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# What do we know about spatial entry?

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**Abstract**

In his oft-cited "What do we know about entry?", Paul Geroski (1995) gave a survey of empirical works on this central topic regarding industrial organization and, more precisely, market dynamics. Surprisingly, his article remains silent on the spatial dimension of these dynamics. This paper gives first accessory support to some of the Geroski's a-spatial observations with reference to firm entries and exits of a selection of retail and consumer service industries in Belgium over the 1998-2001 period. More important is the proposed application of the Exploratory Spatial Data Analysis (ESDA) that has been developed for in-depth exploring of spatial datasets. Evidences are collected at highly disaggregated geographical and industrial levels. They do not only contribute to a better understanding of the geographical patterns of the industries, but they lead to interesting observations regarding industrial organization and market dynamics by examining the space-time structures of entries and exits. These observations may be considered as an opening tribute towards a spatial extension of what Geroski has presented as stylized facts in his 1995 article.

JEL-classification: L11, L80, R12

Keywords: entry, exit, spatial interactions, local market, ESDA

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## 1. Introduction

In his oft-cited "What do we know about entry?", Paul Geroski (1995) gave a brief survey of empirical works on this important topic regarding industrial organization and, more precisely, market dynamics. His survey consisted in two lists of stylized facts and results that are commonly shared by empirical economists. But, surprisingly, his article remains silent on the spatial dimension of actual market dynamics. A simple explanation for this is probably a lack of empirical material to lay down stylized facts or results regarding the spatial dimension. The absence of spatial empirical regularities as regards market dynamics is also noteworthy in Caves' survey of the literature (1998).

What is moreover remarkable is how incidentally the spatial dimension is entering the empirical works on market dynamics. See for example recent contributions by Dejardin (2004), Thomadsen (2005), Houde (2005), Davis (2006), Xiao and Orazem (2007). It appears that nowadays researchers favour the direct use of spatial econometrics for the estimates of models allowing some spatial interactions between located units of observation. This comes out while basic statistical tools, which we refer as exploratory spatial data analysis (ESDA), have been developed for in-depth exploring of spatial datasets, before any explanatory modelling. That way, the research agenda is just reflecting how the concern for causal relationships is currently prevailing over the need for prior statistical approaches that are, by essence, more descriptive.

This paper reports the results of an ESDA applied to the firm entries and exits of a selection of retail and consumer service industries in Belgium over the 1998-2001 period. Evidences are collected at highly disaggregated geographical and industrial levels. They do not only contribute to a better understanding of the general geographical patterns of these industries, but they also lead to interesting observations regarding industrial organization and market dynamics by examining the space-time structures of entries and exits. These observations may be considered as an opening tribute towards a spatial extension of what Geroski has presented as stylized facts in his 1995 paper.

The paper is organized as follows. The next section is devoted to a brief presentation of the specific statistical tools (ESDA) that have been developed for the exploring and measuring of spatial interactions. The third section introduces the dataset on which the analysis has been applied. The results are presented in the fourth section. They include systematic reference to what would be the Geroski's a-spatial stylized observations and, then introduce and discuss the spatialized outcomes. The last section concludes.

## 2. Measuring spatial interactions

The study of data with a location component, for instance firm entries and exits on markets for common goods and services, requires the consideration of two spatial effects, highly linked. Spatial autocorrelation, on the one hand, is detected when the value of a variable in a location is correlated with values of the same variable in the neighbourhood (the neighbourhood being defined by the spatial weight matrix presented below). On the other hand, spatial heterogeneity is characterized by different economic behaviours through space.

Spatial autocorrelation can be positive (polarization of similar values of a variable in a close space) or negative (if dissimilar values are observed in the same neighbourhood) and is captured through the specification of possible interactions. These interactions are summarized in a spatial weight matrix, *W*. Elements of this matrix, called weights and noted $w_{i,j}{}^{*}$, represent the interaction between spatial units *i* and *j* and by convention, $w_{i,i}{}^{*} = 0$. Generally, the matrix is row-standardized (the sum of each line is set to 1) allowing the interpretation of the neighbourhood in terms of weighted average. We thus get $w_{i,j} = w^{*}_{i,j} / \sum_j w^{*}_{i,j}$. The empirical results presented in this study are based on a binary contiguity of order 1 weight matrix. This means that two spatial units will interact if they share a common border or peak. Formally, it is written as:

$$\begin{cases} w_{i,j} = 1 \text{ if units } i \text{ and } j \text{ interact} \\ w_{i,j} = 0 \text{ otherwize} \end{cases}$$

Moreover, this matrix has been row-standardized. We repeated the exercise with other weight matrices (distance based, "k" nearest neighbours) as robustness check. We chose such a definition of interactions since sectors under study have an *a-priori* local structure. Observations are located in space according to the municipality they are associated to, and considering only contiguous municipalities as neighbourhood seems quite appropriate to catch the possible spillovers effects. The second motivation for this choice of *W* lies in the productive organisation of the considered industries, with firms that are quite small and cannot satisfy a large demand.

Let us now present the statistics used to account for spatial effects. They all belong to the Exploratory Spatial Data Analysis (ESDA) and are aimed at highlighting the spatial structure of information under study. Indeed, these tools first capture spatial autocorrelation but also reveal the presence and form of spatial heterogeneity. They also identify atypical locations, outliers and spatial clustering and detect spatial association schemes (Haining, 1990; Anselin, 1998). The ESDA distinguishes global from local spatial dependence. The main measure of the former is the Moran's I index (Moran, 1948; Moran 1950; Cliff and Ord, 1981). For a given sector *i* at period *t*, the Moran statistic is written as (in matrix form):

$$I_{i,t} = \frac{N}{S_0} \frac{x'Wx}{x'x},$$

where *x* is the centred variable of interest, *N* the number of observations, $S_0$ a scaling factor equal to the sum of all elements of *W*, and *Wx* is the spatial lag associated with *x*. The $i^{th}$ row of the spatial lag contains, when *W* is row-standardized, the weighted average of the variable $x$ in the neighbourhood of municipality $i$. A positive (negative) and significant value of the Moran statistic indicates positive (negative) spatial autocorrelation. Inference is based on a Normal approximation. We can think of the Moran's I as the spatial counterpart of the Durbin-Watson statistic in time series. Although measures of global spatial autocorrelation[1] allow the detection of a possible geographical organization of the data, they do not provide any information about the local structure (municipality level). Moran's I is useless concerning local clustering of high or low values, atypical municipalities or existence of extreme values. To remedy these limits, it is necessary to apply methods explicitly aimed for the treatment of local spatial autocorrelation.

Three local statistics exist to study local spatial autocorrelation: the Moran scatter plot, Local Indicators of Spatial Association (LISA) and Getis statistics. The Moran scatter plot (Anselin, 1996), is divided into four quadrants that summarize all spatial associations between observations. For the sake of concreteness, consider the distribution of creation of activities. The HH (LL) quadrant regroups all municipalities having an important (small) number of entries[2] surrounded by municipalities having a large (small) number of creations too. The HL (LH) quadrant is constituted of municipalities with a large (small) number of new firms but whose neighbourhood only registers a low (large) number of entries. Hence, quadrants HH and LL characterize positive spatial autocorrelation whereas quadrants HL and LH describe negative spatial dependence. The main shortcoming of the Moran's I is that even if municipalities can be located in one of each quadrant, there is no mean to assess their significant. The Moran scatter plot should thus be used jointly with LISA statistics.

The second tool to analyse the local structure of a sample are the LISA statistics (Anselin, 1995). For municipality $i$ in period $t$, the statistic is written as:

$$I_{i,t} = \frac{x_{i,t}}{m_0} \sum_j w_{i,j} x_{j,t},$$

where $x_{i,t}$ is the centred variable of interest in municipality $i$ and $m_0$ a measure of the variance of observations. The sum over $j$ implies that only neighbouring values $j \in J_i$ ($J_i$ being the neighbourhood of municipality $i$) are considered. A positive LISA indicates a spatial clustering of similar values (quadrants HH or LL in the Moran scatter plot). On the contrary, a negative value indicates a negative autocorrelation (quadrants HL or LH). In our empirical part, we used the software Spacestat® which provides, for each municipality, the value of the LISA as well as the quadrant of the Moran scatter plot in which the municipality is located. Inference is based on a permutation approach[3] since Anselin (1995) has shown that the true distribution of LISA is unknown. We thus cannot base our inference on a normal approximation.

[1] Other statistics also exist, as the Geary's C or the general statistic Γ, but the Moran's I is the most applied since its results seem more stable (Le Gallo, 2002).

[2] The variable being standardized, a large number of creations means a positive value of the variable.

[3] We used 9999 permutations.

Finally, let us note that LISA are related to a measure of global spatial autocorrelation, the Moran's I in this case, and their extreme values will correspond to observations with the highest impact on the underlying global statistic.

Getis statistics (Getis and Ord, 1992; Ord and Getis, 1995) constitute the last available statistics to assess the local spatial association. Their interest is to locate local pockets of spatial autocorrelation possibly not detected by global measures. Again, it is computed for each spatial unit and its expression[4] is:

$$G_{i,t}^{*} = \frac{\sum_{j} w_{i,j} z_{j,t} - W_i^{*} \bar{z}_t}{s\{(NS_{1i}^{*} - W_i^{*2})/(N-1)\}^{1/2}},$$

where $W_i^{*} = \sum_j w_{i,j}$ , $S_{1i}^{*} = \sum_j w_{i,j}^2$ and $z$ is the variable of interest (not centred). Moreover, $\bar{z}$ and $s$ correspond to the mean (at time $t$) and the standard deviation of the sample. A positive (negative) and significant value of the statistic indicates a cluster of high (low) values of the variable. In other words, Getis statistics classify municipalities in terms of quadrants HH and LL. Getis and Ord (1992) have shown that their statistics are asymptotically normally distributed. Inference can thus be based on a normal assumption.

## 3. Data

The dataset has been collected from the Belgian federal administration Directorate General Statistics (formerly, Belgian National Institute of Statistics - NIS). The number of entries, exits and incumbents are obtained for all the 589 Belgian municipalities. The data are derived from the stock of active taxable firms and self-employed (in the value-added-tax books) at the end of each year, as well as the number of registrations and deletions per year, from 1998 to 2001. Additionally, the number of inhabitants (population) has been used.

The general a-spatial study refers to fifteen retail and consumer service industries composed of firms with similar economic activities. The latter characteristic is obtained by an industrial definition according to the five-digits NACE-Belgium. The selection is, moreover, concerned by sectors that should not be submitted to heavy changes as regards their market structures due for example to the arrival of supermarkets and outlet malls. The selected fifteen industries are the following: *Jewelry*, *Bars*, *Plumbing*, *Real estate*, *Shoe stores*, *Pharmacy*, *Fast food outlets*, *Restaurants*, *Butchery*, *Hairdresser's*, *Clothing*, *Bakeries*, *Painting*, *Caterers*, *Flower shops*.

The ESDA is applied to a short list of three out of the above fifteen industries, namely: *Bars*, *Fast food outlets* and *Hairdresser's*. The sectors were selected because of

[4] We only present the statistic including the municipality $i$ in the calculus. Ord and Getis (1995) also derived a statistic that excludes the reference municipality from the computation.

their relatively high activity and thus facilitate the use of spatial statistical tools (sensitive to zeros appearing in the data).

**4. Results**

The results that are presented in this fourth section refer to what would be the Geroski's (1995) a-spatial stylized observations and then, introduce and discuss the spatialized outcomes. That is, it is noteworthy that only a limited number out of the empirical regularities that were originally in Geroski's article receive a spatial assessment. Indeed, only the three first stylized facts, and even only to a certain extent, are part of the analysis. This is due to the information involved in the data that have been used for this empirical study and what it allows in terms of analysis. As an example, the information is highly disaggregated as regards the geographical and industrial levels, in terms of entry, exit and incumbent firms. These qualities are highly appreciated for a spatial analysis. But its does not include the necessary to assess market penetration, survival or to measure profit.

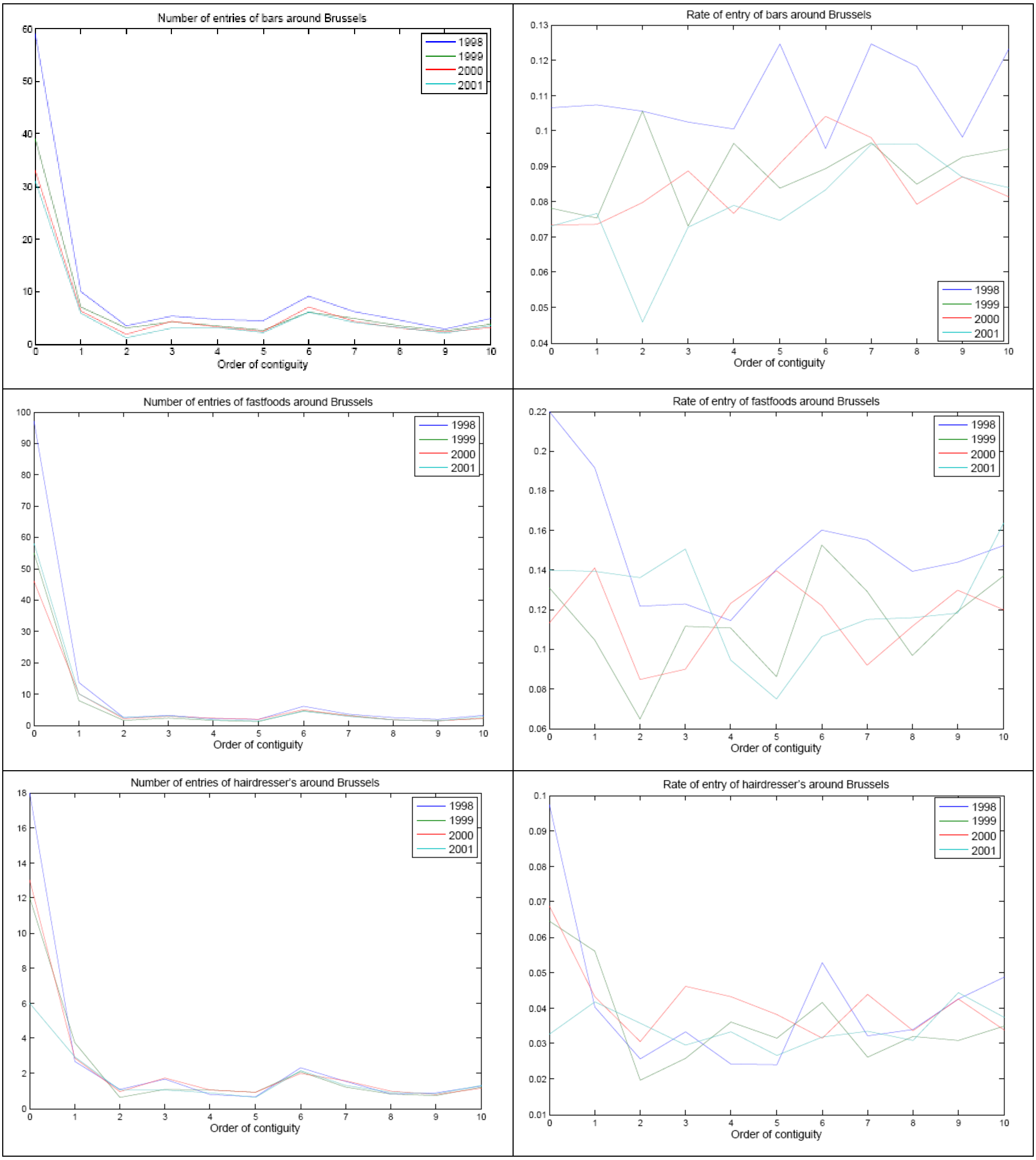
For the above-cited fifteen retail and consumer service industries, annual basic statistics as regards entry, computed over the 1998-2001 period at the country level, reveal annual averages ranging from 569 to 723, whereas minima and maxima are ranging respectively from 87 to 104, and from 1900 to 2934.

The annual entry rate is defined as the total number of firm entries divided by the total number of incumbent and entries, over the year. Statistics are shown in Table 1. The relative figures, with a minimum of 3.48% (butchery) and a maximum of 15.84% (Fast food outlets), give additional confirmation to the overall impression of commonness as regards entry that was Geroski's stylized fact 1.

Figure 1 introduces for the first time the spatial dimension within entry and entry rates. It depicts for three selected industries, bars, fastfoods and hairdresser's, what are the measured entries and entry rates in Brussels and the respective average for municipalities around Brussels, for different order of contiguity. Beware that average measures for some order of contiguity include important cities. For example, order 3 includes measures for Mechelen and Aalst; order 6 includes measures for Antwerp and Charleroi.

The figure leads to the observation that entry is not a regular phenomenon across space since for different order of contiguity, we observe varying entries and rate of entry. However, similar spatial patterns are observable across industries. In other words, there is some industrial regularity regarding spatial heterogeneity. Entry rates may differ largely across space and from one year to another.

Figure 1: Spatial heterogeneity as regards entry and entry rates for three industries, 1998-2001



Geroski's stylized fact 2 emphasizes the very large cross-industry variation in entry. But these differences do not persist over time. This cross-industry variation in terms of entry is already remarkable in Table 1.

Regarding the persistence of these differences, the lecture of Table 2 should bring some clues. Table 2 presents the computation of entry and exit annual growth rates (%) for the selected fifteen industries, over the 1998-2001 period. It suggests very large differences overtime within and between industries. This may be compared with Geroski's additional statement in stylized fact 2 that puts forward that "In fact, most of the total variation in entry across industries and over time is 'within' industry variation rather than 'between' industry variation" (Geroski, 1995, p. 423).

By depicting for bars, fastfoods and hairdresser's, what are the measured entries and entry rates in Brussels and the respective average for municipalities around Brussels, for different order of contiguity and different years, Figure 1 suggests as well spatial and temporal heterogeneity within industry.

Geroski's stylized fact 3 states that entry and exit rates are highly positively correlated. That is, net entry rates (entry rates minus exit rates) are modest fractions of entry rates. This stylized fact emerges from Table 1. Table 3 presents moreover the cross-industrial correlations as regards entry and exit, confirming once again the fact.

Table 3. Cross-industrial correlations between entry and exit rates for selected fifteen industries, 1998-2001

| 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|
| 0.84 | 0.77 | 0.63 | 0.70 |

The remaining of the results section is devoted to the detailed spatial analysis of the dataset.

The first statistic to apply to detect spatial autocorrelation is the Moran's I. However, in this study, we chose not to present its results for two distinct reasons. Firstly, it can be affected by the presence of outliers and a robust version should be used instead. The second reason is that we are mainly interested in the local analysis. Indeed, we would like to detect local clusters, spatial heterogeneity, pockets of non-stationarity, which can only be visualized through the use of local spatial autocorrelation statistics.

Table 1: Entry and exit rates (%) for selected fifteen industries, 1998-2001

| | 1998 | | 1999 | | 2000 | | 2001 | |
|---|---|---|---|---|---|---|---|---|
| | Entry | Exit | Entry | Exit | Entry | Exit | Entry | Exit |
| Jewelry | 4.91 | 5.34 | 4.37 | 6.19 | 4.51 | 5.52 | 4.25 | 6.10 |
| Bars | 11.69 | 15.05 | 9.21 | 14.31 | 9.08 | 14.08 | 8.88 | 13.32 |
| Plumbing | 6.09 | 5.67 | 5.94 | 5.84 | 6.71 | 5.95 | 5.12 | 6.08 |
| Real estate | 7.38 | 6.98 | 8.03 | 7.63 | 7.89 | 7.17 | 6.57 | 7.14 |
| Shoe stores | 8.18 | 10.12 | 6.43 | 9.50 | 6.64 | 10.20 | 6.26 | 8.73 |
| Pharmacy | 4.75 | 5.32 | 4.45 | 4.83 | 3.71 | 5.01 | 4.08 | 4.75 |
| Fastfoods | 15.84 | 13.88 | 11.96 | 13.21 | 12.54 | 12.22 | 12.25 | 11.56 |
| Restaurants | 8.92 | 7.62 | 8.37 | 7.96 | 8.95 | 7.63 | 8.20 | 7.00 |
| Butchery | 3.51 | 7.56 | 3.56 | 7.37 | 3.48 | 8.55 | 3.67 | 8.80 |
| Hairdresser's | 3.81 | 4.42 | 3.57 | 4.31 | 3.77 | 4.51 | 3.58 | 4.77 |
| Clothing | 7.03 | 9.18 | 6.65 | 8.60 | 6.92 | 8.32 | 6.89 | 8.01 |
| Bakeries | 7.33 | 9.55 | 5.95 | 8.94 | 6.44 | 9.33 | 5.57 | 8.81 |
| Painting | 8.29 | 7.68 | 7.44 | 6.58 | 7.58 | 6.25 | 6.31 | 6.67 |
| Caterers | 9.02 | 8.07 | 8.08 | 8.33 | 8.47 | 6.85 | 8.64 | 8.37 |
| Flower shops | 7.65 | 8.04 | 6.90 | 7.76 | 6.41 | 6.85 | 5.22 | 7.83 |

Table 2: Entry and exit annual growth rates (%) for selected fifteen industries, 1998-2001

| | 1998-1999 | | 1999-2000 | | 2000-2001 | | 1998-2001 | |
|---|---|---|---|---|---|---|---|---|
| | Entry | Exit | Entry | Exit | Entry | Exit | Entry | Exit |
| Jewelry | -12.50 | 14.16 | 3.30 | -10.85 | -7.45 | 8.70 | -16.35 | 10.62 |
| Bars | -25.12 | -9.63 | -5.96 | -6.21 | -8.03 | -11.02 | -35.24 | -24.59 |
| Plumbing | -2.54 | 2.92 | 14.34 | 3.22 | -24.92 | 0.55 | -16.33 | 6.82 |
| Real estate | 9.92 | 10.49 | -0.77 | -5.05 | -16.63 | -0.43 | -9.07 | 4.46 |
| Shoe stores | -23.74 | -8.98 | -1.32 | 2.69 | -8.05 | -16.59 | -30.81 | -22.04 |
| Pharmacy | -6.64 | -9.63 | -17.78 | 2.46 | 9.73 | -5.60 | -15.77 | -12.59 |
| Fastfoods | -25.63 | -6.26 | 5.08 | -7.31 | -3.05 | -6.12 | -24.24 | -18.44 |
| Restaurants | -5.95 | 4.78 | 7.32 | -3.90 | -4.38 | -4.25 | -3.49 | -3.59 |
| Butchery | -3.07 | -6.72 | -7.24 | 10.04 | 0.00 | -2.58 | -10.09 | 0.00 |
| Hairdresser's | -7.15 | -3.32 | 4.74 | 3.80 | -6.36 | 4.26 | -8.94 | 4.63 |
| Clothing | -7.12 | -7.97 | 2.95 | -4.26 | -1.91 | -5.08 | -6.20 | -16.36 |
| Bakeries | -21.52 | -9.40 | 5.02 | 1.19 | -16.38 | -8.83 | -31.08 | -16.41 |
| Painting | -8.71 | -12.82 | 3.76 | -3.27 | -11.42 | 13.51 | -16.09 | -4.27 |
| Caterers | -10.20 | 3.42 | 6.82 | -16.18 | 2.13 | 22.37 | -2.04 | 6.08 |
| Flower shops | -10.39 | -4.01 | -7.21 | -11.98 | -20.95 | 11.08 | -34.27 | -6.15 |

Table 4 summarizes the results of the spatial analysis performed over the three sectors of interest, namely bars, hairdresser's and fastfoods. For practical purposes we chose to aggregate first entries and exit from 1998 to 2001 and second, entry and exit rates for the entire period. The reason behind this decision lies in the presence of many zeros in each year entry and exit variables, causing some problems with the local autocorrelation statistics. For all variables considered, Table 4 classifies municipalities (our spatial units) according to their LISA value in the four quadrants of the Moran scatter plot. In each cell, several informations are provided. Firstly, numbers between brackets represent the total amount (without considering significants) of municipalities located in the quadrant. For instance, for total entries in the sector of bars, 76 municipalities are situated in quadrant HH. Then, the second number of the cell, 38 for the preceding example, is the number of significant (at the 5% threshold) municipalities belonging to the quadrant. Let us note that the significant results presented here consider only what we can call "simple" significants, not corrected for the multiple comparison problem.[5] Let us first look at total entries and exits in bars and fastfoods sectors. We first see that the distribution of municipalities between the four quadrants is quite similar. The huge majority of spatial units belong to the LL quadrant, meaning that they are characterized by a relative small number of total entries surrounded by municipalities in the same situation. This can be explained by the rural component of a majority of the Belgian space. This fact is also true (to a weaker extend) when we look at significants. For the hairdresser's sector, results are a bit different since significant municipalities are much more equally distributed across the four quadrants than for the two first sectors. Table 4 also allows identifying spatial heterogeneity. For the three sectors, the main pattern (both for significant and total amount) of spatial association is positive spatial autocorrelation. Indeed, HH and LL quadrants regroup nearly 70% of all municipalities. This also means that they are still 30% of municipalities which follow a different spatial organization. Table 4 shows that few observations are located in the quadrant HL (municipality with a high number of entries/exits surrounded by municipalities with small number of dynamics, i.e. wealthy islet) but most of spatial heterogeneity can be attributed to the "black sheep" situation, meaning a municipality with low dynamic surrounded by very active ones. Looking on a map, we could see that this non-stationnarity pattern occurs in the periphery of urban areas. Another interesting fact concerns the local spatial structure of entries and exits. Rows of Table 4 labeled 'Commons' allow, for each quadrant, seeing whether a municipality with significant entries will also be characterized by significant exits. The result is that for a majority of municipalities, similar local

[5] This problem applies when the neighbourhood of different spatial units contains some common elements. Local statistics for the concerned spatial units then become correlated and a stricter nominal significant threshold should be used. Two corrections of this threshold exist: the Bonferroni and Sidàk approach. The reason why we chose not to report these results is that the Bonferroni correction (which is the less strict of the two) is still too restrictive (threshold going from 0.05 to 0.004) only leaves extreme values as significant. However, results of the adapted significants are available upon simple request to the authors.

spatial structures for total entries and exits are detected, which backs up Geroski's analysis about the correlation between entries and exits.

Looking at entry and exit rates, things are quite different. Firstly, we can note a uniform distribution of municipalities among the different quadrants. From the significants point of view, the finding is the same and moreover, we find that many less municipalities show a significant pattern of local spatial autocorrelation. Rate of entry and exits seems to be randomly distributed across space. A second difference with respect to total entries and exits concerns the local spatial structures of rate of entry and exit. Indeed, rows labeled 'Commons' for entry and exit rates of Table 4 indicate few correspondences between significant entry and exit rates for the three sectors under study.

Table 4: Spatial analysis for Bars, Hairdresser's and Fastfood, 1998-2001

Bars

| | HH | LL | HL | LH |
|---|---|---|---|---|
| Entry | 38 (76) | 88 (328) | 7 (75) | 50 (110) |
| Exit | 40 (75) | 82 (347) | 7 (71) | 43 (96) |
| Commons | 33 (66) | 69 (316) | 5 (59) | 41 (86) |
| Entry rates | 19 (156) | 28 (167) | 14 (132) | 11 (133) |
| Exit rates | 15 (142) | 26 (187) | 18 (132) | 8 (128) |
| Commons | 4 (72) | 8 (94) | 5 (49) | 0 (51) |

Hairdresser's

| | HH | LL | HL | LH |
|---|---|---|---|---|
| Entry | 43 (73) | 27 (299) | 11 (115) | 35 (102) |
| Exit | 44 (84) | 46 (295) | 11 (110) | 42 (100) |
| Commons | 31 (51) | 18 (253) | 6 (77) | 24 (69) |
| Entry rates | 21 (141) | 22 (202) | 13 (117) | 13 (129) |
| Exit rates | 33 (139) | 24 (201) | 12 (125) | 16 (124) |
| Commons | 1 (52) | 5 (98) | 0 (37) | 0 (38) |

Fastfoods

| | HH | LL | HL | LH |
|---|---|---|---|---|
| Entry | 39 (66) | 62 (362) | 7 (74) | 34 (87) |
| Exit | 36 (73) | 59 (359) | 8 (66) | 32 (91) |
| Commons | 31 (58) | 41 (334) | 3 (50) | 27 (72) |
| Entry rates | 16 (138) | 11 (189) | 15 (128) | 16 (134) |
| Exit rates | 15 (135) | 31 (230) | 13 (106) | 18 (118) |
| Commons | 4 (25) | 4 (41) | 3 (41) | 4 (54) |

Table 5: Spatial analysis for Bars, Hairdresser's and Fastfood, 1998-2001

| | Bars | | | |
|---|---|---|---|---|
| | HH | LL | HL | LH |
| Net entry | (341) 33 | (60) 27 | (95) 40 | (93) 8 |
| Net entry rate | (173) 15 | (126) 12 | (1450 19 | (145) 11 |
| | Haidresser's | | | |
| | HH | LL | HL | LH |
| Net entry | 32 (272) | 34 (102) | 30 (127) | 7 (88) |
| Net entry rate | 18 (173) | 21 (148) | 15 (142) | 13 (126) |
| | Fast food | | | |
| | HH | LL | HL | LH |
| Net entry | 24 (132) | 15 (172) | 15 (135) | 21 (150) |
| Net entry rate | 14 (202) | 7 (98) | 21 (161) | 4 (128) |

Looking at net entries (Table 5), the picture is still different. Indeed, Local statistics indicates a predominance of observations located in the HH quadrant, even though significant municipalities are uniformly distributed between quadrants. Moreover, the number of significant municipalities is much lower than for the entries and exits. This point confirms Geroski's stylized fact 3 even when space is accounted for, that net entries (rates) are modest. We also note that for bars and hairdresser's, spatial heterogeneity is rather present under the form of "wealthy islets", highlighting the situations of small urban areas surrounded by rural municipalities with low entrepreneurship activities. Looking at rate of net entry, the parallel can be done with what has been said about entry and exit rates.

To conclude this interpretation of local statistics, let us come back to Geroski's contribution. In his (1995) paper, he insisted on *inter*-sectoral heterogeneity of entries and entry rates. This analysis allows going further on and identifying *intra*-sectoral heterogeneity (spatial heterogeneity). Indeed, we found, within a sector, variation of entry and entry rates according to the location, especially between urban and rural areas.

Let us now look at the persistence of spatial clustering. For the sake of coherence, we will study again the situation of Brussels in the three sectors. The aim is to see whether the significant dynamics in 1998 will lead to significant dynamics in 2001. This information is summarized in Table 6. We chose to report two local statistics, namely the LISA, used above, and the Getis, which provide different insights. Table 6 shows that spatial clustering is quite stable through time. Indeed, for LISA, p-values are all around 5% for all the period for entries and are quite similar for exits too. Looking at Getis statistics, we see that for both entries and exits, the statistic is highly significant, backing up the temporal persistency of spatial clustering. For entry and exit rates, the situation is analogous. In the Getis statistics, we do not find any significants for both entry and exit rates. The picture is nearly the same for the LISA except for rate of entry in 1999 in hairdresser's where the statistic is significant.

Table 6: LISA and Getis local statistics for Brussels, sectors of Bars, Hairdresser's and Fastfoods

| Bars | LISA | | Getis | |
|---|---|---|---|---|
| | Absolute | Relative | Absolute | Relative |
| Entry 98 | 2,65 (0.048) | 0.001 (0.476) | 3,27 (0.001) | -0,093 (0.926) |
| Entry 99 | 2,33 (0.067) | 0.02 (0.253) | 3,06 90.002) | -0.664 (0.506) |
| Entry 00 | 1.91 (0.058) | 0,024 (0.279) | 2,78 (0.005) | -0.640 (0.521) |
| Entry 01 | 1.95 (0.055) | 0,012 (0,391) | 2.81 (0.004) | -0.375 (0.708) |
| Exit 98 | 4.59 (0.018) | 0.016 (0.178) | 4,61 (0.000) | 0.797 (0.425) |
| Exit 99 | 4.30 (0.031) | -0,013 (0.424) | 4,19 (0.000) | -0.250 (0.802) |
| Exit 00 | 3,20 (0.043) | 0,013 (0.382) | 3,54 (0.000) | 0.225 (0.822) |
| Exit 01 | 1,82 (0.047) | -0,017 (0,265) | 2.81 (0.004) | 0.217 (0.828) |
| Hairdresser's | | | | |
| Entry 98 | 4,83 (0.021) | 0,097 (0.342) | 4,38 (0.000) | 0,614 (0.539) |
| Entry 99 | 6,94 (0.000) | 0.356 (0.030) | 6,4 (0.000) | 2.178 (0.03) |
| Entry 00 | 5,04 (0.005) | 0,043 (0,325) | 4,79 (0.000) | 0.455 (0.648) |
| Entry 01 | 2.03 (0.011) | -0,007 (0,283) | 3,99 (0.000) | 0.482 (0.629) |
| Exit 98 | 3,05 (0,007) | 0,052 (0.103) | 4,29 (0.000) | 1.183 (0.237) |
| Exit 99 | 2,81 (0,005) | 0.011 (0.208) | 4,30 (0.000) | 0.732 (0.464) |
| Exit 00 | 3,56 (0.001) | 0,067 (0,060) | 5,14 (0.000) | 1,704 (0.088) |
| Exit 01 | 3,57 (0.023) | 0,133 (0,105) | 4,09 (0.000) | 1.164 (0,244) |
| Fastfood | | | | |
| Entry 98 | 15,66 (0.000) | 0,141 (0.112) | 8,09 (0.000) | 1,279 (0.201) |
| Entry 99 | 9,79 (0.003) | -0,001 (0.375) | 6,35 (0.000) | -0,370 (0.710) |
| Entry 00 | 9,12 (0.001) | -0,004 (0.221) | 6,72 (0.000) | 0.678 (0.498) |
| Entry 01 | 13,26 (0.000) | 0,055 (0,170) | 7,70 (0.000) | 0.970 (0.332) |
| Exit 98 | 11,30 (0.000) | -0,001 (0.393) | 7,25 (0.000) | 0.068 (0.946) |
| Exit 99 | 13.,36 (0.000) | 0,001 (0.287) | 7,75 (0.000) | 0.392 (0.695) |
| Exit 00 | 7,50 (0.012) | 0,007 (0.403) | 5,75 (0.000) | -0.393 (0.694) |
| Exit 01 | 4,69 (0,024) | 0,016 (0.419) | 4,62 (0.000) | -0.353 (0.724) |

## 5. Conclusions

This paper reported the results of an ESDA applied to the firm entries and exits of a selection of retail and consumer service industries in Belgium over the 1998-2001 period. The exercise has included systematic reference to three of the Geroski's a-spatial stylized observations appearing in his oft-cited 1995 article, and has introduced and discussed their spatialized outcomes. As such, it may be considered as an opening tribute towards a spatial extension of Geroski's article.

As regards stylized fact 1 (commonness of entry), the analysis has showed that entry is not a regular phenomenon across space but similar spatial patterns are observable across industries.

With reference to the second stylized fact (large but passing cross-industrial variation in entry), it has been suggested additional spatial elements, such as spatial (and temporal) heterogeneity within industry.

Finally, concerning stylized fact 3 (high correlation between entry and exit rates, with modest net entry rates), the spatial analysis has revealed that entries and exits are highly correlated from the spatial point of view too. This does not hold for entry and exit rates, suggesting dissimilar local spatial structures. The modest net entry rates that were part of Geroski's stylized fact find here their spatial counterpart, as shown by LISA. We may note as well the observation of temporal persistency of spatial clustering.

The paper highlights the presence of spatial intra-sectoral heterogeneity. Notwithstanding implications for the quantitative analysis, this result is to be extended to the study of spatial inter-sectoral heterogeneity, not yet developed.

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