farag et al. 2006; Farag, Schwanen and Dijst 2007; Cao, Chen, and Choo 2013; Zhen, Du and Cao 2018). However, more recent studies have not confirmed a higher affinity toward e-shopping in cities (e.g., Clarke, Thompson, and Birkin 2015; Beckers, Cárdenas, and Verhetsel 2018).

Another perspective in the literature examines the influence of shopping attitudes on channel choice behavior. Here, attitudes refer to psychographic characteristics of consumers, in particular, to “a person’s consistently favorable or unfavorable evaluations, feelings and tendencies towards an object or idea” (Kotler, Wong and Saunders 2005). Shopping attitudes typically found to be explanatory variables of a high affinity toward e-shopping include price sensitivity and convenience. Attitudes which decrease the likelihood of buying online include risk aversion (e.g., uncertainty with respect to the product) and other (believed) disadvantages associated with the online channel (Farag et al. 2007; Burkolter and Kluge 2011; Bezes 2016; Zhai, Cao and Mokhtarian 2017).

Typically, the studies taking an attitudinal-based approach focus on one or two of these aspects. However, Schmid and Axhausen (2019) have also included shopping transaction costs, demographic characteristics, and shopping attitudes into their channel choice model. When examining the case of two goods (e.g., groceries and consumer electronics), they find negative effects of transaction costs on the choice probability of the specific channel (travel time, travel costs, and delivery time). Moreover, Schmid and Axhausen (2019) infer two latent variables from single attitude items (“pro online” and “shopping pleasure” attitude), with the first variable having a positive impact on the likelihood of e-shopping. However, although this study is superior to previous works, it is based on a stated choice experiment, which means that respondents had to choose between fictional alternatives in an artificial setting.

Although store choice is a perennial issue in retail geography and although there is a growing amount of literature detailing multi-channel shopping behavior, there is a significant research gap with respect to an integrated view on (spatial) shopping behavior in the multi-channel context. More precisely, as Suel and Polak (2018) have criticized, there is a significant lack of studies which combine store choice analysis and multi-channel shopping behavior. Both retail location theory and store choice studies only incorporate physical stores, whilst the literature on multi-channel shopping does not consider retail location systems and differences between stores of the same channel, as both are incorporated in an aggregated way. Nevertheless, there are some studies which do undertake a combined analysis. Using a multi-agent system approach, Steiger (2017) investigated both physical and online shopping with respect to consumer electronics stores; however, channel decisions were considered separately from each other in this study. Beckers et al. (2021) constructed an aggregated spatial interaction model for online grocery stores considering, inter alia, the accessibility of physical grocery stores and area-specific household characteristics. The first econometric approach incorporating the online channel in a store choice model is, to the best of the current author’s knowledge, Suel and Polak’s (2017) nested logit model study investigating grocery shopping in terms of travel mode, channel, and store choice. However, although all the aforementioned studies incorporate online and in-store shopping, they do not incorporate the opportunity to combine channels (omni-channel shopping). With respect to consumer electronics stores, Wieland (2021) has utilized another type of micro-econometric model (hurdle model) for shopping behavior incorporating physical and online stores, which includes the opportunity for omni-channel shopping as well (online shop and "order online, pick up in store" service). This modeling concept is the basis for the present investigation of spatial shopping behavior with respect to furniture stores.

Methodology

Modeling approach

The present study aims (1) to include both in-store and online shopping alternatives as well as the opportunity for omni-channel shopping into one store choice model, and (2) to identify the main drivers of consumer store choice in furniture retailing in the multi-channel context. The model design is adapted from the work of Wieland (2021) on multi-channel store choice behavior with respect to consumer electronics stores. Similar to previous store choice and channel choice models, the underlying rationale is probabilistic choice behavior which assumes consumer utility maximization. Following the aforementioned literature on spatial shopping behavior and multi-channel shopping, three types of explanatory variables are considered: (1) shopping transaction costs, (2) shopping attitudes, and (3) objective consumer attributes. Thus, the present analysis operates on a disaggregated level, which means that individual (shopping) decisions are investigated, leading to a micro-econometric store choice model.

The model employed here is an adaptation of the hurdle model (Mullahy 1986) applied to (spatial) shopping behavior. This model is divided into two parts. The first part deals with the probability that the dependent variable is greater than zero, and the second part is employed only for observations greater than zero. Implicitly, the hurdle model represents a two-step decision process with the first part ("participation equation") addressing the question, *if* an individual decides to do something (e.g., spending money for something), whilst the second part ("intensity equation") deals with the issue of *how* it is done (e.g., *how much* money is spent) (Cameron and Triverdi 2005; Crowley, Eakins, and Jordan 2012). The hurdle model is designed for heavily skewed dependent variables with an excess of zero's and is frequently used in modeling individual demand. The estimation is via the Maximum Likelihood technique (Zeileis, Kleiber, and Jackman 2008; Greene 2012).

The interpretation of the hurdle model as a store choice model follows the representations in Wieland (2018, 2021). The dependent variable in the model equals the expenditures of consumer i at (physical or online) store j, denoted S_{ij} hereafter. A utility function describes the utility of store j for consumer i, which consists of an explained part (representative utility), V_{ij}, and an unobserved part, the error term, ε_{ij}:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

Conceptually, and following the literature on multi-channel shopping, affinity toward online shopping is assumed to be mainly driven by consumer attributes of a subjective and objective nature, whilst the decision for a specific (online or physical) store and the related expenditures are assumed to be explained by store characteristics. Therefore, to make this distinction clearer, we differ between channel and store utility. Technically, the representative utility of a shopping alternative j, V_{ij}^{P}, consists of both the store utility, V_{ij}^{S}, and the channel utility, V_{ij}^{C}:

$$V_{ij}^{P} = V_{ij}^{S} + V_{ij}^{C} \tag{2}$$

The first part of the hurdle model explains the choice of shopping alternative j, in particular, the probability that the expenditures of consumer i at alternative j is greater than zero ($S_{ij} > 0$). This probability depends on the utility of shopping alternative j, V_{ij}^{P}. Here, a binary logit model is used for the participation equation:

$$Pr\left[S_{ij} > 0 | V_{ij}^{P}\right] = \frac{e^{V_{ij}^{P}}}{1 + e^{V_{ij}^{P}}} \tag{3}$$

The second part of the hurdle model (intensity or expenditure equation) deals with the amount of expenditure at the *chosen* shopping alternatives (S_{ij} for all $S_{ij} > 0$). This part of the model is operationalized as a truncated Poisson distribution with a Poisson parameter of λ_{ij}. The expected value depends on the store utility, V_{ij}^{S}:

$$E\left(S_{ij}, S_{ij} > 0 | V_{ij}^{S}\right) = \frac{\lambda_{ij}}{1 - e^{-\lambda_{ij}}} \tag{4}$$

where:

$$\ln \lambda_{ij} = V_{ij} \tag{5}$$

The expected value of the store choice hurdle model (including both parts), $E(S_{ij}|V_{ij})$, is the product of the participation probability and the expected value of the expenditure equation:

$$E\left(S_{ij}|V_{ij}\right) = \left(Pr\left[S_{ij} > 0 | V_{ij}^{P}\right]\right)\left(E\left[S_{ij}, S_{ij} > 0 | V_{ij}^{S}\right]\right) \tag{6}$$

Studies on multi-channel shopping behavior frequently identify socio-demographic, spatial, and attitudinal characteristics of consumers as explanatory variables of channel choice (e.g., Clarke, Thompson, and Birkin 2015; Beckers, Cárdenas, and Verhetsel 2018; Zhen et al. 2018; Schmid and Axhausen 2019; Beckers et al. 2021). Thus, the channel utility in the present study, V_{ij}^{C}, includes a set of variables describing the individual consumer i:

$$V_{ij}^{C} = \beta_1 D25_i + \beta_2 D65_i + \beta_3 Dm_i + \beta_4 DE_i + \beta_5 DL_i + \beta_6 LV_i + \beta_7\left(DO_j * D25_i\right)$$
$$+ \beta_8\left(DO_j * D65_i\right) + \beta_9\left(DO_j * Dm_i\right) + \beta_{10}\left(DO_j * DE_i\right) + \beta_{11}\left(DO_j * DL_i\right) + \beta_{12}\left(DO_j * LV_i\right) \tag{7}$$

The influence of channel choice is assessed using interaction terms incorporating the variable describing a consumer characteristic and a dummy variable (DO_j) indicating whether store j is an online store ($DO_j = 1$) or not ($DO_j = 0$). $\beta_1, \ldots, \beta_{12}$ represent the regression coefficients to be estimated. To assess demographic effects, the dummy variables $D25_i$, $D65_i$, Dm_i, and DE_i describe demographic characteristics of consumer i (aged under 25 years old and at least 65 years old respectively, male, and employed). For example, a positive coefficient for the interaction between $D25_i$ and DO_j (β_7) would show that consumers under 25 years are more likely to shop for furniture at online stores than other age groups. The variable DL_i indicates whether consumer i lives in a large city (see the “Data collection and processing” section for the statistical definition). The innovation-diffusion hypothesis states that urban residents are more likely to buy online (Cao, Chen, and Choo 2013). Thus, the coefficient of the respective interaction term $DO_j{*}DL_i$ (β_{11}) must be positive if this hypothesis holds true. To investigate the impact of psychographic characteristics of the consumers, a latent variable is included which represents the affinity toward online shopping of consumer i, LV_i. This latent variable (called “pro online” attitude hereafter), can, according to the work of Schmid and Axhausen (2019), be inferred from single attitude items (see the “Data collection and processing” section for operationalization). If a “pro online” attitude explains the likelihood of buying online, the coefficient of the corresponding interaction term $DO_j{*}LV_i$ (β_{12}) must be positive.

Store utility (V_{ij}^S) includes a set of explanatory variables stemming from both store choice and multi-channel shopping behavior studies and describes the shopping alternatives and the corresponding shopping transaction costs:

$$V_{ij}^S = \gamma_0 + \gamma_1 \ln A_j + \gamma_2 t_{ij} + \gamma_3 \ln C_j + \gamma_4 DCC_j + \gamma_5 sc_j + \gamma_6 Dsco_j + \gamma_7 Dscf_j + \gamma_8 DO_j + \gamma_9 \left(\ln A_j * DO_j\right) + \sum_{g}^{G} \delta_g D_{g_j} \left[+ \zeta \ln S_i \right] \tag{8}$$

where γ_0, …, γ_9, δ_g, and ζ are regression coefficients to be estimated. According to the Huff model (Huff 1962), assortment size of store j (A_j) and travel time between consumer i and store j (t_{ij}) are included as explanatory variables. As the Huff model assumes diminishing marginal utility of assortment, the first variable is log-transformed to interpret the corresponding coefficient as elasticity. Here, assortment size is defined as the number of available articles. A coefficient γ_1 between 0 and 1 is expected. Because online stores regularly offer a considerably larger assortment than physical stores, a check is made as to whether there is a difference of the assortment impact between physical and online stores, assuming that this impact is lower for online stores (γ_9 of the interaction term $\ln A_j{*}DO_j$ should be negative). According to the Huff model and other work from retail location theory, distance-dependent demand is assumed, and thus, the impact of travel time is expected to be negative ($\gamma_2 < 0$). Travel time is equal to zero for online furniture stores. These assumptions have been confirmed several times in studies of physical store choice (e.g., Orpana and Lampinen 2003; Lademann 2007; Briesch, Chintagunta, and Fox 2009; Suárez-Vega, Gutiérrez-Acuña, and Rodríguez-Díaz 2015; Wieland 2015, 2018) and are expected to similarly hold true in the multi-channel context. In addition, possible positive agglomeration economies in terms of a “cumulative attraction” of competing stores (Nelson 1958) must be considered because, in supply-side studies on co-locating, a tendency for clustering of furniture stores was detected (Marstaller 2011; Krider and Putler 2013). To capture this effect, an agglomeration variable for physical store j, C_j, is included. This variable is calculated according to Wieland (2015):

$$C_j = \sum_{\substack{k=1 \\ k \neq j}}^{K} A_k d_{jk}^{-\varphi} \tag{9}$$

Similar to “Hansen accessibility”, spatial proximity to competing stores is operationalized as the distance-weighted sum of all K competing stores. The airline distance between store j and store k is weighted by an exponent of $\varphi = 2$. The “attraction” of these competing stores is measured with their assortment size, A_k. If furniture stores profit from spatial proximity to competitors (cumulative attraction due to comparison shopping), the corresponding coefficient must be positive ($\gamma_3 > 0$).

Several surveys have shown that consumers use different channels during a buying process and/or use the "order online, pick up in store" option (ECC and Hybris 2013; Boniversum 2018; Handelsverband Deutschland and IFH Köln 2019; McKinsey 2019). Implementing an omni-channel strategy was found to increase the turnover of a retailing company (Cao and Li 2015). From a transaction costs perspective—a perspective frequently taken in the literature on multi-channel shopping—shopping transaction costs include search and information costs, with consumers attempting to reduce these costs (Chintagunta, Chu, and Cebollada 2012). Omni-channel retailers run online shops offering information about their assortment, their prices, and their (in-store) product availability, as well as providing the "order online, pick up in store" service (see below for a broader definition of an "omni-channel retailer"). Omni-channel integration may also facilitate product returns ("Buy online, return offline"). Thus, it is assumed that retail companies profit from being omni-channel retailers. To test this influence, a dummy variable in the store utility equation (DCC_j) indicates whether store j is an omni-channel retailer (such as *IKEA, XXXLutz*). The corresponding coefficient is expected to be positive ($\gamma_4 > 0$).

Three variables are included to incorporate the delivery policy of online furniture stores. As delivery charges are considered as important for channel choice (Hsiao 2009; Chintagunta, Chu, and Cebollada 2012; Schmid and Axhausen 2019), the variable sc_j contains the average delivery charges of (online) store j (see below for calculation). Delivery charges are equal to zero for physical stores. As in online furniture retailing the delivery charges are sometimes variable, the dummy variables $Dsco_j$ and $Dscf_j$, respectively, indicate whether the charges depend on the order value, or are free from a certain order value.

To include chain-specific effects (which are outside to scope of this study), G dummy variables are included into the model and indicate whether store j belongs to chain g (Dg_j). As the model is split into two parts, with the latter explaining the amount of expenditure at store j, another control variable reflects the total expenditure of consumer i (S_i).

Data collection and processing

Store choice and expenditures were collected in a self-administered postal survey in two German regions (South Lower Saxony: pop. of 531,814 in 2018; Middle Upper Rhine Region: pop. of 1,043,465 in 2018). The respondents were also given the option to fill out the questionnaire in a web form. The addresses of contacted individuals were drawn as a random sample from official address data. The target population was defined as all residents of 15 years and above. The survey was conducted from March to June 2019.

Shopping behavior was obtained using a revealed-preference approach, which means that (shopping) preferences of individuals were inferred from their actual decisions in real-word situations (Train 2009). In the questionnaire, the individuals were asked about their three last purchases of different goods and the expenditures related to each purchase/shopping trip. For any purchase, the specific shopping destination was noted (e.g., "*IKEA* in street X of municipality Y", "*XXXLutz* online"). The expenditures of consumer i at (physical or online) store j is the dependent variable in the model (S_{ij}).

To construct the "pro-online" attitude (LV_i), and following on from the work of Schmid and Axhausen (2019), 15 attitude items on a 4-point Likert scale (1 = agree, …, 4 = disagree) were included in the questionnaire (see Table 1). Nine of these items stem from the aforementioned study,

Table 1. Items for Latent Variables (Shopping Attitudes); Originally in German, Translated

Item		Adapted from
1	I often order products on the internet	Schmid and Axhausen (2019)
2	Online shopping is associated with risks	Schmid and Axhausen (2019)
3	Bank card/credit card fraud is one of the reasons why I don't like online shopping	Schmid and Axhausen (2019)*
4	The internet has more cons than pros	Schmid and Axhausen (2019)
5	A disadvantage of online shopping is that I cannot physically examine the products	Schmid and Axhausen (2019)
6	Online shopping facilitates the comparison of prices and products	Schmid and Axhausen (2019)*
7	The risk of receiving a wrong product is one of the main reasons why I don't like online shopping	Schmid and Axhausen (2019)
8	No matter if I buy online or in-store: Before buying, I get informed via internet about products and compare prices	Own
9	Online shopping affects the environment, e.g., by transportation	Own
10	Online shopping facilitates poor working conditions, e.g., for the delivery employees	Own
11	Shopping usually is an annoying duty	Schmid and Axhausen (2019)
12	I like to visit shops, even if I don't want to buy something, just for looking around	Schmid and Axhausen (2019)
13	I feel I have no control of my data in the internet	Sinus (2018)
14	I feel that my personal data are sufficiently protected inside and outside the internet	Sinus (2018)
15	In general, the protection of my personal data is very important for me	Sinus (2018)

*Slightly modified.

including statements concerning risk perception of online shopping (product uncertainty, internet fraud), advantages and disadvantages of online shopping, and attitudes toward physical shopping. Six further items were added to the initial nine. The first additional statement aims at investigating pre-purchase information gathering via the internet, as surveys have shown the importance of "Research Online—Purchase Offline" shopping in Germany (ECC and Hybris 2013; HDE 2019). Two additional items incorporate beliefs about the negative impacts of online shopping, namely, environmental impacts and working conditions in the logistics sector, as both issues have been a matter of public debate in the last years (DeWeerdt 2016; Schaer 2018; Kläsgen 2019). Furthermore, three items in the questionnaire refer to the perceived level of internet data protection and stem from a representative survey which was conducted in Germany in 2018 (Sinus 2018). Following Schmid and Axhausen (2019), two factors were extracted by an exploratory factor analysis (principal component extraction, Varimax rotation), of which one was expected to cover a "pro online" attitude; note that this must not be the optimal factor solution but a replication of the aforementioned stated choice study. In the last section of the questionnaire, respondents were asked about their socio-demographic characteristics (e.g., age group, employment status).

All in all, 9,109 randomly sampled individuals were contacted (South Lower Saxony: 3,109; Middle Upper Rhine Region: 6,000). Considering the gross size of the sample and correcting for 355 neutral losses (e.g., invalid address), the response rate was 15.7% (n = 1,375) with 10.0% in South Lower Saxony (n = 297), and 18.6% in the Middle Upper Rhine Region (n = 1,078). Socio-demographic attributes of the respondents are shown in Table 2. Note that the modeling approach is based on individual data and the independent variables include gender and age dummy variables, and thus, there is low risk of substantial biases in the results, even in the event of an over- or under-representation of age or gender groups.

The furniture stores in both survey regions and the relevant online stores were collected in March 2019. After finishing the consumer survey (June 2019), physical stores from outside the particular survey area were included if they were considered as relevant, based on the criterion that

Table 2. Socio-Demographic Characteristics of the Respondents by Survey Area

		Survey area 1 (South Lower Saxony)			Survey area 2 (Middle Upper Rhine Region)		
		Sample 2019		Pop. 2018	Sample 2019		Pop. 2018
Variables	Categories	***n***	%	%	***n***	%	%
Gender	Female	155	52.7	51.1	598	56.5	50.1
	Male	138	46.9	48.9	448	42.3	49.9
	No information	1	0.3	–	12	1.1	–
Age	15 to <18	10	3.4	3.2	22	2.1	3.1
	18 to <25	37	12.7	9.8	89	8.4	9.8
	25 to <45	55	18.8	25.8	247	23.4	29.7
	45 to <65	91	31.2	34.2	425	40.2	33.7
	65 to <75	57	19.5	12.6	158	15.0	11.2
	75	42	14.4	14.5	115	10.9	12.6
Household size	1	56	19.5	n.a.	165	15.7	n.a.
	2	144	50.2	n.a.	478	45.5	n.a.
	3	45	15.7	n.a.	190	18.1	n.a.
	4	36	12.5	n.a.	155	14.7	n.a.
	>4	6	2.1	n.a.	63	6.0	n.a.
Working status	Employed or self-employed	131	45.2	n.a.	601	57.2	n.a.
	Retired	100	34.5	n.a.	291	27.7	n.a.
	School or university	41	14.1	n.a.	91	8.7	n.a.
	Not employed (homemaker m/f)	6	2.1	n.a.	40	3.8	n.a.
	Unemployed	5	1.7	n.a.	7	0.7	n.a.
	Other	7	2.4	n.a.	21	2.0	n.a.
Type of survey	Written survey (mail)	265	89.2	–	957	88.8	–
	Online survey	32	10.8	–	121	11.2	–

Note: Because of missing values, the sample sizes differ for each characteristic.

the stores were recorded as shopping destinations in at least two municipalities. Stores which were not reported as shopping destinations were excluded from the analysis in the respective survey area. Information on both physical and online stores was gathered via desktop research using the websites of the retail chains and stores. For all physical stores, street address and store size (selling space in sqm) were noted, with the latter retrieved from the corresponding retail companies and publicly available information such as in newspapers and urban land use plans. The number of articles in the store assortment, which is an explanatory variable in the store choice model (A_j), was, if available, obtained from the online shops of the corresponding companies and stores, respectively. As most of the chains and some of the independent stores are omni-channel retailers, they provide an online shop which includes an availability check for each store, thus allowing the available number of articles in specific stores to be calculated. This procedure was done in *R* (R Core Team 2019) using self-written functions with the help of the package *httr* (Wickham 2019) for web scraping. Based on the available store information gathered for 45 furniture stores, a regression model was estimated with the number of articles (A_j) as the dependent variable and store size in sqm ($storesize_j$) as well as chain dummies as the independent variables. This model ($R^2 = 0.99$) was used for the interpolation of the number of articles of the remaining 40 stores:

$$\begin{aligned} \ln A_j = {} & 0.873 \ln storesize_j + 1.110\ D_{DaenischesBettenlager_j} + 0.955\ D_{IKEA_j} \\ & + 1.857\ D_{MoebelHeinrich_j} + 0.255\ D_{Moemax_j} + 1.485\ D_{Poco_j} + 0.386\ D_{Porta_j} \\ & + 1.137\ D_{Roller_j} + 0.424\ D_{MobelBoss_j} + 1.439\ D_{XXXLutz_j} + 0.796\ D_{VME_j} \end{aligned} \tag{10}$$

Information about the omni-channel integration of a store/chain was obtained from the corresponding website. An "omni-channel retailer" (indicated by the dummy variable DCC_j in the model) was defined as a store (or chain) which provides an online shop filling the following criteria: (1) Information about the full assortment of both the online shop and the associated outlets, (2) an availability check for each product in a given store, (3) information on in-store prices as well as some product details, and (4) the provision of the "order online, pick up in store" option. The delivery options for online stores were obtained from the websites as well. The variable sc_j equals the delivery charges of store j. If an online store has different charges dependent on the order value, sc_j equals the charges of an order value equal to the average value found in the survey (mean of S_{ij} for store j or the corresponding chain over all respondents), and these policies are captured with the dummy variables $Dsco_j$ and $Dscf_j$.

Table 3 provides an overview by survey region of the physical and online stores which are relevant in the present analysis. There are 40 relevant stores (physical and online) in survey area 1 (South Lower Saxony) and 81 stores in survey area 2 (Middle Upper Rhine Region). On average, the online stores provide a much larger assortment than physical stores. Notable is also that most of the full omni-channel retailers (as defined here, see above) are furniture multi-channel retailing chains (such as *Dänisches Bettenlager*, *IKEA*, *Roller*, or *XXXLutz*), which are present with physical outlets in one or both survey areas and with corresponding online shops.

The street addresses of the survey respondents (residential address) and physical stores were geocoded. An interaction matrix for all m consumers ($i = 1, \ldots, m$) and all n (possible) store alternatives ($j = 1, \ldots, n$) with $m*n$ rows was constructed and the dependent variable S_{ij} (expenditures of consumer i at store j) was calculated from the survey data (Wieland 2015). This interaction matrix contains the chosen stores as well as the stores that were not chosen (just as the choice set in a Discrete Choice analysis), and, thus, the value of S_{ij} is above zero for the chosen stores

Table 3. Characteristics of Relevant Furniture Stores (Physical and Online) by Survey Areas

Stores	No.	Assortment size [no. of items] Mean	SD	Median	Full omni-channel retailers [no.]
Survey area 1 (South Lower Saxony)					
Physical stores	29	5,360.10	7,377.40	2,005.00	17
Online stores	11	5,852,951.95	13,197,905.90	87,972.00	3
Survey area 2 (Middle Upper Rhine Region)					
Physical stores	53	5,677.30	9,475.41	1,512.33	19
Online stores	28	3,060,418.80	9,007,017.10	12,988.00	6

and equal to zero for the non-chosen alternatives. Observed purchases without a record of the corresponding expenditures were excluded from the analysis. Purchases at specialty stores (such as online or physical stores for upholstered furniture only, or promotional goods in department stores or grocery stores) were, additionally, not included. Based on the coordinates, travel times between all consumer and store locations (variable t_{ij} in the model) were calculated, the result of which is defined here as the fastest route between origins and destinations in terms of car driving time in minutes. These steps were performed in *R* (R Core Team 2019) using the package *MCI2* (Wieland 2019), which accesses the *OpenStreetMap* address database (*OSM Nominatim*) and *OSRM* (*OpenStreetMap Routing Machine*).

Based on the underlying address data, each survey respondent was assigned to a municipality type from the German classification system of municipalities ("Stadt- und Gemeindetypen"). The dummy variable DL_i is based on this classification, as the value is equal to one for each respondent living in a "large city", which is a classification for a municipality with at least 100,000 inhabitants (Bundesinstitut für Bau-, Stadt- und Raumforschung 2021). This definition matters for the respondents of two cities in the survey areas (Göttingen in South Lower Saxony with about 130,000 inhabitants and Karlsruhe in the Middle Upper Rhine Region with about 300,000 inhabitants).

All required information including consumer-specific characteristics and the attributes of all stores was assigned to the interaction matrix for each combination of respondent *i* and store *j*. The hurdle model analysis based on this data was performed using the *R* package *pscl* (Zeileis, Kleiber, and Jackman 2008).

Results and discussion

Channel-specific purchases and expenditures

Table 4 shows descriptive statistics of the purchases and expenditures at (physical or online) furniture stores by survey area. In Fig. 1, maps of the two survey areas show the locations of the relevant physical stores, and the empirical share of furniture online expenditures by municipality. In both survey areas, a total of 1,079 purchases were recorded at relevant furniture stores (South Lower Saxony: 216, Middle Upper Rhine Region: 863) equating to a total amount of expenditures equal to 1,013,171 EUR (199,777 and 813,394 EUR respectively).

Whilst about one sixth of all purchases are made online (South Lower Saxony: 17.59%, Middle Upper Rhine Region: 14.95%), the share of expenditures is quite smaller (5.36 and 5.65%, respectively). The empirical share of online expenditures differs significantly between municipalities and municipality types. As shown in the maps, there is a tendency toward higher shares in large cities and suburban municipalities and lower shares in rural regions. The average

Table 4. Channel-Specific Purchases and Expenditures by Survey Areas

	Purchases	Expenditures [EUR]			
Shopping channel	Shares [%]	Shares [%]	Mean [EUR]	SD [EUR]	Median [EUR]
Survey area 1—South Lower Saxony (purchases: 216, expenditures: 199,777 EUR)					
Physical stores	82.41	94.64	1,303.89	3,277.00	300.00
Online stores	17.59	5.36	334.78	554.97	150.00
All stores	100.00	100.00	1,128.68	2,996.72	280.00
Survey area 2—Middle Upper Rhine Region (purchases: 863, expenditures: 813,394 EUR)					
Physical stores	85.05	94.35	1,201.05	2,046.77	420.00
Online stores	14.95	5.65	376.41	470.24	200.00
All stores	100.00	100.00	1,068.85	1,908.84	400.00

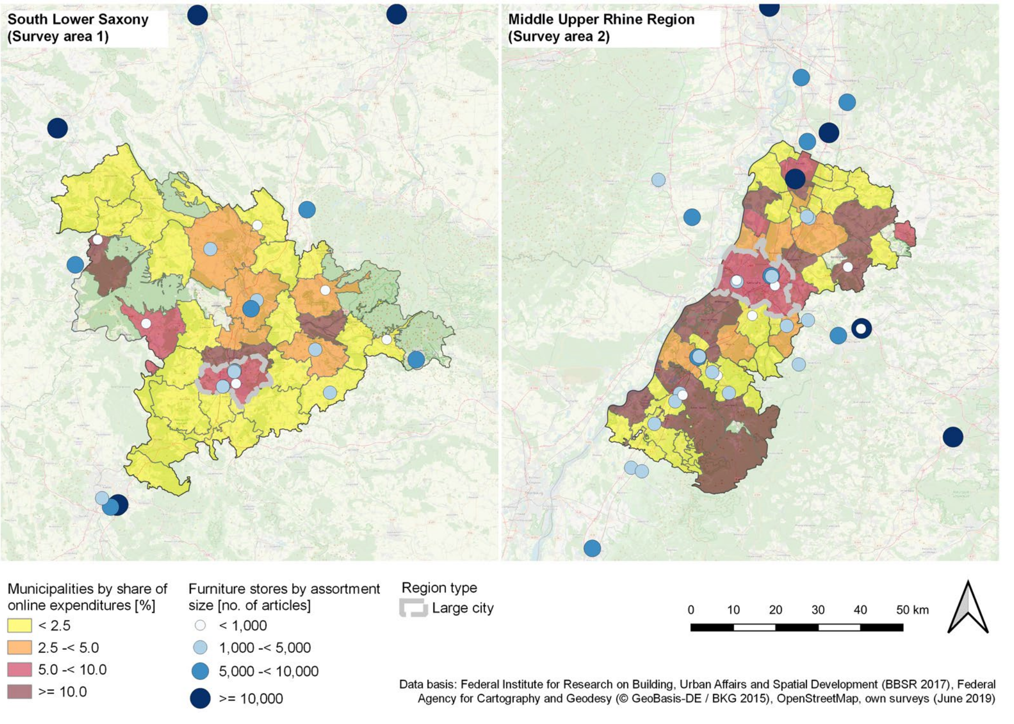

Figure 1. Furniture stores and shares of online expenditures by survey area.

expenditures in physical stores is considerably higher than in online stores, regardless of whether the arithmetic mean, or the median value is taken. This is congruent with the lower shares for online expenditures.

Shopping attitudes: Frequencies and latent variables

As the store choice model includes consumer psychographic characteristics, a closer examination of the attitude items and corresponding latent variables is required. Following on from Schmid and Axhausen's (2019) stated choice experiment, two latent variables were inferred in the present study. See Table 5 for the relative frequencies and factor loadings of the attitude items. The latent variables are continuous and dimensionless with positive and negative values.

When considering relative frequencies, a strong tendency toward using the internet for information gathering before buying, regardless of the channel which is used for the purchase, can be observed. Five sixths of the consumers identified the usefulness of the internet for the comparison of prices and products (sum of “agree” and “rather agree”: 84.3%), and two thirds identified this use no matter which channel is chosen (sum of “agree” and “rather agree”: 66.5%). These descriptive results should be taken into account when interpreting the modeling results with respect to omni-channel retailing. The two items targeting ethical aspects of online shopping show high degrees of accordance (sum of “agree” and “rather agree”: 71.6 resp. 76.0%). The first item, which was focused on online shopping frequency, is nearly equally distributed.

The cumulative percentage of variance explained by the two factors equals 37.9%. This quote of explained variance seems to be relatively low. However, the aim in the current analysis was not to find the optimal factor solution but to replicate the latent variables inferred by Schmid and Axhausen (2019). The first latent variable, which is included into the model (“pro-online” attitude of consumer i, LV_i), was tested for internal consistency with Cronbach’s alpha. Following Schmitt (1996), the resulting value of $\alpha = 0.80$ may be regarded as indicating an acceptable or even good reliability. The “pro online” LV contains ten out of the 15 items, whereas the remaining items can be associated with the second LV, “shopping pleasure”, more precisely, “physical shopping pleasure”, as the items relate to positive views on buying in-store. Keeping in mind that the items are reversely scaled compared to Schmid and Axhausen (2019), the results of the present study—with respect to inferring the two latent variables—are similar to those in the aforementioned Schmid and Axhausen (2019) study. The attributions are quite plausible, example, with respect to the item, “Online shopping is associated with risks”, where a lower approval score increases the value of the “pro-online” LV. The lower a respondent agrees to the statement, “Shopping usually is an annoying duty”, the higher is the “shopping pleasure” factor. It is therefore assumed that the current latent variable LV_i is a sufficient proxy variable for a “pro online” attitude in this study.

Determinants of channel and store choice

For each survey region (South Lower Saxony and Middle Upper Rhine Region), one hurdle model consisting of two model parts was estimated (see Tables 6 and 7). The left column lists the explanatory variables, whilst the middle column contains the coefficients of the participation equation (Pr ($S_{ij} > 0$)), and finally, the right column contains those of the expenditure equation (for all $S_{ij} > 0$). The chain dummies differ between the survey areas as not all furniture retailing chains are represented by physical stores in both regions.

In a first step, the explanatory variables in the channel utility function (V_{ij}^{C}) will be discussed. Congruent over both survey areas, residents of large cities are found to be more likely to buy furniture online, as the coefficient of the interaction term $DO_j{*}DL_i$ (β_{11}) is positive and significant. Thus, the findings of the present study confirm those of older studies on channel choice which tested the innovation-diffusion hypothesis (e.g., Farag et al. 2006, 2007; Cao, Chen, and Choo 2013; Zhen et al. 2018). However, although these results appear to confirm previous studies, it is questionable whether this relationship still holds true given other more recent studies involving European countries which failed to confirm this tendency (e.g., Clarke, Thompson,

Table 5. Relative Frequencies and Factor Loadings of Attitude Items

		Relative frequencies [%]					Factor loading	
Item (translated)		1 = agree	2 = rather agree	3 = rather disagree	4 = disagree	missing	1	2
1	I often order products on the internet	24.4	20.4	27.1	25.7	2.4		0.59
2	Online shopping is associated with risks	25.9	34.4	30.0	6.2	3.5	0.61	
3	Bank card/credit card fraud is one of the reasons why I don't like online shopping	18.6	15.6	31.3	31.0	3.5	0.68	
4	The internet has more cons than pros	8.5	14.1	42.0	31.2	4.2	0.57	
5	A disadvantage of online shopping is that I cannot physically examine the products	58.3	26.3	8.8	3.5	3.1	0.56	
6	Online shopping facilitates the comparison of prices and products	54.3	30.0	7.8	4.0	3.9		0.59
7	The risk of receiving a wrong product is one of the main reasons why I don't like online shopping	12.8	16.1	36.4	31.1	3.6	0.57	
8	No matter if I buy online or in-store: Before buying, I get informed via internet about products and compare prices	38.4	28.1	15.3	15.0	3.2		0.62
9	Online shopping affects the environment, e.g., by transportation	40.8	30.8	19.1	6.1	3.2	0.58	
10	Online shopping facilitates poor working conditions, e.g., for the delivery employees	42.8	33.2	14.9	4.7	4.5	0.63	
11	Shopping usually is an annoying duty	16.0	23.0	33.3	24.4	3.3		0.59
12	I like to visit shops, even if I don't want to buy something, just for looking around	26.8	19.9	25.5	24.9	2.8		0.52
13	I feel I have no control of my data in the internet	26.3	27.3	28.1	14.5	3.8	0.64	
14	I feel that my personal data are sufficiently protected inside and outside the internet	4.8	26.5	42.4	22.3	3.9	0.51	
15	In general, the protection of my personal data is very important for me	64.1	26.3	5.7	1.2	2.6	0.36	

Table 6. Modeling Results for Survey Area 1 (South Lower Saxony)

Explanatory variables	Participation equation coefficients (Zero hurdle model; binomial with logit link)	Expenditure equation coefficients (Truncated Poisson model with log link)
ln number of items$_j$	0.918***	0.361***
	(0.172)	(0.003)
Travel time$_{ij}$	0.088***	0.002***
	(0.007)	(0.0002)
ln clustering$_j$ + 0.0001	0.012	0.048***
	(0.030)	(0.001)
Dummy full omni-channel retailer$_j$	0.857*	0.215***
	(0.520)	(0.008)
Delivery charges$_j$	0.0002	0.027***
	(0.023)	(0.001)
Dummy delivery charges based on order value$_j$	2.527**	2.421***
	(1.156)	(0.091)
Dummy free delivery from a certain order value$_j$	1.090	3.030***
	(1.483)	(0.188)
Dummy online store$_j$	2.258	8.555***
	(2.839)	(0.263)
ln number of items$_j$ Dummy online store$_j$	0.772***	0.761***
	(0.264)	(0.025)
Dummy place of residence is large city$_i$	0.600***	
	(0.227)	
LV pro online$_i$	0.043	
	(0.105)	
Dummy online store$_j$ Dummy place of residence is large city$_i$	1.203***	
	(0.440)	
Dummy online store$_j$ LV pro online$_i$	0.727***	
	(0.238)	
Dummy age < 25$_i$	0.222	
	(0.315)	
Dummy age 65$_i$	0.199	
	(0.318)	
Dummy male$_i$	0.156	
	(0.194)	
Dummy employed$_i$	0.151	
	(0.263)	
Dummy online store$_j$ Dummy age < 25$_i$	1.381*	
	(0.763)	
Dummy online store$_j$ Dummy age 65$_i$	0.994	
	(0.750)	

(Continues)

Table 6. (Continued)

Explanatory variables	Participation equation coefficients (Zero hurdle model; binomial with logit link)	Expenditure equation coefficients (Truncated Poisson model with log link)
Dummy online store$_j$	0.062	
Dummy male$_i$	(0.431)	
Dummy online store$_j$	0.347	
Dummy employed$_i$	(0.538)	
Dummy Dänisches	0.195	2.325***
Bettenlager$_j$	(0.591)	(0.016)
Dummy IKEA$_j$	2.034***	0.061***
	(0.593)	(0.013)
Dummy Poco$_j$	1.410	0.041
	(0.921)	(0.048)
Dummy SB Möbel Boss$_j$	1.121*	0.849***
	(0.673)	(0.025)
Dummy Sconto$_j$	1.044	0.660***
	(0.737)	(0.036)
Dummy XXXLutz$_j$	0.965	0.791***
	(1.029)	(0.058)
Dummy Amazon$_j$	0.103	3.910***
	(1.460)	(0.165)
Dummy eBay$_j$	0.353	2.794***
	(1.416)	(0.161)
ln expenditures$_i$		0.829***
		(0.002)
Constant	7.988***	4.334***
	(1.546)	(0.036)
Observations	5,771	
Log Likelihood	50,693.77	
AIC	101,485.50	

Note: Coefficient standard errors in parentheses.
*$P < 0.1$
**$P < 0.05$
***$P < 0.01$.

and Birkin 2015; Beckers, Cárdenas, and Verhetsel 2018). There is an alternative interpretation, suggesting that this result confirms the efficiency hypothesis instead. Residents of large cities could have a higher online share when shopping furniture because of the lower accessibility of furniture stores in urban areas. In large cities, a considerably lower passenger car density can be detected compared to rural regions (Nobis and Kuhnimhof 2018). Not owning a car is a plausible explanation for buying heavy furniture goods (such as cupboards or beds) at online stores instead of physical stores, especially when considering that large-scale furniture retailers are typically located in commercial areas outside the city center.

Table 7. Modeling Results for Survey Area 2 (Middle Upper Rhine Region)

Explanatory variables	Participation equation coefficients (Zero hurdle model; binomial with logit link)	Expenditure equation coefficients (Truncated Poisson model with log link)
ln number of items$_j$	0.902***	0.016***
	(0.074)	(0.002)
Travel time$_{ij}$	0.102***	0.002***
	(0.004)	(0.0001)
ln clustering$_j$ + 0.0001	0.036	0.015***
	(0.029)	(0.001)
Dummy full omni-channel retailer$_j$	1.315***	0.045***
	(0.383)	(0.007)
Delivery charges$_j$	0.009	0.008***
	(0.007)	(0.0004)
Dummy delivery charges based on order value$_j$	1.200***	0.113***
	(0.356)	(0.018)
Dummy free delivery from a certain order value$_j$	1.008***	0.284***
	(0.340)	(0.016)
Dummy online store$_j$	3.441***	0.468***
	(0.988)	(0.033)
ln number of items$_j$ Dummy online store$_j$	0.796***	0.141***
	(0.086)	(0.003)
Dummy place of residence is large city$_i$	0.519***	
	(0.095)	
LV pro online$_i$	0.019	
	(0.047)	
Dummy online store$_j$ Dummy place of residence is large city$_i$	0.535**	
	(0.212)	
Dummy online store$_j$ LV pro online$_i$	0.320***	
	(0.108)	
Dummy age < 25$_i$	0.071	
	(0.163)	
Dummy age 65$_i$	0.024	
	(0.158)	
Dummy male$_i$	0.026	
	(0.090)	
Dummy employed$_i$	0.103	
	(0.124)	
Dummy online store$_j$ Dummy age < 25$_i$	0.520*	
	(0.295)	
Dummy online store$_j$ Dummy age 65$_i$	1.799***	
	(0.563)	

(Continues)

Table 7. (Continued)

Explanatory variables	Participation equation coefficients (Zero hurdle model; binomial with logit link)	Expenditure equation coefficients (Truncated Poisson model with log link)
Dummy online store$_j$	0.290	
Dummy male$_i$	(0.207)	
Dummy online store$_j$	0.279	
Dummy employed$_i$	(0.255)	
Dummy Dänisches	1.560***	0.936***
Bettenlager$_j$	(0.437)	(0.012)
Dummy IKEA$_j$	2.022***	0.627***
	(0.429)	(0.009)
Dummy Mömax$_j$	0.838*	0.422***
	(0.434)	(0.010)
Dummy Poco$_j$	3.173***	0.892***
	(0.705)	(0.047)
Dummy Roller$_j$	2.496***	0.372***
	(0.457)	(0.011)
Dummy XXXLutz$_j$	1.537***	0.028***
	(0.429)	(0.009)
Dummy Amazon$_j$	1.062**	0.681***
	(0.431)	(0.027)
Dummy eBay$_j$	0.266	1.170***
	(0.463)	(0.027)
ln expenditures$_i$		0.848***
		(0.001)
Constant	8.693***	0.969***
	(0.662)	(0.019)
Observations	47,877	
Log Likelihood	207,738.10	
AIC	415,574.10	

Note: Coefficient standard errors in parentheses.
*$P < 0.1$
**$P < 0.05$
***$P < 0.01$.

With respect to socio-demographic attributes of the consumers, few clear statements can be made. The interaction terms associated with gender and employment status are not significant. The findings with respect to age in survey area 2 are congruent with expectations, as young consumers are more likely to buy online and consumers of age 65 or above are less (interaction between $D25_i$ resp. $D65_i$ and DO_j). However, this cannot be confirmed for the first survey area.

In both survey areas, the expected influence of a "pro online" attitude is confirmed, as the coefficient of the respective interaction term DO_j*LV_i (β_{12}) is positive and significant. This result confirms the findings of Schmid and Axhausen's (2019) experimental study, but in the present case, with respect to real-world shopping behavior. Thus, a positive attitude toward e-shopping predicts a higher likelihood of buying online, which is *not* as self-explanatory as it seems. Stated attitudes need not be congruent with real-world behavior, especially in situations where attitudes are related to ethical issues (e.g., environmental and work-related effects of online shopping). This potential social desirability bias is well known in social sciences (Jann, Krumpal, and Wolter 2019) and has been observed in shopping behavior as well (e.g., Niessen and Hamm 2007; Wheeler, Gregg, and Singh 2019). Moreover, the result is interesting because the effects of socio-demographic characteristics and the place of residence are incorporated separately. One might expect that a "pro-online" attitude is mainly age-specific, but in the present modeling approach, age groups are included as control variables. The innovation-diffusion hypothesis states that people living in cities are more open to e-shopping (Cao, Chen, and Choo 2013); however, in the current study, this effect has been assessed separately as well ("pro online" attitude, see above). Thus, channel choice is found to be predicted by attitudes, place of residence, and socio-demographic characteristics, all of which may individually contribute to the explanation of shopping behavior.

With respect to store utility, the impact of assortment is found to have a significant influence in both model parts. In the participation equations, which reflect store choice probability, the coefficient of $ln\ A_j$, γ_1, is between 0 and 1 in both survey areas (0.918 and 0.902, respectively), which indicates a positive but sublinear impact of assortment on consumer utility. This result is congruent with the assumption of diminishing marginal utility of assortment by Huff (1962), and the findings of several empirical model-based store choice studies (e.g., Orpana and Lampinen 2003; Lademann 2007; Briesch, Chintagunta, and Fox 2009; Tihi and Oruc 2012; Suárez-Vega, Gutiérrez-Acuña, and Rodríguez-Díaz 2015; Wieland 2015, 2018). This positive effect is quite smaller for online stores, which is supported by the negative coefficient γ_9 of the interaction term $ln\ A_j{*}DO_j$ (0.772 and 0.796, respectively). This result was expected because online stores typically provide a much larger assortment compared to physical stores (this expectation was also confirmed in the descriptive analysis in this study; see Table 3), as there is no limitation with respect to selling space. Moreover, the assumption in the Huff model concerning increasing consumer utility induced by assortment as a result of consumer imperfect information is not fully applicable to online stores, as they regularly provide full information about their assortment and current availability of products. The assumed positive effect of assortment on expenditures cannot be confirmed in the expenditure equations. This might be explained by different pricing levels with lower prices in furniture chains with big-box stores and online shops.

In both survey areas, travel time has a significant negative impact on store choice, as the corresponding coefficient γ_2 is below zero in both participation equations. Thus, distance-dependent demand as assumed in classical retail location theory (e.g., Christaller 1933; Huff 1962) is confirmed for furniture retailing in the current study. This result is also congruent with studies on channel choice incorporating different types of channel-specific transaction costs (including travel effort) and the accessibility of physical retail locations, respectively (e.g., Hsiao 2009; Chintagunta, Chu, and Cebollada 2012; Marino, Zotteri, and Montagna 2018; Schmid and Axhausen 2019). However, the positive effect is considerably small with respect to expenditures in South Lower Saxony, and not confirmed in the Middle Upper Rhine Region. This difference might be explained by regional differences in the spatial structure of furniture retailers between the two survey areas, a theme which lies outside the scope of this study.

A positive effect of clustering with competitors cannot be demonstrated. The coefficient of the agglomeration variable C_j, γ_3, is not significant and positive in the participation equation; however, it is significant and negative in the expenditure equation. Thus, the assumption of a cumulative attraction of physical furniture stores resulting from comparison shopping (e.g., Nelson 1958) is not confirmed in the present analysis. In contrast, the coefficients in the expenditure equations suggest that competition effects predominate over positive agglomeration effects, as spatial proximity to competitors *decreases* the average expenditures at a given physical store.

Shopping transaction costs with respect to online shopping do not show the expected impact on store utility, as the coefficient of delivery costs, sc_j, γ_5, is not significant in the participation equations. This might be explained by the specific goods, as furniture products are rarely purchased with relatively high expenditures (see also Table 4) and delivery costs could, therefore, be less important for the consumer decision. When looking at the related control variables, delivery charges which depend on the order value decrease store choice probability but correlate positively with the related expenditures. The effect of free delivery from a certain order value cannot be clearly identified.

In both survey areas, it can be clearly confirmed that furniture retailers profit from being omni-channel retailers. The coefficient of the dummy variable DCC_j, γ_4, is significant and positive in both the participation equations (0.857 and 1.315, respectively) and the expenditure equations (0.215 and 0.045, respectively). Thus, the omni-channel integration of (online or physical) furniture stores increases both their choice probability and the related expenditures in the case of a purchase. This result is in line with expectations, and for the first time, has been confirmed as a significant explanatory variable with respect to (spatial) shopping behavior. Omni-channel retailers (as defined in the current study) provide full information about their assortment and prices, provide the "order online, pick up in store" service, and they also facilitate returns, and thus, reduce consumer transactions costs within the purchasing process.

Several dummy control variables for the furniture chains show a significant impact as well, which might indicate consumer preferences for specific chains (such as *IKEA*). However, these aspects are outside the scope of this study. The control variable for total expenditures by consumer, S_i, correlates, as expected, positively with the expenditures in the stores.

Conclusions and limitations

The aims of the present study are (1) to construct a store choice model which incorporates physical and online stores as well as the opportunity for omni-channel shopping, and (2) to identify the main drivers of spatial shopping behavior given the availability of both channels in furniture retailing. We can conclude that the incorporation of online retailing into store choice models is possible, as the underlying assumptions for store choice in retail location theory, and channel choice in multi-channel shopping behavior research, can be connected. Both lines of research are based on the assumption of utility-maximizing consumer behavior and reducing shopping transaction costs, including opportunity costs incurred through traveling, costs associated with delivery, and efforts connected with searching for and gathering information. The model constructed in this study incorporates physical and online shopping alternatives, whilst explaining consumer behavior in terms of store characteristics and shopping transaction costs, as well as in relation to objective and subjective consumer characteristics. This contributes an advance to the field of retail geography, which has, until now, been characterized by a lack of studies incorporating multi- and omni-channel retailing into store choice models. The present model can be regarded as a special kind of spatial interaction model for retailing, but incorporating non-spatial shopping alternatives; it is, therefore, linked to the popular Huff model (Huff 1962), which might be the most popular store choice model.

The main drivers of (spatial) shopping behavior in a multi-channel environment have been identified. With respect to furniture retailing in two German regions, it has been demonstrated that the preference for online shopping can be explained by psychographic consumer attributes, by place of residence, and to a much lesser extent, by age. The choice of the specific (physical or online) store can be explained primarily by store features—in particular, assortment size and omni-channel integration—as well as by accessibility to physical stores. No evidence for localization economies was found.

Apart from the contribution to the research literature, both the modeling approach and the subsequent findings have significant practical (real-world) applications. First, quantitative store choice models may be utilized in (1) retail location planning for estimating potential sales of new stores, and (2) in the context of spatial planning when estimating purchasing power flows induced by proposed retail projects ("retail impact assessment") (Khawaldah, Birkin, and Clarke 2012; Levy, Weitz, and Grewal 2019; Müller-Hagedorn 2020). Indeed, given that online shopping is relevant for the majority of retail sectors—and exhibits a rising trend—the incorporation of multi- and omni-channel shopping will increase the explanatory power of quantitative store choice models in planning substantially. In general, the model design is transferable to other retail sectors. Considering the basic assumptions of retail location theory, one might expect that the same explanatory variables are relevant but with higher or lower impacts, which could be analyzed by using empirical data on consumer behavior. Example, with respect to furniture (which is infrequently purchased), it is to be expected that travel time has a low impact on store utility compared to groceries or clothing. A similar model was already introduced for consumer electronics (Wieland 2021), showing mostly comparable (but not identical!) results.

Second, the results clearly support the relevance of the online channel for both pre-purchase information and the purchase itself. This point is underscored by (1) the tendency of consumers to gather information online (no matter which channel is chosen for purchase)—a behavioral characteristic shown in the survey—and by (2) the positive impact of omni-channel integration with respect to store choice and expenditures, a demonstrated result of the model analysis. Thus, independent (non-chain) single-channel retailers should be encouraged to expand their sales channels and be supported during subsequent implementation. Independent retailers could join a retail cooperative offering a standardized online shop for its members (such as *VME* for furniture or *Electronic Partner* for consumer electronics, both examples from Germany) and/or such retailers could also be supported by city management institutions.

Despite these positive findings, the current study also faced some limitations. First, with respect to the opportunity for omni-channel shopping, the model constructed in this study only incorporates information as to whether a retailer is an "omni-channel retailer" (as defined in this study) or not. In the model design adapted from Wieland (2021), there is a differentiation between running an integrated online shop, and providing the "order online, pick up in store" service, with remarkable differences in the corresponding impact. This distinction was not possible with respect to furniture stores due to a nearly perfect collinearity between these variables, as most stores with an integrated online shop also provide "order online, pick up in store". Second, the operationalization of delivery charges is quite difficult in online furniture retailing due to staggered delivery costs which vary depending on order value. In the present study, average delivery costs based on average order values were used, and it is questionable whether this indicator represents the range of delivery charges correctly, even in presence of the dummy control variables. Third, in contrast to the aforementioned Wieland (2021) study, delivery time was not included as an independent variable. Marino, Zotteri, and Montagna (2018) have identified delivery time as highly influential with respect to channel choice in furniture retailing; however, the aforementioned study is based on detailed and extensive data from one large furniture retailer. In the current study, such detailed data were not available for each retailer, and of course, delivery time varies between orders. Fourth, not all results describing differences between the two survey areas were able to be clarified, example, differences in the impact of accessibility on expenditures. These differing influences might be explained by specific regional circumstances with respect to the locational structure of furniture retailers; however, these effects have not been investigated in the present study.

Fifth, there is one more general issue related to the present econometric strategy. Although the modeling approach distinguishes implicitly between channel choice, store choice, and the related store expenditures, the model does not reveal whether these decisions are made consecutively or parallel. There might be a hierarchical decision process, which is not addressed by this type of model. Sixth, the current study employs established concepts such as "transaction costs" and "shopping attitudes" but does not cover all possible aspects of these constructs. The operationalization of a "pro online" attitude was adopted from a previous experimental study (Schmid and Axhausen 2019). Certainly, this construct does not include all facets of attitudes toward shopping channels. The same holds true for shopping transaction costs, which may include substantially more effort in terms of the purchasing process (Chintagunta, Chu, and Cebollada 2012). Future studies should address these limitations by extending and improving the present modeling approach.

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Conflict of interest

None.

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