Centrality and Pricing in Spatially Differentiated Markets: The Case of Gasoline

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Abstract

This paper highlights the importance of 'centrality' for pricing. Firms characterized by a more central position in a spatial network are more powerful in terms of having a stronger impact on their competitors' prices and on equilibrium prices. These propositions are derived from a simple theoretical model and tested empirically for the retail gasoline market in Vienna (Austria). We compute different measures of network centrality by using information on the locations of gasoline stations in the road network. Results from a spatial autoregressive model confirm that the strategic interaction in pricing between competitors is significantly related to their degree of centrality.

Keywords: Network Centrality, Spatial Differentiation, Gasoline Prices

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1 Introduction

In his seminal book *The Theory of Monopolistic Competition*, Chamberlin (1948) refers to the gasoline market as a prototype for what he calls 'localized competition'.[1] At the retail level consumers face transportation (time) costs when switching between gasoline stations; this introduces spatial product differentiation into an otherwise homogeneous product market. The importance of spatial product differentiation for market outcomes (the existence and exploitation of local market power, for example) is typically investigated in economic models in the tradition of Hotelling (1929), Vickrey (1964) and Salop (1979). The present paper argues that these models ignore an important dimension of spatial product differentiation and market power: the centrality of firms.

Centrality, defined as the extent to which agents are connected to other agents, is among the most fundamental concepts in the social network literature. In networks of agents connected via friendship, acquaintanceship, or professional links, researchers found centrality to be associated with an agent's social status, power, and influence. In describing a widely studied star-shaped network structure, for example, Brass and Burkhardt (1992, p. 191) note that "[m]ost people would simply look at the diagram and declare [the central agent] the most powerful".

Whether firms characterized by a more central position in a network unfolded in space are more powerful than other firms, however, has not yet been investigated in detail in economic models. The canonical model of spatial competition, as formulated by Salop (1979), for example, assumes that firms are distributed equidistantly (symmetrically) in a circular market. Per definition, the number of direct competi-

[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 recognizes 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).

tors (the two adjacent neighbors) and the distances between competitors - and thus the extent to which firms are connected to other firms - is the same for all firms. Firms are different, but they are 'equally different' (spatially homogeneous). Therefore, the specific location of an individual firm in space is irrelevant. This simplifying assumption reduces the complexity of spatial models considerably but at the same time preclude an analysis of the importance of spatial heterogeneity and centrality for firms' pricing behavior.

The aim of the present paper is to implement the concept of centrality in a simple theoretical model of spatial product differentiation and investigate its importance for market power and firms' pricing behavior empirically. We compare price setting for 'central' and 'remote' firms in a modified version of Chen and Riordan's (2007) spokes model.[2] By analyzing the retail gasoline market in the metropolitan area of Vienna econometrically,[3] we provide first empirical evidence on the importance of centrality for strategic pricing decisions.

A key advantage of the retail gasoline market for this purpose is that the concept of centrality is based on a definite and easy-to-visualize physical foundation: Gasoline stations are connected through a network of roads and intersections and can be characterized by different degrees of centrality (interconnectedness) within

[2]Note that a few other studies also deviate from the traditional Hotelling and Salop model and consider alternative spatial structures. von Ungern-Sternberg (1991) presents a model in which firms (consumers) are located at the corners (along the edges) of a pyramid. Braid (1989) extends the Hotelling (1929) model to a three-way intersection with more than two firms, and Fik (1991) as well as Fik and Mulligan (1991) analyze pricing in different grid structures. Balasubramanian (1998), Bouckaert (2000) and Madden and Pezzino (2011) study a market in which consumers buy either from firms located on the Salop circle or from a firm located at the center of the circle. This spatial structure applies to competition between different types of firms: high street retail stores (perimeter) and internet/mail order stores (center). Competition between traditional high street retail firms is again symmetric in these models. Irrespective of the spatial structure chosen, none of these studies provide empirical evidence on the importance of centrality for firm pricing and market performance.

[3]The empirical literature analyzing competition in gasoline markets has mainly focused on the impact of spatial differentiation on price levels and price dispersion (Netz and Taylor, 2002; Barron et al., 2004; Lewis, 2008), on market concentration and the role of independent stations (Hastings, 2004; Pennerstorfer, 2009; Houde, 2012), as well as on the existence of asymmetries in price adjustment (Borenstein et al., 1997; Bachmeier and Griffin, 2003; Verlinda, 2008) and Edgeworth cycles (Noel, 2007a,b; Atkinson et al., 2009; Lewis and Noel, 2011). An excellent survey of this literature is available in Eckert (2011).

this network. More central stations (a) directly compete with more rivals and (b) are more important competitors for each of these rivals. Borrowing different measures of network centrality from the social network literature, we actually find that strategic price interaction between firms are significantly related to these measures, as predicted by our extended spokes model.

Section 2 of this paper briefly presents a modified version of Chen and Riordan's (2007) spokes model. Section 3 describes the data and reports the results of our econometric analysis. Section 4 concludes.

2 The model

Following Chen and Riordan (2007), we describe the market as a set of spokes with a common core (the market center). The number of spokes ($N \geq 2$) is fixed. Each spoke has a constant length (l). Consumers are uniformly distributed along each spoke. To avoid discontinuities in the demand curve, we assume that the net utility of consumption is strictly positive and that each consumer purchases exactly one unit of the product per period, i.e. the market is covered. The net utility equals the utility of the product (s) minus the price charged (p) and minus transportation costs consumers face when consuming at the location of a specific firm. Transportation costs are equal to the product of the distance consumers have to travel to the firm of their choice and constant per unit transportation costs (t). The locations of firms are exogenously given and fixed. Our model deviates from Chen and Riordan (2007) in two ways: First, each consumer attributes a value (s) to all (not just two) varieties (firms) provided in a local market. Second, we do not assume that the distance to the center (d) is identical for all firms. There is always exactly one central firm (C) and a finite number of $1 \leq n \leq N-1$ remote firms (R_i), with $i = 1, 2, ..., n$. The central firm is the supplier closest to the market center, thus $d_C < d_i, \forall i$.[4] Firms sell a spatially differentiated but otherwise homogeneous product ($s_C = s_i = s$) at constant marginal costs ($c_C = c_i$). Fixed costs are normalized to zero for convenience.

Figure 1 illustrates a simple network for the case of three firms (a central supplier C and $n = 2$ remote suppliers R_i, with $i = 1, 2$) in a market of $N = 4$ spokes. Note that the central firm is characterized by the fact that it is a direct neighbor of all other firms in the market, whereas all other firms are direct neighbors of one competitor only (the central firm). This stronger degree of connectedness to competitors associated with the central position of firm C in the network of spokes in Figure 1 establishes a special role for this agent in the determination of market prices.

[Figure 1]

A marginal consumer located at x_i is indifferent between patronizing the central (C) or the remote firm (R_i) if

$$s - p_C - t(d_C + x_i) = s - p_i - t(d_i - x_i), \tag{1}$$

which leads to

$$x_i = \frac{p_i - p_C + t(d_i - d_C)}{2t}. \tag{2}$$

Profits (π) for the central and the remote firms are given by

$$\pi_C = (p_C - c_C)\left[\sum_{i=1}^{n} x_i + l(N - n)\right], \tag{3}$$

$$\pi_i = (p_i - c_i)(l - x_i). \tag{4}$$

[4] Note that the concept of centrality in the present analysis focuses on the location of stations relative to their competitors and not relative to other factors, for example the clustering of consumers around specific loci. Anderson et al. (1997) investigate the effects of concentration of consumers on particular ('central') locations in detail.

Maximizing profits with respect to p_C and p_i leads to

$$p_C = \frac{1}{2}\left[\frac{\sum_{i=1}^{n} p_i}{n} + t\left(\frac{\sum_{i=1}^{n} d_i}{n} - d_C\right) + c_C\right] + tl\left(\frac{N-n}{n}\right), \tag{5}$$

$$p_i = \frac{1}{2}\left[p_C + t(d_C - d_i) + c_i\right] + tl. \tag{6}$$

A comparison of the price reaction functions for the central firm and the remote competitors reveals the impact of centrality on pricing behavior. Three effects are worth to be highlighted.[5]

Proposition 1. *Centrality implies an asymmetry in the firms' strategic pricing behavior: Firms respond more strongly to price changes by a central firm than to price changes by a remote firm.*

Proposition 1 can easily be verified since $\partial p_i/\partial p_C = 1/2 > 1/2n = \partial p_C/\partial p_i$ and $\partial p_j/\partial p_i = 0, \forall n > 1$. Figure 1 suggests that two remote firms never compete for the same customer. A price change of the remote firm i thus has no direct impact on all other remote firms and will directly influence one competitor only: the central firm. If n is large, a change in the price of one remote competitor will thus be of relatively minor importance and will trigger a relatively small price response only. The central firm, on the other hand, has n direct competitors and a price change of this firm will have a direct impact on all remote firms. According to Proposition 1, the optimal price response of a central firm to a price change by one remote firm decreases with the number of remote firms (n). In terms of the influence of one agent on the other agent's actions, the central firm is indeed the most powerful one.

Proposition 2a. *Firms' prices increase with their centrality (a shorter distance to the center) and decrease with the centrality of their direct competitors, ceteris paribus.*

Proposition 2b. *Assuming that a unique pure strategy Nash equilibrium in*

[5]The following propositions also hold in a more general case with an arbitrary number of firms on each spoke (Firgo, 2012).

prices exists in which the market area of the central firm exceeds its own spoke,[6] *the price of the central firm exceeds the price charged by a remote firm if* $N/n > 2 - (d_i - d_C)/l$.

Propositions 2a can be easily verified since $\partial p_C/\partial d_C < 0$, $\partial p_C/\partial d_i > 0$, $\partial p_i/\partial d_i < 0$ and $\partial p_i/\partial d_C > 0$. Moving closer to the center implies supplying a larger market segment which increases the own price and reduces those of competitors. A proof of Proposition 2b is provided in appendix A. The third effect reveals that centrality influences the degree of price transmission of idiosyncratic exogenous shocks.

Proposition 3. *The impact of an exogenous shock induced by the central firm on equilibrium market prices is stronger than the impact of the same shock emanating from a remote firm.*

The intuition behind this proposition again is that the central firm has a larger number of direct competitors than each remote firm. A formal proof of proposition 3 is also provided in appendix A. The following section aims at providing empirical evidence for these propositions.

3 Data and empirical results

The empirical analysis is conducted for the retail gasoline market, which seems particularly appropriate for this purpose for several reasons. First, gasoline is a rather homogeneous product. The main source of product differentiation is the location of a gasoline station. Second, establishing a new gasoline station (or closing down an existing one) is a quite costly endeavor, which corresponds well with our assumption of exogenously given locations (at least in the short run). Third, the 'network centrality' of gasoline stations is fairly easy to conceptualize and measure

[6]To keep the analysis tractable, we restrict the parameters of the model such that in equilibrium the market area of the central firm exceeds its own spoke. This requires that a remote firm has no incentives to lower prices in order to capture the consumer located at the intersection of the spokes, and that $x_i > 0$. Conditions for the existence of an interior equilibrium are discussed in appendix A.

based on their locations within the network of roads.

For the present analysis we use price data for the retail diesel market[7] in the Vienna metropolitan area, collected by the Austrian Chamber of Labor ('Arbeiterkammer') within one particular day every three months between October 1999 and March 2005 (a total of 22 points in time). The number of price observations available ranges from 144 to 152 per period. This data set is merged with data on the geographical locations (and other characteristics) of all 273 gasoline stations in Vienna. Using data from ArcData Austria and the ArcGIS extension WIGeoNetwork, we link the geographical location of each gasoline station to information on the Viennese road system. This allows us to generate 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.[8]

Let the element w_{ij} of the spatial weights (distance decay) matrix $\boldsymbol{W}$ of dimension $m \times m$ (with m being the total number of gasoline stations) be the squared inverse of the driving time from station i to station j, if station j is within a critical driving time (5 minutes) from i, and $w_{ij} = 0$ otherwise. The fact that the spatial structure of gasoline stations in an urban area can be more complex than suggested by Figure 1 (e.g. several stations can be located along a particular road) makes it difficult to measure centrality properly. A clear-cut dichotomy between central and remote competitors thus appears inappropriate for an empirical application; rather, the spatial structure of gasoline stations is characterized by different degrees of centrality within the network of roads.

In the following, we adopt three different measures of centrality from Opsahl et al. (2010).[9] The 'degree of centrality', first introduced by Freeman (1979), measures

[7]Unlike in North America, diesel-engined vehicles are very common in many European countries. The share of cars with diesel engines was more than 50% in Austria as of 2005 (Statistik Austria, 2006).

[8]Measuring distance in driving time (minutes) rather than driving distance has the advantage of controlling for different speed limits.

[9]A comprehensive review of different measures of network centrality is available in Borgatti and Everett (2006) as well as in Opsahl et al. (2010).

the number of times a particular gasoline station is among the H nearest neighbors of other gasoline stations. The degree centrality (dc) of station j in network $\boldsymbol{G}$ is given by[10]

$$dc_{Hj} = \sum_{h=1}^{H} \sum_{i=1}^{m} g_{hij}, \tag{7}$$

where $g_{hij} = 1$ if station j is the h^{th}-nearest neighbor of station i and $g_{hij} = 0$ otherwise.

A generalization of this measure is suggested by Opsahl et al. (2010) for the case of weighted networks. In a weighted network the links between nodes can be of different strengths whereas in an unweighted network all links are of identical strength Jackson (2008). Following Opsahl et al. (2010) we define the weighted degree of centrality (wdc) as

$$wdc_{Hj} = \sum_{h=1}^{H} \sum_{i=1}^{m} (H - h + 1) g_{hij}. \tag{8}$$

An additional measure of centrality, which relies on the closeness of competitors relative to all other competitors within a network, is 'closeness centrality' (cc). We adopt this concept of centrality by measuring the closeness of a station j if it is among the H-nearest neighbors of another station i relative to closeness of the remaining $(H-1)$-nearest neighbors of i:

$$cc_j = \sum_{i=1}^{m} \left[g_{ij} w_{ij} / \sum_{j=1}^{m} g_{ij} w_{ij} \right]. \tag{9}$$

More details on these centrality measures as well as a numerical example for a stylized network are provided in appendix B. Table 1 reports descriptive statistics

[10] We define the neighborhood (network) matrix $\boldsymbol{G}$ of dimension $m \times m$ such that the element $g_{ij} = 1$ if station j is among the H-nearest neighbors of station i and $g_{ij} = 0$ otherwise. We then split the matrix $\boldsymbol{G}$ into H matrices $\boldsymbol{G}_h$, with $h = 1, \ldots, H$, so matrix $\boldsymbol{G}_h$ reflects h^{th}-nearest neighbor relations, and $\boldsymbol{G} = \sum_{h=1}^{H} \boldsymbol{G}_h$. We set $H = 5$ for our basic specifications, but we also experiment with different values for H to check the robustness of our results.

for these centrality measures as well as for all other variables used in the empirical model.

[Table 1]

The theoretical model suggests that pricing decisions of station i are influenced by i's own degree of centrality, but also by the degree of centrality of neighboring stations. The specification of the empirical model that accounts for both effects, is given by the following spatial autoregressive (SAR) model:

$$\boldsymbol{p} = \rho_1 \boldsymbol{W}\boldsymbol{p} + \rho_2 \boldsymbol{W}\boldsymbol{C}\boldsymbol{p} + \boldsymbol{X}\boldsymbol{\beta} + \gamma \boldsymbol{C}\boldsymbol{\iota} + \boldsymbol{\epsilon}. \tag{10}$$

In equation (10) $\boldsymbol{p}$ is the $M \times 1$ vector of prices, where M is the total number of observations in a repeated cross section of $t = 22$ periods. The matrices $\boldsymbol{W}$ and $\boldsymbol{C}$ are of dimension $M \times M$. $\boldsymbol{W}$ is the block diagonal spatial weights matrix containing t blocks of dimension m_t, where m is the number of observations in t. $\boldsymbol{C}$ is a diagonal matrix with the element c_{jj} measuring the degree of centrality of station j. $\boldsymbol{X}$ is an $M \times k$ matrix of k explanatory variables including a constant, $\boldsymbol{\iota}$ is an $M \times 1$ unit vector, and $\boldsymbol{\epsilon}$ is the $M \times 1$ vector of i.i.d. error terms. ρ_1 and ρ_2 are the coefficients of spatial autocorrelation, $\boldsymbol{\beta}$ is the $k \times 1$ vector of coefficients of the exogenous variables in $\boldsymbol{X}$, and γ measures the impact of centrality on a station's price level. To facilitate the interpretation of the spatial autoregressive parameter ρ_1 (ρ_2), the matrix $\boldsymbol{W}$ ($\boldsymbol{W}\boldsymbol{C}$) is row-normalized in order to obtain a spatially weighted (spatially and centrality weighted) average price of rivals. Following Pinkse et al. (2002) and Pinkse and Slade (2010) equation (10) can be interpreted as a set of reaction functions obtained from a simultaneous pricing game. The parameter estimate of ρ_1 measures the (spatially weighted) price interaction between neighboring stations. An asymmetry in price adjustment between central and remote firms is captured by the parameter ρ_2. A positive parameter estimate of ρ_2 implies that prices respond more strongly to price changes by more central stations (as suggested by Proposition 1).

Note that the identification of strategic pricing interaction between (neighboring) firms in equation (10) is impeded by the existence of a common time-varying price component as well as spatially correlated unobservable determinants of gasoline prices. First, fluctuations in gasoline prices over time caused by changes in crude oil prices, for example, typically account for a large share of the total price variation. Even if there was no strategic interaction between gasoline stations, prices of neighboring stations would still be correlated because of this common time-varying component. Therefore, we include time fixed effects that completly remove price fluctuations that are common to all gasoline stations. Any remaining correlation between prices of neighboring stations can not be driven by common exogenous price shocks. Second, there may be regional factors having an impact on gasoline prices that are quite difficult to observe or measure. Omitting spatially correlated variables from the regression equation causes the residuals to be spatially correlated and thus violates the assumtion of i.i.d. errors. To explicitly account for the spatial correlation of residuals, we compare the results from the SAR model with those obtained from a general spatial autocorrelation (SAC) model. The signs and significance of the explanatory variables remain the same, although the magnitudes of the parameter estimates vary slightly by a statistically insignificant amount. Details of these (and a number of other) robustness tests are reported in appendix C.

The parameter estimates of the key variables from different specifications of the reduced form of the spatial autoregressive (SAR) model in equation (10) are reported in Table 2.[11]

[11] The reduced form of equation (10) equals $\boldsymbol{p} = (\boldsymbol{I} - \rho_1 \boldsymbol{W} - \rho_2 \boldsymbol{WC})^{-1}(\boldsymbol{X\beta} + \gamma \boldsymbol{C\iota} + \boldsymbol{\epsilon})$, where $\boldsymbol{I}$ is an $M \times M$ identity matrix. This data generating process illustrates the simultaneity of the SAR model and indicates that the estimation of equation (10) using OLS leads to biased and inconsistent results. Therefore, we choose maximum likelihood estimation applying the log-likelihood function for SAR models proposed by Anselin (1988).

[Table 2]

The following discussion focuses on spatial price interactions and on the impact of different centrality measures. Note that the empirical model includes a large number of control variables (station and location characteristics as well as time fixed effects) that have been found to be important in explaining retail gasoline prices in previous studies. The parameter estimates for these variables are discussed and reported in Tables C.1 and C.2 in the appendix.

The parameter estimates of a benchmark model that does not explicitly control for differences in centrality (assuming $\rho_2 = 0$ and $\gamma = 0$) are reported in column [1]. Similar to previous studies conducted on the retail gasoline market (Netz and Taylor, 2002; Pennerstorfer, 2009), we find a positive parameter estimate of ρ_1 that is significantly different from zero at the 1%-level. Prices of gasoline stations are expected to increase by 0.632 cents per liter following a (spatially weighted) average price increase of 1 cent by all relevant neighbors.

Columns [2] - [4] report parameter estimates of the extended model using the three different measures of centrality defined above. Centrality is found to have a significant impact on the strategic price interaction between competitors. In all specifications reported in Table 2, the parameter estimates of ρ_2 are positive and significantly different from zero at the 1%-level (5%-level) for dc and wdc (for cc). The intensity of the price interaction increases significantly with the centrality of neighbors, which corresponds to Proposition 1. A particular gasoline station responds more strongly to prices of a central competitor than to prices of a remote rival. The inclusion of centrality significantly improves the explanatory power of the models: a likelihood ratio (LR)-test clearly rejects the 'restricted' model [1] in favor of the models including degree centrality (model [2]) and weighted degree centrality (model [3]) at the 1%-level of significance. The LR-test also rejects model [1] at the 10%-level of significance in favor of model [4], which uses closeness centrality.

The parameter estimates of centrality for the level of prices are positive but only significantly different from zero at the 10%-level in case of weighted degree centrality (variable WEIGHTED) in model [3]. Note that the positive effect of centrality on the level of prices in the theoretical model (Proposition 2) results from the demand enhancing effect of an increase in centrality. Since the empirical models reported in Table 2 directly control for differences in consumer demand by including several locational characteristics, centrality does not turn out to to have a significant direct impact on the level of prices in most specifications.

It is important to note that the parameter estimates of ρ_1 and ρ_2 only account for the direct response of prices to those of neighboring stations. To address the third implication of our modified spokes model, i.e. the effect of centrality on the transmission of shocks to the general price level (Proposition 3), we need to consider that each price change also triggers feedback effects to and from all neighbors in the market. Starting with equilibrium prices, an exogenous (cost) shock for a particular station i will not only change i's own price but also the prices of its first-order neighbors, which again triggers price adjustments by the neighbors' neighbors (second-order neighbors of station i) including feedback effects to station i itself. To calculate the total effect[12] of shocks on equilibrium prices, we use the estimates of ρ_1 and ρ_2 from specification [2] and apply a bootstrap simulation technique to account for the uncertainty of the estimated parameter values.[13] Figures 2 and 3 illustrate the relationship between centrality and the transmission of (cost) shocks. The total effect (including all feedback effects) of a positive shock emanating from one gasoline station is measured by the vertical axis, the centrality of the station inducing the shock is depicted on the horizontal axis.

[12] For a detailed description of the calculation and the interpretation of direct, indirect and total effects in the presence of spatial dependence see LeSage and Pace (2009).

[13] Each parameter is drawn randomly from a normal distribution with the mean and the standard deviation obtained from the regression in column [2] of Table 2. We normalize ρ_1 and ρ_2 so they sum up to ρ for each draw. This assumption is justified as we cannot reject the restriction of $\rho = \rho_1 + \rho_2$ on the basis of the results of specifications [1] and [2].

[Figure 2 + Figure 3]

According to Figure 2, an exogenous cost shock that triggers a price increase of 1 cent for a station with a median degree of centrality of 5 leads to an additional increase in its price (after considering all feedback effects to and from neighboring firms) of 14 %. Thus, the total price increase of this station is 1.14 cents per liter. In contrast, the price increase is 1.08 (1.18) in case of a remote (central) supplier with a degree centrality of 3 (of 8). Similarly, Figure 3 shows that a price increase of 1 cent from a gasoline station with a degree centrality of 3 (5) [8] leads to an aggregate increase in the prices of all other stations in the market by 0.75 (1.59) [3.43] cents. Again, this price effect on all other gasoline stations in the market increases with the degree of centrality of the station initially inducing the shock. Gasoline stations with a higher degree of centrality tend to be neighbors to more stations, to be relatively closer to other stations, and are thus more influential in affecting neighboring stations.

In order to confirm that the results are not driven by specific geographic definitions we use in our model specifications, the regressions were also run using perturbations of these definitions. Tables C.1 and C.2 (in appendix C) report estimation results based on different neighborhood criteria determining a station's centrality, as well as different specifications of the spatial weights matrix $\boldsymbol{W}$. The parameter estimates of SAC models including a spatial autoregressive process in the residuals are reported in Table C.3. The results of model specifications including a spatially lagged price vector based on an interaction between the spatial weights matrix $\boldsymbol{W}$ and location characteristics (traffic flows, brands, or ownership) in addition to the centrality based lag are summarized in Table C.5. Our main findings remain robust and unaltered by all of these modifications.

4 Conclusions

The present paper extends the spokes model introduced by Chen and Riordan (2007) to highlight the importance of centrality for pricing. Firms are characterized by different degrees of centrality within a network unfolded in space. The specific position of a firm in the network (its degree of centrality) relative to its competitors determines the intensity of competition between firms. Central suppliers are found to be more powerful in the sense of (a) exerting a stronger impact on their neighbors, and (b) having a stronger impact on equilibrium market prices.

We also provide first empirical evidence on the impact of network centrality on pricing by adopting different measures of network centrality from the literature on social networks. The retail gasoline market in the Vienna metropolitan area is particularly suitable for the present purpose since (a) spatial differentiation is the most important dimension of product differentiation in this market, (b) the degree of centrality between competitors can be implemented and measured on the basis of a simple, intuitive and easy-to-visualize physical foundation (the location of stations in the network of roads), and (c) this metropolitan area is characterized by a rather homogeneous density of consumers.

Econometric results from a spatial autoregressive model confirm that the strategic interaction in pricing between competitors is significantly related to the degree of centrality of gasoline stations. A particular gasoline station reacts more strongly to a central competitor than to a remote one. In addition, the impact of a price change by an individual gasoline station on equilibrium prices increases with the degree of centrality of this station.

Our results have important implications for the effects of joint ownership and mergers between gasoline stations. Gasoline stations are often members of a network of multi-station firms (large chains of gasoline stations) and are coordinating their pricing behavior within the network. The effects of joint-ownership (and mergers between firms) will depend on the specific geographical position of the gasoline stations involved. Coordination of prices between a number of remote gasoline stations will have less effects on social welfare than price coordination in cases involving central stations.

It would be an interesting extension of the present analysis to explore the relationship between centrality and price leadership. Atkinson et al. (2009, p. 585) find "that price reductions radiate outwards from the initial source like a falling sequence of dominos". Investigating whether the timing and the speed of price adjustment (the dynamics of the 'domino effect') is influenced by the degree of centrality of gasoline stations, however, would require high frequency data.

The present paper further underlines the need to analyze entry and exit decisions in the context of centrality. In contrast to traditional spatial models in which firms and consumers are distributed symmetrically and the specific location of a firm in space is irrelevant, the location of individual suppliers in space constitutes and important strategic decision in the present framework. Entry at a central location will have a strong impact on incumbents since it creates additional direct competition for customers for many of these incumbents. Entry at a remote position on the other hand will have a minor effect on few incumbents only, with the effect of entry quickly ebbing as the distance from the location of the entrant increases. We hope that our contribution spurs further research in this direction.

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References

Anderson, S. P., Goeree, J., and Ramer, R. (1997). Location, location, location. *Journal of Economic Theory*, 77(1):102–127.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Doordrecht, Kluwer Academic Publishers.

Atkinson, B., Eckert, A., and West, D. S. (2009). Price matching and the domino effect in a retail gasoline market. *Economic Inquiry*, 47(3):568–588.

Bachmeier, L. J. and Griffin, J. M. (2003). New evidence on asymmetric gasoline price responses. *The Review of Economics and Statistics*, 85(3):772–776.

Balasubramanian, S. (1998). Mail versus mall: A strategic analysis of competition between direct marketers and conventional retailers. *Marketing Science*, 17(3):181–195.

Barron, J. M., Taylor, B. A., and Umbeck, J. R. (2004). Number of sellers, average prices, and price dispersion. *International Journal of Industrial Organization*, 22(8-9):1041–1066.

Borenstein, S., Cameron, A. C., and Gilbert, R. (1997). Do gasoline prices respond asymmetrically to crude oil price changes? *Quarterly Journal of Economics*, 112(1):305–339.

Borgatti, S. P. and Everett, M. G. (2006). A graph-theoretic perspective on centrality. *Social Networks*, 28(4):466–484.

Bouckaert, J. (2000). Monopolistic competition with a mail order business. *Economic Letters*, 66(3):303–310.

Braid, R. M. (1989). Retail competition along intersecting roadways. *Regional Science and Urban Economics*, 19(1):107–112.

Brass, D. J. and Burkhardt, M. E. (1992). Centrality and power in organizations. In Nohira, N. and Eccles, R. G., editors, *Networks and Organizations: Structure, Form and Action*, pages 191–215. Boston, Harvard Business School Press.

Chamberlin, E. (1948). *The Theory of Monopolistic Competition*. Cambridge [et al.], Harvard University Press, 6th edition.

Chen, Y. and Riordan, M. H. (2007). Price and variety in the spokes model. *The Economic Journal*, 117(522):897–921.

Eckert, A. (2011). Empirical studies of gasoline retailing: A guide to the literature. *Journal of Economic Surveys*. Forthcoming.

Fik, T. J. (1991). Price competition and node-linkage association. *Papers in Regional Science*, 70(1):53–69.

Fik, T. J. and Mulligan, G. F. (1991). Spatial price competition: A network approach. *Geographical Analysis*, 23(1):79–89.

Firgo, M. (2012). Centrality and pricing in spatially differentiated markets. Doctoral Thesis, WU Vienna University of Economics and Business, available online at http://epub.wu.ac.at/3461, last accessed 29/11/2012.

Freeman, L. C. (1979). Centrality in social networks: Conceptual clarification. *Social Networks*, 1(3):215–239.

Hastings, J. S. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in Southern California. *American Economic Review*, 94(1):317–328.

Hotelling, H. (1929). Stability in competition. *The Economic Journal*, 39(153):41–57.

Houde, J.-F. (2012). Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review*, 102(5):2147–2182.

Jackson, M. O. (2008). *Social and Economic Networks*. Princeton [et al.], Princeton University Press.

LeSage, J. and Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Boca Raton [et al.], CRC Press.

Lewis, M. (2008). Price dispersion and competition with differentiated sellers. *The Journal of Industrial Economics*, 56(3):654–678.

Lewis, M. and Noel, M. (2011). The speed of gasoline price response in markets with and without edgeworth cycles. *The Review of Economics and Statistics*, 93(2):672–682.

Madden, P. and Pezzino, M. (2011). Oligopoly on a Salop circle with centre. *The B.E. Journal of Economic Analysis & Policy*, 11(1). Published Online.

Netz, J. S. and Taylor, B. A. (2002). Maximum or minimum differentiation? Location patterns of retail outlets. *The Review of Economics and Statistics*, 84(1):162–175.

Noel, M. (2007a). Edgeworth price cycles, cost-based pricing, and sticky pricing in retail gasoline markets. *The Review of Economics and Statistics*, 89(2):324–334.

Noel, M. (2007b). Edgeworth price cycles: Evidence from the Toronto retail gasoline market. *Journal of Industrial Economics*, 55(1):69–92.

Opsahl, T., Agneessens, F., and Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, 32(3):245–251.

Pennerstorfer, D. (2009). Spatial price competition in retail gasoline markets: Evidence from Austria. *The Annals of Regional Science*, 43(1):133–158.

Pinkse, J. and Slade, M. E. (2010). The future of spatial econometrics. *Journal of Regional Science*, 50(1):103–117.

Pinkse, J., Slade, M. E., and Brett, C. (2002). Spatial price competition: A semiparametric approach. *Econometrica*, 70(3):1111–1153.

Salop, S. C. (1979). Monopolistic competition with outside goods. *Bell Journal of Economics*, 10(1):141–156.

Statistik Austria (2006). Kfz-bestand 2005. available online at http://www.statistik.at/web_de/static/kfz-bestand_2005_021489.pdf, last accessed 29/11/2012.

Verlinda, J. A. (2008). Do rockets rise faster and feathers fall slower in an atmoshpere of local market power? Evidence from the retail gasoline market. *The Journal of Industrial Economics*, 56(3):581–612.

Vickrey, W. S. (1964). *Microstatics*. New York, Harcourt, Brace and World.

von Ungern-Sternberg, T. (1991). Monopolistic competition on the pyramid. *The Journal of Industrial Economics*, 39(4):355–368.

A Mathematical Appendix

Proof of Proposition 2b

In order to facilitate the analysis, but without a loss of generality, we assume that all remote firms are located equidistantly at distance $d_i = d_j, \forall j$ from the center. Assuming equilibrium prices, R_i's demand is equal to $1 - x$ and the demand for C equals $N - n + nx$. The Nash equilibrium prices of the central firm (p_C^*) and remote firms (p_i^*) based on the price reaction functions in equations (5) and (6), and the locations of the marginal consumers (x_i^*) are given by

$$\begin{aligned} p_C^* &= \frac{1}{3}\left(d_i - d_C + 2l\left(2\frac{N}{n} - 1\right)\right)t + c, \\ p_i^* &= \frac{1}{3}\left(d_C - d_i + 2l\left(\frac{N}{n} + 1\right)\right)t + c, \\ x_i^* &= \frac{1}{6}\left(d_i - d_C - 2l\left(\frac{N}{n} - 2\right)\right) > 0. \end{aligned} \tag{A.1}$$

The equilibrium prices in (A.1) reveal that there are two components that determine whether the central firm charges higher prices than the remote firms: $d_i - d_C$, which is the difference between C and R_i in the distance to the center, and the ratio of spokes to remote firms (N/n). From (A.1) it follows that $p_C^* > p_i^*$ if and only if $N/n > 2 - (d_i - d_C)/l$. The smaller the number of spokes not occupied by remote firms, the stronger are the incentives for C to lower its price to capture consumers from central parts of spokes hosting remote firms. If the number of empty spokes is large, capturing consumers from remote firms by lowering the price results in a large decrease in Cs revenues generated by the demand coming from empty spokes. Therefore, Cs equilibrium prices are higher the higher the ratio N/n, ceteris paribus. From (A.1) it further follows that in order to assure that $x_i^* > 0$, condition $N/n < 2 + (d_i - d_C)/(2l)$ must hold. Note that $N/n \leq 2$ is a sufficient condition for $x_i^* > 0$ as $(d_i - d_C)/(2l) > 0$.

Further, it is plausible to assume that a remote firm does not try to undercut the central firm to capture the consumer located at the market center and therefore all consumers located at empty spokes. Due to R's locational disadvantage the price of R_i has to be lower than C's by at least $t(d_i - d_C)$ in order to capture the consumer at the market center. Competition for consumers located at empty spokes can be considered as a Bertrand game with homogeneous products and different marginal costs: The firm that charges the lowest delivered price at the market center gets all consumers located at empty spokes. In a price war R_i has to lower its mill price to zero (marginal costs) before C has to do so. Therefore, starting a price would completely erode R_i's profits.[14]

Proof of Proposition 3

Starting from equilibrium prices, the total impact of ∂c_C on equilibrium prices (p_C^*) and (p_i^*) is denoted in (A.2), the total impact of ∂c_i on equilibrium prices (p_C^*) and (p_i^*) in (A.3).

$$\frac{\partial p_c^* + \sum_{i=1}^{n} \partial p_i^*}{\partial c_C} = \frac{1}{2}\partial c_C + n\frac{1}{2^2}\partial c_C + \frac{1}{2^3}\partial c_C + n\frac{1}{2^4}\partial c_C + \frac{1}{2^5}\partial c_C + \ldots, \tag{A.2}$$

$$\frac{\partial p_c^* + \sum_{i=1}^{n} \partial p_i^*}{\partial c_C} = \frac{1}{2}\left(\sum_{a=0}^{\infty}\left(\frac{1}{2}\right)^{2a} + n\sum_{a=0}^{\infty}\left(\frac{1}{2}\right)^{2a+1}\right)\partial c_C,$$

$$\frac{\partial p_c^* + \sum_{i=1}^{n} \partial p_i^*}{\partial c_i} = \frac{1}{2}\partial c_i + \frac{1}{2^2 n}\partial c_i + \frac{1}{2^3}\partial c_i + \frac{1}{2^4 n}\partial c_i + \frac{1}{2^5}\partial c_i + \ldots, \tag{A.3}$$

$$\frac{\partial p_c^* + \sum_{i=1}^{n} \partial p_i^*}{\partial c_i} = \frac{1}{2}\left(\sum_{a=0}^{\infty}\left(\frac{1}{2}\right)^{2a} + \frac{1}{n}\sum_{a=0}^{\infty}\left(\frac{1}{2}\right)^{2a+1}\right)\partial c_i.$$

Assuming that $\partial c_C = \partial c_i = \partial c$ the difference between the total impact of C and P_i is equal to

[14] For a detailed discussion see Firgo (2012).

$$\left|\frac{\partial p_C^* + \sum_{i=1}^{n} \partial p_i^*}{\partial c_C}\right| - \left|\frac{\partial p_C^* + \sum_{i=1}^{n} \partial p_i^*}{\partial c_i}\right| = \partial c \frac{n^2-1}{2n} \sum_{a=0}^{\infty} \left(\frac{1}{2}\right)^{2a+1}, \tag{A.4}$$

$$\lim_{a\to\infty} \partial c \frac{n^2-1}{2n} \sum_{a=0}^{\infty} \left(\frac{1}{2}\right)^{2a+1} = \partial c \frac{n^2-1}{3n} > 0, \forall\, n > 1.$$

B Details on the Measures of Centrality and a Numerical Example

The three centrality measures used – degree centrality (dc), weighted degree centrality (wdc) and closeness centrality (cc) – provide information on a node's connectivity within a network but emphasize different aspects. Table B.1 provides descriptive statistics of the three centrality measures and different values of H for all 273 gasoline stations in Vienna. Table B.2 reports the correlation between these measures.

[Table B.1 + Table B.2]

Localized competition is characterized by competition between adjacent firms in the market space which are equivalent to adjacent nodes in a network. The propositions derived from our theoretical model are mainly related to the number of direct competitors a firm has. Thus, a criterion measuring a firm's centrality within the network space should be based on the concept of degree centrality. Also, it might be useful to put a higher weight on nearer neighbors to account for the fact that firms are not distributed equidistantly in space, which is ignored in dc but included in wdc (cc) by weighting the order of near neighbors (by weighting neighborhood relative to the closeness of other neighbors).

[Figure B.1 + Table B.3]

As an illustration of the different measures we consider the simple network of four nodes (A,B,C,D) illustrated in Figure B.1 and calculate centrality for $H = 2$. The numbers in Figure B.1 indicate the distance between two nodes. The network of Figure B.1 can be translated into the network matrix $\boldsymbol{G}_{H=2}$ and a spatial weights matrix $\boldsymbol{W}$ using the squared inverse of the driving time between two nodes.

$$\boldsymbol{G}_{H=2} = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}, \quad \boldsymbol{W} = \begin{bmatrix} 0 & (1/4)^2 & (1/3)^2 & (1/5)^2 \\ (1/4)^2 & 0 & (1/1)^2 & (1/3)^2 \\ (1/3)^2 & (1/1)^2 & 0 & (1/2)^2 \\ (1/5)^2 & (1/3)^2 & (1/2)^2 & 0 \end{bmatrix}.$$

The centrality measures for the nodes of this network are reported in Table B.3. The measure 'degree centrality' (dc) simply counts the number of in-degrees for each node, which is equal to the sum over all rows for each column in matrix $\boldsymbol{G}$. The measure 'weighted degree centrality' (wdc) weights a nearest neighbor relation higher than a second-nearest neighbor relation as in equation (10). For node B, wdc is equal to 4 because B is the nearest neighbor of C (factor 2) and the second-nearest neighbor of A and D (each factor 1). For the measure 'closeness centrality' we need the row normalized version $\boldsymbol{G}^{cc^*}$ of the Hadamard product $\boldsymbol{G}^{cc} = \boldsymbol{G} \odot \boldsymbol{W}$, which is equal to

$$\boldsymbol{G}^{cc^*} = \begin{bmatrix} 0 & 0.3600 & 0.6400 & 0 \\ 0 & 0 & 0.9000 & 0.1000 \\ 0 & 0.8000 & 0 & 0.2000 \\ 0 & 0.3077 & 0.6923 & 0 \end{bmatrix}.$$

A node's 'closeness centrality' (cc) is the sum of weights it has as a neighbor of other stations in the transformed network matrix $\boldsymbol{G}^{cc^*}$. For example, B's 'closeness centrality' (cc) is equal to $0.36 + 0.8 + 0.3077 = 1.4677$.

C Robustness Checks and a Detailed Description of the Econometric Results

This section provides a description of the modifications of the basic specifications to check the robustness of our results as well as an interpretation of the estimation results of some other variables used in the empirical models. Modifications include variations of the spatial weights matrix (speed of distance decay and market delimitation), variations of the number of neighbors when calculating our measures of centrality, the inclusion of a spatial autoregressive process in the residuals as well as additional spatial lags weighted by other attributes of the location (in addition to centrality).

The parameter estimates on all variables included in specification [1] to [4] and variations of the model with respct to the spatial weights matrix and the number of neighbors calculating our measures of centrality are reported in Table C.1 and Table C.2.

[Table C.1 + Table C.2]

Specifications [5] to [7] in Table C.1 show the results of models in which the centrality matrix C is interacted with a binary weights matrix $\boldsymbol{W}$ based on neighborhood ($w_{ij} = 1$ if j is within a 5 minutes driving distance of i and $w_{ij} = 0$ otherwise) rather than with a spatial weights matrix based on distances. In specifications [5] to [7] the coefficient of the second spatial lag (ρ_2) captures the centrality of neighbors but not the relative distances to these neighbors. Note that the parameter estimates of ρ_2 (ρ_1) are smaller (larger) in specifications [5] to [7] compared to specifications [2] to [4]. However, the coefficients are still positive and significantly different from zero. The likelihood ratio tests reject the restricted model (which excludes our measures of centrality) in specification [1] in favor of the extended models (specifications [5] to [7]).

We also check the robustness of our results with respect to the construction of the network $\boldsymbol{G}$ determining a station's centrality. In specification [8] ([9]) of Table C.2 we set $H = 2$ ($H = 10$). The slope parameter of $\boldsymbol{W}\boldsymbol{C}^{dc}\boldsymbol{p}$ in specification [8] is much smaller (but still significantly different from zero) than in specifications [2] and [9] but $H = 2$ seems to be an extremely narrow criterion to construct the network $\boldsymbol{G}$. The coefficient in [9] is very similar to the coefficient in [2] and thus very robust with respect to the variation of $H = 5$ to $H = 10$. Again, the likelihood ratio test rejects [1] in favor of [8] and [9].

In specifications [10] and [11] of Table C.2 we use the inverse of the driving time instead of the squared inverse to determine the weights in $\boldsymbol{W}$. The coefficients hardly change compared to model [1] and [2]. Finally, specifications [12] and [13] of Table C.2 show the results when using a critical distance of 10 minutes of driving time instead of 5 minutes for the construction of $\boldsymbol{W}$. A 10 minutes radius raises the number of observations from 3,051 to 3,188 as stations with no neighbors within 5 minutes had to be dropped from the sample in specifications [1] to [11]. On the other hand, for many stations the number of neighbors included in $\boldsymbol{W}$ using a 10 minutes radius increases substantially. Using a 10 minutes radius slightly increases the slope of the reaction function. The LR-Test again rejects the model excluding the centrality measures in favor of our extended specifications.

In all estimations mentioned so far, a large number of control variables have been included. In line with previous empirical findings in spatially differentiated markets we find that an increase in spatial differentiation has a positive and significant impact on prices. An increase in the distance to the next neighbor (DISTANCE NEXT) by one minute is expected to directly increase the price of a station by 0.12 to 0.19 cents.[15]

[15]We only report and interpret the estimates of the direct effects of the explanatory variables. The

To approximate demand and cost in the different districts of Vienna we use the variables COMMUTERS, log POPDENS and log PREMISES. An increase in the rate of commuters (COMMUTERS) in a district by ten percentage points is expected to directly increase the price by 0.12 to 0.15 cents. The results are significant and robust in all specifications reported in Tables C.1 and C.2. The population density (log POPDENS) in a district, however, does not have a significant direct impact on prices. The variable log PREMISES accounts for differences in costs across districts. An increase of the price for premises by one percent directly increases the price of gasoline by about one cent (0.82 to 1.36). This impact is also significantly different from zero in all specifications.[16] A number of dummy variables account for various characteristics of the locations of gasoline stations. The price at a station is expected to be lower by about 0.9 cents per liter if it is owned by the DEALER. Small stations (SMALL) tend to charge lower prices by about 0.2 cents compared to bigger stations. The coefficient of TRAFFIC indicates that prices are about 0.2 cents higher if the station is located along a road with heavy traffic. Stations offering attendance service (SERVICE) charge higher prices by about 0.8 cents compared to stations exclusively offering self service. The three major brands operating in Austria (BP, OMV and SHELL) charge significantly higher prices than unbranded stations. Some minor brands (AGIP, ARAL, ESSO and JET) also charge higher prices than unbranded stations.

Table C.3 reports regression results obtained from a model that includes a spatial autoregressive process in the error term. The model specification is the same as in equation (10), except that $\boldsymbol{\epsilon} = \lambda \boldsymbol{W}^{error} \boldsymbol{\epsilon} + \boldsymbol{\upsilon}$, instead of assuming $\boldsymbol{\epsilon}$ to be i.i.d. The

total effects include the direct effects and feedback effects due to spatial dependence. The partial derivatives of $\boldsymbol{\beta}$ correspond to the total effects and are equal to $(1 - \rho_1 - \rho_2)^{-1}\boldsymbol{\beta}$. See LeSage and Pace (2009) for details.

[16] For the districts I to IX and district XIX no prices for premises are available in our data. The dummy variable PREMISES N/A accounts for missing prices for premises in these districts. The coefficient is strong in magnitude and significance. However, this is not a surprise as the districts I to IX are very central districts in which prices of premises tend to be higher than in other districts. District XIX hosts some of the most exclusive neighborhoods of Vienna and thus premises can also be expected to be high.

model specifications [14] to [17] correspond to the basic configurations [1] to [4] (excpect for the inclusion of the spatial error process). The parameter estimate of λ is rougly 0.4, statistically significant and quite stable for all speficiations summarized in Table C.3. The estimated slope parameters on $\boldsymbol{WCp}$ are virtually unaffected in specification [15] and [16] (compared to model [2] and [3]) and increase in specification [17] (compared to model [4]). All parameter estimates of ρ_2 are statistically significant at the 1%-level. In contrast, the spatially weighted price of neigboring stations ignoring the centrality of stations, $\boldsymbol{Wp}$, does not have a statistically significant impact on stations' prices. The parameter estimates of centrality on the price levels are again not significantly different from zero.

[Table C.3]

As an additional robustness check we adress concerns that central locations might be characterized by particular locational attributes and that the more pronounced influence on local prices might come from these attributes rather then from the (direct) impact of the centrality on the intensity of price interaction. Table C.4 below shows some degree of correlation of our measures of centrality and some attributes of the station: Stations characterized by a high degree of centrality are more frequently located next to busier roads, are slightly more often controlled by major brands (BP, OMV and SHELL) and are also slightly more often dealer- rather than company-owned. Of course, the variables on centrality are negatively correlated with the distance to the next neighbor.

[Table C.4]

To show that the higher degree of spatial interaction from central staions comes from the stations' centrality rather than from other attributes, we interact the spatial weights matrix with a number of these characteristics that show a considerable amount of correlation with our measures of centrality. The matrices $\boldsymbol{M}^{Traffic}$,

$\boldsymbol{M}^{Brand}$ and $\boldsymbol{M}^{Company}$ are – similar to the matrix $\boldsymbol{C}$ – diagonal matrices. $m_{ii}^{Traffic}$ equals two if road traffic at the location is heavy and one otherwise. m_{ii}^{Brand} is set equal to three if a particular station is controlled by one of the major brands (OMV, BP or SHELL), two if diesel is sold under a minor brand, and one if the station is unbranded. $m_{ii}^{Company}$ equals two if the location is owned by a company and one if the location is owned by the dealer.[17] Therefore, locations characterized by heavy traffic flows, stations that are owned by major brands or by companies have higher weights, ceteris paribus, when interacting the spatial weights matrix $\boldsymbol{W}$ with $\boldsymbol{M}$.

The parameter estimates are summarized in Table C.5. Specification [18] only includes a spatially and centrally (applying the concept of degree centrality) lagged average price vector, $\boldsymbol{WC}^{dc}\boldsymbol{p}$. The spatially lagged price ($\boldsymbol{Wp}$) is left out, as the respective parameter estimate turns out to be insignificant (see specification [2] in Table 2). If we interact $\boldsymbol{W}$ with one of the matrices defined above, the parameter estimate on $\boldsymbol{WC}^{dc}\boldsymbol{p}$, ρ_2, remains positive and statistically significant throughout all models (specification [19] to [21]). The parameter estimates on the additional interaction terms, ρ_3, are also positive and significant for $\boldsymbol{WM}^{Brand}\boldsymbol{p}$ and $\boldsymbol{WM}^{Company}\boldsymbol{p}$ (specification [20] and [21]), but statistically insignificant for $\boldsymbol{WM}^{Traffic}\boldsymbol{p}$ (model [19]). If we also include a spatial process in the residuals (specification [22] to [25]), ρ_2 remains quite stable in size and is again positive and statistically significant in all models. In contrast, all parameter estimates on $\boldsymbol{WMp}$ are statistically insignificant. We thus conclude that the inclusion of additional interaction effects does not affect the main conclusion of our analysis: the strategic interaction between competitors is significantly related to their degree of centrality.

[Table C.5]

[17] Setting the 'reference categories' (i.e. low traffic, unbranded or dealer-owned stations) to zero rather than one means that prices of these stations have no impact on other stations' prices at all, which seems rather implausible. Consequently, reducing all diagonal elements of the $\boldsymbol{M}$-matrices by one does not give significant parameter estimates on any variable $\boldsymbol{WMp}$, while leaving the effect of $\boldsymbol{WC}^{dc}\boldsymbol{p}$ hardly unaffected. These estimation results are not reported in the text but available from the authors upon request.

Figure 1: A stylized network of firms

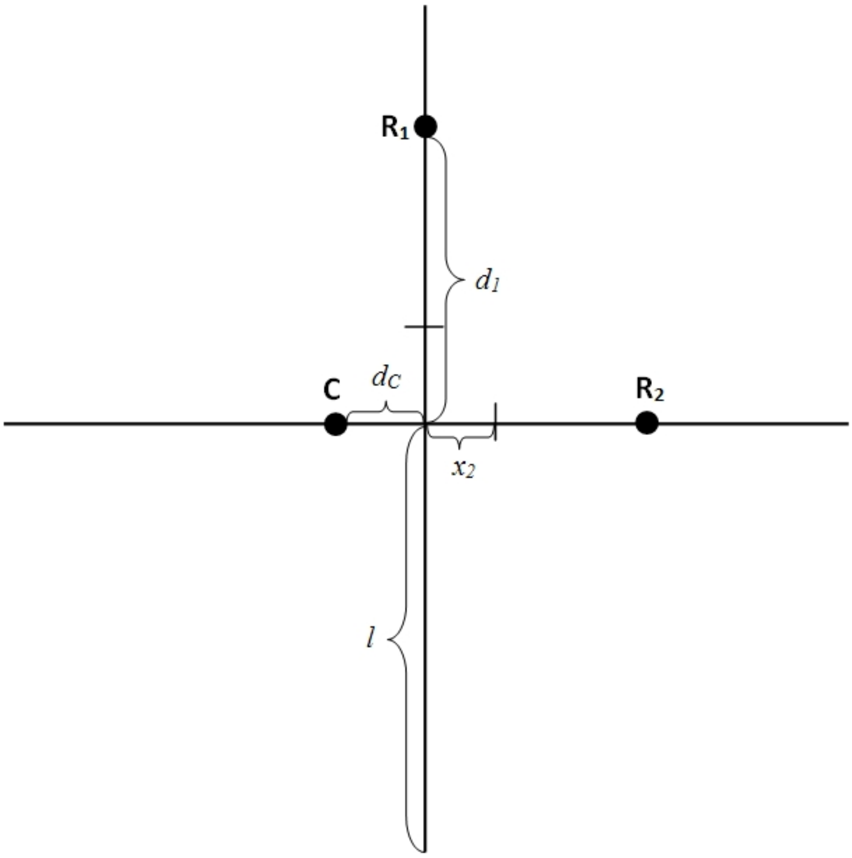

Figure 2: The impact of a price shock on the initiator by centrality

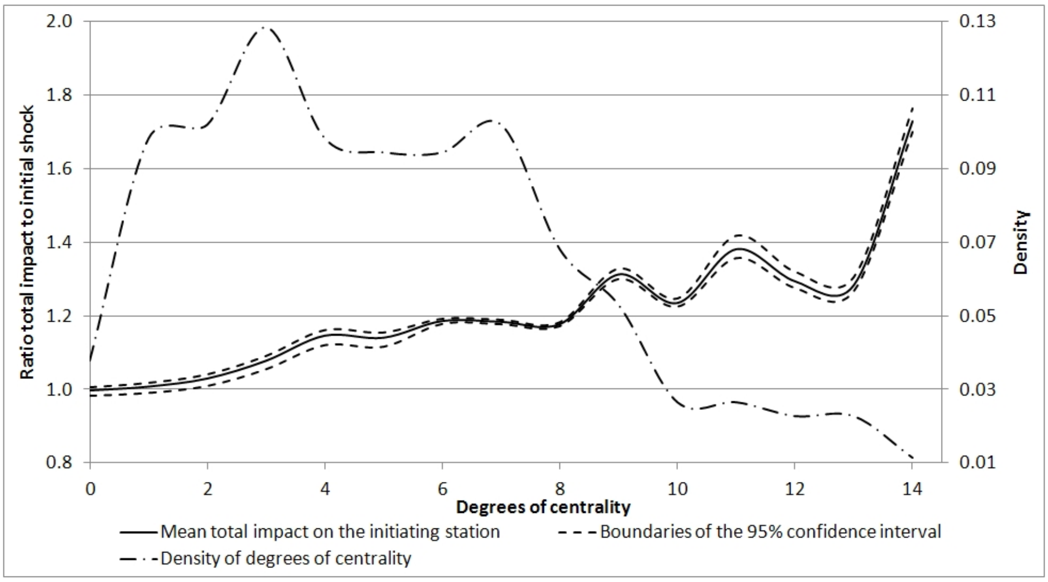

Figure 3: The impact of a price shock on other stations by centrality

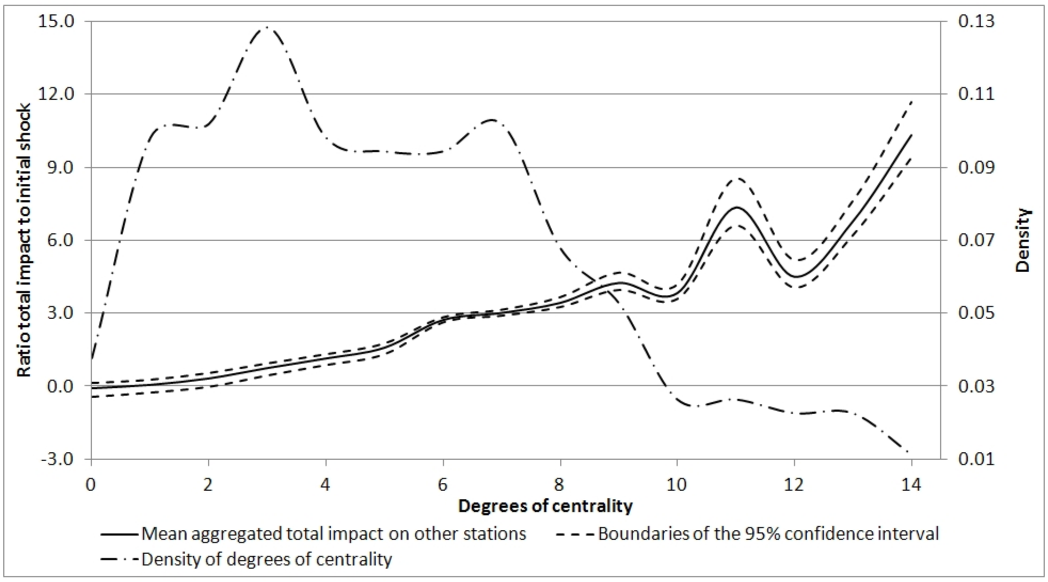

Figure B.1: Example of a network

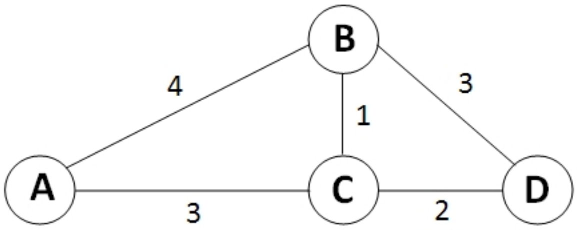

Table 1: Definition and descriptive statistics of the variables

		Mean Std. Dev.	Min Max
Dependent Variable			
PRICE	Price of one liter diesel in Euro cents	75.515 6.449	62.426 92.900
Centrality measures			
DEGREE (*dc*)	Degree centrality for $H = 5$	5.915 3.399	0 17
WEIGHTED (*wdc*)	Weighted degree centrality for $H = 5$	16.897 9.675	0 47
CLOSENESS (*cc*)	Closeness centrality for $H = 5$	1.136 0.561	0 3.137
Location characteristics			
DISTANCE NEXT	Driving time to the nearest neighbor in minutes	1.668 0.980	0.050 4.680
COMMUTERS	Ratio incoming plus outgoing commuters to population in percent on a district level	43.897 5.680	34.942 78.071
log POP DENS	Log of the population density of the district in inhabitants per square km	8.495 0.804	7.196 10.127
log PREMISES	Log of the average land price for premises in the district in Euros per square meter	0.167 0.373	0 5.638
TRAFFIC	Dummy variable set equal to one if road traffic at the location is heavy	0.768	0 1
DEALER	Dummy variable set equal to one if the location is owned by the dealer	0.210	0 1
SERVICE	Dummy variable set equal to one if the location offers attendance service	0.334	0 1
SMALL	Dummy variable set equal to one if the ground surface of the site is $< 800m^2$	0.287	0 1
Dummies for missing at random variables			
MISS PREMISES	Dummy variable set equal to one if information on prices for premises is missing	0.167	0 1
MISS OWNER	Dummy variable set equal to one if information on ownership is missing	0.033	0 1
MISS SERVICE	Dummy variable set equal to one if information on attendance service is missing	0.053	0 1
MISS SIZE	Dummy variable set equal to one if information on the ground surface is missing	0.011	0 1
Fixed effects			
Brands	9 brands, unbranded stations left out as a reference group		
Time Periods	22 periods, first period left out as a reference group		
# of observations: 3,051			

Table 2: Regression output of the ML-estimations of gasoline prices

Dependent variable: PRICE								
Specification	[1]		[2]		[3]		[4]	
Centrality	None		Degree		Weighted		Closeness	
Variables	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
$\boldsymbol{Wp}$	0.632	0.013***	-0.044	0.114	0.130	0.120	0.370	0.130***
$\boldsymbol{WC}^{dc}\boldsymbol{p}$			0.680	0.113***				
$\boldsymbol{WC}^{wdc}\boldsymbol{p}$					0.504	0.119***		
$\boldsymbol{WC}^{cc}\boldsymbol{p}$							0.263	0.129**
CONSTANT	18.223	1.735***	17.101	1.748***	17.240	1.750***	17.806	1.767***
DEGREE (dc)			0.010	0.008				
WEIGHTED (wdc)					0.005	0.003*		
CLOSENESS (cc)							-0.060	0.057
Locational characteristics	yes		yes		yes		yes	
Brand fixed effects	yes		yes		yes		yes	
Time period fixed effects	yes		yes		yes		yes	
ℓ	-4,428.272		-4,409.280		-4,417.770		-4,425.682	
σ^2	1.851		1.852		1.856		1.854	
LR-Test of specification [1] against [2] to [4]			37.984		21.005		5.180	
p-value ($\chi^2, df = 2$)			0.000		0.000		0.075	

# of observations: 3,051; *** significant at 1%, ** significant at 5%, * significant at 10%;
Centrality measures based on $H = 5$;
Construction of $\boldsymbol{W}$: Squared inverse of driving time to neighbors within 5min driving time;

Table B.1: Descriptive statistics of the centrality measures

Centrality (H)	Mean	Std. Dev.	Min	Max
dc (5)	5.256	3.712	0.000	21.000
wdc (5)	15.242	10.663	0.000	55.000
cc (5)	0.982	0.660	0.000	3.220
dc (2)	1.960	1.575	0.000	7.000
wdc (2)	2.934	2.394	0.000	13.000
cc (2)	0.976	0.770	0.000	4.020
dc (10)	10.982	7.740	0.000	42.000
wdc (10)	58.700	39.967	0.000	216.000
cc (10)	0.992	0.618	0.000	3.140
# of gasoline stations: 273				

Table B.2: Correlation of the centrality measures

	dc (5)	*wdc* (5)	*cc* (5)	*dc* (2)	*wdc* (2)	*cc* (2)	*dc* (10)	*wdc* (10)	*cc* (10)
dc (5)	1.000	0.975	0.865	0.806	0.830	0.801	0.890	0.955	0.814
wdc (5)	0.975	1.000	0.878	0.887	0.899	0.863	0.890	0.958	0.820
cc (5)	0.865	0.878	1.000	0.762	0.810	0.880	0.843	0.881	0.960
dc (2)	0.806	0.887	0.762	1.000	0.961	0.900	0.766	0.829	0.699
wdc (2)	0.830	0.899	0.810	0.961	1.000	0.956	0.850	0.885	0.743
cc (2)	0.801	0.863	0.880	0.900	0.956	1.000	0.839	0.865	0.819
dc (10)	0.890	0.890	0.843	0.766	0.850	0.839	1.000	0.977	0.855
wdc (10)	0.955	0.958	0.881	0.829	0.885	0.865	0.977	1.000	0.865
cc (10)	0.814	0.820	0.960	0.699	0.743	0.819	0.855	0.865	1.000
# of gasoline stations: 273									

Table B.3: Centrality in the network example

	dc	wdc	cc
A	0	0	0
B	3	4	1.4677
C	3	6	2.2323
D	2	2	0.3000

Table C.1: Results of the ML-estimations of gasoline prices (full table I)

Dependent variable: PRICE																					
Specification	[1]			[2]			[3]			[4]			[5]			[6]			[7]		
Ciritical distance in $\boldsymbol{W}$	5 min			5 min			5 min			5 min			5 min			5 min			5 min		
Inverse of distance in $\boldsymbol{W}$	Squared			Squared			Squared			Squared			Squared			Squared			Squared		
Centrality (H)	None			Degree (5)			Weighted (5)			Closeness (5)			Degree (5)^{a}			Weighted (5)^{a}			Closeness (5)^{a}		
Variables	Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.	
$\boldsymbol{Wp}$	0.632	0.013	***	-0.044	0.114		0.130	0.120		0.370	0.130	***	0.465	0.030	***	0.474	0.030	***	0.474	0.030	***
$\boldsymbol{WC}^{dc}\boldsymbol{p}$				0.680	0.113	***							0.213	0.033	***						
$\boldsymbol{WC}^{wdc}\boldsymbol{p}$							0.504	0.119	***							0.202	0.034	***			
$\boldsymbol{WC}^{cc}\boldsymbol{p}$										0.263	0.129	**							0.201	0.034	***
CONSTANT	18.223	1.735	***	17.101	1.748	***	17.240	1.750	***	17.806	1.767	***	13.727	1.842	***	13.808	1.848	***	14.025	1.869	***
DEGREE				0.010	0.008								0.013	0.008							
WEIGHTED							0.005	0.003	*							0.006	0.003	*			
CLOSENESS										-0.060	0.057								-0.043	0.057	
DISTANCE	0.174	0.027	***	0.177	0.029	***	0.188	0.029	***	0.153	0.033	***	0.182	0.029	***	0.188	0.029	***	0.154	0.033	***
NEXT																					
COMMUTERS	0.014	0.006	**	0.012	0.006	**	0.012	0.006	**	0.014	0.006	**	0.013	0.006	**	0.013	0.006	**	0.014	0.006	**
log POPDENS	-0.001	0.042		-0.026	0.043		-0.018	0.043		-0.019	0.043		0.014	0.042		0.013	0.042		0.003	0.043	
log PREMISES	0.828	0.262	***	1.047	0.265	***	1.021	0.266	***	0.952	0.271	***	1.059	0.265	***	1.072	0.265	***	1.076	0.266	***
DEALER	-0.878	0.236	***	-0.892	0.236	***	-0.884	0.237	***	-0.896	0.237	***	-0.840	0.236	***	-0.843	0.237	***	-0.852	0.237	***
SMALL	-0.212	0.072	***	-0.203	0.072	***	-0.211	0.072	***	-0.211	0.072	***	-0.207	0.072	***	-0.205	0.072	***	-0.204	0.072	***
TRAFFIC	0.177	0.067	***	0.170	0.069	**	0.161	0.068	**	0.197	0.069	***	0.164	0.069	**	0.159	0.068	**	0.201	0.069	***
SERVICE	0.874	0.120	***	0.811	0.121	***	0.813	0.121	***	0.857	0.121	***	0.833	0.121	***	0.821	0.121	***	0.835	0.121	***
PREMISES N/A	4.728	1.400	***	5.943	1.416	***	5.787	1.420	***	5.411	1.449	***	5.933	1.414	***	6.001	1.416	***	6.022	1.420	***
DEALER N/A	-0.992	0.258	***	-1.063	0.260	***	-1.049	0.259	***	-0.994	0.259	***	-0.949	0.260	***	-0.950	0.259	***	-0.907	0.259	***
SIZE N/A	-0.176	0.294		-0.203	0.294		-0.191	0.294		-0.158	0.294		-0.274	0.294		-0.269	0.294		-0.248	0.294	
SERVICE N/A	1.479	0.195	***	1.527	0.196	***	1.508	0.195	***	1.479	0.196	***	1.463	0.196	***	1.453	0.195	***	1.432	0.196	***
BRAND_AGIP	1.097	0.273	***	1.101	0.273	***	1.107	0.273	***	1.052	0.274	***	1.160	0.273	***	1.157	0.273	***	1.102	0.273	***
BRAND_ARAL	2.322	0.333	***	2.246	0.334	***	2.281	0.334	***	2.251	0.335	***	2.284	0.334	***	2.289	0.334	***	2.234	0.335	***
BRAND_AVANTI	0.221	0.256		0.255	0.256		0.249	0.256		0.201	0.256		0.320	0.256		0.315	0.256		0.291	0.257	
BRAND_BP	1.817	0.260	***	1.754	0.260	***	1.769	0.261	***	1.781	0.261	***	1.856	0.260	***	1.846	0.260	***	1.832	0.260	***
BRAND_ESSO	1.182	0.273	***	1.095	0.273	***	1.106	0.274	***	1.132	0.274	***	1.194	0.273	***	1.178	0.273	***	1.182	0.273	***
BRAND_JET	0.549	0.295	*	0.526	0.296	*	0.548	0.296	*	0.494	0.297	*	0.592	0.296	**	0.589	0.296	**	0.525	0.297	*
BRAND_OMV	1.511	0.265	***	1.458	0.265	***	1.468	0.265	***	1.469	0.265	***	1.526	0.265	***	1.515	0.265	***	1.506	0.265	***
BRAND_SHELL	1.481	0.267	***	1.464	0.267	***	1.468	0.268	***	1.444	0.268	***	1.553	0.267	***	1.540	0.267	***	1.507	0.268	***
BRAND_STROH	0.186	0.243		0.113	0.244		0.140	0.244		0.156	0.244		0.227	0.243		0.229	0.243		0.229	0.243	
Time period fixed effects	yes			yes			yes			yes			yes			yes			yes		
# of Obs.		3,051			3,051			3,051			3,051			3,051			3,051			3,051	
ℓ		-4,428.272			-4,409.280			-4,417.770			-4,425.682			-4,406.697			-4,408.190			-4,409.948	
σ^2		1.851			1.852			1.856			1.854			1.852			1.853			1.854	
LR-test					37.984			21.005			5.180			43.149			40.164			36.648	
p-value ($\chi^2, df = 2$)					0.000			0.000			0.075			0.000			0.000			0.000	

*** significant at 1%, ** significant at 5%, * significant at 10%;
LR-tests of the respective nested specification without centrality (H0) against the particular H1;
[a] In [5] to [7] the centrality matrix is interacted with a $\boldsymbol{W}$ matrix containing zeros and ones only instead of distances;

Table C.2: Results of the ML-estimations of gasoline prices (full table II)

Dependent variable: PRICE																		
Specification	[8]			[9]			[10]			[11]			[12]			[13]		
Ciritical distance in $\boldsymbol{W}$	5 min			5 min			5 min			5 min			10 min			10 min		
Inverse of distance in $\boldsymbol{W}$	Squared			Squared			Single			Single			Squared			Squared		
Centrality (H)	Degree (2)			Degree (10)			None			Degree (5)			None			Degree (5)		
Variables	Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.	
$\boldsymbol{Wp}$	0.394	0.101	***	0.027	0.126		0.685	0.014	***	-0.012	0.109		0.780	0.014	***	0.212	0.137	
$\boldsymbol{WC}^{dc}\boldsymbol{p}$	0.239	0.100	**	0.607	0.126	***				0.698	0.108	***				0.564	0.135	***
$\boldsymbol{WC}^{wdc}\boldsymbol{p}$																		
$\boldsymbol{WC}^{cc}\boldsymbol{p}$																		
CONSTANT	17.851	1.740	***	16.812	1.765	***	13.878	1.791	***	12.331	1.804	***	6.349	1.789	***	6.143	1.795	***
DEGREE	0.035	0.018	*	0.003	0.004					0.014	0.008					0.005	0.008	
WEIGHTED																		
CLOSENESS																		
DISTANCE NEXT	0.188	0.029	***	0.178	0.030	***	0.165	0.028	***	0.180	0.029	***	0.119	0.025	***	0.124	0.026	***
COMMUTERS	0.013	0.006	**	0.014	0.006	**	0.015	0.006	***	0.011	0.006	**	0.016	0.005	***	0.013	0.005	**
log POPDENS	-0.009	0.043		-0.024	0.043		0.023	0.043		-0.004	0.043		-0.006	0.041		-0.027	0.041	
log PREMISES	0.893	0.263	***	1.108	0.269	***	0.925	0.265	***	1.267	0.270	**	1.226	0.254	***	1.368	0.257	***
DEALER	-0.869	0.237	***	-0.859	0.237	***	-0.826	0.239	***	-0.852	0.239	***	-1.047	0.219	***	-1.049	0.219	***
SMALL	-0.199	0.072	***	-0.203	0.072	***	-0.219	0.073	***	-0.210	0.072	***	-0.189	0.068	***	-0.189	0.068	***
TRAFFIC	0.161	0.067	**	0.174	0.068	**	0.200	0.068	***	0.183	0.069	***	0.171	0.064	***	0.176	0.066	***
SERVICE	0.816	0.122	***	0.831	0.121	***	0.824	0.122	***	0.798	0.122	***	0.865	0.117	***	0.829	0.117	***
PREMISES N/A	5.087	1.406	***	6.247	1.437	***	5.196	1.417	***	7.072	1.441	***	6.798	1.359	***	7.602	1.373	***
DEALER N/A	-0.972	0.259	***	-1.036	0.259	***	-0.826	0.261	***	-0.954	0.262	***	-0.954	0.253	***	-1.003	0.254	***
SIZE N/A	-0.162	0.294		-0.203	0.294		-0.328	0.297		-0.344	0.297		-0.324	0.291		-0.313	0.291	
SERVICE N/A	1.437	0.196	***	1.510	0.196	***	1.391	0.197	***	1.496	0.198	***	1.477	0.186	***	1.497	0.186	***
BRAND_AGIP	1.094	0.273	***	1.071	0.275	***	1.128	0.276	***	1.163	0.276	***	0.920	0.246	***	0.920	0.246	***
BRAND_ARAL	2.308	0.334	***	2.247	0.335	***	2.272	0.337	***	2.226	0.337	***	2.017	0.317	***	1.987	0.317	***
BRAND_AVANTI	0.253	0.256		0.234	0.256		0.354	0.259		0.370	0.258		0.021	0.238		0.029	0.238	
BRAND_BP	1.790	0.261	***	1.768	0.261	***	1.865	0.263	***	1.825	0.263	***	1.580	0.241	***	1.547	0.241	***
BRAND_ESSO	1.150	0.273	***	1.122	0.273	***	1.227	0.276	***	1.142	0.276	***	0.963	0.254	***	0.900	0.255	***
BRAND_JET	0.554	0.296	*	0.509	0.297	*	0.549	0.299	*	0.572	0.299	*	0.271	0.275		0.268	0.276	
BRAND_OMV	1.482	0.265	***	1.479	0.265	***	1.531	0.268	***	1.502	0.267	***	1.309	0.245	***	1.278	0.246	***
BRAND_SHELL	1.457	0.268	***	1.477	0.268	***	1.545	0.270	***	1.551	0.270	***	1.288	0.248	***	1.290	0.248	***
BRAND_STROH	0.183	0.243		0.130	0.244		0.291	0.246		0.187	0.246		0.028	0.230		-0.002	0.230	
Time period fixed effects	yes			yes			yes			yes			yes			yes		
# of Obs.		3,051			3,051			3,051			3,051			3,188			3,188	
ℓ		-4,423.672			-4,416.161			-4,433.833			-4,411.083			-4,571.913			-4,562.817	
σ^2		1.853			1.855			1.896			1.888			1.818			1.819	
LR-test		9.199			24.222						45.501						18.192	
p-value ($\chi^2, df = 2$)		0.010			0.000						0.000						0.000	

*** significant at 1%, ** significant at 5%, * significant at 10%;
LR-tests of the respective nested specification without centrality (H0) against the particular H1;

Table C.3: Results of the ML-estimations of gasoline prices including spatial dependence in the rediduals

Dependent variable: PRICE												
Specification	[14]			[15]			[16]			[17]		
Ciritical distance in $\boldsymbol{W}$ and $\boldsymbol{W}^{error}$	5 min			5 min			5 min			5 min		
Inverse of distance in $\boldsymbol{W}$	Squared			Squared			Squared			Squared		
Elements in $\boldsymbol{W}^{error}$	Binary			Binary			Binary			Binary		
Centrality (H)	Degree (5)			Degree (5)			Degree (5)			Degree (5)		
Variables	Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.		Coef	Std.Err.	
$\boldsymbol{Wp}$	0.435	0.018	***	-0.164	0.122		-0.048	0.129		-0.0277	0.1457	
$\boldsymbol{WC}^{dc}\boldsymbol{p}$				0.625	0.122	***						
$\boldsymbol{WC}^{wdc}\boldsymbol{p}$							0.497	0.129	***			
$\boldsymbol{WC}^{cc}\boldsymbol{p}$										0.463	0.145	***
$\boldsymbol{W}^{error}\boldsymbol{\epsilon}$	0.432	0.023	***	0.400	0.024	***	0.416	0.023	***	0.437	0.024	***
CONSTANT	30.290	2.437	***	28.190	2.378	***	28.961	2.416	***	29.692	2.518	***
DEGREE				0.013	0.008							
WEIGHTED							0.004	0.003				
CLOSENESS										-0.061	0.055	
DISTANCE NEXT	0.150	0.027	***	0.160	0.029	***	0.164	0.029	***	0.125	0.033	***
COMMUTERS	0.028	0.007	***	0.025	0.007	***	0.026	0.007	***	0.029	0.007	***
log POPDENS	-0.041	0.052		-0.059	0.052		-0.055	0.052		-0.064	0.053	
log PREMISES	0.972	0.362	***	1.085	0.353	***	1.073	0.358	***	1.131	0.367	***
DEALER	-0.605	0.237	**	-0.638	0.237	***	-0.624	0.237	***	-0.619	0.237	***
SMALL	-0.247	0.071	***	-0.244	0.071	***	-0.253	0.071	***	-0.244	0.071	***
TRAFFIC	0.237	0.067	***	0.210	0.069	***	0.211	0.069	***	0.253	0.069	***
SERVICE	0.844	0.119	***	0.792	0.119	***	0.795	0.119	***	0.813	0.119	***
PREMISES N/A	5.400	1.930	***	6.070	1.882	***	5.981	1.909	***	6.267	1.956	***
DEALER N/A	-0.772	0.258	***	-0.846	0.259	***	-0.824	0.259	***	-0.777	0.259	***
SIZE N/A	-0.339	0.285		-0.342	0.286		-0.347	0.286		-0.337	0.285	
SERVICE N/A	1.354	0.194	***	1.398	0.195	***	1.381	0.194	***	1.360	0.194	***
BRAND_AGIP	1.368	0.270	***	1.352	0.270	***	1.360	0.270	***	1.313	0.270	***
BRAND_ARAL	2.408	0.329	***	2.341	0.329	***	2.357	0.329	***	2.309	0.330	***
BRAND_AVANTI	0.617	0.258	**	0.623	0.258	**	0.629	0.259	**	0.603	0.258	**
BRAND_BP	2.136	0.261	***	2.056	0.261	***	2.078	0.261	***	2.090	0.261	***
BRAND_ESSO	1.495	0.274	***	1.404	0.274	***	1.422	0.275	***	1.436	0.274	***
BRAND_JET	0.725	0.292	**	0.696	0.293	**	0.715	0.292	**	0.653	0.293	**
BRAND_OMV	1.806	0.263	***	1.728	0.263	***	1.749	0.264	***	1.747	0.263	***
BRAND_SHELL	1.803	0.268	***	1.752	0.268	***	1.767	0.269	***	1.757	0.269	***
BRAND_STROH	0.501	0.244	**	0.417	0.244	*	0.452	0.244	*	0.459	0.244	*
Time period fixed effects	yes			yes			yes			yes		
# of Obs.		3,051			3,051			3,051			3,051	
ℓ		-4,389.884			-4,375.899			-4,381.287			-4,384.2361	
σ^2		1.901			1.894			1.899			1.8995	
LR-test					27.970			17.194			11.296	
p-value ($\chi^2, df = 1$)					0.000			0.000			0.001	

*** significant at 1%, ** significant at 5%, * significant at 10%;
LR-tests of the respective nested specification without centrality (H0) against the particular H1;

Table C.4: Correlation of centrality measures and location characteristics

	$dc(5)$	$wdc(5)$	$cc(5)$	TRAFFIC	MAJOR	MINOR	DEALER	DISTANCE NEXT
dc (5)	1.0000	0.9750	0.9071	0.1758	0.0393	-0.0252	0.0210	-0.2997
wdc (5)	0.9750	1.0000	0.9059	0.1758	0.0358	-0.0249	0.0315	-0.3075
cc (5)	0.9071	0.9059	1.0000	0.1872	0.0369	-0.0290	0.0043	-0.3767
TRAFFIC	0.1758	0.1739	0.1872	1.0000	0.2932	-0.0277	-0.3939	-0.1282
MAJOR	0.0393	0.0358	0.0369	0.2932	1.0000	-0.6949	-0.4146	0.0203
MINOR	-0.0252	-0.0249	-0.0290	-0.0227	-0.6949	1.0000	-0.2500	-0.0436
DEALER	0.0210	0.0315	0.0043	-0.3939	-0.4146	-0.2500	1.0000	0.0347
DISTANCE_NEXT	-0.2997	-0.3075	-0.3767	-0.1282	0.0203	-0.0436	0.0347	1.0000

Table C.5: Regression output of the ML-estimations of gasoline prices controlling for various characteristics of stations

Dependent variable: PRICE																								
Specification	[18]			[19]			[20]			[21]			[22]			[23]			[24]			[25]		
Centrality	Degree			Degree			Degree			Degree			Degree			Degree			Degree			Degree		
Variables	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
$\boldsymbol{WC}^{dc}\boldsymbol{p}$	0.632	0.013	***	0.587	0.113	***	0.286	0.086	***	0.308	0.097	***	0.464	0.017	***	0.557	0.123	***	0.423	0.097	***	0.385	0.107	***
$\boldsymbol{WM}^{Traffic}\boldsymbol{p}$				0.050	0.113											-0.096	0.123							
$\boldsymbol{WM}^{Brand}\boldsymbol{p}$							0.355	0.086	***										0.047	0.097				
$\boldsymbol{WM}^{Company}\boldsymbol{p}$										0.331	0.097	***										0.085	0.107	
$\boldsymbol{W}^{error}\boldsymbol{\epsilon}$													0.397	0.024	***	0.400	0.024	***	0.389	0.024	***	0.388	0.024	***
CONSTANT	18.018	1.742	***	17.160	1.750	***	18.038	1.752	***	17.859	1.753	***	28.079	2.367	***	28.091	2.379	***	27.888	2.355	***	27.919	2.352	***
DEGREE	0.011	0.008		0.010	0.008		0.010	0.008		0.010	0.008		0.013	0.008		0.013	0.008		0.013	0.008		0.012	0.008	
Locational characteristics	yes			yes			yes			yes			yes			yes			yes			yes		
Brand fixed effects	yes			yes			yes			yes			yes			yes			yes			yes		
Time period fixed effects	yes			yes			yes			yes			yes			yes			yes			yes		
ℓ	-4,427.486			-4,409.256			-4,400.983			-4,403.575			-4,376.804			-4,376.503			-4,376.706			-4,376.509		
σ^2		1.851			1.848			1.826			1.829			1.890			1.893			1.889			1.887	
LR-Test					36.460			53.007			47.822						0.603			0.197			0.590	
p-value ($\chi^2, df = 1$)					0.000			0.000			0.000						0.437			0.657			0.442	

# of observations: 3,051; *** significant at 1%, ** significant at 5%, * significant at 10%;
LR-tests of the respective nested specification without spatila lag based on (non-spatial) station characteristics (H0) against the particular H1;