Chapter 7
Summary and Conclusions

7.1 Introduction
In this thesis we study local marketing, which we define as the customization of marketing mix variables to the store level based on consumer, competitor, and store characteristics. Our aim is to enhance the knowledge about local marketing.
In previous chapters we studied:

i. the origin of local marketing (Chapter 2)
ii. the implementation of local marketing in practice (Chapter 3)
iii. existing models for local marketing, their shortcomings and available data (Chapter 4)

We also developed models that can be used to define local marketing decisions (Chapters 5 and 6). This chapter consists of a summary in Section 7.2. We discuss limitations and directions for future research in Section 7.3.

7.2 Summary
Definition and history of local marketing (Chapter 2)
In this chapter we study the definition and history of local marketing. We compare several definitions of local marketing and discuss the term micro marketing. This study resulted in the definition of local marketing given in the introduction to this chapter.

We consider the history of local marketing both from retailer and manufacturer perspectives. About a century ago, retailers applied local marketing implicitly as storekeepers often owned only one store. Over time local marketing tended to disappear due to increased retailer concentration and a focus on homogeneity between stores. Retailers then focused on applying the same marketing mix in all stores. Since 1970s on there has been a shift to a more market oriented approach. Positioning and differentiation have received increased attention. In the last decade, we can see that retailers have been using improved customer information systems to customize the marketing mix at the store level.

About a century ago manufacturers paid no attention to customization at the store level. They focused on products and production. Over the years
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Manufacturers have faced increasingly demanding retailers. Retailers have forced manufacturers to guarantee profit margins, pay slotting fees, and produce private labels. Manufacturers reacted to these changes by approaching retailers more directly. They focused on cooperation in order to avoid conflicts. Local marketing initiated by the manufacturer can be seen as a further development of this strategy.

Local marketing in practice (Chapter 3)

In this chapter we consider the following questions about the application of local marketing in the Dutch supermarket practice:

- Why is local marketing applied?
- How is local marketing applied?
- What are the possible compositions of the marketing mix given a local marketing strategy?

We study these questions in both a qualitative and quantitative way. We conducted exploratory in-depth interviews (qualitative) with respondents from varying retail backgrounds. We interviewed nine store managers from five chains as well as three head offices from retail chains and eight manufacturers.

We performed a written survey for the quantitative study. The outcomes from the in-depth interviews were used to develop the survey. We sent the survey to all manufacturers of national brands in the Netherlands, of which 49 (35 percent) responded. We asked manufacturers questions on (i) the variables they use to differentiate between supermarkets, (ii) how they apply local marketing, (iii) the degree to which they apply local marketing in supermarkets per marketing instrument and in total, (iv) the score on variables that might predict the degree to which they apply local marketing. We also used additional data on these manufacturers supplied by ACNielsen. Importantly, the survey measured the application of local marketing from the manufacturers’ point of view. The reason we focused on manufacturers for data collection is that such data are difficult to obtain at the store- or chain level.

Almost all manufacturers in the Netherlands (96 percent) differentiate in some way between stores. We find that chain type (used by 85 percent) and store size (56 percent) are the most frequently used variables.

Manufacturers need a sales force to apply local marketing. We find that 69 percent of the Dutch manufacturers have a sales force. Manufacturers use profit potential and a store manager’s willingness to cooperate as criteria to select stores. Manufacturers may provide their sales forces with a tool to apply local
marketing. This is a stand-alone computer system that provides advice on the marketing mix based on store- and market characteristics. In the sample, 36 percent of the manufacturers have such a tool.

We studied the restrictions on the use of marketing instruments for local marketing. These restrictions are instrument specific and differ between chains and ownership type. We find that privately owned stores tend to be less restricted (and more motivated) to apply local marketing. We find that regular price is not suitable for local marketing and hence is hardly ever used. By contrast, shelf design and assortment are suitable for local marketing and hence these instruments are very frequently used. Additionally, we find that manufacturers apply less local marketing in chain-owned stores than in privately owned stores.

Finally, we calibrate a model to study what drives the manufacturers’ application of local marketing. We find that the application of local marketing is determined by category size, differences in purchase behavior between stores, manufacturer market share, and the importance of a good relationship with the store manager.

Models and store profile data (Chapter 4)
In this chapter we study models and data for local marketing. We illustrate the models in practice with local marketing related services from ACNielsen. These services are Familytrack, Local Marketing, and Assortman. We note that in practice the models merely focus on sales potential and do not explain instrument effects from store profiles.

We discuss and compare four models in the marketing literature that relate store profiles to instrument effects. These studies are Hoch et al. (1995), Montgomery (1997), Mulhern et al. (1998), and Campo et al. (2000). In our evaluation of these models we find that:

• The models have many parameters. Hence, restrictions have to be imposed as the number of observations per store is low.
• Competitor characteristics are based on distance and not on choice criteria. Additionally, competition is not considered from the consumer point of view.
• Consumer characteristics are based on consumers living within a certain radius or within the trade area and not on consumer behavior. None of the studies distinguishes between actual- and potential customers.
Furthermore, we observe that models that estimate sales potential are based on between-store variation. The use of these data potentially leads to biased estimates (see also Chapter 6).

We also compare data on store, competitor, and consumer characteristics in the Netherlands. We focus on consumer data and discuss different sources including customer card data, individual household databases and aggregated household databases.

Sales decomposition within and across categories using daily data from one store (Chapter 5)

In this chapter we develop a model to determine store-specific instrument effects using daily data from a single store. Models for a single store implicitly account for differences between stores. We use daily data instead of weekly data to increase the number of observations. Current models use weekly data. With such data it is difficult to calibrate complex models for a single store.

We specify an additive model to decompose price promotions within- and across categories. We decompose the price effects into effects on: (i) the brand for which the price is changed (own effect), (ii) other items of the same brand (within- and across categories), and (iii) items of other brands (within and across categories). These effects can be both substitution and complementary effects. We split the effects into negative and positive effects to accommodate the a priori unknown sign of the cross category effects. All effects are expressed as a percentage (fraction) of the total positive effect (the sum of all positive effects).

We address several specification issues inherent to daily data for one store. These issues include (i) proportional effects, (ii) day-of-the-week effects, and (iii) trends in the data.

Previous decomposition studies only consider within-category effects. Omission of cross-category effects may lead to either over or underestimated price promotion effects. We find both positive (average across categories is 9 percent\(^1\)) and negative cross category effects (average is 10 percent). We find few effects on other items of the same brand.

Similarity-based spatial methods to estimate shelf space elasticities (Chapter 6)

In this chapter we consider the use of cross-sectional data to estimate marketing instrument effects. Cross-sectional data potentially lead to biased estimates. We

\(^1\) Calculated as the sum of the effects on manufacturer’s items and items of other brands.
focus on shelf space elasticities. Current models for local marketing use data across stores to determine potential sales and instrument effects. Moreover, if instruments do not vary over time (as with many instruments in historical data), cross sectional variation is the only variation available.

The problem with cross-sectional variation is that unobserved retailer behavior may lead to biased results. This occurs when the instrument is determined by unobserved factors which are correlated with sales. In the case of shelf space this implies that the correlation between sales is higher than we would have expected based on the causal effect of shelf space on sales. Consequently, \textit{OLS} will lead to overestimated shelf space elasticities. Specifically, the assumption in \textit{OLS} of zero correlation between predictor variables and the error term is violated (endogeneity).

In this chapter we use a spatial structure based on store profiles to model the correlation between the error term and the predictor variables. The spatial structure defines which stores are contiguous in a space spanned by the store profile variables. The model uses this structure to relate the error terms of each store to its contiguous neighbors. This approach builds on the work of Bronnenberg and Mahajan (2001), who use geographical coordinates. We argue that in our application (stores instead of markets) it makes more sense to define contiguity in terms of store profile variables. This should apply to other data as well.

We specify a model for purely cross-sectional data (the \textit{SPATIAL}-model), as well as a model for cross-sectional and time series data (the \textit{SPATTEMP}-model). We compare the \textit{SPATIAL}-model to (i) an \textit{OLS}-model, (ii) an \textit{OLS}-model with control variables (\textit{OLSC}), and (iii) a model with a spatial structure based on geographic locations, used by Bronnenberg and Mahajan (\textit{SPATIALBM}). For the cross-sectional and time series data, we compare the \textit{SPATTEMP}-model to (i) a fixed-effects model (\textit{FE}), which avoids the endogeneity related to cross-sectional variation, and (ii) a model with a spatial structure based on geographic locations (\textit{SPATTEMPBM}).

The \textit{OLS} estimates (no correction for endogeneity) for the shelf space elasticities are highly biased upward. Their average is about 0.85, whereas methods that account for endogeneity have an average of about 0.21.

Our results suggest that models with a spatial structure based on store profile lead to unbiased estimates. For example, the \textit{SPATIAL}-model provides average shelf space elasticity estimates that are close to the average estimate from the \textit{FE}
model. The OLSC-model, including control variables corrects only for some of the retailer behavior. In our application SPATIALBM turns out to be inadequate. The shelf-space elasticity estimates from this model differ strongly from the prior value for each brand. We find that models that use time series variation in addition to cross-sectional variation provide similar average shelf-space elasticity estimates. However, SPATTEMP has slightly smaller standard errors than either FE or SPATTEMPBM.

7.3 Limitations and future research

There is a number of issues that deserve more attention in future research into local marketing. These issues are:

- Measurement of local marketing activities at the retail-level
- Store competition
- Variable selection
- Explaining store-specific instrument effects
- Heterogeneity in the SPATIAL-model
- Other applications of the SPATIAL-model

We elaborate these issues below.

**Measurement of local marketing activities at the retail-level**

In Chapter 3 we measure the manufacturers’ use of local marketing. We decide to measure local marketing from the manufacturers’ point of view for practical reasons, such as the efforts needed and expected cooperation. Future research may be able to measure local marketing by observing the actual use of marketing instruments in stores. This may lead to more objective information about the adoption of local marketing and the customization of the marketing mix to the store level.

**Store competition**

Current models do not accommodate store competition correctly. Competition should be modeled from the consumer point of view. For one consumer a given competing store may be a much closer substitute than it is for another customer. Spatial interaction models such as Huff’s model offer opportunities to model competition correctly. Unfortunately, the detailed data needed to calibrate such models is not yet available. When such data become available, these models may be developed. Additionally, such models may account for interaction between
variable selection
In Chapter 5 we consider cross-category effects between category pairs. We consider category pairs as the number of observations is too low to include instruments of multiple categories simultaneously. Future studies may consider methods to select relevant marketing instruments from a large set of possible marketing instruments. In this way a great number of categories can be considered. We propose using a stepwise regression method. These methods select predictor variables based on an incremental $F$-value. However, we note the following complications:

i. A stepwise regression method may select wrong predictor variables due to multicollinearity between possible predictor variables; that is, a predictor that is not relevant but is correlated with a relevant predictor may be included instead of the relevant predictor.

ii. If the number of selected predictor variables is low, it may be argued that the estimated relationships are coincidental. That is, if we consider a large number of instruments we are likely to find some variables that are correlated with sales. Previous research suggests that this problem will occur as the odds of finding cross-category effects in less related categories are low.

explaining store-specific instrument effects
The model presented in Chapter 5 provides item specific parameter estimates for one store. Future research may explain these parameters as a function of store layout variables such as location in the store, distance to other products, shelf position, package size, perishability (see Raju, 1992).

heterogeneity in the spatial-model
In Chapter 6 we use similarity in store profiles to construct a spatial weight matrix to correct for endogeneity in cross-sectional data. Future studies may adapt the SPATIAL-model in such a way that it accommodates heterogeneous effects across stores. We suggest two possibilities: (1) To model the parameters as random effects like Bronnenberg and Mahajan (2001). In a second step these parameter estimates may be modeled as a function of store profile variables. (2) To estimate...
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store profile dependent effects in one single step using the approach of Montgomery (1997).

Other applications of the SPATIAL-model
We apply the model proposed in Chapter 6 to shelf-space elasticities. Future studies may apply this model to other instruments that do not show variation (or minimal variation) over time such as, store layout, selling products over a counter or not, price gaps, etc. We also suggest studying the model’s applicability to other situations where endogeneity problems exist and profile data are available.