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Assortments and local competition in retailing

Michel Calciu michel.calciu@univ-lille1.fr

Sylvain Willart sylvain.willart@univ-lille1.fr

LEM (Lille Economie et Management) – CNRS IAE de Lille Université Lille 1

Assortments and local competition in retailing

Abstract

We study the impact of local competition on assortments' attractiveness. The first aim of our paper is to provide a simple and reproducible way to delineate a store trading area using widely available census data. The second aim is to develop a model of retail sales that takes into account competition intensity as well as assortment composition factors (namely price level and variety). We use spatial econometrics techniques (SAR model) in order to account for proximity between stores.

Keywords: Assortments, Competition, Location, Micro-marketing, Trade area, Spatial econometrics

Retailing

Location, prices, and variety are known to be the main drivers of stores' attractiveness (Hoch & al., 1999). But location is a long term decision; it can not be changed once settled. Prices and variety however, are assortments' dimensions that can be changed or adjusted during the lifetime of a retail unit.

Montgomery (1997) shows for example, that retailers can increase their profits by carefully setting the price of their products depending on the socio-demographic composition of their customer catchment area. Campo et al. (2000) have also emphasized that sales in each given store aisle can be differently affected by the characteristics of the stores' catchment area.

However, both studies suffer from lack of precision when setting the retail outlet's trade area or customer catchment area which is the basis of further analysis. Montgomery (1997) uses a purely competitive approach ("the five nearest stores"), and Campo & al. (2000) use catchment areas indicated by stores themselves, an *ad hoc* definition which is hard to replicate for further studies.

A first objective of this paper is to suggest a method to delineate store catchment areas that is quick and easy to replicate. Therefrom we develop a purchase (sales) model that takes into account both retail area demand and store offer assortment factors (price and variety in particular). This model is estimated using *spatial auto-regressive* techniques having their origin in geographic analysis and that allow taking store proximity into account. The idea behind is that, when controlling for assortment effects, stores that are close to each other tend to have similar sales results.

1 The data

1.1 Spatial data: store and census tract locations

The location data concerning the 50130 French iris census tracts with their centroids ("middle points" in geographic terms) expressed in Lambert projection units (used worldwide in geographic studies) had to be converted into latitudes and longitudes. Another data set regrouped a list of 2071 store locations from two French regions and their neighboring surroundings. The two regions are Centre which is South from Paris and Aquitaine a South-West border region of France (see figure 1b). The store locations' longitude and latitude have been collected using the Application Interface (API) of the Google Map web service. These data can be seen in Figure 1a, each black point represent an IRIS census tract and each red point represents a store. Besides these location data, the panel company IRI has provided sales data for 870 stores (Figure 1b) and the socio-demographic composition of the IRIS zones.

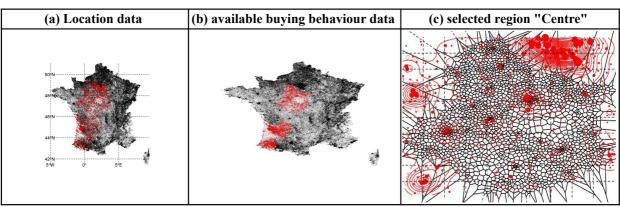


Figure 1 - Stores' and census tracts' locations

At this stage our analysis is focused on region « Centre » whose stores and census tracts (customers) are rather evenly distributed (see figure 1c) and where biased spatial behaviour

problems related to stores located near the country border are be avoided. Figure 1c shows the region's "Centre" 2410 iris census tracts and 870 stores of which 371 are located within the region and the other ones are in its surroundings.

1.2 Customer census and store sales data

As previously indicated we use data from three different sources and numerous variables are available for each of them:

- a- IRI retailer panel: reports the sales in euro and volume for 317 supermarkets and hypermarket from the region "Centre". Sales data cover 42 categories of fast-moving consumer goods.
- b- INSEE (French statistical government unit): socio-demographic composition of the region "Centre" (about fifty variables concerning age, income and composition of households) . Those data are split by "Iris" zones the most disaggregated geographic units of INSEE, each regrouping about 3000 inhabitants (IRIS areas in towns are spatially smaller in towns than on the countryside).
- c- IMDS (Geomarketing focused department of IRI): addresses of all stores from the region Centre (including some stores that are not present in the IRI panel, for example Hard-Discounters), and location of Iris tracts.

2 Trading areas delineation

2.1 From Iris locations to Iris frontiers (Voronoï Diagrams)

The IRIS census tracts form a partition of the French territory. We only have information concerning their gravity center. In order to transform those "points" into "surfaces" we use Delauney (1932, 1934) triangulation of centroids in order delineate the surrounding nearest neighbor area or the Voronoï (1907,1908) polygons, known also as Thiessen-Alter (1911) or Dirichlet (1850) polygons (see figure 1c).

2.2 Huff model

In order to infer the spatial behaviour of customers belonging to each iris census tract we used gravity models, they estimate the probability with which buyers from different places visit a distribution point depending on the utility associated to that point and on the distance. The utility varies positively with a measure of attractiveness and inversely with a certain power of distance. Consumers compensate the disutility caused by an extra distance with the utility of an increase in attractiveness. The predecessor of these models is Reilly's "law of retail gravitation" according to which trade area boundary between two centers is determined by the distance between them and their relative sizes. Huff (1964, 1966) was the first to suggest a probabilistic formulation of a gravity model. His model based on Luce's (1959) axiom of choice, states that the probability that a customer patronizes a facility is proportional to its floor area and inversely proportional to a power of the distance to it.

We computed this probability in two steps. First attractiveness (Aij) of store j on census tract i is calculated .

$$A_{ij} = S_j d_{ij}^b \tag{1}$$

where Sj is the store's surface, dij is the distance between census tract i and store outlet j, and b is the negative power of d. Here b is -2 as in the newtonian gravity law and S and d are scaled values. Second the probability of a census tract i to visit store j is proportional to the

attraction and must sum up to one:

$$P_{ij} = \frac{A_{ij}}{\sum_{j=1}^{J} (A_{ij})}$$
 (2)

In order to accelerate calculations we use a matrix approach. Let \mathbf{s} be a vector of store surfaces of size J, where J is the number of stores, here 870. \mathbf{D} is the matrix of the negative powers of distances between the I here 2410 census tracts and the J, here 870 stores. The the attractiveness matrix is

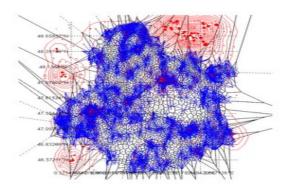
$$A = (diag(s) \times D')' \tag{3}$$

and the probability matrix is

$$P = diag((\mathbf{A} \times \mathbf{1})^{-1})\mathbf{A} \tag{4}$$

The inferred spatial choice of stores for customers from the analyzed census tracts are given in Figure 2. It shows contour-lines of attraction probabilities around stores and customer flows from census tracts to stores.

Figure 2 - Spatial customer behavior inferred by attraction models



3 Explanatory variables for store sales

3.1 Competition measures within trade areas

The probability matrix gives us essential information on IRIS/stores relationship. First of all we know the probability for consumers in each IRIS to go to a particular store (p_i) ; and conversely, the weight (p_s) of each IRIS tract in a given store's clientele (the latter is computed with respect to the exact number of households in each IRIS).

Building on the probability matrix, we compute a set of measures that account for the competition each store faces in its retail trade area. First, we count the number of IRIS included in each store's trade area (nbiris). Then, we compute, for each store, the total surface of its competitors (TSurf). This total surface is weighted by the share each IRIS tract represents in the retail area of the considered store.

In order to capture some strategic aspects of local competition, we identify retail chains that are present in a store's trading area. Knowing the local impact of the presence of a retail chain is of great importance for retail chain managers, but also for public regulators when asked to redefine retail unit location rules. Thus, we compute a variable for each chain indicating its presence in a store's trade area. This variable is first constructed as a dummy variable (1 if present, 0 if not), and then weighted by the importance of the competition between the store

under consideration and stores from a given retail chain, and then aggregated over each trade area. This reveals which retail chains can be considered locally as the most important competitors.

3.2 Variables concerning assortment

In addition to competition variables, we use the IRI panel data to describe stores' assortments. For each assortment *category x store*, we compute a median price (Mprix), and an indicator of variety (Pvar). The latter is the ratio between the number of product-types a store is offering divided by the total number of product-types within a category available in all the stores.

These assortment dimensions are consistent with what is known about the reasons conducting consumers to choose a given store (Hoch et al., 1999); they regroup store price-level and variety within product categories.

These variables are computed for each of the 42 categories and in each of the 317 stores of the panel. They have then been scaled and aggregated by store. The important number of categories offers a quite accurate representation of the overall store assortment.

4 Spatial modeling of store sales

Using explanatory variables on local competition and assortments, we develop a store level model explaining store sales (in euro). Stores being spatially located, we opt for spatial econometric modeling.

Spatial econometrics is a growing tool for marketing in general and for retailing in particular. The particularity of the modeling approach we have chosen comes from the specification of the variance-covariance matrix which is very similar to the one used in auto-regressive time-series modeling (AR1). Instead of considering store sales at time t linked to sales at time t-l, we consider that those sales are linked to the sales of neighboring stores at the same time t. Like in AR1 models, the resulting correlation parameter λ indicates store sales dependence upon sales in neighboring stores. Such models are naturally called SAR(p): Spatially Auto-Regressive. Argument p indicates the number of nearest neighbors the store sales are correlated with.

The estimated model is:

Sales $_s = \alpha + \beta_1 \times Mprix_s + \beta \times Pvar_s + \gamma_1 \times nbiris_s + \gamma_2 \times Tsurf_s + \tau \times X_{chains} + \varepsilon_s$ (5) where β 's are the coefficients associated to assortment variables, γ 's are associated to local competition variables, X_{chains} is a vector indicating the presence of retail chains in each retail area, and ε_s are spatially autocorrelated residuals. The explained variable (Sales) is actually the logarithm of each store's euro sales for all 42 analyzed categories.

Estimation is run under the R system (v.2.12) using spdep library for spatial statistics. Results are displayed in Table 1.

Table 1: Results from the spatial model

Mprix Pvar nbiris WTSurf WASM WAUC WCAS WCHA WCOR WCRF WECO WGEA Variables Coefficients 0.13 0.87 0.01 0 3.42 1.25 -2.94 0.65 -1.52 -0.131.56 -1.883,42 3,44 t-values 2,63 16,54 9,88 3,57 -0.723,73 -2.13-0.425,97 -3,97

Variables WGEA WHDT WITM WLCL WMNP WSHO WSPY lambda LogLik

Coefficients -1,88 0.89 1,3 0,22 -0.14-0.120,48 0.13 -163.17,67 0.97 -0.04t-values -3,97 4,02 -0.162,2

5 Results, conclusion and managerial implications

We can note that price has a significant positive effect, which seems rather counter-intuitive. Let us remember that the explained variable is sales in euro; there is usually a double effect of a price increase on euro sales, a negative one on volume, and a positive one on value. In our case, value effect offsets volume effect, resulting in a positive relationship between euro sales and price. Turning to variety, we find a strongly significant positive effect on sales. This suggests that, when local competition is taken into account, variety is more effective than price to increase store sales. This result is particularly interesting as it clearly indicates that a price war would have less impact than a diversified assortment policy.

Unsurprisingly, we find that the size of the trading area, expressed by the number of IRIS tracts (nbiris), has a significant positive impact on store sales. Similarly but more surprisingly the total surface of competitors (WTSurf) has a positive effect. This is not in line with classical economic thinking. Indeed, it indicates that the number and size of competitors is positively influencing store sales. However, this result can be explained by the increased attractiveness of stores located close to each other. Following our results, a commercial district with five stores for example is selling more than five isolated stores.

In this study, we choose to analyze strategic competition along with economic competition. In the retail industry, stores may benefit from being located close to each other as shown before, but not all chains have such "beneficial" effects on sales when located in a competitor's trading area. As to this study, the presence of chains like Auchan, Ecomarché or Intermarché in a store's trade area has a positive effect on sales, while the presence of other chains like Cora or Géant has a negative effect. In France there is a quite fierce competition between retail chains at national level, but many economists and politicians think that local competition is too soft. Such results can be extremely useful to orient both managerial decisions on local competitive strategies, but also local public administration decisions. In the latter case it can help decide whether allowing the presence of a new outlet from a given chain can help reinvigorate a commercial area and/or increase local competition.

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