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An extended Huff-model for robustly benchmarking and predicting retail network performance

Matthias De Beule [a,*], Dirk Van den Poel [a], Nico Van de Weghe [b]

[a] Faculty of Economics and Business Administration, Ghent University, Tweekerkenstraat 2, B-9000 Ghent, Belgium
[b] Department of Geography, Ghent University, Krijgslaan 281 (S8), B-9000 Ghent, Belgium

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A B S T R A C T

This study proposes a modified Huff model that takes directly into account spatial competition between stores of the same brand, brand attraction based on actual brand performance and spatially variable substitution. The model uses only publicly available or easily acquirable data as input, whereas model output is extensively validated on various levels. These levels include comparison of modeled and real market shares on block, store and brand level for the Belgian food market. Results show that multi-objective optimization of model parameters yields comparable results on block level to other models in the literature but improved results on store and brand levels, thereby ensuring model robustness. This robustness also enables the application of the model for various business purposes as store location determination, leaflet distribution optimization, store and store concept benchmarking, without loss of spatial generality.

Introduction

To monitor operational performance, retailers rely more and more on objective store benchmarks. Benchmarks are objective in a way that they quantify internal and external influences on store performance (store size, brand, competition, geodemographic characteristics of consumers, etc.) to obtain a measure indicating the performance of the management. The more fine-grained such store benchmark is, based on for instance loyalty card information, the more targeted improvement actions can be defined. A store benchmark on a fine-grained block level is therefore more valuable than a benchmark on an aggregate store level for defining and monitoring the impact of marketing actions such as door-by-door leaflet drops. In expansion strategy, accurately predicting turnover for a new outlet is also of primary importance for today's retailers. An accurate turnover prediction can quickly indicate whether it is still worthwhile to pursue a scarce city center development opportunity or to accurately assess the opportunity cost on the future network of opening a new store outside the city center, where supply of potential location alternatives is still more abundant.

In the next chapters, we propose a Huff-model that provides both a robust benchmark for current stores and an accurate turnover prediction for new stores, applied to the Belgian food market. In chapter 2, we explain in what ways our new approach extends the current state-of-art on store benchmarking and prediction techniques. Chapter 3 covers the development of the new model. In chapters 4 and 5, we explain what data we use as input and validation data and how model performance is measured. In chapter 6 we discuss the performance of our model after optimization, both in comparison with other Huff-models and of the individual contribution to overall effectiveness of the model of the different model building blocks. Finally, in chapter 7, the results of this study are summarized and managerial implications and limitations for using this model in practice are discussed.

Literature and own approach

Many approaches to benchmarking and predicting turnover exist, ranging from simple methods as experience and analogs, over regression analyses to more complex methods as spatial interaction modeling and neural networks (Wood & Tasker, 2008).

Already in 1964, Huff showed that gravity modeling techniques can have a significant contribution to solving these retail network management issues (Huff, 1964). By calculating customer's probabilities for store patronage, the Huff model embodied an important milestone in scientifically assessing store trade areas. The model states that the market share of a store in a given region is

* Corresponding author. Technologiepark 3, B-9052 Zwijnaarde, Belgium. Tel.: +32 (0)92415635; fax: +32 (0)92415656.
E-mail addresses: matthias.debeule@geointelligence.be, Matthias.DeBeule@UGent.be (M. De Beule).

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proportional to the utility for consumers in this region generated by this store to the total utility generated by all stores in the neighborhood of this region.

Ever since the formulation of the basic model in 1964, many extensions have been proposed to improve the predictive accuracy of this type of gravity model. Lakshmanan and Hansen (1965) argued that a non-linear relationship between attraction and store size increases patronage prediction accuracy because the utility trade-off between store size and travel distance was now more flexible. Nakanishi and Cooper (1974) proposed a strategy to estimate model parameters using ordinary least square estimations when a log transformation is applied to the different drivers of store attraction. Stanley and Sewall (1976) added brand image to the attractiveness drivers of a store. Ghosh (1984) was the first to account for spatial non-stationarity of the parameters used in a gravity model, because the relevance and impact of different drivers of store attractiveness can vary across geographic regions. Orpana and Lampinen (2003) introduced different store concepts in the gravity model based on the size of grocery stores. A separate set of parameters for each store concept was estimated to model the varying impact of store attractiveness drivers on each store concept as they serve a different shopping purpose.

Next to finding the right drivers and estimation procedures, many applications of the Huff model have been proposed and tested in literature. These applications include university campus selection (Bruno & Improta, 2008), store selection in the furniture market (Cliquet, 1995), the choice of movie theater (Davis, 2006), and the analysis of spatial access to health services (Wan, Zhan, Zou, & Chow, 2012; Wan, Zou, & Sternberg, 2012). The most common application in both literature and practice however, is found in the grocery market, since it is one of the most saturated markets, for which benchmarking and a predictive model is most valuable.

We argue that in current approaches proposed in the literature several shortcomings can be found. Firstly, very few research has looked into the impact of the spatial configuration of the store networks and more specifically how the presence of multiple stores of the same retail chain in a customer's choice set can influence store results in that area. Secondly, we noticed a lack of variety of information used to validate the proposed models. This is mainly due to the fact that most, if not all, papers focus solely on answering one management issue. For example, Orpana and Lampinen (2003), Yingru and Liu (2012), and Sandikcioglu, Özden, and Sayin (2008) focus solely on the prediction accuracy for retail locations. For this purpose they only use information on a store level, which yielded good results for their purpose. Less research has been conducted on block level, based on questionnaires or loyalty card information. Gauri, Pauler, and Trivedi (2009) use such block level information and gravity modeling techniques for a store performance benchmark exercise. Although the results on block level for the performance benchmark were good, the results on a more aggregate store level were less satisfactory. None of the existing work on gravity modeling has incorporated results on a higher level, the food retail chain, despite being readily available in a nation's database of financial statements. A final shortcoming can be found in the type of input data used in existing gravity models. Collecting a wide variety of input data to capture more influencing factors (Jones & Simmons, 1993) can be extremely time consuming or very costly when bought. Retailers are therefore often reluctant to acquire these data because the marginal benefit of incorporating these data in practice has become questionable. In this paper, we show how easily available information can be used for maximum applicability and results in practice, ensuring high return on investment.

This paper aims at constructing a robust gravity model for the whole Belgian grocery market, using an extensive set of easy-to-gather input and validation data. In doing so, we address the three aforementioned shortcomings. Firstly, the state of art of the Huff-model is extended by incorporating more spatially influencing factors, such as brand recognition and internal cannibalization of sales between stores of the retail chain. The inclusion of such factors can provide valuable insights in a retail chain's network expansion strategy. Secondly, block level information drawn from a grocery retailer's Customer Relationship Management database is used in addition to annual store turnovers from the same grocery retailer and annually reported group turnovers for all competitors as reported in their financial statements. Validation on these three levels is applied for an improved robustness of the proposed model. Lastly, in our approach, only easy-to-gather input data on a national scale is used. Therefore, we limit our model to the store surface and the store brand as a measure of store attractiveness. Addresses and brands of stores can easily be acquired using company websites and common knowledge of the competitive landscape. While calculating surfaces on a large scale can be time consuming, the spread of freely accessible aerial photographs (Google Earth, Bing Maps) (Yingru & Liu, 2012) and more detailed socio-economic permits have sped up its calculation considerably.

Model development

Starting from the basic Huff model, this section explains the extensions that seek to improve predictive and benchmarking accuracy on block, store and chain level.

Basic Huff model

As a starting point for our model we use the Huff model as proposed in 1964. It states that the patronage probability P_{ij} of a store j for inhabitants and workers in a given region i (henceforth named 'residents of block i') is equal to the proportional utility of this store (U_{ij}) compared to the total utility generated by all N stores in the neighborhood of this region:

$$P_{ij} = \frac{U_{ij}}{\sum_{q=1}^{N} U_{iq}} \tag{1}$$

The utility generated by grocery store j for residents of block i is calculated as:

$$U_{ij} = \frac{A_j}{D_{ij}^{\beta}} \tag{2}$$

The value A_j represents the aspatial attractiveness component for store j. In the basic Huff model, store size is used for A_j. As mentioned in Section Literature and own approach, it is however possible to incorporate more drivers for aspatial store attractiveness by averaging or multiplying different drivers. D_{ij} is the distance between store j and the centroid of block i. In most research, Euclidian distance based drive times are used. However, with recent technology advances, the calculation of fastest route drive times has become feasible, even for large scale projects. The parameter β shows the relationship between distance and attractiveness of the store.

To translate probabilities from Formula 1 into monetary allocations, it is assumed that the total spending potential of a block is divided evenly according to the store visit probabilities P_{ij} for all stores j in close proximity.

$$F_{ij} = P_{ij} {*} SP_i \tag{3}$$

Where F_{ij} equals the monetary flow between store j, and block i and SP_i is the total spending potential on groceries of all residents of block i.