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Spatial Interactions in Location Decisions: Empirical Evidence from a Bayesian Spatial Probit Model

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Abstract

In the past few decades spatial econometric models have become a standard tool in empirical research. Nevertheless applications in binary-choice models remain scarce. This paper makes use of Bayesian Spatial Probit Models to model and estimate spatial interactions in location decisions. For this purpose, we focus on the Austrian retail gasoline market, which is going through a process of remarkable structural changes. A short analysis shows that, during the last decade 10.9% of the stations had left the market and a percentage of 29.6% had either left the market or had changed the brand. This paper aims at investigating this process. A special characteristic of this market is the local competition structure which is characterized by spatial dependencies along local competitors. To capture these spatial dependencies and since the dependent variable is binary in nature (an exit had taken place or not), we apply a Bayesian spatial probit model using MCMC estimation on station level data for the whole Austrian retail gasoline market. Our results suggest, that the decision to leave the market, does not only depend on own characteristics, but also on competitors. In particular, we find the exit decisions to exhibit a negative spatial correlation. Moreover, our model allows to quantify spatial spillover effects of this market.

Keywords: Bayesian Spatial Probit Model, Exit, Gasoline retailing, Spatial competition.

JEL Code: L13, L81, C21

1 Introduction

Economists have long recognized a central tradeoff in spatial location choice: 'stealing' customers by locating closer to competitors comes at the cost of intensified price competition (Marshall, 1920). While there is a large volume of theoretical research analyzing strategic location decisions, only very few empirical studies (Seim (2006) and Watson (2005)) explicitly consider the spatial dimension when investigating firms' entry and/or exit decisions. The present paper uses a unique panel-data set for retail gasoline stations in Austria for the period from 2003 to 2011 to investigate firms' exit decisions econometrically. The geographical location of each gasoline station is linked to information on the Austrian road system which allows generating accurate measures of distance (measured in driving time in minutes) as well as the neighborhood relations between all gasoline stations in the network of roads.

In the past few decades the Austrian retail gasoline market has experienced considerable structural changes. According to the annual reports of the Austrian Economic Chamber the number of gasoline stations has decreased from 4,061 in 1988 to 2,575 stations at the end of 2011. This corresponds to a decline by almost 37%.¹ Between 2003 and 2011, 10.9% of the stations were shut down and 29.6% had either left the market or had changed the brand. The aim of this paper is to identify the key factors of and to shed light on the rationalization process of the Austrian retail gasoline market.

In terms of econometric methods to investigate this issue, it is important to note that individual exit decisions are binary in nature (exit 'yes' or 'no'). To investigate discrete exit choices in a spatial context, we apply a Bayesian spatial probit model using MCMC estimation (LeSage (2000) and LeSage and Pace (2004)) on station level data for the Austrian gasoline market.² These types of models account

¹Similar changes have been observed for the US and Canadian gasoline markets (Eckert and West, 2005).

²In the past thirty years spatial econometric models have become a standard tool in empirical research. Nevertheless applications in binary-choice models remain scarce. Anselin (2010) provides an excellent overview of the development of this field.

for spatial correlation between observations and are appropriate when oligopolistic interdependencies are characterized by spatial spillovers. In this model we incorporate the spatial competition structure of the gasoline market to test if distance and local market characteristics, as well as individual and neighboring station characteristics have an influence on the exit probability of a gasoline station.

A special characteristic of the gasoline market is that competition is highly localized. Consumers typically prefer to buy gasoline at stations in the neighborhood of their residence (van Meerbeek, 2003) or at stations lying on their commuting path (Houde, 2012). Search and transportation costs play a crucial role in the demand for gasoline. Therefore, as in most spatial markets, retailers recognize only their nearest neighbors as relevant competitors (Benson et al., 1992). Despite the many stations in the analyzed market, oligopolistic interdependencies are present in each of these local markets. Market structure is characterized by a few large companies or retail chains, so called 'majors', dominating the market and operating outlets in most local markets. On the other hand, smaller retail chains are also present in the market which are called 'minors'. There also exists a large number of small firms ('independent' or 'unbranded' stations) which are only active in a few or even only one local market. Further, gasoline is a homogeneous product with respect to its chemical properties and stations differentiate by providing additional services (shops, opening hours, attendant service etc.) as well as in terms of space. Previous studies for the gasoline market suggest that the spatial interdependence between adjacent competitors can have significant price effects. Pennerstorfer (2009) and Firgo et al. (2012) analyze different aspects of pricing in this market and provide evidence for the existence of spatial correlation. Ignoring this neighborhood effects can lead to biased parameter estimates (LeSage and Pace, 2009).

The contribution of this paper should on the one hand be a detailed analysis of the exits in the Austrian retail gasoline market, as to our knowledge no such study exists. Therefore, its first aim is to net out the influencing parameters of these movements. On the other hand, in our model we will also incorporate the different types and the ownership structure of stations. In this paper we also evaluate the

consequences on the exit probability due to a merger in the Austrian gasoline market. Götz and Gugler (2006) analyzed the correlation between market concentration and product variety in the Austrian gasoline market and found that a more concentrated market lowers the product variety. Put differently, a higher market concentration, due to merger for example, indicates exits. At the beginning of 2003, BP, a major brand of the Austrian gasoline market acquired 98 gasoline stations of the minor ARAL. BP's acquisition of the ARAL stations, which were dispersed all over the country, caused changes in the market concentration of local markets which included an ARAL station, whereas others (submarkets not including an ARAL station) remained unaffected. These binary and differential changes can be used to test if merger have an effect on the rationalization process of an industry.³

Early work regarding retail location comes from Hotelling (1929), who shows how the own location as well as the location of rival firms effect the own profit maximization. Reilly (1931), for instance, established a retail gravitation law and related it to shopping behavior and store location decision. Clustering behavior which is often observed in retail industries was explained, among others, by Fujita and Smith (1990), Brown (1994), Hinloopenaand and van Marrewijk (1999).

Our paper makes also a contribution to the broader literature on entry and exit, which can be divided into inter- and intra-industry studies. Berry and Reiss (2007) give an excellent overview for work on structural models of entry, exit and market concentrations, who in a game-theoretical framework analyze the long run equilibrium number of firms. Geroski (1995) surveys empirical work regarding entry, exit and turnover patterns in different industries. He established seven stylized facts about entry, exit and industry dynamics and linked the empirical evidence to the theory.⁴ He summarizes papers which analyze the location decisions of homogeneous and heterogeneous firms within and between industries. The majority of this research has been done for the manufacturing sector.

³Related studies who analyze some aspect of mergers in the gasoline market are among others: Eckert and West (2006), Hastings and Gilbert (2005), Taylor and Hosken (2007), Simpson and Taylor (2008), Taylor and Zimmerman (2010), Pennerstorfer and Weiss (2013).

⁴Another survey on this research topic is from Caves (1998).

A closely related paper to ours is Eckert and West (2005). The authors estimate a probit model using station, market structure, demographic, locational and firm type characteristics as explanatory variables to test different rationalization hypotheses for the Canadian gasoline market in the period from 1991 to 2002.⁵

The existing literature on entry and exit in the retail industry uses spatial explanatory variables to incorporate the spatial dimension of competition of this markets. In contrast, we use the geographical information on stations to model the spatial dependency among stations explicitly via an autoregressive spatial probit model, similar to LeSage et al. (2011). LeSage et al. (2011) analyze reopening decisions of establishments located on three major streets in New Orleans six months after they were destroyed by Hurricane Katrina. The authors state that the decision to reopen a firm is likely to depend on decisions made by neighboring firms, since firms offering complementary services can experience spatial spillovers. In order to test the existence of spatial dependence and since the dependent variable is binary (1 for reopened firms and 0 otherwise), they apply a binary spatial probit model. In the model estimation LeSage et al. (2011) control among others for flood depth, firm size and income.

Our empirical analysis explicitly controls for the various station, market and demographic characteristics, spatial neighborhood effects as well as the ownership structure of gasoline stations (membership in large networks). Furthermore, these type of models allow for differentiating between direct as well as indirect effects of exogenous variables (the effect of variables on the exit probability of the observed station as well as the effect on the exit probability of neighboring stations).

In general, we find a significant negative spatial correlation regarding the exit decision of stations in the Austrian gasoline market. This result suggests, that the probability to exit the market is lower if the neighbor left the market. Overall, it seems that the exit of stations is not only influenced by own characteristics but also by competitors characteristics and by the composition of the own limited market.

⁵Eckert and West (2005) do not ignore the possibility of spatial correlation. Moran's I test does not reject the null hypothesis of no spatial correlation in the estimated errors which implies that estimating a simple probit model is appropriate.

Moreover, this work adds to the empirical literature on structural changes of the gasoline industry and improves our knowledge of firms' entry and exit behavior. Finally, this paper contributes to the spatial econometric literature of discrete choice model applications.

The rest of the paper is organized as follows: in section 2 we describe the data, section 3 introduces the estimation procedure and reports the empirical results and section 4 concludes.

2 Data

The empirical analysis utilizes three different data sets. The first contains information on the spatial and site characteristics of all gasoline stations in Austria in the year 2003 collected by Experian Catalist. The second data set contains the same information for all active stations in the year 2011 obtained from Petrolview, a split-off company from Catalist⁶. By merging the two data sets, we are able to identify the structural changes which occurred in this market between 2003 and 2011. We categorized the stations into four groups: still active, changed brand, shut down and new station. If a station is active both in 2003 and 2011 in the same place and under the same brand, it was categorized as 'still active'. The category 'changed brand' represents stations that are operated on the same location but have changed their brand between 2003 and 2011. If a gasoline station no longer is operated in 2011, it was classified in the third category 'shut down'. Stations which are only present in the dataset from 2011 represent market entries and thus were classified as 'new stations'. The third data set contains information on the population and size of the municipalities and the districts of this region, as a part of the population census collected by the Austrian statistical office in 2001. Table 1 reports descriptive statistics for all metric and dummy variables included in the empirical model. The variables used in the estimations can be grouped into three blocks. In the first group we control for the competition and spatial characteristics of local markets. 'NO. IN-

⁶See www.catalist.com and www.petroview.com for company details.

DEPENDENTS' measures how many of the ten nearest neighbors are independent stations. Assuming that independent competitors set prices more aggressively would suggest a positive impact of this variable on exit probabilities. 'AVERAGE DISTANCE' represents the average distance to the ten nearest neighbors and therefore measures the degree of spatial differentiation. We expect this variable to lower the exit probability as a greater distance to the neighbors reduces the intensity of competition. The variable 'DEALER' equals one if a station is operated by a dealer and zero otherwise. A dealer-owned stations is an indicator for a franchised outlet, whereas a company-owned station is a vertically integrated station. Further, we include the information if the stations belongs to one of the ten major brands or not (UNBRANDED) to test for an asymmetry in the exit probability between these two types of stations. The probability of exiting the market might also be related to characteristics of the individual gasoline station. The variable 'SHOP' indicates if the station has an convenient shop. The dummy variable '24H OPEN' equals one if the stations is operated non-stop and zero otherwise. Further, we include a group of dummy variables (SPEED: $< 40km/h$, SPEED: $40 - 60km/h$, SPEED: $61 - 80km/h$, SPEED: $80 - 100km/h$) which indicate the speed limit of the street were the station is located. The category 'SPEED: $80 - 100km/h$ ' serve as the reference category and therefore is excluded from the estimation. 'ATTENDANT' is also a binary explanatory variable containing the information if the station offers an attendant service or not. The variables 'SIZE $\leq 800m^2$ ', 'SIZE: $800-2000m^2$ ', 'SIZE $> 2000m^2$ ' are dummy variables which measure the ground surface of the location. Again, 'SIZE $> 2000m^2$ ' as the reference category is excluded from the estimation. In addition to these station characteristics, we also consider proxy-variables for regional differences in demand: 'COMMUTERS' represents the ratio of incoming plus outgoing commuters to population on a district level and 'POPDENS' measures the population density on a district level in 1000 inhabitants per km^2 . The variable 'PURCHASE POWER' represents the ratio of inhabitants to employed people and serves as a proxy for the purchase power on a district level. For these variables, we expect to find a negative impact on the probability of exit since a higher value of

these variables indicates a higher demand and therefore a lower exit probability. As stated in the previous section, in the beginning of 2003 all 98 ARAL stations of the Austrian gasoline market were acquired by BP. To test if the merger of ARAL and BP has an effect on the exit probability of these stations, in our model we included the dummy variable 'ARAL', which equals one if the station was an ARAL station. Following Götzt and Gugler (2006) we expect a positive effect of this variable on the exit probability since a higher market concentration is argued to lead to more exits.

Table 1: Definition and descriptive statistics for empirical model

Symbol	Definition	Mean (Std.Dev.)	Minimum	Maximum
Competition and Spatial Variables				
NO. INDEPENDENTS	Number of stations within the then nearest neighbors which are independent stations	2.089 (1.593)	0	9
AVERAGE DISTANCE	Average distance to the ten nearest neighbors measures in driving time in minutes	36.046 (24.046)	0.01	99.97
DEALER	Dummy variable which is set equal to one if the location is owned by a dealer	0.349 (0.477)	0	1
UNBRANDED	Dummy variable which is set equal to one if station does not belong to one of ten major brands	0.238 (0.426)	0	1
ARAL	Dummy variable which is set equal to one if station is an ARAL outlet	0.036 (0.019)	0	1
Location Specific Variables				
SHOP	Dummy variable which is set equal to one if the location has a convenience store	0.758 (0.426)	0	1
24H OPEN	Dummy variable which is set equal to one if the location is operated non-stop	0.171 (0.376)	0	1
SPEED: $\leq 40km/h$	Dummy variable which is set equal to one if the speed limit on the main road next to the location is smaller than 40km/h	0.066 (0.249)	0	1
SPEED: 40 – 60km/h	Dummy variable which is set equal to one if the speed limit on the main road next to the location is between 40 and 60km/h	0.748 (0.434)	0	1
SPEED: 61 – 80km/h	Dummy variable which is set equal to one if the speed limit on the main road next to the location is between 61 and 80km/h	0.142 (0.349)	0	1
SPEED: 81 – 100km/h	Dummy variable which is set equal to one if the speed limit on the main road next to the location is between 81 and 100km/h (baseline category)	0.023 (0.149)	0	1
ATTENDANT	Dummy variable which is set equal to one if the location has an attendant service	0.267 (0.442)	0	1
SIZE $\leq 800m^2$	Dummy variable which is set equal to one if the ground surface of the location is smaller than 800m ²	0.343 (0.475)	0	1
SIZE: 800 – 2000m ²	Dummy variable which is set equal to one if the ground surface of the location is between 800 and 2000m ²	0.384 (0.486)	0	1
SIZE > 2000m ²	Dummy variable which is set equal to one if the ground surface of the location is bigger than 2000m ² (baseline category)	0.248 (0.432)	0	1
Indicators of demand and value of alternative use				
POPDENS	Population density of the municipality level in 1000 inhabitants per km ²	10.196 (26.019)	0.016	255.891
PURCHASE POWER	Ratio of inhabitants to employed people on a district level	0.482 (0.030)	0.073	1.105
COMMUTERS	Ratio of incoming plus outgoing commuters to population on a district level	0.537 (0.106)	0.177	0.829
PROPERTY	Log of average property prices in the district in Euros per square meter 2005	2.544 (2.232)	0	5.637
# of observations: 2738				

For the purpose of estimating the exit probability of one station, we defined the binary dependent variable as follows:

$$exit = \begin{cases} 1, & \text{if category 'changed brand' or 'shut down'} \\ 0, & \text{if category 'still active'} \end{cases} \quad (1)$$

The motivation for this definition of the dependent variable lies in the theoretical definition of exit. In theory a firm decides to leave the market if the value of exiting (sell-off value) is greater than the discounted expected profits of staying in the market. It should be clear, that the stations which belong to the category 'shut down' exited the market, since these stations are not longer operated in 2011. On the other hand, when a stations' brand changed it means that the ownership of this station changed between 2003 and 2011. Suppose, an OMV station in 2003 was operated as a Shell station in 2011.⁷ On the one hand this means an exit for OMV and on the other hand, a new entry for Shell. Therefore, if a station was operated on the same location but has changed its brand between 2003 and 2011, the the company or dealer which operated the station in 2003 exited the market. However, if the station was only renamed, due to a merger or an acquisition (such as the ARAL stations which where acquired by BP), it was not classified as an exit.

Our paper also addresses the question whether the exit probability is different for the different types of outlets ('branded' and 'unbranded' stations).

Table 2: Exits by station types

	Unbranded	Branded	Total
Exit	220	617	837
Percentage of all Exits	26.28%	73.72%	100%
Percentage in station category	33.63%	28.22%	

Nr. of stations = 2,822; Unbranded = 654; Branded = 2,168

Table 2 reports the number of exits of the Austrian gasoline market by station types. From all 837 station exits between 2003 and 2011 the majority (73.72%)

⁷In this period there was no acquisition between these two companies.

are branded stations. However, the table suggests that the share of exiting stations seems to be larger for unbranded stations compared to branded stations. Whereas 33.63% of all unbranded stations exited, only a portion of 28.22% of all branded stations left the market. In the econometric model we test whether there is an asymmetry in the exit probability of branded and unbranded stations and if the presence of an unbranded station has an impact on the exit probability of branded stations which was stated by Eckert and West (2005).

Before we are able to estimate a spatial model some important consideration on how to use the geographical information of the stations to define the local markets for the gasoline industry have to be made. For estimation of the exit probability of a station we treat the whole Austrian gasoline market as a network of firms which are connected through the Austrian road system. Therefore, we attach the information on geo-coordinates of the stations to the road network and calculate distances from one station to all others using GIS-software. By calculating distances, which are measured in driving time (minutes) and thus incorporate speed limits, we are able to account for local competition.

A number of different definitions for local markets exist in the empirical literature on the gasoline industry. Some use a critical value of distance or a certain number of neighbors for creating the local competition criterion. For example, Slade (1987) studies price-wars in the gasoline industry of Vancouver and defines a single local market as a street segment. Pinske and Slade (1998) investigate the spatial pattern of contracting in the Vancouver gasoline industry using six different metrics of closeness; all of them are some measure of physical distance between firms and are used in the form of a spatial weight matrix. Other studies using critical distances for defining local competitors are Hastings (2004), Netz and Taylor (2002), Pennerstorfer (2009). For identifying the local competitors of one station when estimating the exit probability, we adopt the approach from Firgo et al. (2012) who use a critical number of neighbors. They argue that using a critical distance is appropriate in an area where the density of firms and consumers is homogenous (e.g. a metropolitan area), whereas it is hard to find an adequate critical distance in areas where the

distribution of both is heterogeneous. In our analysis, we include all stations of the Austrian gasoline market, thus there are observation in urban and rural regions. For this reason, we use a critical number of neighbors for defining the local competitors of one firm, as this enables us to control for the different distribution of consumers and firms in the sample. How these local markets and neighborhood relations enter the estimation is described in more detail in the next section.

3 Estimation and Results

Since the dependent variable in this case is binary, firm i had exit the market or not, a model for the analysis of binary outcomes has to be applied. A conventional probit model would explain variation in the binary dependent variable y using the matrix of exogenous variables \mathbf{X} which is associated with the vector of estimated parameters β , under the assumption that the observations are independent of each other. However, in case of spatially dependent observations, standard logit or probit estimations results in inconsistent and inefficient parameter estimates (McMillen, 1992). Spatial correlation in the residuals could be the result of similar unobserved characteristics of adjacent competitors or could indicate the existence of a strategic interdependence in exit decisions between neighbours: whether or not an individual gasoline stations survives might not only depend on its own characteristics but could also be influenced by characteristics of its neighbors. McMillen (1992) further notes that both cases of spatial dependence produce heteroscedastic errors, which are responsible for the inconsistent parameter estimates. To account for this spatial interdependence, we apply a Bayesian spatial probit model, which was introduced by LeSage (2000) and extends earlier work by Albert and Chip (1993). This spatial autoregressive probit model has the following form:

$$\begin{aligned}
 y^* &= \rho \mathbf{W} y^* + \beta \mathbf{X} + \epsilon, \\
 \epsilon &\sim N(0, \mathbf{I}_n \sigma^2)
 \end{aligned}
 \tag{2}$$

where y^* represent the latent underlying unobservable utility level of the exit decision

(e. g.: expected profit) of dimension $m \times 1$ with m being the total number of gasoline stations. The block diagonal spatial weights matrix \mathbf{W} captures the spatial structure of the market (closeness between the individual gasoline stations). More specifically, the element w_{ij} of the spatial weights (distance decay) matrix \mathbf{W} of dimension $m \times m$ is the inverse of the driving time from station i to station j , if station j is among the ten nearest neighbors of i , and $w_{ij} = 0$ otherwise. Using the inverse of the driving distance puts a higher weight on closer neighbors. By construction, \mathbf{W} is row-stochastic (non-negative and row sums equal 1). This results in the $m \times 1$ vector $\mathbf{W}y^*$ consisting of the spatially weighted average of competitors utility or profit from leaving the market. $\mathbf{W}y^*$ represents the mechanism for modeling strategic interaction between gasoline stations in the decision to leave the market. ρ is the spatial correlation coefficient of the lagged dependent variable and measures the strength of dependence.

The k exogenous variables are represented by the matrix \mathbf{X} (including a constant) of dimension $m \times k$ and β is the $k \times 1$ vector of coefficients of the exogenous variables. ϵ is the $m \times 1$ vector of independent and identically distributed errors. The explanatory variables included in \mathbf{X} are location specific characteristics (convenience stores, opening hours, attendant service, surface area), demand indicators (commuting rates, population growth rates, a purchasing power proxy), the speed limit of the street where the gas station is located and property prices as indicators for the value of alternative use. Furthermore, we include dummy variables to capture the impact of branded and unbranded stations, which indicate if the station operates independently or belongs to one of ten major brands of the Austrian retail gasoline industry.

The Bayesian approach⁸ of modeling binary dependent variables treats the binary 0/1 observations of y as the unobserved net utility concerned with the exit/no exit decisions, where the unobserved utility underlies the observed choice outcomes. For example, in our case where the binary observed variable represents the closed/not closed status of the stations, the decision to close the station would be made if the net

⁸For an introduction in Bayesian Econometrics see Koop (2003) and Koop et al. (2007).

profit when shutting down versus staying in the market would be greater than zero. The Bayesian way of estimating this latent profit is to replace it with parameters that are estimated. In the case of a SAR probit model and when the estimates of the unobserved parameter values y^* are given, one can proceed to estimate the remaining model parameters β and ρ from the same conditional distributions that are used in the continuous dependent variable variant of the SAR model.⁹

More formally, the choice to exit/not exit the market depends on the difference in the net profit: $\pi_{1i} - \pi_{0i}$, $i = 1, \dots, n$ associated with the 0/1 indicators. π_{1i} represents the profit of firm i when leaving the market and π_{0i} represents firm i 's profit of staying in the market. The probit model assumes that this difference $y^* = \pi_{1i} - \pi_{0i}$ follows a normal distribution. We do not observe y^* , only the choice made, which are reflected in

$$y_i = \begin{cases} 1, & \text{if } y_i^* > 0 \\ 0, & \text{if } y_i^* \leq 0 \end{cases} \quad (3)$$

If the vector of latent profits y^* would be known, we would also know y , which led Albert and Chip (1993) to conclude $p(\rho, \sigma^2 | y^*) = p(\rho, \sigma^2 | y^*, y)$. This means, if one views y^* as an additional set of parameters to be estimated, then the joint conditional posterior distribution for the model parameters β and σ takes the same form as in the continuous dependent variant of the Bayesian regression problem, rather than the problem involving a binary vector y . This approach was used by LeSage and Pace (2009) to implement a Bayesian MCMC estimation procedure for the spatial probit model. To carry out the MCMC procedure, it is necessary to derive the full set of conditional posterior distributions for all parameters of interest as well as for latent variables. Gelfand and Smith (1990) show that sampling from the sequence of complete posterior distributions for all model parameters produces a set of estimates that converge in the limit to the (joint) posterior distribution of the parameters. To derive the conditional posterior distributions, we first need

⁹See LeSage and Pace (2009), chapter 5 and 10.

to define prior distributions for all parameters. In Bayesian econometrics investigators specify distributions, which represent prior beliefs about the distribution of parameters before seeing the data. This prior information is combined with the data distribution to produce posterior distributions which are the basis for inference. The posterior distribution in this case represents a matrix-weighted average of sample and prior information, but the weights are strongly influenced by the quantity of data and available prior information. Therefore, if our prior information about the parameter distribution is very limited and we have a big data set (like in our case), then the posterior distribution puts more emphasis on the model and sample data information, embodied in the likelihood. In this case Bayesian methods as well as frequentists methods rely almost entirely on the model and sample data information to provide inference for the parameters of interest. In our estimation, the prior distributions are taken to be diffuse wherever possible and conjugate priors elsewhere, which are described in detail in Appendix A. Put differently, we let the data and the model speak.

When rearranging equation 2 so that the dependent variable y^* appears on the left hand side only, one comes to the following expressions:

$$\begin{aligned} y^* &= (\mathbf{I}_m - \rho\mathbf{W})^{-1}\beta\mathbf{X} + (\mathbf{I}_m - \rho\mathbf{W})^{-1}\epsilon, \\ \mathbf{S}(\rho) &= (\mathbf{I}_m - \rho\mathbf{W})^{-1} = \mathbf{I}_m + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \rho^3\mathbf{W}^3 + \dots \end{aligned} \tag{4}$$

$\mathbf{S}(\rho)$ is the so called spatial spillover matrix which acts like a multiplier matrix and captures the spatial spillover effects of higher - order neighboring relations.

Due to the non-linearity in the normal probability distribution the parameter estimates $\hat{\beta}$ of non-spatial probit models do not have the same marginal effects interpretation as in standard regression problems. Thus the change in the dependent variable y due to changes in the explanatory variable x_r is determined by the standard normal density in the following way:

$$\partial E[y|x_r]/\partial x_r = \phi(x_r, \beta_r)\beta_r \quad (5)$$

where β_r is a non-spatial probit model estimate and $\phi(\cdot)$ is the density of the standard normal distribution.

In the SAR Probit model the non-spatial model estimates β_r are replaced with $E(\partial y/\partial x_r') = (\mathbf{I}_m - \rho\mathbf{W})^{-1}\mathbf{I}_m\beta_r$, which is a $m \times m$ matrix. The diagonal elements represent the direct effects - the effect of the change in the i th observation of the exogenous variable x_{ir} on the own observation y_i . The off-diagonal elements capture the indirect or spatial spillover effects - the effect of the change in the i th observation of the exogenous variable x_{ir} on other observations y_j , $j \neq i$. By replacing β_r in equation 5 we can calculate the marginal effects for the spatial probit model. For reporting issues we again have adopted the approach from LeSage and Pace (2009), who built average summary measures for the diagonal and off-diagonal elements of the coefficient matrix and thus report average direct, indirect and the average total effects being the sum of the direct and indirect effects.

The estimated coefficients, standard deviations, direct, indirect and total effects are reported in table 3. As already noted, the parameter estimates β from the SAR probit model cannot be interpreted as the effect on the probability of a station to exit the market due to changes in the explanatory variables.

The first point to note is that the spatial correlation coefficient ρ that is associated with the spatial lag of the dependent variable Wy is significantly different from zero at the 5% level. Thus the estimated coefficient ρ of -0.08 points to a negative spatial dependence in firms' decision to exit the market. Namely, the probability to exit for a particular gasoline station declines if its' neighbor is more likely to exit the gasoline market, *ceteris paribus*. Estimation experiments suggest that the effects of regional and firm characteristics on the probability of exit would be biased if these strategic interactions between neighboring competitors are ignored.

The effect estimates for the SAR Probit model are given in columns 4-6. These are the basis for inference for the effect of changes of explanatory variables on the exit probability of gasoline outlets as well as the spatial spillover effects on neighboring

stations. Within the group of competition and spatial explanatory variables the average distance to the ten nearest neighbors exerts a significant and negative direct effect, implying a decrease in the exit probability of 0.42%, for a increase in the average distance to the ten nearest neighbors by one minute. Thus, exits are more likely for gasoline stations in markets where the degree of spatial differentiation is low: the probability of exit decreases with the average distance to the ten nearest neighbors. This finding is consistent with empirical studies on price setting in the gasoline market: a high density of gasoline stations is found to intensify competition and reduce prices. In contrast with the findings of Eckert and West (2005), we found no effect for the number of discount neighbors on the closure probability of gasoline stations in the Austrian market. Additionally, our regression results show that there is no interrelation in the main model specification of exits and Aral stations which were acquired by BP which is in contrast with the findings of Götz and Gugler (2006), who expect a positive effect on exit due to higher market concentration. Nevertheless, the ARAL dummy stays insignificant in other model specifications with different spatial weight matrices and number of MCMC draws. However, our results suggests that stations operating non-stop have a lower exit probability of 3.15% compared to stations which have shorter opening hours. Worthwhile to point out is that the indirect effect of this variable exhibits a positive and highly significant effect - a station operated non-stop would actually raise the exit probability of its neighbors.

Moreover, small and medium size stores had a positive direct effect, increasing the probability of exiting. For categorical variables such as store size, we interpret the magnitude of the effects as how a change in category from the omitted category (in this case big size stations) would influence the probability of shutting down.

The population density has a negative direct impact in the exit probability of stations, whereas stations offering an attendant service are more likely to exit. It is important to note, that the spatial spillover effects represented by the indirect effect for the variables size, attendant service and population density all have the opposite sign compared to the direct effect. The other explanatory variables of this group,

namely, the speed limit of the street where the station is located, a purchase power proxy, commuters and property prices do not contribute to the explanatory power of the SAR probit model.

Overall, in accordance with the findings of previous studies¹⁰, our results suggest the exit probability to be lower for large gasoline stations that are open for 24 hours and located in a region with a high population density.

¹⁰Eckert and West (2005) observe that gasoline station in the Vancouver market operating non-stop have a lower exit probability. Carranza et al. (2012) examine the effect of a price floor in Quebec on station shutdown and find a negative effect for convenient stores, number of pumps and number of islands, but a positive effect for full service on the exit probability of gasoline stations.

Spatial Bayesian Probit Estimation

Dependent Variable: EXIT

	Coefficient	Sd. Dev.	Direct	Indirect	Total
Constant	-0.622	0.5599*			
Competition and Spatial Variables					
NO. INDEPENDENTS	-0.0168	0.0192	-0.005	0.0004	-0.0046
AVERAGE DISTANCE 10NB	0.0042	0.0034*	-0.001	0.0001	-0.0011
DEALER	-0.0728	0.0674	-0.021	0.0019	-0.0198
UNBRANDED	0.0725	0.0792	0.021	-0.0018	0.0195
ARAL	0.1036	0.1492	0.033	-0.002	0.030
Location Specific Variables					
SHOP	0.0296	0.0790	0.008	-0.0008	0.0078
24H OPEN	-0.0315	0.0301***	-0.099	0.0083	0.0907
SPEED: $\leq 40km/h$	-0.904	0.2000	-0.038	0.0031	-0.0352
SPEED: $40 - 60km/h$	-0.1413	0.1800	-0.053	0.0044	-0.0491
SPEED: $61 - 80km/h$	-0.1097	0.1919	-0.041	0.0033	-0.0382
ATTENDANT	0.2540	0.0678***	0.078	-0.0069	0.0715
SIZE $\leq 800m^2$	0.4365	0.0787***	0.138	-0.0120	0.1264
SIZE: $800 - 2000m^2$	0.3395	0.0732***	0.107	-0.0093	0.0979
Indicators of demand and value of alternative use					
POPDENS	-0.0022	0.0017*	-0.0007	0.0001	-0.0006
PURCHASE POWER	-0.5331	0.9367	-0.169	0.0150	-0.1546
COMMUTERS	0.0947	0.3973	0.033	-0.0029	0.0309
PROPERTY	-0.0001	0.0006	-0.0001	0.0001	0.0000
Spatial Correlation					
Wy	-0.0821	0.0525**			

***significant at 1%, **significant at 5%, *significant at 10%

Dummies for missing values and fixed effects for the 9 Austrian federal states included.

Table 3: SAR Estimation

To proof the robustness of the main model, we estimate the exit probability with different spatial weight matrices (five and fifteen nearest neighbors) and vary the number of draws within the Bayesian estimation process. In both cases there are only minuscule changes in the estimation results. Furthermore, the estimation of the main model was also carried out with a redefined dependent variable. Namely, in this definition of exit we exclude the stations which changed their brand, so that the dependent variable captures only real physical shutdowns. For the most part estimation results do not change. Explanatory variables presented in table 3 stay significant. In addition, the dummy variable SHOP contributes to the explanatory power of the model with a negative sign, which means that the exit probability of stations running a shop decreases. With this alternative definition of the dependent variable we also find negative spatial correlation, however, the spatial correlation parameter ρ is significant only at the 10% level.

4 Conclusion

The present paper examines the shutdowns of retail gasoline stations in the Austrian market by estimating a Bayesian spatial probit model. The estimation results are in line with related empirical studies of the rationalization process in this market. The network of gasoline stations in Austria tends to fewer, bigger stations with no attendant service, but other costumer attracting features like extended opening hours. With a spatial econometric model we are able to capture the local competition character of this market. The exit probability of gasoline stations in Austria exhibit a negative spatial correlation, meaning that the shutdown of neighboring stations lowers the competitions in a local market and that this event has a spillover effect on other stations in this market. Our results thus provide some first empirical evidence on spatial interactions in firms strategic location decisions in the (Austrian) gasoline market.

In future research, the direct and indirect effects of explanatory variables as well as the effects of ownership structure (membership in large networks) on location

decisions need to be investigated in more detail. The literature proposes also other estimators for binary spatial models, for example McMillen (1992) - EM-estimator, Beron and Vijverberg (2004) - recursive importance sampling (RIS) and Pinsky and Slade (1998) - GMM estimator. To additionally proof the robustness of the results, estimation could be carried out with these methodologies. However, Calabrese and Elkink (2014) who compare the performance of these estimators for specific types of models through an extensive Monte Carlo simulation study, conclude that when focusing on spatial autocorrelation only and with a low level of spatial dependence - which is the case for our data - the Bayesian estimation methodology (LeSage, 2000) outperforms the other estimators. Additional space for future research could be found by separation of our dependent variable. It would be an improvement for the estimation to separately analyze the categories "shut down" and changed brand". However, this extension would require an multivariate spatial probit model which raise additional estimation difficulties. We hope that empirical research along these lines will improve our knowledge of firms' entry and exit behavior in a spatial context and thus contribute to our understanding of the determinants of local market power.

Appendix A Prior distributions

Since the introduction of prior distributions in the modeling process is a crucial aspect of Bayesian estimation methods - the specified prior distributions for the model parameters are combined with the likelihood function to produce the posterior distributions - we want to describe our choice of priors in more detail. Equation 6 shows the spatial autoregressive probit model. In this model we want to estimate the model parameters $\theta = (\beta, \sigma, \rho)$ and therefore we have to specify prior distributions for these parameters. Following LeSage and Pace (2009) the vector β and σ^2 is assigned a normal inverse gamma (NIG) prior. This form of prior makes the normal prior for β conditional on an inverse gamma prior distribution for the model parameter σ^2 . Equation 7 specifies that the prior distribution for β follows a multivariate normal distribution conditional on σ^2 and the marginal distribution for σ takes the form of a inverse gamma distribution.

$$\begin{aligned} y^* &= \rho \mathbf{W} y^* + \beta \mathbf{X} + \epsilon, \\ \epsilon &\sim \text{N}(0, \mathbf{I}_n \sigma^2) \end{aligned} \tag{6}$$

$$\begin{aligned} \pi(\beta, \sigma^2) &\sim \text{NIG}(c, T, a, b) \\ &= \pi(\beta | \sigma^2) \pi(\sigma^2) \\ &= \text{N}(c, \sigma^2 T) \text{IG}(a, b) \end{aligned} \tag{7}$$

The parameters of the posterior distribution are a weighted average of the prior values and the likelihood, which is represented by the model and the data. Since we have a great deal of uncertainty regarding the prior distribution but a large data set, we want to put more weight on the data and the model. Therefore, we need to set appropriate distribution parameters for our prior distributions. The multivariate normal prior for β can be made almost diffuse by choosing $c = 0$ and setting T equal to a diagonal matrix whose elements are sufficiently large (very large prior

variance for β). The prior distribution of σ can be made uninformative by setting the parameters of the inverse gamma prior distribution $a = b = 0$. Since the spatial correlation parameter ρ plays a very important role in our model, we need to clarify the prior distribution for this parameter. Sun et al. (1999) argue that the feasible range for the parameter ρ is restricted in the following way: this parameter must lie in the interval $[\lambda_{min}^{-1}, \lambda_{max}^{-1}]$ where λ_{min} and λ_{max} represent the minimum and maximum eigenvalues of the row-stochastic spatial weight matrix \mathbf{W} . Therefore, we assign a uniform prior over the restricted support region for ρ (see equation 8), which makes all outcomes within the feasible range equally possible.

$$\pi(\rho) \sim U(\lambda_{min}^{-1}, \lambda_{max}^{-1}) \quad (8)$$

We obtain the following joint posterior distribution:

$$p(\beta, \sigma^2, \rho | y, X, W) \propto f(y, X, W | \beta, \sigma^2, \rho) \pi(\beta, \sigma^2) \pi(\rho), \quad (9)$$

where $f(\cdot)$ denotes the probit likelihood and $\pi(\cdot)$ represents the prior density of the parameters.

Worthwhile to note is that the priors for β and σ are independent from that for ρ , which does not imply independence in the posterior distributions for these parameters.

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