Spatial Concentration and Local Market Power: Evidence from the Retail Gasoline Market

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Abstract

We investigate how ownership structure (coordinated behaviour of multi-station firms) and market geography (the distribution and sequencing of stations in space) jointly influences gasoline prices. The canonical model of differentiation is extended to account for an asymmetric distribution of firms in space. An econometric analysis using an unbalanced panel of gasoline stations in Austria for the period 2000 to 2005 suggests that equilibrium prices increase with the distance between rivals, the distance between stations of the same firm as well as the degree of 'spatial clustering'. The econometric model is used to conduct simulation experiments that illustrate how price effects of mergers depend on the proximity and identity of stations. A central implication of our analysis is that the location of stations becomes critical when competition is localized.

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1. Introduction

In his seminal book on 'The Theory of Monopolistic Competition', Chamberlin refers to the gasoline market as a prototype for what he calls 'localised competition'.[1] At the retail level consumers face transportation (time) costs when switching between gasoline stations, which introduces spatial product differentiation into an otherwise homogenous product market. Spatial product differentiation is the basic source for the fact that gasoline markets are often suspected of the existence and exploitation of local market power.

The existing theoretical and empirical literature to investigate the existence of local market power typically builds on Salops' (1979) model of spatial competition. The canonical model of spatial competition, as formulated by Salop, assumes that (a) firms set prices independently and (b) firms are distributed equidistantly in the market. These two assumptions (symmetric distribution in space as well as independent pricing behaviour of firms) however contrast sharply with important characteristics of the gasoline market.

For one thing, establishing a new gasoline station (or closing down an existing one) is a very costly activity. The assumption of a symmetric distribution of stations in space would require all incumbents to relocate as soon as one new gasoline station is opening up (or an existing one is closing down). Since this is very unlikely to happen, an asymmetric distribution of firms in space with a larger number of competitors in one area and a low supplier density in another area will develop. Given this asymmetric spatial distribution of stations, some stations compete more intensively than others.

Secondly, gasoline stations often are members of a network of multi-station firms (large chains of gasoline stations) and are coordinating their pricing behaviour within the network. Coordinated price setting within multi-station retailers raises concerns about the lack of competition in this market and possible detrimental effects for consumers. Recent mergers between large firms have reinforced these concerns.[2]

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1 In Chamberlin's model competition is global in the sense that each firm competes directly with all other firms in the industry. However, Chamberlin recognises that in some markets competition is localized: 'Retail establishments scattered throughout an urban area are an instance of what might be called a "chain" linking of markets. Gasoline filling stations are another. In either of these cases the market of each seller is most closely linked (having regard only to the spatial factor) to the one nearest to him, and the degree of connection lessens quickly with distance until it becomes zero" (Chamberlin, 1948, p. 103).

2 Several authors (Borenstein and Shepard, 1996; Borenstein, Cameron and Gilbert, 1997; Barron, Taylor and Umbeck, 2004) found that retail gasoline prices are significantly related to market power in the industry. Hastings (2004) found evidence that a merger caused rival firms' prices to rise. Götz and

This paper investigates the impact of coordinated behaviour of multi-station firms as well as the distribution and sequencing of stations in space on gasoline prices. The analysis suggests that both, the coordination of behaviour as well as the spatial distribution of firms (the sequence of firms) influences equilibrium prices and that the effects of these factors on prices are interrelated.

This interrelationship between the effects of coordinated behaviour and the sequence of stations in space can be illustrated in a simple example. First consider (as a reference situation) a sequence of five independent firms (*A-B-C-D-E*) distributed equidistantly on one segment of the market (a road). Each firm competes for customers with its two neighbours. In this case, which corresponds to Salop (1979), the specific sequence of firms (the order in which the firms are located on the circle) is irrelevant. If the five stations however do not set prices independently but coordinate their pricing behaviour (by being a member of a multi-station firm) ownership and the sequence of firms becomes relevant. Consider the case of two firms (*A* and *B*) and five stations, where firm *A* controls three stations and firm *B* controls two. The specific sequence A_1-B_1-A_2-B_2-A_3 is characterised by the fact that the two neighbours of a particular location are both members of competing firms. Competition again will be intense and equilibrium prices will be identical to the reference situation with five independent firms.[3] If, however, the sequence of stations is A_1-A_2-A_3-B_1-B_2, only two locations (A_3 and B_1) would intensively compete for consumers. By choosing neighbouring positions for their stations, firms avoid price competition since a smaller number of their stations will then face competition from rivals. Stations A_1, A_2, and B_2 are 'sheltered' from competing rivals. One should expect the intensity of competition to be lower and thus the equilibrium prices to be higher if firms are 'spatially clustered' in this way.

This example also suggests that the distribution and sequencing of stations in space also has implications for competition policy and the evaluation of mergers between multi-outlet suppliers. Levy and Reitzes (1992) discuss a merger's anticompetitive impact on prices in a spatial model as well as the implications for competition policy in greater detail. According to our knowledge, the present paper is the first attempt to investigate these effects empirically for an actual merger in the gasoline market as well as on the basis of counterfactual experiments.

Gugler (2006) investigate the impact of mergers on spatial differentiation in the Austrian gasoline market.

3 This is an application of the result established in Braid (1986) according to which a merger between two stores has no effect on the Nash equilibrium if the merging stores are not adjacent to each other.

The following Section 2 discusses the relationship between the spatial distribution of stations and equilibrium prices in more detail. The implications of the theoretical model will be tested for an unbalanced panel of gasoline stations in Austria for the period 2000 to 2005. Section 3 describes the data and the definition of variables. Regression estimates that demonstrate the links between ownership structure, market geography and prices are reported in Section 4. Finally, results from simulations of an actual merger as well as some counterfactual experiments, reported in Section 5, will demonstrate that the effect of a merger on gasoline prices varies significantly with the proximity of the merging outlets. Section 6 summarizes and concludes.

2. A spatial model

We follow Salop's (1979) seminal analysis on spatial product differentiation and assume that individual firms and consumers are located along a unit-length circle.[4] Each consumer has an inelastic demand for one unit of a homogenous product. Competition occurs between neighbouring firms/stations only. Assume that there are M independent firms (decision makers), each of them controlling prices of multiple gasoline stations. The total number of stations on the circle is N. Denote the number of adjacent stations on the circle controlled by the same firm i with n_i, with $i = 1, \ldots, M$. As a summary measure for different sequences of stations in the market (spatial cluster) let us define: $SC \equiv \frac{\sum_{i=1}^{M} \frac{n_i}{M}}{N}$, with $\frac{1}{N} \leq SC \leq 1$. If all stations are controlled by one firm only (local monopoly), we would have $n_i = N$, $M = 1$, and $SC = 1$). The opposite case of N independent firms (as in Salop, 1979) is represented by $n_i = 1$, $N = M$, and $SC = \frac{1}{N}$. Note that the same result ($SC = \frac{1}{N}$) is also obtained in the case where stations of two independent firms ($M = 2$) are perfectly staggered on the circle ($n_i = 1$).

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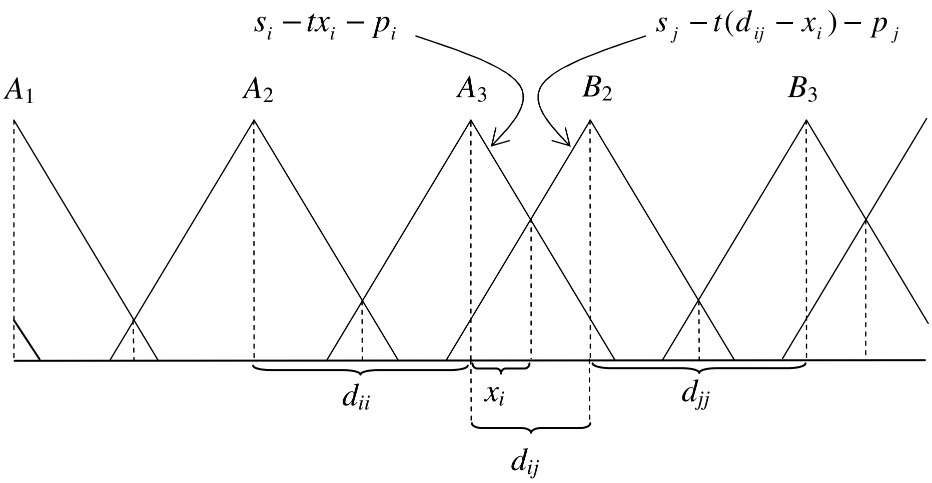
4 In contrast to Martinez-Giralt and Neven (1988), we do not examine the firms' choice of geographic location here since reallocation costs are prohibitive in the gasoline market (Netz and Taylor, 2002). Instead we assess how their inherited locations affect their pricing decisions.

Figure 1 illustrates one segment of the circle with a specific sequence of stations. For simplicity, let us focus on price setting of two rival firms (*A* and *B*).[5] The sequence A_1-A_2-A_3-B_1-B_2 is described by $n_A = 3$ and $n_B = 2$, for example. Distances between locations are denoted d_{ii}, d_{jj} and d_{ij}, where d_{ii} (d_{jj}) is the distance between two locations of the same firm *i* (*j*) and d_{ij} is the distance between locations of competing firms *i* and *j*.

FIGURE 1. – CONSUMER UTILITY AND LOCATION OF SUPPLIERS.



Following Salop (1979), the utility of a consumer located at a particular point on the circle between stations of competing firms *i* and *j* (between A_3 and B_1 in Figure 1) is $s_i - tx_i - p_i$ if the consumer purchases at a location from firm *i,* and $s_j - t(d_{ij} - x_i) - p_j$ if the consumer purchases at a location from firm *j* (where x_i is the distance between the consumer's location and that of *i*'s nearest station, and *t* are transportation costs). A consumer is indifferent if $x_i = \frac{s_i - s_j - p_i + p_j + td_{ij}}{2t}$. Consumers located between two stations of the same firm purchase at one of the two stations of this firm.[6]

Prices are set simultaneously by the independent firms (decision makers). Price discrimination within firms is not possible, all stations of a particular firms charge the same price. Firms *i*

[5] Focusing on the behaviour of two independent firms can be justified by the result established by Braid (1986), according to which the sequences of firms *A-B-A* and *A-B-C* gives the same level of prices in equilibrium.

[6] In order to avoid discontinuous demand functions, we assume that s_i and s_j is sufficiently large so that all consumers buy at least one unit of the product, i.e. the market is covered. The implications of this assumption are discussed in Perloff, Suslow, and Deguin (2006) and Sanner (2007).

and j aim at maximizing profits $\pi_i = (p_i - c_i)[2x_i + (n_i - 1)d_{ii}]r$ and $\pi_j = (p_j - c_j)[2(d_{ij} - x_i) + (n_j - 1)d_{jj}]r$, where r is the number of times the same sequence of stations is repeated on the unit circle. Computing $\frac{\partial \pi_i}{\partial p_i} = 0$ and $\frac{\partial \pi_j}{\partial p_j} = 0$ and solving for p_i and p_j gives:

(1)
$$p_i = \frac{1}{2}[s_i - s_j + p_j + td_{ij} + t(n_i - 1)d_{ii} + c_i]$$
$$p_j = \frac{1}{2}[s_j - s_i + p_i + td_{ij} + t(n_j - 1)d_{jj} + c_j]$$

Using the fact that $[2d_{ij} + (n_i - 1)d_{ii} + (n_j - 1)d_{jj}] = \frac{1}{r} = \frac{n_i + n_j}{N} = 2SC$ if the same sequence of stations is repeated *r* times on the full unit-circle, prices in equilibrium are:

(2)
$$p_i = \frac{1}{3}[2c_i + c_j + s_i - s_j + td_{ij} + t(n_i - 1)d_{ii} + 2tSC]$$
$$p_j = \frac{1}{3}[2c_j + c_i + s_j - s_i + td_{ij} + t(n_j - 1)d_{jj} + 2tSC]$$

Equilibrium prices are determined by the firms and its rivals' marginal costs as well as product characteristics, the distance between rivals, the distance between adjacent stations controlled by the same firm as well as the sequence of stations represented by our measure of spatial clustering *SC*. A stronger preference for a particular firm will increase prices of this firm and decrease the competitor's price ($\frac{\partial p_i}{\partial s_i} > 0, \frac{\partial p_i}{\partial s_j} < 0$), ceteris paribus. The price of the product at a station of firm *i* increase with the distance between stations controlled by the same firm (d_{ii}) as well as the distance between stations from rival firms (d_{ij}). Further, equilibrium prices are higher if stations of a particular firm are 'spatially clustered' ($\frac{\partial p_i}{\partial SC} > 0$). A high degree of spatial clustering implies that only a small number of stations from rival firms intensively compete for consumers and the intensity of competition in this market is thus low. Note, that p_i also increase with the number of subsequent stations from the competing firm ($\frac{\partial p_i}{\partial n_j} > 0$ since $\frac{\partial SC}{\partial n_j} > 0$). Having a strong competitor (in terms of a large number of adjacent stations in a particular market) is good for the firm. An increase in the number of adjacent stations of the competitor (n_j) raises his price p_j and reduces the aggressiveness of price competition.

Equilibrium prices will be identical to marginal costs if there are no differences in consumer preference between firms ($s_i = s_j$) and spatial differentiation does not exist ($d_{ii} = d_{ij} = d_{jj} = 0$). In Salop's (1979) model, individual locations of identical firms ($c_i = c_j$ and $s_i = s_j$) are distributed symmetrically on the circle ($d_{ii} = d_{ij} = d = \frac{1}{N}$) and firms are staggered in space ($n_i = 1$ for all $i = 1,...M$). In this case, our measure of spatial clustering is $SC = \frac{1}{N}$ and the pricing equation (2) simplifies to: $p_i = c_i + \frac{t}{N}$.

In the symmetric Salop model, the number of independent firms (*N*) in the market fully characterises the degree of spatial differentiation. In an asymmetric spatial model, where a subset of firms coordinates their pricing behaviour, the total number of firms is a poor measure of spatial differentiation. An empirical analysis should aim at considering the degree of coordination in price setting between stations as well as the spatial distribution of stations by differentiating between the distances between competing stations and the distance between stations controlled by the same firm as well as by measuring the degree of spatial clustering of stations (the sequence of stations). The impact of these three dimensions of spatial differentiation on gasoline prices will be investigated empirically in the following section.

3. Data and Empirical Specification

The empirical analysis uses data on gasoline prices collected by the Austrian Chamber of Labour ('Arbeiterkammer'). This data set comprises quarterly observations on prices of diesel[7] from December 2000 until March 2005 for an unbalanced sample of 595 to 1,370 gasoline stations in Austria (18.708 observations in total). Data on prices are merged with data for the geographical location as well as a number of specific characteristics of individual gasoline stations (whether the station has service bays, a convenience store, the number of pumps, …).[8] We supplement the individual data with demographic data (population density, commuting behaviour and importance of tourism) of the municipality, where the gasoline

7 Contrary to the USA, diesel-engined cars are common in many European countries. For the time period under investigation, the share of cars powered by diesel instead of gasoline increased steadily and reached 51.2% in 2005 (Statistik Austria 2006).

8 Unfortunately, data on the quantity of gasoline purchased at individual stations is not available. Estimation of a structural model of pricing (as in Pinkse and Slade, 2004) thus is impossible.

station is located. This information was collected by the Austrian statistical office ('Statistik Austria') in 2001. Finally, information on land prices for each year on a district level is obtained from the Chamber of Commerce ('Wirtschaftskammer').

Theoretical models of spatial competition start out from the premise that a firm does not compete with all other firms in a particular area but with its nearest neighbours only (no overlapping market areas). In the present paper we define neighbours on the basis of Thiessen polygons (Dale 2005 p. 52 f.). A Thiessen polygon defines an area around each location such that all points in this area are closer to this location than to any other location (see Appendix A for a detailed description). Two locations are direct competitors (or neighbours) if the Thiessen polygons generated by these locations are adjacent.

We measure the distance between locations on the basis of information about the structure of the road network. Using data from ArcData Austria and the ArcGIS extension WIGeoNetwork (WIGeoGIS 2006), the geographical location of the individual gasoline stations are linked to information on the Austrian road system to generate accurate measures of distance.[9] All neighbouring locations are divided into those operated by the same firm as well as those operated by rival firms, and the average driving distance for both groups (d_{ii} and d_{ij}) is calculated (see Table 1 for details).

On the basis of the Thiessen polygons, we also calculate the number of adjacent stations that are operated by the same firm (n_i and n_j). If, for example, two (three) stations are neighbours and are operated by the same firm, they belong to one 'spatial cluster' and we set $n_i = 2$ ($n_i = 3$). We set $n_i = 1$ if a location is an unbranded firm or if the location does not have adjacent locations operated by the same firm. A similar procedure is applied to define the size of the cluster for all neighbouring firms (n_j). From this, we compute our measure of the sequence of locations (spatial cluster) for each stations (*SC*). An illustration of this procedure to compute *SC* is provided in the appendix.

The gasoline market in Austria is dominated by a small number of independent firms, each of them operating a large number of stations. Roughly half of all stations are controlled by only three firms, which we call 'major brands' or 'majors'. Seven 'minor brands' control nearly 30% of all stations, whereas the rest are unbranded stations. We treat all unbranded stations as

[9] We are thankful to Manfred M. Fischer and Petra Staufer-Steinnocher for supporting this analysis by providing access to the data and tools. Sources: ArcData Austria and WIGeoNetwork, WIGeoGIS GmbH Vienna (geodata and software, licensed to the Institute for Economic Geography and GIScience, WU Wien), ESRI ArcGIS geographic information system, Redlands, CA (Campus Sofware License WU Wien)

independent firms. All independent firms (majors, minor brands and unbranded stations) are distinguished by dummy variables.

The definition of all variables as well as some descriptive statistics is provided in Table 1.

TABLE 1. – DEFINITION AND DESCRIPTIVE STATISTICS OF VARIABLES USED.

		Mean (Std.Dev.)	Minimum Maximum
Dependent Variable			
PRICE	Price of one litre diesel (in Euro cent)	76.723 6.553	58.9 99.5
Spatial Characteristics			
DIST	Average driving distance all neighbours in kilometres (*d*)	5.671 4.351	0.229 25.379
DIST-RIVAL	Average driving distance all neighbouring stations of rivalling brands in kilometres (d_{ij})	5.588 4.42	0.042 29.939
DIST-FIRM	Average driving distance to neighbouring stations of the same brand in kilometres. Entry is zero if none of these competitors are of the same firm (d_{ii})	2.451 5.001	0 29.829
SC	Index of sequence of locations (spatial cluster)	0.287 0.170	0.071 2.666
Location and Regional Characteristics			
GARAGE	Dummy variable which is set equal to one if location has a service bay	0.571	0 1
CAR WASH	Dummy variable which is set equal to one if location has a car wash facility	0.7098	0 1
SHOP	Dummy variable which is set equal to one if location has a convenience store	0.865	0 1
SERVICE	Dummy variable which is set equal to one if location has attendant service	0.239	0 1
OPEN	Dummy variable which is set equal to one if location is open 24 hours a day	0.155	0 1
DEALER	Dummy variable which is set equal to one if location is owned by the dealer	0.28	0 1
MEDIUM	Dummy variable which is set equal to one if plot size of the location is between 800 and 2,000 m²	0.432	0 1
LARGE	Dummy variable which is set equal to one if plot size of the location is larger than 2,000 m²	0.308	0 1
COMM	Number of commuters (commuting into and out of the municipality by their own car) divided by the sum of commuters and non-commuters of the municipality	0.515 0.109	0.192 0.829
TOUR	Number of overnight stays of tourist per month divided by the number of inhabitants of the municipality	1.733 7.192	0 302.177
POPDENS	Population density (in thousand inhabitants per square	1.3	0.004

	kilometre) of the municipality	2.93	25.589
COUNTRY	Dummy variable which is set equal to one if the speed limit on the main road next to the location is between 61 and 80 km/h	0.133	0 1
EXPRESS	Dummy variable which is set equal to one if the speed limit on the main road next to the location is between 81 and 100 km/h	0.018	0 1
HIGHWAY	Dummy variable which is set equal to one if the speed limit on the main road next to the location is larger than 100 km/h	0.023	0 1
PLAND	Land price in Euro per m^2.	107.506 66.204	13.1 280.8

[1] WIGeoNetwork links the location at a certain point of the road network. If two locations are on the opposite sides of a road, the driving distance is 0.

As stated before, the sample consists of an unbalanced panel data set, where observations with missing information on prices are assumed to be 'missing at random'.[10] The econometric model contains fixed time effects and random unit- (station) specific effects. As we observe spatial autocorrelation in the data, both individual random effects and the remainder error follow a spatially autoregressive process. As Baltagi (2005) notes, „[i]ncomplete [or: unbalanced] panels are more likely to be the norm in typical economic empirical settings." However, Pfaffermayr (2009) seems to be the first who tackles the problem of incomplete panels in a spatial panel data setting.[11]

The full, yet unobserved model, can be stated as

(3) $$\mathbf{p} = \mathbf{X}\beta + \mathbf{u}.$$

$\mathbf{p}$ is the vector if prices and of dimension $NT \times 1$, $\mathbf{X}$ is the matrix of exogenous variables (including $T - 1$ fixed time effects) of dimension $NT \times k$ and $\mathbf{u}$ is the $NT \times 1$ vector of residuals, including a random individual effect and a remainder error. As usual in spatial panels (but contrary to non-spatial panels) all observations of the first period are stacked on all observations of the second period and so on. In modeling the residuals we follow Kapoor et al. (2007) and assume that both the individual random effects as well as the remainder error follow the same spatial autoregressive process:[12]

10 See Little and Rubin (2002), Scheffer (2002) and Horton and Kleinmann (2007) for a more comprehensive treatment of the topic of missing data.

11 For an analysis of missing observations of spatially correlated data in a cross section see Haining et al. (1989) and LaSage and Pace (2004).

12 Baltagi et al. (2009) and Pfaffermayr (2009) use a more general approach, where the individual random effects and the remainder error can follow different spatial autoregressive processes. As this complicates the – already burdensome – numerical solution of the likelihood function, we refrain from

(4) $$\mathbf{u} = \lambda(\mathbf{I}_T \otimes \mathbf{W})\mathbf{u} + \boldsymbol{\varepsilon} \quad \text{with} \quad \boldsymbol{\varepsilon} = \mathbf{Z}_\mu \boldsymbol{\mu} + \mathbf{v}$$

$$\mathbf{u} = (\mathbf{I}_T \otimes (\mathbf{I}_N - \lambda \mathbf{W})^{-1})(\mathbf{Z}_\mu \boldsymbol{\mu} + \mathbf{v})$$

$\mathbf{I}_T$ ($\mathbf{I}_N$) is the identity matrix of dimension *T* (*N*). Information of spatial adjacency is stored in a spatial weights Matrix $\mathbf{W}$ of dimension $N \times N$ (for the construction of the matrix see below) and λ is the spatial autoregressive parameter. The block-diagonal matrix $\mathbf{I}_T \otimes \mathbf{W}$ indicates the dependence of the residuals across space and within time, but not across time. The error term $\boldsymbol{\varepsilon}$ includes a $N \times 1$ vector of unit specific random effects and a $NT \times 1$ vector of remainder errors. $\mathbf{Z}_\mu = \mathbf{e}_T \otimes \mathbf{I}_N$ is of dimension $NT \times N$ with $\mathbf{e}_T$ being a vector of ones of dimensions *T*. Both $\boldsymbol{\mu}$ and $\mathbf{v}$ are assumed to be iid and are distributed as $N(0, \sigma_\mu^2)$ and $N(0, \sigma_v^2)$, respectively. The variance-covariance matrix $\boldsymbol{\Omega}_u$ can be stated as:

(5) $$\boldsymbol{\Omega}_u = \sigma_v^2 (\mathbf{I}_T \otimes (\mathbf{I}_N - \lambda \mathbf{W})^{-1})(\phi \mathbf{Z}_\mu \mathbf{Z}_\mu^{\mathrm{T}} + \mathbf{I}_{NT})(\mathbf{I}_T \otimes (\mathbf{I}_N - \lambda \mathbf{W}^{\mathrm{T}})^{-1}) = \sigma_v^2 \boldsymbol{\Sigma}_u$$

with $\phi = \frac{\sigma_\mu^2}{\sigma_v^2}$ and where $\mathbf{I}_{NT}$ is an identity matrix of dimension *NT*.

We have full information on the exogenous variables (summarized in **X**) and on the spatial information of all gasoline stations. We therefore can construct the (time-invariant) spatial weights matrix $\mathbf{W}$ for all observations. However, out of $NT = 50{,}652$ observations we only have price information on $n_O = 18{,}708$ stations. Prices on all other $n_M = 31{,}944$ observation are missing and are denoted with a subscript *M*. Incomplete or missing observations are assumed to be ‘missing at random’. In a non-spatial panel, one would simply leave out the missing observations. This is not an option here, because “[i]n a panel with spatial error structure the unit specific effects as well as the random remainder disturbances spatially multiply into all other observations” (Pfaffermayr 2009 p. 2), as denoted by equation (4).

The model using observed data only can be stated as:

(6) $$\mathbf{p}_O = \mathbf{X}_O \beta + \mathbf{u}_O$$

$\mathbf{p}_O = \mathbf{S}_O \mathbf{p}$ and $\mathbf{u}_O = \mathbf{S}_O \mathbf{u}$ are vectors of dimension n_O and $\mathbf{X}_O = \mathbf{S}_O \mathbf{X}$ is a matrix of dimension $n_O \times k$. $\mathbf{S}_O$ is a selector matrix of dimension $n_O \times NT$ and is constructed by skipping all rows of $\mathbf{I}_{NT}$, where prices are not observed. The matrix $\mathbf{S}_M$ of dimension $n_N \times$

following them. Anselin (1988) and Baltagi (2005) restrict the spatial process to the remainder error only, which seems to be less appropriate in this context. Econometric tests to solve this question on statistical grounds, however, do not exist by now.

NT can be constructed in the same fashion, by skipping all rows of $\mathbf{I}_{NT}$, when prices are observed. Using these selector matrices, $\boldsymbol{\Sigma}_u$ can be partitioned as follows:

(7) $$\boldsymbol{\Sigma}_u = \begin{pmatrix} \mathbf{S}_O\boldsymbol{\Sigma}_u\mathbf{S}_O^{\mathrm{T}} & \mathbf{S}_O\boldsymbol{\Sigma}_u\mathbf{S}_M^{\mathrm{T}} \\ \mathbf{S}_M\boldsymbol{\Sigma}_u\mathbf{S}_O^{\mathrm{T}} & \mathbf{S}_M\boldsymbol{\Sigma}_u\mathbf{S}_M^{\mathrm{T}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\Sigma}_{u,OO} & \boldsymbol{\Sigma}_{u,OM} \\ \boldsymbol{\Sigma}_{u,MO} & \boldsymbol{\Sigma}_{u,MM} \end{pmatrix}$$

Note that by specifying $\boldsymbol{\Sigma}_{u,OO}$ (the relevant part of $\boldsymbol{\Sigma}_u$), we use information on the location of all data, including missing observations. The log-likelihood function for the observed data is given by (Paffermayr 2009 p. 13):[13]

(8) $$\ln \mathrm{L}_O\,(\lambda, \phi, \sigma_v^2, \beta) = -\frac{n_O}{2}\ln(2\pi) - \frac{n_O}{2}\ln\sigma_v^2 - \frac{1}{2}\ln\left|\boldsymbol{\Sigma}_{u,OO}\right| - \frac{1}{2\sigma_v^2}\mathbf{u}_O^{\mathrm{T}}\boldsymbol{\Sigma}_{u,OO}^{-1}\mathbf{u}_O$$

The concentration of the likelihood-function with respect to σ_v^2 and β simplifies the maximization. However, the optimization remains cumbersome, as one has to calculate the determinant and the inverse of the $n_O \times n_O$ matrix $\boldsymbol{\Sigma}_{u,OO}$ in every step of the numerical maximization procedure. We therefore either restrict our estimation to the non-spatial case ($\lambda = 0$), or we restrict our sample to 4 periods only (with $t = 1, 6, 13, 18$), which reduces n_O to 4,467.

The *i*,*j*-element of the spatial weights matrix **W** (see equation (4) and (5)), w_{ij}, is larger than zero if *i* and *j* are neighbours, i.e. the Thiessen polygons of these observations are adjacent. We use two different specifications: the weights are either binary (denoted by superscript *B*) or weighted by the inverse distance (denoted by superscript *D*). The weights matrix **W** is row normalized and, by convention, no observation can be neighbour of itself (the main diagonal contains only zeros). w_{ij} can formally be expressed as:

(9) $$w_{ij}^B = \begin{cases} \dfrac{1}{\sum_{j=1}^{N} w_{ij}}, & \text{if } i \text{ and } j \text{ are neighbours and } i \neq j \\ 0, & \text{otherwise} \end{cases}$$

$$w_{ij}^D = \begin{cases} \dfrac{\frac{1}{d_{ij}}}{\sum_{j=1}^{N} w_{ij}}, & \text{if } i \text{ and } j \text{ are neighbours and } i \neq j \\ 0, & \text{otherwise} \end{cases}$$

with d_{ij} indicating the (road) distance between observation *i* and *j*.

4. Empirical Results

[13] Note that we use a slightly different notation here.

Table 2 reports the parameter estimates of five specifications of a random-effects model. Model [1], [2] and [5] are non-spatial, i.e. λ is restricted to 0. The first specification is based upon the canonical model of spatial competition (Salop, 1979) and uses the average distance of station i to all neighbours (*DIST*) as an explanatory variable. All other specifications extend this model by distinguishing between the distance to rival firms (*DIST-RIVAL* corresponds to d_{ij} in the theoretical model) and the average distance to other locations operated by the same firm (*DIST-FIRM* corresponds to $(n_i - 1)d_{ii}$ in the theoretical model) as well as by introducing a measure of the sequence of locations (the degree of spatial clustering SC). The residuals in model [3] and [4] follow a spatial autoregressive process, but the sample is restricted to 4 time periods only ($t = 1, 6, 13, 18$). In model [3] we use a binary spatial weights matrix, whereas we opt for an inverse distance based weights matrix in specification [4]. Model [5] is restricted to the non-spatial case ($\lambda = 0$) and to 4 time periods.

Consistent with Salop's model (equation 2) as well as previous empirical studies, gasoline prices increase with the average distance to neighboring stations (*DIST*). According to Table 3, a 10 km increase in distance on average raises gasoline prices by 0.89 cent. Using the average distance to all neighbors however is a poor proxy for the degree of spatial differentiation. If stations are not symmetrically distributed in space, the theoretical analysis has shown that additional variables are to be included to characterize product differentiation in space. On the basis of a statistical test (F-test), the results in Table 2 clearly reject the specification of model [1] in favor of the extended model (specification [2]) [14].

The results reported in model [2] indicate that the effect of distance depends upon whether stations are operated by the same firm or by a rival. The effect of distance is positive and significantly different from zero only if the neighboring station is operated by a rival firm. A 10 km increase in distance (*DIST-RIVAL*) raises prices by 0.86 cent. The parameter estimate for the distance of stations operated by the same firm (*DIST-FIRM*) also is positive; the effect however is not significantly different from zero. Stations operated by different firms compete most vigorously.

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[14] The Null-hypothesis in specification [2] *DIST-RIVAL* = *DIST-FIRM* and *SC* = 0 is rejected on basis of an F-test at the 1% level.

TABLE 2. – RESULTS OF (SPATIAL) RANDOM-EFFECTS MODELS ON GASOLINE PRICES.

Explanatory Variables	Symbol	Coeff. [1]	(t-value)[1] [1]	Coeff. [2]	(t-value)[1] [2]	Coeff. [3][2]	(t-value) [3][2]	Coeff. [4][2]	(t-value) [4][2]	Coeff. [5]	(t-value)[1] [5]
Constant		86.544	(211.64)	86.277	(208.17)	84.873	(183.26)	85.094	(163.28)	86.525	(159.34)
Spatial Characteristics											
Average distance to all neighboring stations	*DIST*	0.089	(7.21)								
Average distance to rival stations	*DIST-RIVAL*			0.086	(7.27)	0.051	(4.50)	0.041	(3.55)	0.068	(4.10)
Average distance to stations of same firm	*DIST-FIRM*			0.002	(0.93)	0.001	(0.78)	0.001	(0.83)	0.002	(0.77)
Sequence of outlets (spatial cluster)	*SC*			1.182	(4.81)	0.220	(0.88)	0.196	(0.75)	1.251	(3.02)
Location and Regional Characteristics											
Location has a service bay	*GARAGE*	–0.254	(–2.51)	–0.266	(–2.64)	–0.044	(–0.64)	–0.008	(–0.11)	–0.238	(–1.83)
Location has a car wash facility	*CAR WASH*	–0.192	(–1.49)	–0.195	(–1.51)	–0.180	(–2.13)	–0.110	(–1.31)	–0.191	(–1.13)
Location has a convenience store	*SHOP*	–0.058	(–0.33)	–0.056	(–0.31)	0.140	(1.19)	0.114	(0.98)	–0.078	(–0.33)
Location has a full-service attendant	*SERVICE*	–0.129	(–0.84)	–0.106	(–0.70)	0.513	(4.82)	0.463	(4.38)	–0.025	(–0.12)
Location is dealer owned	*DEALER*	–0.088	(–0.64)	–0.078	(–0.58)	–0.183	(–2.04)	–0.198	(–2.23)	–0.238	(–1.36)
Size of the location > 800m^2 and < 2000m^2	*MEDIUM*	0.309	(2.40)	0.334	(2.59)	0.149	(1.68)	0.119	(1.34)	0.397	(2.43)
Size of the location > 2000 m^2	*LARGE*	0.417	(2.78)	0.429	(2.86)	0.177	(1.70)	0.170	(1.60)	0.270	(1.42)
Share of Commuters	*COMM*	–3.569	(–7.58)	–3.493	(–7.41)	–0.477	(–0.89)	–0.946	(–1.51)	–3.988	(–6.28)
Share of Tourists	*TOUR*	0.005	(1.24)	0.004	(1.12)	–0.001	(–0.36)	0.001	(0.34)	0.026	(2.25)
Population Density	*POPDENS*	–0.204	(–12.15)	–0.203	(–12.05)	0.000	(–0.46)	0.000	(–1.04)	–0.127	(–5.79)
Land Price	*PLAND*	0.010	(11.46)	0.009	(10.84)	0.007	(4.38)	0.008	(4.55)	0.008	(7.09)
Traffic speed: 61-80 km/h	*COUNTRY*	0.178	(1.23)	0.176	(1.22)	–0.019	(–0.19)	–0.024	(–0.23)	–0.034	(–0.18)
Traffic speed: 81-100 km/h	*EXPRESS*	1.646	(4.50)	1.635	(4.48)	1.353	(5.72)	1.537	(6.05)	1.483	(2.84)
Traffic speed: > 100 km/h	*HIGHWAY*	4.436	(12.70)	4.404	(12.58)	5.555	(22.84)	5.588	(21.49)	4.888	(8.72)
Location is open for 24 hours	*OPEN*	0.067	(0.45)	0.042	(0.29)	0.260	(2.70)	0.343	(3.51)	0.190	(0.99)
Dummy variables for missing observations	*MISSING*	yes (6)		yes (6)		yes (6)		yes (6)		yes (6)	
Dummy variables for retail chains	*CHAIN*	yes (10)		yes (10)		yes (10)		yes (10)		yes (10)	
Dummy variables for time period	*TIME*	yes (17)		yes (17)		yes (3)		yes (3)		yes (3)	
R^2 within [between]		0.832 [0.693]		0.833 [0.695]						0.893 [0.791]	
R^2 overall [ρ]		0.777 [0.301]		0.777 [0.300]		[0.438]		[0.438]		0.845 [0.234]	
σ_μ [σ_v]		1.652 [2.520]		1.651 [2.519]		0.832 [1.257]		0.832 [1.257]		2.834 [1.567]	
Λ						0.836		0.836			
Number of observations		18,708		18,708		4,467		4,467		4,467	

1) The t-ratios are based on heteroscedasticity consistent estimates of the covariance matrix (White, 1980).
2) Preliminary Results

Further, equation (2) suggests that prices at station *i* are influenced by the specific sequence of firms in the neighborhood (spatial clustering). This hypothesis is supported by the empirical results of model [2]. Prices increase with *SC*, the effect of this variable is significantly different from zero. This has interesting implications for evaluating the effects of takeovers in the retail gasoline market. The importance of this effect will be evaluated in more detail in a simulation experiments described in Section 5. Note that – consistent with the theoretical model – our measure of spatial clustering (*SC*) is calculated on the basis of the number of adjacent stations for each firm, rather than information on output and sales. This has the advantage that our measure of spatial clustering is less subject to the kind of endogeneity problems mentioned by Evans et al. (1993).

We get basically the same results if the model is restricted to 4 time periods only (model [5]), however, these findings are only partially confirmed by the spatial models. Using a binary spatial weights matrix (model [3]) or an inverse-distance based matrix (model [3]) we find a positive and statistically significant influence of the average distance to rivals (*DIST-RIVAL*) on prices, although the size of the parameter (0.051 in model [3] and 0.041 in model [4]) is smaller than in specification [2] and [5]. Again, the distance to stations of the same firm (*DIST-FIRM*) has no influence on prices. The influence of spatial clustering (*SC*) seems to be less important in the spatial econometric models: The coefficient drops from 1.182 in model [2] (and 1.251 in model [5]) to 0.220 in model [3] and 0.196 in model [4] and is not statistically significant from zero. This comes as a surprise, as ignoring a spatial process in the residuals effects the efficiency of a model, but leaves the coefficients unbiased and consistent (Anselin, 1988). The coefficients of model [3], [4] and [5] are therefore expected to be the same. We suspect that we face an (empirical, not theoretical) identification problem: As the spatial (*DIST-RIVAL, DIST-FIRM* and *SC)* and regional characteristics (*COMM*, *TOUR*, *POPDENS* and *PLAN*) have a spatial structure by construction, it might be difficult to identify their influence on prices if a spatial autoregressive process in the disturbances is included in the model. Differences in size and significance of the coefficients on regional characteristics between spatial and non-spatial models also point in this direction. As the results of the spatial models [3] and [4] are only preliminary, and as the results of model [5] confirm those of specification [2], we will focus on model [2] in interpreting the results.

Despite the fact that the physical attributes of gasoline are essentially identical across stations, consumers will not consider individual stations as perfect substitutes. Some consumers perceive gasoline sold by major-brand stations to be of superior quality, for example. The purchase of gasoline is sometimes linked to purchases of other goods (items from a convenience store, repair services), and stations may differ in the waiting time required to make the gasoline purchase in periods of peak demand. These differences in station characteristics are represented by s_i and s_j in equations (1) and (2) in the formal model. The empirical analysis attempts to capture station-specific characteristics by including a number of control variables. If the gasoline station also offers additional services and is equipped with a service bay (*GARAGE*) as well as a car wash (*CAR WASH*), gasoline prices are significantly lower. Firms use the lower gasoline prices to attract customers some of which, once they patronize the location, spend money on these additional services. Whether or not the gasoline station also sells items in a convenience store (*SHOP*) as well as the availability of a full-service attendant (*SERVICE*) does not significantly influence gasoline prices. The parameter estimates are negative but not significantly different from zero in both cases. Similarly, we do not observe significant differences in pricing between dealer-owner and company owned stations. The parameter estimate of a dummy variable (*DEALER*), which is set equal to one if the station is dealer-owned, is not significantly different from zero.

Large gasoline stations tend to charge significantly higher prices, ceteris paribus. If the size of a station is measured in square meter, we find that the parameter estimates for the dummy variables for medium-sized (between 800 and 2000 m^2) and large locations (larger than 2000 m^2) are both positive and significantly different from zero. The left out category are small stations which are smaller than 800 m^2. A larger station will have a shorter waiting time required to make the gasoline purchase in periods of peak demand and the reduced time-costs compensates consumers for higher gasoline prices.

To capture any perceived quality differences between major-brand stations and discounters, 10 dummy variables for the different brands are included. A dummy variable is set equal to one if the station offers gasoline from a particular major-brand and is zero otherwise. The parameter estimates are not reported in Table 2 but are available from the authors upon request.

Table 2 suggests that prices are significantly lower in areas with a large share of individuals who daily commute to a different region by car (*COMM*). Following Diamond's (1979) seminal 'tourist-trap model', search-theoretic models suggest a positive relationship between equilibrium prices and consumer search costs. Given that search costs are lower for commuters, the significant and negative parameter estimate reported in Table 2 is consistent with this literature. Similarly, a large number of tourists in a particular region could indicate a larger share of uninformed consumers, since their incentives to collect information on gasoline prices will be particularly small. The results reported in Table 2 however do not support this interpretation. The positive parameter estimate for the variable *TOUR* is not significantly different from zero.

Note that the theoretical as well as the empirical analysis do not consider the location decisions of individual firms endogenously. Assuming the location of gasoline stations to be exogenously determined is justified in the present context given the high entry and exit costs in the retail gasoline market. It is however important to consider the implications of this assumption for the interpretation of the parameter estimates. If regional differences in fixed costs and consumer density determine the location decisions of gasoline stations, the observed relationship between spatial concentration and prices might capture some of these underlying regional differences in fixed costs and demand conditions. Since station-specific sales cannot be observed in our data, we try to proxy regional differences in fixed costs and demand conditions with additional control variables.

Gasoline prices differ significantly between regions. Gasoline in remote areas (low level for our measure of population density '*POPDENS*') and areas with high land prices (*PLAND*) turns out to be significantly more expensive.

The type of road, where the gasoline station is located, turns out to be important for gasoline prices. Compared to the reference group (stations located at roads with a speed limit below 60 km/h) gasoline prices are significantly higher if the gasoline station is located at an expressway (*EXPRESS*) or a highway (*HIGHWAY*), ceteris paribus. The price increase is 1.64% in the first and 4.40% in the second case.

A station's opening hours can also be interpreted as a proxy for consumer demand since an increase in demand should raise the potential gain of a station from staying open additional hours. The parameter estimate for a dummy variable, indicating whether or not the station is open for 24 hours a day (*OPEN*) turns out to be insignificant in both specifications however.

Table 2 includes six additional dummy variables (*MISSING1*, ..., *MISSING6*) to control for the impact of missing observations in the explanatory variables. The dummy variables are set equal to one if information on the explanatory variable is not available for a particular location. Finally, 17 dummy variables for the different time-periods are included, the parameter estimates are not reported but are available from the authors upon request.

5. Price effects of mergers

In May 2002, BP announced its plan to acquire sole control of Veba Oel AG, which at the time was also active in the Austrian retail gasoline market (under the 'Aral' brand). The EC concluded that the notified operation does not raise serious doubts as to its compatibility with the common market and with the EEA agreement (case No. COMP/M.2761).[15] As a consequence of this acquisition, 98 gasoline stations that were operated by 'Aral' before 2003 are fully controlled by BP after 2003 (see Table 3).

TABLE 3. – NUMBER OF LOCATIONS OF EACH FIRM.

	# of obs.	
	before 2003	after 2003
BP[1]	482	580
OMV	463	463
SHELL	359	359
Majors	1,304	1,402
	(46.34%)	(49.82%)
Minor brands	858	760
Unbranded stations	652	652
	(53.66%)	(50.18%)
Total	2,814	2,814

[1] BP took over a minor brand by the end of 2002

We use this case as an example to illustrate the consequences of mergers between independent multi-station firms and to illustrate the importance of the spatial distribution of stations for gasoline prices. Different simulation experiments are carried out on the basis of the parameter estimates reported in Table 2, equilibrium prices under the various scenarios are summarized in Table 4.[16]

As a reference scenario, we use parameter estimates reported in column [1]. Note that on the basis of Salop's canonical model of spatial differentiation, no significant price changes for gasoline are to be expected as a consequence of this take-over. As both brands (BP and Aral)

15 It should be noted that this transaction in fact is a follow up to the BP/E.ON case (M.2533), where BP acquired 51% of the shares of Veba Oel. This operation was put into effect on 1st February 2002.

16 To account for the uncertainty in the estimated parameters we draw the coefficients randomly from the distribution given by the estimation results reported in Table 2 and repeat this process 10.000 times to derive distributions rather than point estimates for expected changes in prices. As the average changes reported in Table 4 are distributed normally (using a test developed by D'Agostino et al. (1990) and Royston (1991)), we report t-values rather than confidence intervals to judge the significance of the expected changes in prices.

charge above average prices,[17] gasoline prices of the 98 gasoline stations taken over increase only moderately (+ 0.013 cent per litre). All other gasoline stations are not expected to change prices at all, since the total number of gasoline stations as well as average distance to all neighbours remains unchanged.

TABLE 4. – ESTIMATED EFFECTS OF SIMULATED TAKE-OVERS.

	Mean	Std. Dev.	t-value
Price effects due to ACTUAL take-over			
Estimated price effects on the basis of symmetric spatial model (column [1] in Table 2)			
Effect on all stations	0.000	0.010	0.04
Effect on stations that are taken over	0.013	0.296	0.04
Effect on all neighbouring stations	0	0	-
Effect on all BP stations	0	0	-
Estimated price effects on the basis of asymmetric spatial model (column [2] in Table 2)			
Effect on all stations	0.033	0.014	2.54
Effect on stations that are taken over	0.032	0.301	0.11
Effect on all neighbouring stations	0.107	0.026	4.15
Effect on all BP stations	0.050	0.015	3.35
Price effects due to RANDOM take-over			
Only (randomly selected) adjacent stations are taken-over			
Effect on all stations	0.073	0.014	5.28
Effect on stations that are taken over	0.658	0.216	3.04
Effect on all neighbouring stations	0.175	0.032	5.40
Effect on all BP stations	0.100	0.025	4.05
Only (randomly selected) non-adjacent stations are taken-over			
Effect on all stations	0.010	0.007	1.42
Effect on stations that are taken over	0.539	0.203	2.66
Effect on all neighbouring stations	0.017	0.014	1.18
Effect on all BP stations	–0.005	0.001	–4.82

If, however, gasoline stations are not symmetrically distributed in space and (a subset of) stations coordinate their pricing behaviour, a take-over does not only affect former Aral-stations, but will indirectly also affect other gasoline stations, as some pricing externalities

[17] The coefficients (t-values) of the dummy-variables for the two brands in column [1] of Table 2 are 1.365 (6.92) for BP and 1.452 (6.21) for Aral. A t-test does not reject the null-hypothesis of no difference between the two parameter estimates.

will be internalized. Stations, which have been rivals before now are operated by the same firm for example, the degree of spatial clustering and the distance to rival stations as well as to stations controlled by the same firm changes. Price effects are to be expected not only for neighbouring stations but may trickle down to stations located further away as well.

Table 4 suggests that the average price increase of this take over is 0.033 cents per litre. This effect is significantly different from zero, and – assuming that the demand for diesel remains unchanged – would correspond to an increase in consumers' expenditures for diesel of about 2.51 million € per year.[18] However, the magnitude of price adjustment differs substantially between gasoline stations. A large number of stations are not affected at all as the spatial concentration of their neighbours does not change due to this take-over. Note, that the price increase for the 98 former Aral-stations taken over turns out not to be significantly different from zero. As mentioned before, Aral-stations already charged relatively high prices before the take-over. A significant price increase, on the other hand, is to be expected for neighbouring stations and BP-stations. Prices of neighbouring stations (BP-stations) on average increase by 0.107 (0.050) cents per litre.

To put these numbers into perspective and to further illustrate the importance of the location of stations that are taken over, we carry out two additional simulation experiments. In the first we assume that BP takes over 98 <u>randomly</u> selected stations among the group of those stations that are <u>adjacent</u> to one BP station. If only adjacent stations are taken over, price effects are much stronger since spatial clustering increases substantially. Prices of all stations increase by 0.073 cents per litre on average. The rise in prices of stations that are taken over is much larger (plus 0.658 cents per litre). Note that BP charges above average prices and a take-over of randomly selected (cheaper) brands boosts prices of these stations significantly. The calculated price effect for neighbouring stations is plus 0.175 cents per litre, prices on all BP stations on average increases by 0.100 cents per litre. All price effects are significantly different from zero.

In the second counterfactual experiment, we assume that BP takes over 98 <u>randomly</u> selected locations from the group of stations, which are <u>non-adjacent</u> to BP stations. If none of the acquired locations are adjacent to BP-stations, the price effect on all stations on average will be smaller (plus 0.010 cents per litre) since the degree of spatial clustering does not change significantly. The effect on the stations taken over again is significant (plus 0.539 cents per litre) since BP stations charge above average prices. However, the effect of this take-over on all neighbouring stations will be small (plus 0.017 cents per litre). Note that prices of all BP

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[18] In 2007, 7.6 billion litres of diesel have been sold at gasoline stations in Austria.

stations decline as a consequence: by taking over non-adjacent stations, the spatial concentration of BP-stations does not increase, while the degree of spatial clustering of rivalling brands will decrease in some local markets, with a negative effect on both (local) market power and prices. As a consequence, average prices of BP stations decline by 0.005 cents per litre.

Note that we assumed the number of stations to be unchanged as a consequence of the merger. Götz and Gugler (2006) argue that mergers in the retail gasoline market are likely to reduce the number of stations as long as exit costs are high in relation to output-specific fixed costs. They also find empirical support for the effect of mergers on the number of stations and suggest that ignoring this effect for empirical merger analysis would lead to an underestimation of the market power of the remaining stations. If the exit of stations increases prices of remaining stations, our estimates of price changes due to mergers are conservative.

6. Conclusions

This paper investigates how ownership structure and market geography jointly influences gasoline prices. We distinguish between various dimensions of spatial differentiation: (a) the number of firms in a market, (b) the distance between competitors as well as stations controlled by the same firm, as well as (c) the degree of spatial clustering (sequence of firms on the road).

Controlling for station characteristics, we find evidence that distance between stations has a positive impact on gasoline prices. As expected, the price effect of spatial differentiation is stronger if stations are members of rival chains. Spatial differentiation of gasoline stations has a smaller positive effect on prices if neighbouring gasoline stations belong to the same chain. In contrast to most of the previous (theoretical and empirical) spatial pricing analysis, the present study explicitly accounts for an asymmetric distribution of stations in space. The localised nature of competition in this case implies that the identity and location of each gasoline station is key in determining price effects. The econometric analysis suggests that an increase in our measure of spatial clustering reduces the degree of competition between firms and increases equilibrium prices.

The econometric model is used to conduct simulation experiments that illustrate how price effects of mergers depend on the proximity and identity of stations. Mergers increase prices more for stations that are located close to each other than for stations that are located further apart.

With respect to merger analysis and competition policy, a central implication of our analysis is that regional ‘submarkets’ are potentially relevant for antitrust analysis. Price increases as a consequence of mergers will not be uniform in space. As Levy and Reitzes (1996) conclude on the basis of a theoretical analysis: ‘the focus on a simple market definition and concentration does not do justice to the more complex nature of markets with localised competition’ (p. 439). The empirical results derived in the present paper fully support this conclusion.

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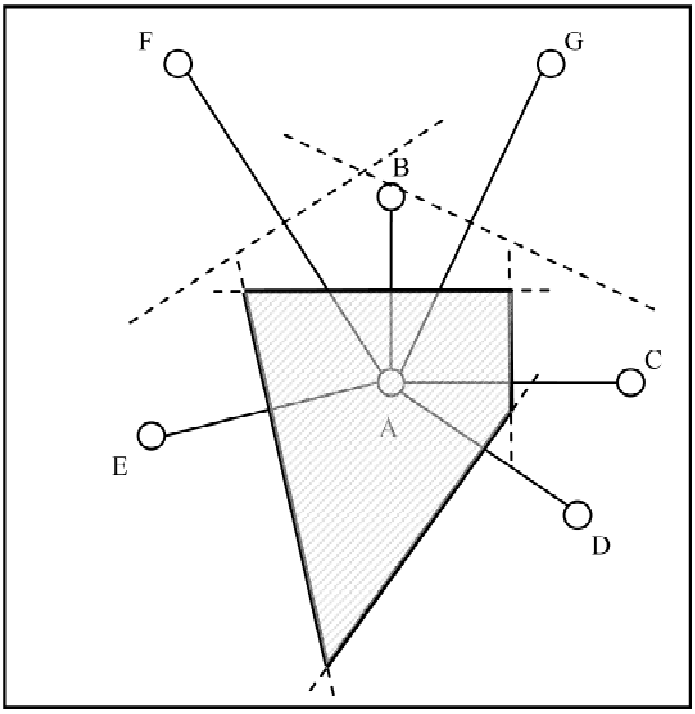
Appendix A:

The construction of Thiessen polygons is illustrated in Figure 2 below (see Dale 2005 p. 52 f. for an introduction to this topic or Kalnins 2003 for an application): To construct the polygon around observation A, one has to construct a perpendicular bisector of each line between location A and any other location. In each direction from location A, the closest bisector forms the boundaries of the polygon around A. From all points within the polygon, observation A is the closest location. For all points on the border line between observation A and E, these two observations are the closest location. As there is no single point, from which both A and (for example) F is the closest location, this pair of observations does not share a common boundary and are therefore not considered to be neighbours.

FIGURE 2. – THIESSEN POLYGONS.



Appendix B:

As an illustration Figure 3 shows Thiessen polygons generated by locations of three different major brands (A, B and C) and by fringe firms (F). If two adjacent polygones (i.e. two neighbouring locations) are of the same major brand (A, B or C), they are called ‘subsequent stations’ and belong to the same ‘spatial cluster’. The boundary of two polygons is a dotted line if they belong to the same spatial cluster, and a solid line else. Fringe firms are treated as independent locations, the size of a cluster of a fringe firm is therefore one (by definition).

The number of subsequent stations (the size of the cluster) of the location indicated by a bold B (in the middle of the figure) is two. The five remaining neighbours, that do not belong to firm B, belong to four different clusters: Two clusters of fringe firms of size one, a spatial cluster of firm A in the north-west of size two and a spatial cluster of firm C in the south of size three. In this local market we observe $M = 5$ independent firms (clusters) and $N = 7$ stations. $\sum_{i=1}^{M} n_i$ is the sum of all clusters in the local market and equals 9. The indicator of spatial clustering, SC, therefore is $SC = \frac{\sum_{i=1}^{M} \frac{n_i}{M}}{N} = \frac{\frac{9}{5}}{7} = \frac{9}{35}$.

FIGURE 3. – THIESSEN POLYGONS AND THE SIZE OF SPATIAL CLUSTERS.