# On Store format, Category Space Allocation, and Opportunities for Micromarketing.

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**Abstract**

This paper examines the impact of store format on the benefits that retailers can obtain from micromarketing strategies. Retail chains adopting a micromarketing strategy, tailor their marketing mix to the characteristics of the local market in which each store outlet operates. The present research spells out the conditions for micromarketing to be beneficial, and how these benefits depend on store format. It also indicates how the pattern of adjustments to local conditions differs between formats. The research concentrates on the comparison of two store formats (super versus hypermarkets) in a grocery shopping context, and studies the impact of location-specific allocation of store space to categories as a case in point. The outcomes of the study have conceptual as well as managerial relevance, and may prove particularly useful for multi-format retailers.

**Key-words**: Store Format, Micromarketing, Category Space Allocation

## 1. Introduction

The recent retail management literature has shown a growing interest in micromarketing. Trading zones of different outlets - with distinct socio-demographic profiles and competitive conditions – constitute natural 'micromarkets' that may warrant tailor-made marketing mix strategies. Besides pricing adjustments (see, e.g., Hoch et al. 1995, Montgomery 1997), an important issue in a retailer's micromarketing strategy consists of allocating scarce resources - such as merchandising budgets or store space - to various categories. The availability of store level data on category performance, coupled with the advent of geographical information systems (see e.g. Curry 1993), has indicated that category roles and category attractiveness may well vary with location characteristics. Some papers demonstrate the potential profit gains from making category resource allocation idiosyncratic to stores (see, e.g., Grewal et al.1999, Campo et al. 2000). These papers shed light on the implications of location-specific category management for various outlets of a given *store format* – typically supermarkets and specialty stores.

Since store format affects both category and store level performance (Desmet and Renaudin 1998, Tang et al. 2001), and is bound to shape the impact of location characteristics on category and store performance (Grewal et al. 1999), the question arises whether the results on micromarketing profitability apply to other store formats as well. This is particularly relevant for retailers operating multiple store formats like, for instance, Ahold and Wal Mart who opened up convenience stores and hypermarkets under the same banner as their traditional supermarket stores. For such retailers, two important questions arise:

(i) whether or not to adopt micromarketing strategies in each of the store formats and, if so,

(ii) whether different patterns of resource allocation should be adopted for each store format. Different patterns could refer to differences in the nature of the *location variables* driving optimal resource allocation, as well as to the *categories* receiving more or less resources under given local market conditions.

The purpose of this paper is to shed more light on these issues. In section 2, we develop a general framework specifying the conditions under which micromarketing can be profitable. Section 3 links these conditions to store format. The discussion concentrates on two dominant retail formats for grocery shopping (supermarkets and hypermarkets), and on the allocation of store space (one of the scarce retailer resources) to categories. Even so, many of the insights may generalize to other types of resources and store formats. Section 4 describes the data and methodology used for the empirical analysis, the results of which are discussed in section 5. Conclusions and directions for future research are presented in the last section.

**2. Benefits from Local Category Resource Allocation: General Framework**

In allocating scarce store resources to categories, any retailer operating several, geographically spread store outlets, faces two basic options. One is to adopt a 'global' approach, in which case the proportion of the available resource assigned to a category is the same in each store. Alternatively, the retailer can make the spread of resources over categories dependent on the store's local market characteristics[i]. Figure 1 specifies three general conditions for such a micromarketing approach to be beneficial. <Insert Figure 1>

The first condition is '*Trading zone heterogeneity across stores'*. Obviously, adjusting resource allocation to local market characteristics only makes sense if the latter differ between stores. Core micromarketing characteristics are the competitive conditions, and the socio-demographic profile of inhabitants, in the store's trading zone (the surrounding geographical area from which it draws most of its customers) (see Hoch et al. 1995, Campo et al. 2000).

The second condition, '*Local dependence',* refers to differences in the relative attractiveness of categories offered by a store, as a result of differences in local market characteristics. Trading zone heterogeneity is a necessary but not sufficient condition for local dependence. For local category resource allocation to make sense, these trading zone differences must also *translate into* differences in category appeal. This may occur for various reasons. As demonstrated by previous research, there is a clear link between customers' socio-demographic profiles and their propensity to purchase certain categories (see, e.g. Grewal et al 1999, Campo et al.2000). In addition, given overall product attractiveness, the share of category purchases captured by a store may vary with the strength of competition (number and attractiveness of other stores located in the same trading area).

A last condition is referred to as *'Actionability'*, or the extent to which a retailer can improve store profit by reallocating resources as a function of local category appeal. Unless the retailer disposes of adjustable and effective resources (such as shelf space and sales promotion budgets) that can be manipulated to enhance category performance, local differences in category attractiveness cannot be actively exploited. Through reallocations of these resources in favor of locally attractive product categories, the effect of location characteristics on category performance can be reinforced. To the extent that improved category performance also translates into higher store sales and profits (directly and indirectly, through increased store attractiveness), the micromarketing approach to resource allocation can contribute to an increase in overall chain profits (see Figure 1). In addition to these positive own store effects, the profitability of a micromarketing strategy further depends on potential cannibalisation effects, local resource allocation in one store format increasing its attractiveness at the disadvantage of other outlets of the same retailer[ii]. Taken together, these effects will determine ‘actionability’: the possibility to improve chain profit through local adjustments of category resource shares.

**3. Store Formats and Local Category Resource allocation**.

The following discussion concentrates on the distinction between supermarkets and hypermarkets, which is essentially based on differences in store size and assortment composition[iii]. Compared to supermarkets – with an average store surface of about 1500 to 4000 m$^2$ – hypermarkets are larger in size (4000 to 10000 m$^2$). Hypermarkets also offer a wider and deeper assortment of products, with more emphasis on non-food, non-routinely purchased items and more peripheral services (e.g. dry cleaning, shoe repair; see Kotler 2000, Kahn and McAlister 1997). Below, we indicate how the characteristics of supermarkets and hypermarkets influence each of the conditions for micromarketing to be beneficial.

*Trading zone heterogeneity across stores.* Trading zones are expected to differ more strongly between supermarket than between hypermarket outlets, because of their size and type of location. First, following traditional gravity models, store choice is based on a trade-off between store distance and store attractiveness (see e.g. Huff 1964, Jain and Mahajan 1979) – the latter increasing with store size, assortment width and variety, and the availability of additional services (see e.g. Gripsrud and Horverak 1986). As hypermarkets score high on these dimensions, they will serve large trading zones, which tend to be internally heterogeneous (cover distinct neighbourhoods with divergent socio-demographic characteristics and competitive conditions, Curry 1993 and Dibb 2000), but fairly comparable across outlets (each hypermarket trading zone comprising a highly similar 'mix of neighbourhoods'). Supermarkets, in contrast, attract most of their business from the immediately surrounding area, their smaller trading zones being internally homogeneous (covering only a few neighbourhoods with fairly specific population and competitive characteristics), but quite different across stores. Moreover - unlike hypermarkets - supermarkets are located in divergent geographical areas, ranging from small country towns to highly urbanized city centers[iv] – each with their own population and competitive profile. Based on these observations, we expect trading zone heterogeneity between outlets to be larger for supermarkets than for hypermarkets, both in terms of population characteristics as local competitive conditions.

*Local dependence.* Supermarkets are expected to depend more strongly on local market characteristics than hypermarkets. A first reason is that hypermarkets draw only selectively from the potential customers inhabiting the trading zone, typically attracting large basket shoppers (often time-constrained, double-income families; see Tang et al.2001, Messinger and Narasimhan 1998) and multi-purpose shoppers (consumers combining general merchandise shopping with other, less frequent purchases; see Leszcyc and Timmermans 2001). For other types of shoppers, the advantages of a more varied assortment and additional time-saving services may not compensate for the hypermarket's higher transaction costs (time and effort needed to reach the store and/or to locate the needed items among the store's extensive assortment). The supermarket format, with its lower transaction costs, may be more feasible here, and for this reason, appeal to a much broader range of shoppers and shopping situations (see e.g. Merrilees and Miller 1997). Its customer profile will, therefore, more fully reflect the population characteristics of the trading zone. Second, given their smaller size (lower transaction costs) and larger proportion of small baskets (lower variable costs of store switching), supermarkets tend to be more vulnerable to local competition (see Gijsbrechts et al. 2003). We hypothesize, therefore, that local dependence is higher for supermarkets than for hypermarkets.

*Actionability.* In assessing the viability of space as a marketing instrument in supermarkets versus hypermarkets, we are confronted with conflicting forces. On the one hand, previous research shows that once a threshold level is exceeded, category response to space allocations exhibits decreasing marginal returns (see, e.g. Desmet and Renaudin 1998). This suggests that for hypermarkets, with their larger store surface, space is a less powerful instrument. On the other hand, the hypermarket shelves must host a much wider and deeper assortment than is offered in supermarkets, especially in the non-food department. This may more than offset the storage space available, again turning space into a scarce (and more effective) resource. Finally, the responsiveness to space is strongly shaped by the role of the category, which is bound to differ across store formats. The previous discussion demonstrates that there are no clear theoretical arguments why space should be more or less effective in supermarkets or hypermarkets. Empirical evidence on space elasticities in these formats is also ambiguous. While Thurik (1988) suggests space effects to be more pronounced in larger stores, a practitioner study (LSA 1995) reports the opposite, Desmet and Renaudin (1998) reporting no significant differences in category space effects according to store size[v]. For these reasons, no directional hypothesis is offered on the actionability of space-based micromarketing strategies for supermarkets versus hypermarkets.

In summary, we expect supermarkets to score higher on trading zone heterogeneity and local dependence than hypermarkets. If they also exhibit higher actionability (stronger space response), they are the most 'promising' format to reap micromarketing benefits. An empirical analysis of these effects is presented below.

**4. Data and Methodology**

*Data.* The data are obtained from a large European retail chain, operating supermarkets as well as hypermarkets under the same umbrella name. Some supermarkets from the chain are located within the trading zone of a hypermarket of that same chain, and vice versa. It follows that micromarketing approaches in one format may lead to cannibalisation of sales in the other format. Information is available on category sales and category store space for 2 subsequent years, for 17 product categories encompassing the whole store offer (an overview of these categories can be found in Figure 2's legend). The data cover 100 national store outlets: 52 supermarkets and 48 hypermarkets. For each store, information is available on store size and trading zone characteristics like competition and the socio-demographic profile of inhabitants. Table 1 provides an overview of the relevant variables and their measures. <insert Table 1>

*Methodology.* To address our research questions, two models are estimated for each format, based on pooled time series and cross-section data (all outlets of a format). *First*, a 'category sales share' model is estimated to assess the impact of trading zone characteristics on category appeal. Like Campo et al. (2000), we use an attraction-type model linking the share of a category in total store sales (dependent variable) to category space shares and location variables (store and trading zone characteristics). In particular, the following specification applies (for clarity of exposition, time indices have been omitted from the equation):

$$SV_{i,j} = \frac{Att_{i,j} * \prod_{m \varepsilon C_i} Cross_{i,j,m}}{\sum_c Att_{c,j} * \prod_{m \varepsilon C_c} Cross_{c,j,m}} \tag{1}$$

$$Att_{i,j} = \beta_{0,i} * \prod_s SS_{j,s}^{\beta_{2,i,s}} * \prod_r \exp(\beta_{3,i,r} * L_{ij,r})$$

$$Cross_{i,j,m} = \prod_s SS_{j,r}^{\gamma_{i,m,s}}$$

where $SV_{ij}$ and $SS_{ij}$ are the sales and space share of category i in store j, resp., $Att_{ij}$ is the intrinsic attractiveness of category i in store j, $Cross_{i,j,m}$ the cross-effect of category m on category i in store j, $L_{ij,r}$ is location variable r for (category i and) store j, $C_i$ is the set of product categories with potential asymmetric cross-category space effects on the value share of category i, and $\beta_{0,i}$, $\beta_{2,i,s}$, $\beta_{3,i,r}$, $\gamma_{i,m,s}$ are parameters.

The intrinsic attractiveness of category i in store j ($Att_{ij,}$) is specified as a function of location variables and own category space variables. The factor $Cross_{i,j,m}$ comprises asymmetric cross-effects, allowing the share of a product category to increase (decrease) when more space is assigned to complementary (substitute) categories. For more details on asymmetric attraction models and their rationale in the context of category sales shares, see Foekens et al. (1997), and Campo et al. (2000). Core location variables included in the model are the trading zone characteristics of interest: the local population characteristics ($Pop_{1j}$ to $Pop_{4j}$); competition from other super/hypermarket chains in the trading area ($Comp_{1j}$) and category-specific competition from specialty stores ($Comp_{2ij}$). In addition, other covariates are included to ensure unbiased estimation of the effects of interest :store size ($STSize_j$), degree of urbanization ($Urb_j$) and number of people working but not living in the area ($Work_j$) (see Campo et al. 2000 for a similar approach).

*Second*, we estimate a multiplicative[vi] store sales ($S_j$) model. Besides the location variables mentioned[vii] above we include, following Reinartz and Kumar (1999), trading zone potential ($Pot_j$) as an additional covariate in the store sales model. A key explanatory variable for our purposes is total store attraction ($AttSt_j$), the denominator of the category sales share model. This variable is similar in nature to the 'inclusive value' in purchase incidence models (see, e.g., Bucklin and Gupta 1992), its coefficient indicating to what extent the categories' attractiveness, on the whole, affects store level sales. In this way, the effect of category space allocation on overall store performance can be assessed. The store sales model also accounts for cannibalization effects within the chain, through the 'average attraction of other outlets of the chain located in store j's trading zone' ($AttOth_j$). If micromarketing would render these outlets more appealing, we can assess to what extent this backfires upon the performance of store j. To avoid endogeneity bias in our cannibalization estimate, we further include the number of other chain outlets ($Outlets_j$) as an explanatory variable[viii]:

$$S_j = \delta_0 * (\prod_r \exp(\delta_{2,r} * L_{i,j,r})) * (AttSt_j^{\mu}) * \exp(\rho_1 * Outlets_j) * (AttOth_j^{\rho_2}) \qquad (2)$$

where $\delta_{2,j}$, $\mu$, $\rho_1$ and $\rho_2$ are parameters, and variables are defined as above.

## 5. Findings

*Trading zone heterogeneity.* Table 2 provides a summary of location characteristics (store averages and standard deviations) of each format. The averages for each store format comply with the characteristics specified above: hypermarkets get a more substantial share of their sales from non-food categories than supermarkets, and have substantially larger trading zones (both in geographical size as in number of resident households). Moreover, the standard deviations (and resulting coefficients of variation) indicate that the variation in population and competition characteristics is higher for supermarkets than for hypermarkets, confirming the hypothesised difference in trading zone heterogeneity[ix].

*Local dependence.* Local dependence is assessed on the basis of the category sales share model in equation (1)[x]. Table 3 provides summary results for hypermarkets and supermarkets. In each format, five models are estimated, ranging from a base model with constants only, to a 'full model' including constants, space effects and the full set of location variables, with in-between specifications as clarified in Table 3. The upper panel of Table 3 provides summary statistics on the coefficient estimates for the full model[xi]. The lower panel compares the goodness of fit across model versions.

As a first test of the local dependence condition, we consider to what extent location variables - on the whole – improve model fit, and thus explain differences in category sales shares across outlets. The model including all location variables outperforms a model with space variables only ($p<.01$), pointing to local dependence in each format. As expected, location characteristics have a higher contribution to fit (increase in $R^2$, see Table 3b) for supermarkets than hypermarkets. Interestingly, while category appeal in hypermarkets depends on both population profiles and local competition, competitive variables are hardly salient for supermarkets and lead to a significant but only very modest improvement in fit.

Next, we examine the sensitivity (elasticities) of categories sales shares with respect to specific location variables. Figures 2 and 3 picture the category sales share elasticities for the local population and local competition variables, based on the full model. As expected, the elasticities with respect to the local population profile are more pronounced for supermarkets than for hypermarkets, be it that the pattern of effects is different between both formats. For competitive variables, in contrast, the impact seems less pronounced for supermarkets than for hypermarkets. Especially in non-food categories, hypers appear more sensitive to local specialty store competition.

*Actionability.* As indicated in section 2, local dependence is a necessary but not sufficient condition for micromarketing. It remains to be seen to what extent resource (in our application: space) reallocations allow to actually translate these local category differences into improved performance.

To this end, we first trace the impact of category space allocation on (i) category sales shares, (ii) overall store sales and (iii) cannibalization to other chain outlets. Figure 4 pictures the *category sales share* elasticities for supermarkets and hypermarkets. A striking pattern emerges: while the space impact is almost identical for food categories, non-food categories reveal systematically and substantially more sensitive to space in hypermarkets than in supermarkets. This can be explained by the fact that the assortment composition – while identical for stores of a given format – differs substantially across formats, especially for non-food categories. Whereas supermarket non-food assortments are typically constrained to a limited number of frequently purchased products (e.g. video tapes in the Audio-Video category), the hypermarket's non-food department also comprises a wide variety of more expensive, durable products (e.g. TV sets). As indicated in the literature on shelf space effects (see e.g. Urban 1998), these non-routinely purchased products may be more responsive to space changes, store space playing a more important role in drawing customer attention and signaling product importance. In addition, the assumption that the hypermarkets' huge assortment makes store space relatively more scarce, may especially hold for non-food categories, which often contain several bulky products. Based on the results of the *store sales* model (see Table 4), we find the impact of category space allocation on store level results to be comparable for both formats, estimated coefficients for the 'store attraction' variable ($AttSt_j$) being in the same value range. Interestingly, *cannibalization* effects from other chain stores in the trading zone ($AttOth_j$) are only significant for supermarkets ($p<.05$, 1-tailed), not for hypermarkets. Yet, even for supermarkets, they remain very small in size compared to the 'own store' effect. We conclude that, on the whole, space shifts across non-food categories lead to more pronounced effects for hypermarkets than for supermarkets, while shifts among food categories trigger similar effects in both formats.

Next, we compute the increase in chain profit obtained from local category space allocation. Lacking specific data on handling costs, we construct 'approximate' profit functions, details on which are provided in Appendix 2. For each store format separately, we calculate profit maximizing category space shares (i) under the global scenario, imposing the same allocation for all outlets in the format, and (ii) in a full micromarketing setting, allowing the allocation to be idiosyncratic to the store. Besides these two 'pure' scenarios, we consider two additional options, in which space allocation is tailored to local conditions for some product categories only.

Based on the previously discussed difference in findings for food and non-food categories, and the fact that a micromarketing approach for all categories may be too demanding in terms of space management, we also consider the following scenarios: (iii) micromarketing is adopted only for categories within the food department, restricting the space shares of non-food categories to be similar across outlets and (iv) a fourth scenario where the reverse holds (global space assignments for food items, micromarketing for non-food items). The results[xii] for these four scenarios in each of the store formats are compared in Figure 5, taking the global approach (scenario (i)) as the benchmark case.

Comparing the two 'pure' scenarios (i) and (ii), we find that the % profit increase per store is strikingly similar in both formats. Despite their stronger trading zone heterogeneity and local dependence, supermarkets – because of their lower space actionability in a subset of categories – do not lead to higher % gains from local space allocation[xiii]. Note that while the gain in both formats amounts to only 1 % of gross profit[xiv], it represents approximately 13% of net store profit (after all costs have been deducted) – a non-negligible figure.

The outcomes of scenarios (iii) and (iv), in contrast, are quite revealing. For supermarkets, the improvement in overall store profits obtained by local variations for non-food categories (scenario iv) is rather weak, because of their low responsiveness to space. As a result, adjusting the space shares for food products *only*, allows to reap almost all of the micromarketing gains. For hypermarkets, the reverse pattern holds, benefits from local space reallocations predominantly being generated by non-food categories. Local food space reallocations only provide a very modest gross profit improvement, which may not pay off for additional space management efforts and costs. It follows that local adjustment for non-food categories *alone* may be the more sensible option for hypermarkets. In brief, while the overall benefits from local space allocation appear comparable across formats (in terms of % profit increase per outlet), the drivers of these benefits, and the allocation patterns that allow to efficiently realize them, are substantially different.

## 6. Conclusions, limitations, future research

Our research contributes to the literature conceptually as well as managerially. On the conceptual side, we provide a framework that spells out the conditions for location-specific category resource allocation to be beneficial: heterogeneous trading zones, dependence of category appeal on local market conditions, and actionable, powerful resources to begin with. We also bring in an important moderating characteristic - store format - that affects these conditions.

The framework helps retailers to *efficiently* anticipate the benefits from store specific-space allocation. Indeed, it allows them to proceed in a stepwise fashion, checking subsequently whether trading zones are heterogeneous and whether significant local dependence effects prevail, before engaging in the complex exercise of determining store specific category space allocations and predicting their profit implications. In case one store format scores highest on each of the conditions, multi-format retailers can take this as a clear signal of where to start with their micromarketing endeavors. If both formats exhibit micromarketing potential (as in our application), the framework and its intermediate results helps multiformat retailers identify for each format (i) the key drivers of local dependence on which systematic information collection is needed to adopt micromarketing, and (ii) which subsets of product categories (food vs non-food) are prime candidates for a localized approach. While this analysis concentrates on space allocation and is carried out for hypermarkets compared to supermarkets, our framework for assessing micromarketing gains may carry through to other store formats, and to re-allocation of other types of scarce resources, like merchandising budgets or store flyer space.

Besides illustrating the foregoing arguments, our application generates some interesting managerial insights. It confirms the expectation that supermarkets have more heterogeneous trading zones, and depend more strongly on local population characteristics, than hypermarket outlets. Interestingly, however, category appeal varies more strongly with local competition in hypermarkets than in supermarkets. This finding is consistent with Leszcyc and Timmermans (2001)'s observation that for more expensive items - more likely to be focal categories in hypermarkets than in supermarkets - consumers tend to weigh the offer against that of local specialty stores. While the space effectiveness for food categories is similar in both formats, space is found to be more powerful among non-food categories in hypermarkets than in supermarkets. A possible explanation lies in the role of these categories, which tend to be more focal and purchased in a non-routine fashion in hypermarkets. As a consequence of these differences in trading zones, local dependence and space effects, we find that supermarkets have an interest in locally adjusting the space shares of food categories, while hypermarkets should primarily adapt the space shares of non-food products to local conditions. The resulting profit improvement per outlet is comparable across formats. Note that these results are strongly shaped by format differences in responsiveness to space. For other marketing resources (e.g. sales promotion budgets or store flyer space) that generate, say, equally strong responses in both formats, we expect the benefits from location-specific allocation to be higher for supermarkets than for hypermarkets. Two additional findings may warrant further attention. First, while the category sales shares in supermarkets are relatively insensitive to local competition – a finding in line with previous work by Hoch et al. (1995) and Gijsbrechts et al. (2003) - this is not true for hypermarkets, where especially non-food categories suffer from the presence of local specialty stores. In contrast, supermarket stores seem to experience more cannibalization than vice versa.

Clearly, our results are based on data for only one chain and country. Future research should shed light on the generalizability of these findings. Also, analysis of individual household behavior in supermarkets versus hypermarkets, or qualitative data on household buying motives and processes per store format and category, may further our insights into the need for micromarketing approaches in each format. Finally, applying our framework to other formats – including, for instance, virtual stores - and resource types is a fruitful avenue for future research.

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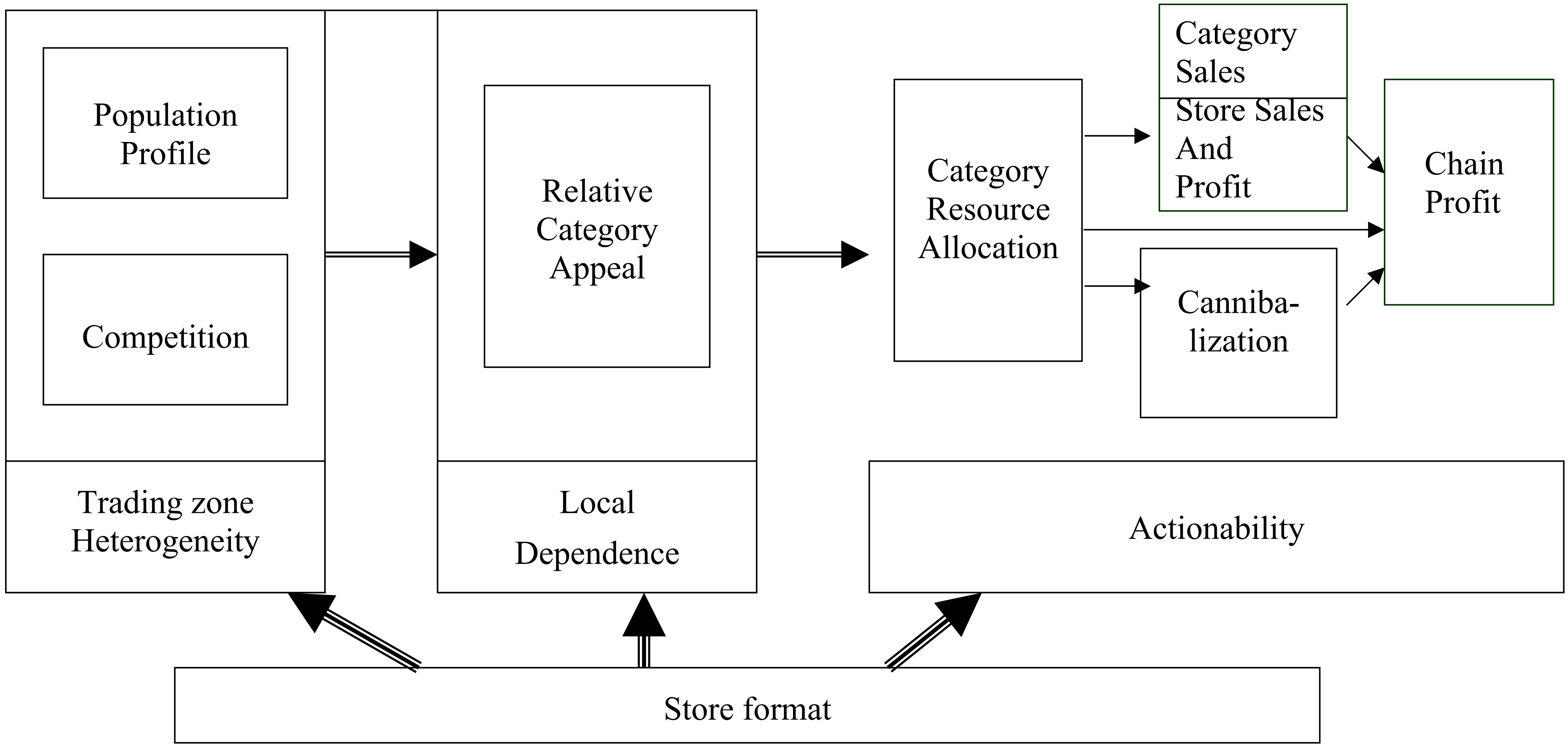
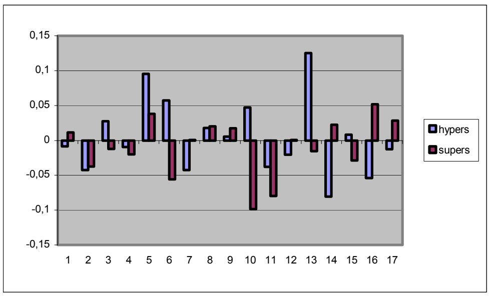
**Figure 1: Impact of store format on benefits from local category resource allocation**

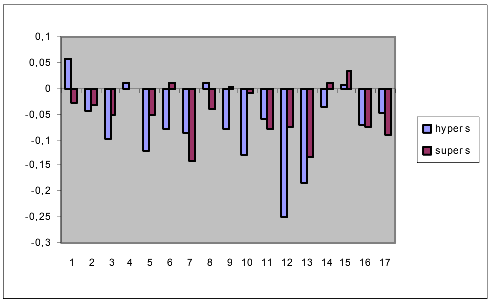


## Figure 2: Impact of Local Competition on Category Space Shares (Elasticities)

Competition from other Chains



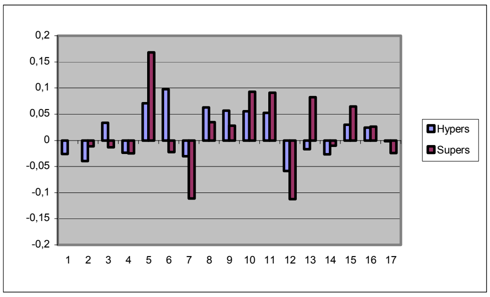

Competition from Specialty Stores



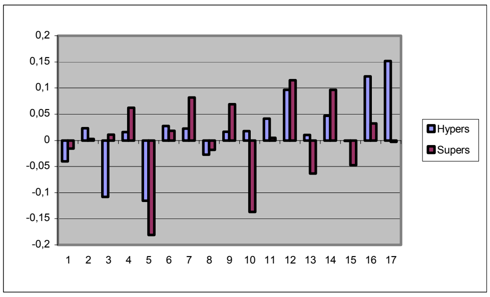

## Figure 3: Impact of Population Profile on Category Sales Share

(% share increase resulting from marginal increase in population presence)

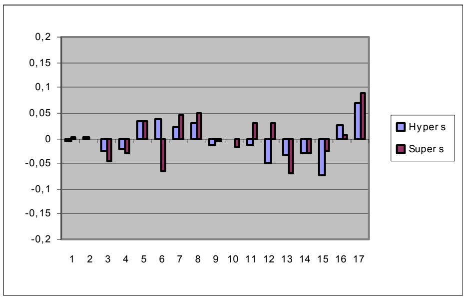
Young Families



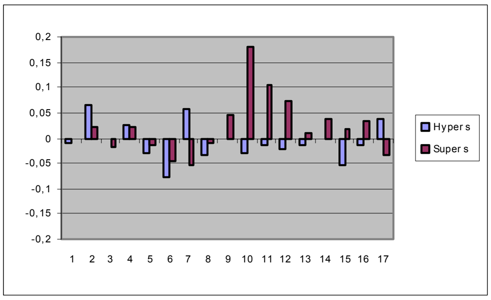

Less well-to-do



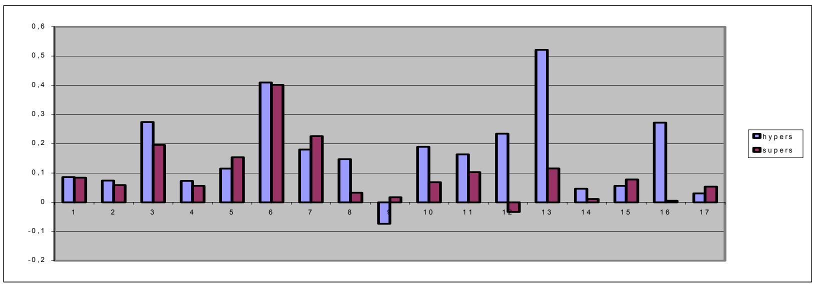

Middle Class




Single Child



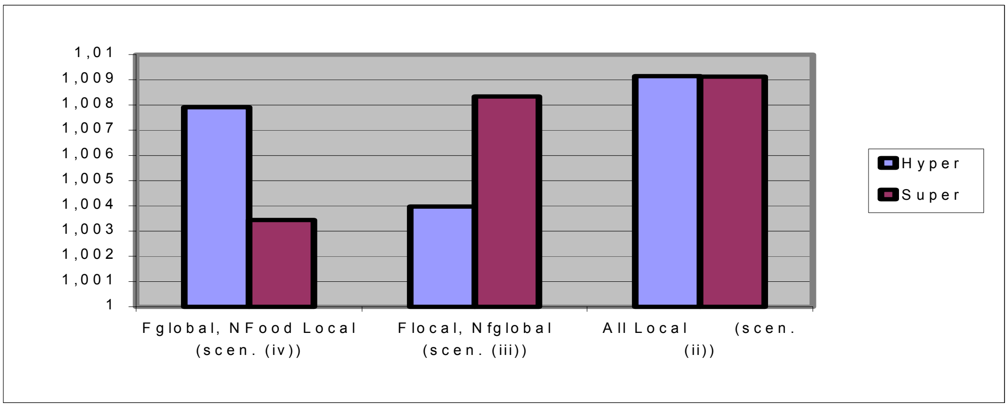

## Figure 4: (Own) Space Effects on Categories ‘ Sales Share in Supermarkets and Hypermarkets (Elasticities)




| | | |
|---|---|---|
| 1.Groceries | 7.Bakery | 13.Audio/Video |
| 2.Meat | 8.Health&Beauty Care | 14.Household Products |
| 3.Produce | 9.Men’s Wear | 15.Fabrics (Interior) |
| 4.Dairy/Fine Meat, Self Service | 10.Lady’s Wear | 16.Leisure, Outdoor |
| 5.Dairy/Fine Meat, Counter | 11.Children’s Wear | 17.Leisure, Indoor |

## Figure 5: Profit Improvement for Alternative Local Space Allocation Scenarios

**(ratio of local over global space allocation profits)**




## Table 1: Variables included in the models and their measurement

| Variable | Description | Measurement | Model[b] | |
|---|---|---|---|---|
| **CategoryVariables** | | | | |
| **$SV_{ij}$** | Category share in store sales | Ratio of category i's sales (monetary value over total sales (monetary value), in store j | 1 | D |
| **$SS_{ij}$** | Category share in store space | Ratio of category i's over total space in store j | 1 | E |
| **Store Variables** | | | | |
| **$S_j$** | Store sales | Total sales of store j (monetary value) | 2 | D |
| **$StSize_j$** | Store space/size | Surface of store j in square meters | 1,2 | E |
| **$AttSt_j$** | Total attraction of the store | Denominator of the category sales share model (1) for store j | 2 | E |
| **$AttOth_j$** | Total attraction of other outlets of the chain in the trading zone | For other outlets of the chain present in trading zone of store j: average of their denominators in model (1) (a value larger than 1). If no other outlets are present, $AttOth_j$ is set equal to 1. | 2 | E |
| **Trading Zone Variables: Local Population characteristics*** | | | | |
| **$Pop_{1j}$** | Young Families | Loading of store j's trading zone on Factor indicating the presence of 'Young Families', 'Less well-to-do', 'Middle Class' and 'Single Child' families[a] | 1,2 | E |
| **$Pop_{2j}$** | Less well-to-do | | 1,2 | E |
| **$Pop_{3j}$** | Middle Class | | 1,2 | E |
| **$Pop_{4j}$** | Single Child | | 1,2 | E |
| **Trading Zone Variables: Local Competition** | | | | |
| **$Comp_{1j}$** | Competition from other chains | Surface of store j/(Total Competitive Chains' Store Surface in trading zone of j) | 1,2 | E |
| **$Comp_{2ij}$** | Competition from category specialty stores | Number of Specialty stores selling category i in trading zone of store j | 1 | E |
| **Trading Zone Variables: Additional Covariates (Control Variables)** | | | | |
| **$Work_j$** | Passers-by | Households working but not living in trading zone of store j (as % of local population) | 1,2 | E |
| **$Urb_j$** | Degree of urbanization | Dummy variable equal to 1 for highly urbanized areas | 1,2 | E |
| **$Pot_j$** | Trading zone potential | Number of households living in trading zone of store j | 2 | E |
| **$Outlets_j$** | Within-chain competition | Number of own chain outlets in store j's trading zone | 2 | E |

[a]Family characterizations are similar to those of other widely used geodemographic segmentation systems, such as ACORN and MOSAIC (see Curry 1993, Dibb 2000),'Young Families' referring to areas with young families with children, 'Less well-to-do' to multiracial areas with single and low income families, 'Middle Class' to areas with upper middle class families, and 'Single Child' to areas with mature adults and single child families. More details on the classifications can also be found in Campo et al (2000).

[b]D=dependent, E=explanatory

**Table 2: Characteristics for Supermarkets and Hypermarkets: Means and Variability (standard deviation SD and coefficient of variation VC)**

| | Supermarkets | | | Hypermarkets | | |
|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **VC** | **Mean** | **SD** | **VC** |
| **Store Variables** | | | | | | |
| Store Size ($StSize_j$) | 1727.42 | 428.51 | .248 | 6092.33 | 1445.58 | .237 |
| Sales Share Food | .814 | .023 | .028 | .632 | .035 | .055 |
| Space Share Food | .740 | .076 | .103 | .431 | .044 | .102 |
| **Trading Zone characteristics: Size** | | | | | | |
| Trading zone potential ($Pot_j$) | 6162.370 | 1981.84 | .321 | 14155.00 | 4595.16 | .325 |
| Surface (in squared km) | 175.50 | 101.50 | .578 | 826.31 | 290.76 | .352 |
| **Trading Zone Characteristics: Local Population**[a] | | | | | | |
| Young Families ($Pop_{1j}$) | -.192 | .921 | | .031 | .822 | |
| Less well-to-do ($Pop_2j$) | -.004 | .979 | | -.238 | .581 | |
| Middle Class ($Pop_{3j}$) | -.043 | .944 | | .043 | .913 | |
| Single Child ($Pop_4j$) | -.007 | 1.042 | | -.001 | 1.042 | |
| **Trading Zone Characteristics: Local Competition** | | | | | | |
| Chain Competition ($Comp_1j$) | .238 | .144 | .606 | .296 | .135 | .144 |
| Competition from specialty stores ($Comp_{2ij}$): | | | | | | |
| Groceries | 39.644 | 28.418 | .716 | 28.875 | 16.478 | .571 |
| Meat | 28.144 | 17.350 | 0.616 | 24 | 15.878 | 0.662 |
| Produce | 6.8 | 5.145 | 0.756 | 6.062 | 5.617 | 0.927 |
| Dairy/fine meat (c) | 34.944 | 20.790 | 0.594 | 29.645 | 20.264 | 0.684 |
| Dairy/fine meat (ss) | 34.944 | 20.790 | 0.594 | 29.645 | 20.264 | 0.684 |
| Fish | 4.733 | 4.989 | 1.054 | 3.208 | 3.806 | 0.684 |
| Bakery | 39.666 | 24.74 | 0.623 | 33 | 18.569 | 0.563 |
| Health&Beauty | 7.911 | 7.260 | 0.917 | 4.791 | 3.822 | 0.798 |
| Men's W | 17.666 | 20.533 | 1.162 | 9.041 | 8.068 | 0.892 |
| Ladies' W | 17.466 | 19.830 | 1.135 | 9.937 | 10.199 | 1.026 |
| Childrens' W | 12.766 | 10.894 | 0.853 | 9.104 | 7.809 | 0.858 |
| Shoes | 17.644 | 17.599 | 0.997 | 11.458 | 8.723 | 0.761 |
| Audiovideo | 40.477 | 31.972 | 0.789 | 25.416 | 17.588 | 0.692 |
| Household | 17.477 | 18.332 | 1.049 | 13.187 | 9.203 | 0.698 |
| Fabrics | 22.866 | 19.659 | 0.859 | 14.895 | 11.873 | 0.797 |
| Leisure outdoor | 20.777 | 14.995 | 0.721 | 15.208 | 11.622 | 0.764 |
| Leisure indoor | 47.655 | 47.220 | 0.990 | 25.520 | 18.656 | 0.731 |

[a] These variables, by construction, have mean values close to zero, so that no VC is computed.

## Table 3: Estimation Results for the Category Sales Share Model

| Table 3a: Estimated Coefficients in the full model: summary of results | | |
|---|---|---|
| **Number of significant effects[a] (p<.05) for:** | **Supermarkets** | **Hypermarkets** |
| Space Shares: | | |
| Own (max=17) | 13 | 15 |
| Cross (max=272) | 14 | 32 |
| Local Population Characteristics: | | |
| $Pop_{1j}$ (max=16[b]) | 6 | 10 |
| $Pop_{2j}$ (max =16) | 8 | 11 |
| $Pop_{3j}$ (max=16) | 7 | 3 |
| $Pop_{4j}$ (max=16) | 10 | 7 |
| Local Competition: | | |
| From other chains ($Comp_{1j}$) (max=16) | 3 | 3 |
| From specialty stores ($Comp_{2ij}$) (max=17) | 8 | 15 |
| **Table 3b: Goodness of fit : SSR ($R^2$) for full model compared to alternative models[c]** | | |
| Model with constants only | 279.5 | 120.2 |
| Model with constants and space effects | 264.3 (.054) | 72.0 (.401) |
| Model with constants, space effects and selected local variables: all except local population profile | 191.6 (.315) | 44.0 (.634) |
| Model with constants, space effects and selected local variables: all except local competition | 235.7 (.157) | 55.4 (.539) |
| Full Model with constants, space effects and all local variables | 197.2 (.295) | 48.9 (.593) |

[a] All significant coefficients for which we have sign expectations (Own space effects and Competition from category specialty stores) have the expected sign, except for the own space effect for Men's wear in hypermarkets.
[b] Groceries serve as the reference category
[c] Differences in fit significant at 5% level for all paired model comparisons in a format

## Table 4: Estimation Results for the Store Sales Models

| **Variable** | **Coefficient (T-value)** | |
|---|---|---|
| | **Supers** | **Hypers** |
| **Constant** | 5.975 (7.13) | 7.92 (10.81) |
| **$Pop_{1j}$** | .024 (1.11) | -.136 (-5.80) |
| **$Pop_{2j}$** | -.046 (-2.37) | -.144 (-3.29) |
| **$Pop_{3j}$** | -.023 (-1.29) | -.148 (-7.23) |
| **$Pop_{4j}$** | .013 (.843) | -.029 (-1.68) |
| **$Comp_{1j}$ (*)** | .079 (2.30) | .098 (3.01) |
| **$Urb_j$** | .059 (1.37) | .136 (2.63) |
| **$StSize_j$ (*)** | .642 (7.12) | .218 (2.06) |
| **$Work_j$ (*)** | -.041 (-1.46) | -.123 (-4.22) |
| **$Pot_j$** | .00005 (4.04) | .00003 (5.59) |
| **$AttSt_j$ (*)** | 3.075 (4.40) | 3.476 (5.10) |
| **$Outlets_j$** | .076 (1.04) | -.031 (-.50) |
| **$AttOth_j$ (*)** | -.187 (-1.68) | .143 (1.42) |
| **$R^2$** | .704 | .902 |

(*) Variables incorporated in multiplicative form (other variables in exponential form).

## Appendix 1: Estimating and testing the category sales share and store sales models

*Model estimation*. Like Campo et al (2000), and similar to the suggestions in Carpenter et al (1988), we estimate the category sales share model, which is an asymmetric attraction model, in three steps. In a first step, we ignore the $Cross_{ijm}$ terms in equation (1)), and estimate the parameters in the symmetric part only. This is done by applying the linearization procedure proposed by Naert and Bultez (1973), and by applying SUR to the remaining 16 equation ratios. Next, we identify significant ($p<.05$) cross-space effects by regressing the residuals of step 1 against all other category space shares. Third, we re-estimate the full model, including the symmetric part as well as the significant cross-effects.

The store sales model is linearized using a logarithmic transformation, and then estimated on the combined store outlet-year data.

Both models were tested for collinearity in each store format, and did not reveal any problems( Belsey, Kuh and Welsh test: all condition indices below 30).

*Endogeneity of Space Effects in the category sales share model.* First, to rule out spurious space share effects, we run regressions with category space shares as dependent, and location characteristics as explanatory variables. In all, the $R^2$ are significant at the 5% level for 4 out of the 34 regressions only Moreover, in these four regressions, different location variables are significant for different categories. This rules out the possibility that space shares have already been systematically set on the basis of location characteristics. The latter case would imply that their coefficients reflect local market differences rather than space responsiveness, and are seriously inflated because of their alignment with local category needs. Next, we conduct a Hausman test, using lagged (previous year) values and location characteristics as instruments for space shares. Instrumental variables reveal insignificant in the augmented regression including instruments as well as observed space shares, at the 5% level. This leads to the conclusion that space shares are, indeed, exogeneous.

*Pooling tests.* We conduct pooling tests on format differences for models 1 and 2. Since model 1 can be seen as an 'aggregate' version of the MNL model, its coefficients may be identified up to a scale constant only. For equation 1, we therefore adopt the pooling test suggested by Swait and Louviere (1993). For both models, the test results strongly reject pooling across formats ($p<.01$). For the category sales share model, the Swait and Louviere (1993) test reveals a significant but small difference in the scale parameter for both formats (with a scale parameters of .88 for hypermarkets compared to 1 for supermarkets). This difference in scale parameter, accounts for only .2 % of the increase in loglikelihood when going form the pooled model to separate (format specific) models, such that most of the difference between formats can be attributed to different effects of explanatory variables rather than error variance.

## Appendix 2: Benefits from Local Category resource allocation

The analyses below are carried out for each store format separately. For convenience of notation, we drop the format subscript.

For each outlet j of a given format, let profit be defined as:

$$P_j = \sum_i (S_j SV_{ij} M_i - RC_{ij})$$

where $M_i$ is the gross margin for category i and $RC_{ij}$ represents the replenishment cost. In these profit functions, replenishment costs are specified to be proportional to the ratio of category sales and space within the store (see Bultez et al 1988 and Campo et al 2000 for a similar approach):

$$RC_{ij} = \psi_i \frac{S_j SV_{ij}}{StSiz_j SS_{ij}}$$

Besides the estimated parameters, inputs for the profit functions are based on data obtained from the retailer and on previous literature. To determine $M_i$, gross margin *indices* (relative to groceries) for each category (data provided by the retailer), are combined with an average gross margin estimate for groceries of 25%. The replenishment cost parameter for each category, $\psi_i$, is set in such a way that on average, replenishment costs account for 70% of the category's gross profit (see Bultez and Naert 1988).

In the profit expression, $S_j$, $SV_{ij}$ and $RC_{ij}$ are functions of the categories' space share $SS_{ij}$.
The following optimization problems are considered:

Scenario (i): $\underset{SS_{i.}}{Max} \quad \sum_j P_j \quad subject \quad to \quad \sum_i SS_{i.} = 1$

Scenario (ii): $\underset{SS_{ij}}{Max} \quad \sum_j P_j \quad subject \quad to \quad \sum_i SS_{ij} = 1 \quad \forall j$

Scenario (iii): $\underset{SS_{nf,.},SS_{f,j}}{Max} \quad \sum_j P_j \quad subject \quad to \quad \sum_{nf} SS_{nf,.} + \sum_f SS_{f,j} = 1 \quad \forall j$

Scenario (iv): $\underset{SS_{f,.},SS_{nf,j}}{Max} \quad \sum_j P_j \quad subject \quad to \quad \sum_f SS_{f,.} + \sum_{nf} SS_{nf,j} = 1 \quad \forall j$

where for the space share variables; i indexes all categories, f only food categories, nf only non-food categories, j refers to a space share applied in store j, and "." to a common space share across stores of the format.

+For each scenario, optimal space shares are identified through an iterative procedure based on the SHARP optimization rule (see Campo et al. 2000 for more details). To keep this procedure tractable, we apply it to a simplified profit function in which store cannibalization effects are ignored. In a next step, we then perform a grid search around the space shares of the previous step, using profit functions in which cannibalization is accounted for. In neither case did cannibalization notably alter the optimal space shares.

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[i] In addition, retailers can adopt geographical segmentation strategies situated in between these two extreme cases, for instance, by adjusting resource allocation to characteristics of larger regional areas (e.g. countries, provinces). Yet, in light of the decreasing cultural (macro) and increasing lifestyle (micro) differences, combined with the availability of more detailed retail performance and geographical information, the outlet-based segmentation strategy appears to be the most interesting case to evaluate micromarketing benefits.

[ii] For a given store format, store outlets are typically located in non-overlapping trading zones. This is often not the case across formats, where outlets of one format (say, convenience stores) may be situated within the trading zone of outlets of another format (say, supermarkets). For the multiformat retailer, this entails a risk of cannibalisation.

[iii] Super- and hypermarkets form an interesting case for studying the mediating effect of store format on micromarketing benefits, as they allow to cancel out the potentially confounding effect of differences in store image. Whereas super- and hypermarkets of the same chain usually have similar store images, other store formats are often positioned in a substantially different way (e.g., EDLP versus HiLo stores, with radically different price/quality positionings). expectations on decreasing returns, and the exponential model gives a better fit. For details on which variables are included exponentially or multiplicatively, see table 4.

[iv] As a consequence of (i) their smaller trading areas, and (ii) the smaller store size, which makes location in city centres with high real estate prices affordable.

[v] As indicated in section 2, actionability will be further affected by (category) profit margins and store cannibalisation effects. As there are no a priori reasons why category profitability and cannibalization would differ between super- and hypermarkets, we do not take these elements up in the discussion.

[vi] In fact, our model is a mixture of a multiplicative and an exponential model. Some variables enter the specification exponentially because (i) they may take on non-positive values, or (ii) there are no a priori expectations on decreasing returns, and the exponential model gives a better fit. For details on which variables are included exponentially or multiplicatively, see table 4.

[vii] Except for category-specific competition, which only intervenes in the category sales share model.

[viii] Endogeneity problems may arise to the extent that stores located in an high-potential area and/or with large trading zones, are more likely to have other outlets of the same chain, and hence a higher value for $AttOth_j$, in these trading zones. This would create a spurious positive correlation between store sales $S_j$ and other outlets' attraction $AttOth_j$. Separately accounting for the *presence* of other outlets strongly alleviates this spurious effect, and allows us to interpret the coefficient of $AttOth_j$ as the impact of changes in the attraction of other chain outlets, GIVEN their presence.

[ix] Based on a Wilcoxon Signed Ranks test on the standard deviations and coefficients of variation of Table 2's location characteristics, we find that the heterogeneity across outlets is substantially higher for supermarkets than for hypermarkets (p<.01).

[x] Before estimating equation (1) for supermarkets and hypermarkets, tests are conducted to rule out endogeneity bias in the space share effects, and to check whether pooled estimation across formats does not provide any better results than format-specific estimation. Details on these tests, and on the estimation procedure, are given in Appendix 1.

[xi] Details can be obtained from the authors.

[xii] In the interest of space, we concentrate on the profit implications of the scenarios. It is important to note, however, that in each scenario, the resulting optimal space shares have face validity. Moreover, the allocations remain quite distinct for supers compared to hypers, thus preserving the 'identity' of both formats. If this were not the case, managerial constraints could be imposed on feasible space share ranges per category per format.

[xiii] Given that the chain operates 136 supermarkets and 57 hypermarkets (only a subsample of which were available for our analysis), and that absolute profits in a hypermarket outlet are about 2.15 those in a supermarket, the absolute gain from micromarketing is slightly higher in the supermarket format.

[xiv] The profit functions specified in appendix 2 and maximized in our optimisation problems are 'gross profits', before deducting (fixed) costs of personnel, infrastructure, and the like.