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Network Centrality and Market Prices: An Empirical Note*

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Abstract

We empirically investigate the importance of centrality (holding a central position in a spatial network) for strategic interaction in pricing for the Austrian retail gasoline market. Results from spatial autoregressive models suggest that the gasoline station located most closely to the market center – defined as the 1-median location – exerts the strongest effect on pricing decisions of other stations. We conclude that centrality influences firms' pricing behavior and further find that the importance of centrality increases with market size.

Keywords: Network Centrality, Spatial Competition, Retail Markets, Gasoline Prices
JEL code: C21, D43, L11, L81, R12

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1 Introduction and Background

The theory of social networks has provided a number of important insights for explaining social phenomena in a wide variety of disciplines from psychology to economics (Borgatti et al., 2009). It is a fundamental axiom in social network research that the centrality of a node's position within a network determines the opportunities and constraints that it encounters and thus plays an important role in determining a node's power to influence other nodes and the network as a whole (Ballester et al., 2006, 2010; Bramoullé et al., 2014; Helsley and Zenou, 2014).

This paper contributes to a growing body of research on networks in industrial organization by investigating the importance of centrality for firms' pricing behavior empirically. While textbook models on spatial markets typically make strong symmetry assumptions, recent theoretical work in industrial organization devotes more attention to firm heterogeneity and the implications of specific positions within a network for firm performance. Vogel (2008), for example, studies location decisions of firms that differ in their marginal costs. In equilibrium, more efficient firms will be more isolated and will set higher markups (because their competitors offer relatively poor substitutes). In Braid (2013) and Firgo et al. (2015) firms are located in a network of links and nodes that can be interpreted as roads and intersections. Both papers argue that 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.

In networks with spatial patterns similar to a star graph, Freeman (1979) shows that the centrality of the central node relative to remote nodes increases monotonically with the number of nodes, which holds for a number of different concepts of centrality. This suggests that the importance of a central supplier relative to remote firms in a pricing game increases with the number of firms in a local market.

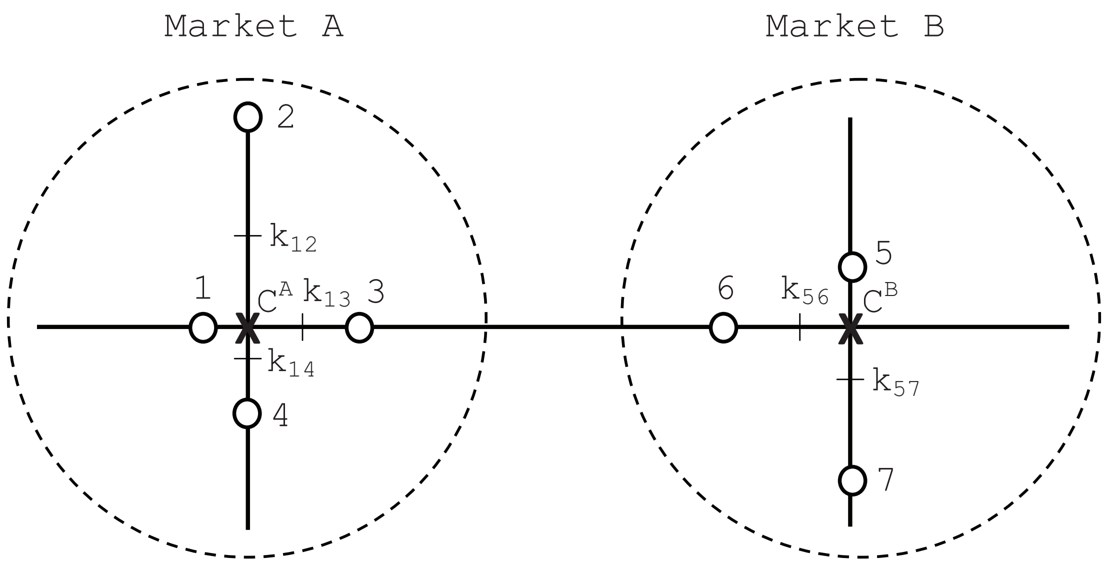
The following simple example illustrates the importance of centrality in firms' price interactions and outlines our contribution to the (scarce) empirical literature. Assume that seven firms (nodes) are located in a network of roads (edges) as in Figure 1. Firms 1 to 4 are assigned to market A, firms 5 to 7 to market B.[1] Using standard assumptions in spatial competition models with respect to product characteristics, production costs and consumer behavior, this simple network suggests that firms 1 and 5 will have a more 'central' position in their markets than all other firms. Centrality, defined as the extent to which agents are connected to other agents, provides these two firms with a dominant role in strategic price interactions between

[1] The definition of markets will be discussed in more detail later.

firms. In market A (B), firm 1 (5) competes for the same marginal consumer $k_{1,j}$ ($k_{5,j}$) with all other j firms in this market. In contrast, the 'remote' firms (2, 3, and 4 as well as 6 and 7) compete for the same marginal consumer with the 'central' supplier only, but do not compete directly with other remote firms within their market. In their pricing decisions, remote firms will thus consider only the price charged by the central firm, but not the prices charged by other remote firms. The central firm, on the other hand, takes the prices charged by all other firms in the local market into account. Therefore, centrality endows the central supplier with a dominant role in strategic price interactions between firms in the respective local market: In their own pricing decisions remote firms will consider only the price charged by the central supplier, but not other remote firms' prices.

There is only very little empirical work on the importance of centrality in firms' pricing decisions.[2] In the remainder of the article we explore empirically whether central suppliers indeed play a more prominent role in pricing games in the Austrian retail gasoline market.

Figure 1: Centrality on intersecting roads



Notes: The solid lines denote the road network, the white dots the firms, and the centers of the local markets are labeled by **X**. k_{ij} indicates the location of the marginal consumer (for particular prices and transportation costs) indifferent between purchasing at firm i or firm j, and the dashed lines denote the local market boundaries.

[2]Firgo et al. (2015) assign different degrees of centrality to each supplier. The present paper is more closely related to a star-shaped graph which implies a dichotomous distinction between one central supplier and (all other) remote firms.

2 Data and Identification of Market Centers

The empirical application is based on data for the geographical locations of the complete population of gasoline stations in Austria collected by the company Catalist in August 2003. Using the software ArcGIS, the geographical coordinates of each gasoline station are located and plotted on a map. The routing tool WiGeoNetwork by WiGeoGIS calculates distances between all gasoline stations. To account for differences in speed limits and one-way roads, all distances are measured in driving time.These spatial data are merged with an unbalanced panel of station-level pricing data collected and provided by the Austrian Chamber of Labor nationwide on a particular day every three months between October 1999 and March 2005 for a total of 23 points in time. These data are supplemented by Catalist data on station characteristics and regional data by Statistics Austria.

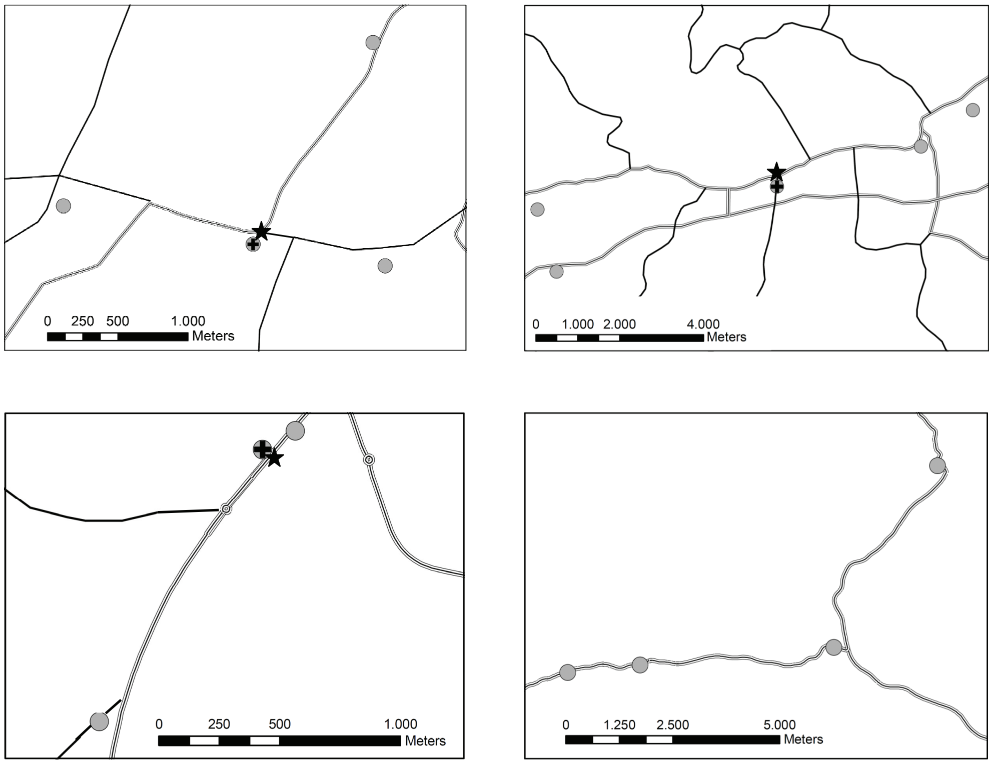
We follow Pinkse et al. (2002) and define markets via nearest-neighbor-relations. Each observation is connected to its spatially nearest neighbor, and all stations are considered to be in the same local market as long as they are connected by nearest-neighbor-relations. Applying this market definition all 2,814 gasoline stations are assigned to 761 non-overlapping local markets.[3]

The market center is defined as the unique point which minimizes the sum of distances to all gasoline stations in the local market (i.e. the 1-median location; see Hakimi, 1964). Potential market centers are restricted to points located on the road network. In Figure 1, C^A and C^B represent the market centers for markets A and B. The central supplier (firm 1 in market A and firm 5 in market B) is the station located most closely to the market center, while all other stations are denoted as remote suppliers. Using actual data for the Austrian retail gasoline market, Figure 2 illustrates four different local markets, their road networks, gasoline stations and market centers.

Observations are included in the empirical analysis only if prices are observed for all stations in the respective local market in a particular time period, which reduces the size of the initial sample to 501 stations in 171 local markets. We further exclude observations in 79 markets where a unique central position cannot

[3]In Figure 1, for example, this approach defines two separate markets, comprising firms 1 to 4 and firms 5 to 7, respectively. The fact that this implies no interaction between local markets is a reasonable assumption in our application. In our sample, the average driving time to the closest station outside the respective local market is 4.3 minutes longer than the shortest (and 1.7 minutes longer than the average) distance to rivaling firms within the local market. This suggests that local markets (as defined by nearest-neighbor-relations) are only loosely related to other local markets.

Figure 2: Empirical examples of local markets and their centers



Notes: Each map represents a local market. Gasoline stations are marked by gray dots, the market centers by stars and the central stations by plus signs. Major (minor) roads are depicted by triple (single) lines.

be identified.[4] Eventually, the empirical analysis is based on an unbalanced panel of 343 stations in 92 different markets comprising three to six competitors (2,920 observations in total). Summary statistics are provided in Table 1:[5] PRICE denotes nominal retail prices of diesel[6] measured in Euro-cents per liter, CENTRAL is a dummy variable indicating whether a particular station is the central supplier, and DIST TO CENTER measures the driving time (in minutes) from the gasoline station to the local market center.

[4]In 'linear city' (Hotelling, 1929) markets with an even number of firms, a unique (1-median) central location does not exist.

[5]The definition of all other variables and summary statistics related to them are reported in Appendix A (available online).

[6]Unlike in North America, diesel-engined vehicles are most popular in Austria, accounting for more than 50% of registered passenger vehicles in 2005 (Statistics Austria, 2006).

Table 1: Summary statistics

Variable	Mean	(S.D.)	Min.	Max.	# of Obs.
PRICE	75.600	(6.423)	61.900	92.000	2,920
CENTRAL	0.268	(0.443)	0	1	2,920
DIST TO CENTER	2.468	(3.660)	0	23.640	2,920

3 Model Specification and Results

The following econometric model has frequently been estimated to account for spatial interactions in pricing between neighboring firms (Pennerstorfer, 2009).

$$\boldsymbol{p} = \rho \boldsymbol{W} \boldsymbol{p} + \boldsymbol{X} \beta + \epsilon, \tag{1}$$

with $\boldsymbol{p}$ as the vector of prices. $\boldsymbol{W}$ is a spatial weights matrix of dimension $N \times N$ (N is the total number of observations) and summarizes the dependence structure between gasoline station i at time t and station j at time u. The typical element $w_{it,ju} = 1$ if stations i and j are in the same local market, $i \neq j$ and $t = u$, and zero else. $\boldsymbol{X}$ includes station- and location-specific characteristics, time period fixed effects as well as dummy variables for each local market, with $\boldsymbol{\beta}$ as the respective vector of parameters to be estimated and $\boldsymbol{\epsilon}$ as the error term. Parameter ρ measures the pricing interaction between neighboring gasoline stations.

This model, however, does not allow measuring differences in the importance of central and remote suppliers in pricing interactions. To explore such differences explicitly, we extend this model in various ways. First, we explore whether the intensity of price interaction between pairs of stations changes with market size:

$$\boldsymbol{p} = \sum_{s=3}^{6} \boldsymbol{M}_s \left(\rho_s \boldsymbol{W} \boldsymbol{p}\right) + \boldsymbol{X} \beta + \epsilon. \tag{2}$$

The size of the market (i.e. the number of stations within a market) is denoted by s ($s = 3, ..., 6$). $\boldsymbol{M}_s$ is a diagonal matrix of dimension $N \times N$ with $m_{s,it,it} = 1$ if station i is located in a market of size s, and 0 else. As the effect of one station's decision on other stations' decisions is expected to diminish as the number of stations in a local market increases (Barron et al., 2008), separate parameters (ρ_s) are estimated for markets with different numbers of stations.

Second, to explore whether interaction in pricing between stations depends on the stations' positions within the network (centrality), we estimate the following model:

$$\boldsymbol{p} = \sum_{s=3}^{6} \boldsymbol{M}_s \left(\rho_s^{C\to R}\boldsymbol{WCp} + \rho_s^{R\to C}\boldsymbol{CWp} + \rho_s^{R\to R}\boldsymbol{RWRp}\right) + \boldsymbol{X\beta} + \boldsymbol{\epsilon}. \quad (3)$$

$\boldsymbol{C}$ ($\boldsymbol{R}$) is a diagonal matrix with element $c_{it,it} = 1$ ($r_{it,it} = 1$) if station i is a central (remote) supplier, and 0 else. Parameter $\rho^{C\to R}$ can be interpreted as the effect of the price of a central supplier on a remote competitor within the same local market (i.e. $\rho^{C\to R} = \frac{\partial p_{it}}{\partial p_{jt}}$ for station i as a remote and station j as the central supplier), $\rho^{R\to C}$ as the effect of a remote supplier's price on the central supplier's price (i.e. $\rho^{R\to C} = \frac{\partial p_{it}}{\partial p_{jt}}$ for station i as the central supplier and station j as a remote supplier), and $\rho^{R\to R}$ as pricing interaction between two remote suppliers (i.e. $\rho^{R\to R} = \frac{\partial p_{it}}{\partial p_{jt}}$ for both station $i \neq j$ as remote suppliers). If gasoline stations located most closely to a market center actually exert the strongest effect on pricing decisions of other stations, we would expect to find $\rho_s^{C\to R} > \rho_s^{R\to C}$ and $\rho_s^{C\to R} > \rho_s^{R\to R}$.

Clearly, competitor prices on the right hand side of equations (2) and (3) are endogenous and OLS will produce biased results. As a common solution in applied spatial econometrics the reduced form of the regression equation is estimated via maximum likelihood (see Anselin, 2001 for an overview). Cost shocks over time, which are common to all stations (such as fluctuations of crude oil prices), are captured by fixed time effects. Spatial autocorrelation due to differences in local demand or costs across markets are controlled for by local market-level fixed effects.

Results from the benchmark specification (equation (2)) are reported in column [1] of Table 2. This model does not allow for asymmetries and restricts the parameters such that $\rho_s^{C\to R} = \rho_s^{R\to C} = \rho_s^{R\to R} = \rho_s$. All parameter estimates for ρ_s are significantly positive; a higher price charged by one station is associated with higher prices of rival stations within the same local market. In addition, column [1] clearly suggests that the interaction in pricing between neighboring stations (ρ_s) becomes smaller as the number of stations (s) increases.

Column [2] in Table 2 reports parameter estimates of the model in which the pricing interaction parameters ρ_s are allowed to differ between central and remote suppliers (equation (3)). In small markets (with three stations only; $s = 3$) our results suggest that there is hardly any difference in the parameters ρ_s between central and remote stations. The two-sample t-tests reported in Table 3 indicate that none of the null hypotheses $\rho_3^{C\to R} = \rho_3^{R\to C}$, $\rho_3^{C\to R} = \rho_3^{R\to R}$ and $\rho_3^{R\to C} = \rho_3^{R\to R}$ can be rejected at any reasonable level of significance. Thus, centrality does not seem to matter in small markets.

Table 2: Results of the maximum likelihood estimations

Specification	[1]			[2]		
	Coef.	(S.D.)	Sign.	Coef.	(S.D.)	Sign.
ρ_3	0.317	(0.005)	***			
ρ_4	0.212	(0.004)	***			
ρ_5	0.166	(0.003)	***			
ρ_6	0.131	(0.004)	***			
$\rho_3^{C\to R}$				0.306	(0.033)	***
$\rho_3^{R\to C}$				0.311	(0.006)	***
$\rho_3^{R\to R}$				0.335	(0.032)	***
$\rho_4^{C\to R}$				0.288	(0.029)	***
$\rho_4^{R\to C}$				0.207	(0.004)	***
$\rho_4^{R\to R}$				0.177	(0.015)	***
$\rho_5^{C\to R}$				0.438	(0.002)	***
$\rho_5^{R\to C}$				0.163	(0.004)	***
$\rho_5^{R\to R}$				0.079	(0.001)	***
$\rho_6^{C\to R}$				0.403	(0.103)	***
$\rho_6^{R\to C}$				0.127	(0.004)	***
$\rho_6^{R\to R}$				0.061	(0.027)	**
CONSTANT	29.682	(1.269)	***	29.017	(1.303)	***
CENTRAL	0.238	(0.162)		1.674	(0.822)	**
DIST TO CENTER	0.039	(0.018)	**	0.033	(0.018)	*
CENTRAL $\times$ DIST TO CENTER	0.077	(0.365)		0.178	(0.361)	
Market Fixed Effects		Yes			Yes	
Time Fixed Effects		Yes			Yes	
Station-Specific Characteristics		Yes			Yes	
Location-Specific Characteristics		Yes			Yes	
ℓ		-4,688.585			-4,669.098	
σ_μ^2		0.315			0.302	
σ_ν^2		1.965			1.943	

Notes: # of obs.: 2,920; *** significant at 1%, ** significant at 5%, * significant at 10% level. Inference is based on a variance-covariance matrix of ϵ that is clustered at the station level (with $\epsilon_{it} = \mu_i + \nu_{it}$, $\mu_i \sim IID(0, \sigma_\mu^2)$ and $\nu_{it} \sim IID(0, \sigma_\nu^2)$). Parameter estimates on station- and regional-specific control variables are reported in Table 5 in Appendix B (available online).

However, we find that centrality matters in larger markets. Figure 3 illustrates the parameter estimates for ρ_s, $\rho_s^{C\to R}$, $\rho_s^{R\to C}$, and $\rho_s^{R\to R}$ for markets of different size s obtained from column [2] of Table 2. The parameter estimates for ρ_s, $\rho_s^{R\to C}$, and $\rho_s^{R\to R}$ decline with the size of the market, which corresponds to the results obtained in column [1]. Interaction in pricing between two neighboring stations becomes less intense as the number of stations (s) increases. In contrast, the parameter estimates for $\rho_s^{C\to R}$, i.e. the impact of the central supplier on price-setting of remote firms, remains stable (or even increases slightly) as market size increases. The difference between parameter estimates for $\rho_s^{C\to R}$ and all other ρ_s parameters is significantly different from zero at the 1% significance level for all markets with $s \geq 4$ stations. Including state-fixed effects and/or regional characteristics instead of local market-fixed effects hardly affects the parameter estimates (the results are shown in Appendix C, available online).

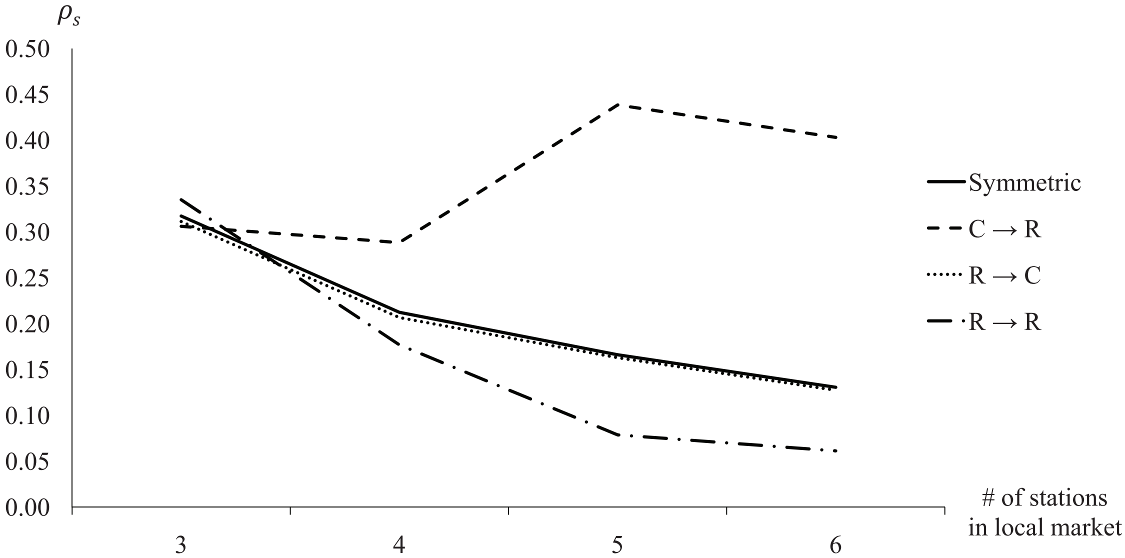
Our results thus add empirical evidence to the literature on (social) networks investigating the linkage between centrality and performance. We conclude that (a) centrality matters for firms' pricing behavior and (b) this effect of centrality becomes more important as the size of the market (i.e. the number of firms in this market) increases. Future research should provide additional empirical evidence using alternative concepts for delimiting markets by applying new methods for identifying 'the key player' (Ballester et al., 2006) and by investigating the importance of centrality in different market environments.

Table 3: t-test statistics for asymmetry in the spatially autoregressive parameters

Market Size	Number of Observations	$\rho_s^{C\to R} = \rho_s^{R\to C}$	$\rho_s^{C\to R} = \rho_s^{R\to R}$	$\rho_s^{R\to C} = \rho_s^{R\to R}$
$s = 3$	1,176	0.215	0.887	1.034
		(0.830)	(0.375)	(0.301)
$s = 4$	1,016	3.891	4.768	2.652
		$(0.000)^a$	$(0.000)^a$	$(0.008)^a$
$s = 5$	470	89.449	317.510	28.957
		$(0.000)^a$	$(0.000)^a$	$(0.000)^a$
$s = 6$	258	3.792	4.557	3.476
		$(0.000)^a$	$(0.000)^a$	$(0.001)^a$

Notes: ^{a} significant at the 1% level; p-values in parentheses. Test statistics are based on two sample t-tests with unequal variances for the respective parameter estimates.

Figure 3: Asymmetry in the spatially autoregressive parameters



Notes: The solid line denotes the slope parameter ρ_s (on the vertical axis) depending on the number of stations in a local market (horizontal axis) in the symmetric case (specification [1]). The dashed (dotted) [chain dotted] line denotes the parameter $\rho_s^{C\to R}$ ($\rho_s^{R\to C}$) [$\rho_s^{R\to R}$] of specification [2] in Table 2.

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Appendix

A Additional Explanatory Variables

The data on prices are supplemented by station- and location-specific characteristics to account for product, demand and cost heterogeneity. Summary statistics of these variables are provided in Table 4. Station characteristics include the information on whether a gasoline station is independent or BRANDED, owned by a company or by the DEALER, offers full attendance SERVICE and has a surface of more than 2,000 square meters (SIZE $>$2,000m^2). Location-specific attributes include information on whether the station is located along a HIGHWAY and whether it is located at a road with heavy TRAFFIC.[7] These data are also provided by Catalist.

Table 4: Summary statistics of additional variables

Variable	Mean	(S.D.)	Min.	Max.	# of Obs.
Station-Specific Characteristics:					
BRANDED	0.852	(0.355)	0	1	2,920
DEALER	0.275	(0.447)	0	1	2,829
SERVICE	0.257	(0.437)	0	1	2,692
SIZE $>$2,000m^2	0.344	(0.475)	0	1	2,849
Location-Specific Characteristics:					
HIGHWAY	0.012	(0.109)	0	1	2,746
TRAFFIC	0.732	(0.443)	0	1	2,746
(1 − CENTRAL) × DIST CENTRAL^a	0.265	(0.365)	0	2.720	2,137
CENTRAL × AV DIST REMOTE^b	3.205	(2.656)	0.130	16.250	783
(1 − CENTRAL) × AV DIST REMOTE^a	3.275	(3.251)	0.040	18.510	2,137

Notes: ^{a} (^{b}) Summary statistics of this variable are calculated for remote (central) stations only.

The other location-specific characteristics reported in Table 4 are based on the exact location of the stations and the market center in each local market and summarize information on the locations of the other stations in the market with respect to the market center. (1 − CENTRAL) × DIST CENTRAL is only different from zero if an observation regards a remote station and the value reflects the distance between the central station of the market and the center. CENTRAL × AV DIST REMOTE is the average distance of all remote stations to the market center for

[7] For each gasoline station the data contain four categories of traffic levels (very heavy, heavy, medium, low) that the station is assigned to by the surveyors of the company Catalist. The variable TRAFFIC is equal to one if traffic is considered to be (very) heavy and is zero otherwise.

the central observation. If an observation regards a remote station, this variable is equal to zero. On the other hand, $(1 - \text{CENTRAL}) \times$ AV DIST REMOTE is only different from zero if a station is considered to be remote. It describes the average distance of all other remote stations (excluding the observation itself) to the market center. These variables are included to capture the spatial heterogeneity within a local market and are again measured in driving time (in minutes).

As revealed by the number of observations in Table 4, information is missing on some variables for a very small fraction of observations. As the data are missing (completely) at random and the share of missing data is very small, missing information is replaced by zeros in the estimations and dummy variables equal to one are included if the information is missing for an observation, and zero otherwise.

B Parameter Estimates of Other Explanatory Variables

Table 5 reports results obtained from estimating equations (2) and (3), and summarizes parameter estimates of station- and location-specific characteristics of model specifications [1] and [2] which are not explicitly shown in Table 2.

C Sensitivity Analysis

In the model specifications reported in the main part of this article we include dummy variables for each local market to account for unobserved heterogeneity. As a robustness test we include regional characteristics instead of market-level fixed effects. The respective regional characteristics include the ratio of in- and out-commuters (COMMUTERS) to the population of the municipality hosting a gasoline station. The variable TOURISM is the number of touristic overnight stays in the municipality in the month observed (measured in 1,000). The degree of urbanization is measured by the population density (POP DENSITY). To account for regional cost differences we include the prices for factory PREMISES (in Euros per square meter) and the share of alpine surface and woods (ALPS+WOODS) in the municipality (in percent). The latter controls for remoteness associated with higher transportation costs on the supply side. These data are provided by Statistics Austria. Summary statistics on these variables are reported below in Table 6.

The results of the regression analysis are reported below in Table 7. Data on tourism and population density are included in logarithmic terms, and specification

Table 5: Results of the maximum likelihood estimations (continued)

Specification	[1]			[2]		
	Coef.	(S.D.)	Sign.	Coef.	(S.D.)	Sign.
Station-Specific Characteristics:						
BRANDED	0.946	(0.193)	***	0.993	(0.191)	***
DEALER OWNED	-0.190	(0.143)		-0.189	(0.141)	
SERVICE	-0.271	(0.150)	*	-0.240	(0.150)	
SIZE $> 2,000$	0.360	(0.123)	***	0.348	(0.122)	***
Location-Specific Characteristics:						
HIGHWAY	6.293	(0.404)	***	6.110	(0.401)	***
TRAFFIC GOOD	0.196	(0.146)		0.167	(0.144)	
$(1-$ CENTRAL$)\ \times$						
DIST CENTRAL	0.240	(0.319)		0.296	(0.317)	
CENTRAL $\times$						
AV DIST REMOTE	0.029	(0.040)		0.040	(0.040)	
$(1-$ CENTRAL$)\ \times$						
AV DIST REMOTE	0.020	(0.084)		0.040	(0.084)	
ℓ		-4,688.585			-4,669.098	
σ^2_μ		0.315			0.302	
σ^2_ν		1.965			1.943	

Notes: # of obs.: 2,920; *** significant at 1%, ** significant at 5%, * significant at 10% level. Inference is based on a variance-covariance matrix of ϵ that is clustered at the station level (with $\epsilon_{it} = \mu_i + \nu_{it}$, $\mu_i \sim IID(0, \sigma^2_\mu)$ and $\nu_{it} \sim IID(0, \sigma^2_\nu)$).

Table 6: Sensitivity Analysis: Summary statistics of additional variables

Variable	Mean	(S.D.)	Min.	Max.	# of Obs.
Regional Characteristics:					
COMMUTERS	35.037	(13.836)	11.482	110.760	2,920
TOURISM	124.689	(238.389)	0.009	836.691	2,467
POP DENSITY	1,262.806	(2,534.873)	4.166	18,153.518	2,920
PREMISES	119.909	(67.629)	15.800	280.800	2,836
ALPS+WOODS	38.346	(26.359)	0	87.236	2,920

[4] includes state fixed effects, depending on the federal state where the station is located.[8] The parameter estimates on $\rho_s^{C\to R}$, $\rho_s^{R\to C}$ and $\rho_s^{R\to R}$ are hardly affected by this alteration. As in the main specification [2] reported in Table 2, the null hypotheses $\rho_3^{C\to R} = \rho_3^{R\to C}$, $\rho_3^{C\to R} = \rho_3^{R\to R}$ and $\rho_3^{R\to C} = \rho_3^{R\to R}$ cannot be rejected at any reasonable level of significance, whereas the parameter estimates for $\rho_s^{C\to R}$ are significantly larger compared to all other ρ_s parameters for all markets with $s \geq 4$ stations.

These results also suggest that centrality does not matter in very small markets, but becomes more important as the size of the market increases, and therefore confirms the finding of the main part of this article.

[8] Austria is divided into 9 federal states.

Table 7: Sensitivity Analysis: Results of the maximum likelihood estimations

Specification	[3]			[4]		
	Coef.	(S.D.)	Sign.	Coef.	(S.D.)	Sign.
$\rho_3^{C\to R}$	0.324	(0.032)	***	0.347	(0.032)	***
$\rho_3^{R\to C}$	0.324	(0.006)	***	0.335	(0.005)	***
$\rho_3^{R\to R}$	0.344	(0.031)	***	0.344	(0.032)	***
$\rho_4^{C\to R}$	0.260	(0.027)	***	0.246	(0.027)	***
$\rho_4^{R\to C}$	0.214	(0.004)	***	0.222	(0.004)	***
$\rho_4^{R\to R}$	0.203	(0.014)	***	0.221	(0.014)	***
$\rho_5^{C\to R}$	0.482	(0.002)	***	0.549	(0.002)	***
$\rho_5^{R\to C}$	0.161	(0.003)	***	0.167	(0.003)	***
$\rho_5^{R\to R}$	0.063	(0.001)	***	0.048	(0.001)	***
$\rho_6^{C\to R}$	0.331	(0.082)	***	0.322	(0.083)	***
$\rho_6^{R\to C}$	0.129	(0.003)	***	0.133	(0.003)	***
$\rho_6^{R\to R}$	0.082	(0.021)	***	0.090	(0.021)	***
CONSTANT	26.788	(1.116)	***	25.107	(0.932)	***
CENTRAL	1.808	(0.826)	**	1.801	(0.824)	**
DIST TO CENTER	0.029	(0.020)		0.030	(0.021)	
CENTRAL × DIST TO CENTER	-0.092	(0.234)		-0.090	(0.242)	
Station-Specific Characteristics:						
BRANDED	0.886	(0.181)	***	0.874	(0.183)	***
DEALER OWNED	-0.172	(0.139)		-0.242	(0.141)	*
SERVICE	-0.017	(0.143)		-0.120	(0.148)	
SIZE $> 2,000$	0.299	(0.114)	***	0.218	(0.113)	*
Location-Specific Characteristics:						
HIGHWAY	5.498	(0.388)	***	5.289	(0.404)	***
TRAFFIC GOOD	0.099	(0.131)		0.296	(0.131)	**
(1 − CENTRAL) × DIST CENTRAL	0.132	(0.155)		0.148	(0.156)	
CENTRAL × AV DIST REMOTE	0.043	(0.044)		0.040	(0.046)	
(1 − CENTRAL) × AV DIST REMOTE	0.008	(0.034)		-0.011	(0.032)	
Regional Characteristics:						
COMMUTERS	0.005	(0.005)		0.002	(0.004)	
ln TOURISM	0.026	(0.035)		-0.005	(0.029)	
ln POP DENSITY	-0.052	(0.062)		-0.130	(0.059)	**
ln PREMISES	0.099	(0.117)		0.309	(0.100)	***
ALPS+WOOD	0.004	(0.003)		0.003	(0.003)	
Market Fixed Effects		No			No	
Time Fixed Effects		Yes			Yes	
State Fixed Effects		Yes			No	
ℓ		-4,773.373			-4,832.620	
σ_μ^2		0.407			0.500	
σ_ν^2		1.949			1.885	

Notes: # of obs.: 2,920; *** significant at 1%, ** significant at 5%, * significant at 10% level. Inference is based on a variance-covariance matrix of ϵ that is clustered at the station level (with $\epsilon_{it} = \mu_i + \nu_{it}$, $\mu_i \sim IID(0, \sigma_\mu^2)$ and $\nu_{it} \sim IID(0, \sigma_\nu^2)$).