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Centrality and Pricing in Spatially Differentiated Markets

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Centrality and Pricing in Spatially Differentiated Markets

Matthias Firgo

February 2012
To my friend Berni,

You will never be forgotten.
Acknowledgments

When I started working on this thesis in 2008, I was wondering about a lot of things, for instance: How am I ever going to manage to write a thesis? What exactly am I supposed to do? And what the hell is spatial econometrics? Right now I am still asking myself a lot of questions (probably even more than when I started) but a lot of the things I was wondering about in 2008 I have become familiar with, so finally I managed the process of writing a thesis. However, this was only made possible through the help and support of several people who I owe a great debt of gratitude: First and foremost I want to thank Prof. Christoph Weiss for the great support and the friendly atmosphere in the supervision of this thesis, his valuable ideas, inputs and comments during countless discussions. Moreover, I am indebted to Prof. Weiss for employing me as a Research and Teaching Associate at the Institute for Economic Policy and Industrial Economics at Vienna University of Economics and Business (WU). Without this employment, I would have never had the chance to write this thesis. Further, I would like to thank my second supervisor, Prof. Klaus Gugler, for the friendly support and his very helpful comments. I also want to thank the two other members of my doctoral committee, Prof. Harald Badinger and Prof. Thomas Grandner, for their constructive feedback.

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Big thanks go out to my family and friends for their long lasting support and for the good times we have had together (not only) during the last few years. Most especially, I would like to thank my girlfriend Steffi for helping me to take my mind off things when I needed to and for showing me what really matters in life.
Abstract

The existing theoretical and empirical literature to investigate the existence of local market power is typically based on spatial competition models in the tradition of Hotelling’s (1929) linear city and Salop’s (1979) circular city. In models of this kind, strong assumptions are made that lead to a spatial homogeneity (symmetry) of firms in a highly stylized one-dimensional market space. However, some of these assumptions are hardly satisfied in many (retail) markets. The present thesis builds on a recent model by Chen and Riordan (2007), in which the market is characterized by a star-shaped graph with a central intersection. In an extension of Chen and Riordan, I distinguish between firms close to the center and firms in the periphery of a spatial market. This spatial heterogeneity leads to an asymmetric competition between firms. A central firm directly competes with a larger number of firms than remote firms do.

The implications of the theoretical model are tested in two empirical applications to the retail gasoline market of Vienna and Austria. Using station level data on diesel prices, I estimate price reaction functions for gasoline stations in two different approaches. In the first approach the Austrian retail gasoline market is divided into numerous highly localized and delimited markets. The second approach analyzes the metropolitan area of Vienna and treats the whole market as one big network of gasoline stations, which are connected through the road network. In both approaches I apply econometric spatial autoregressive (SAR) models. The estimated parameters of the slopes of the reaction functions are used to evaluate the impact of individual gasoline stations on equilibrium market prices depending on their location within the market (network). All results obtained provide evidence for (more) central suppliers serving as a stronger reference in pricing than (rather) remote suppliers. Thus, the assumption of a symmetry in spatial competition which is usually implied by spatial competition models in theoretical and applied research, is rejected.
Kurzfassung


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1 Introduction and Motivation

In many (retail) markets, consumers have to travel from their own location to the location of a supplier of their choice in order to consume a product. These travels imply transportation costs, which can be either monetary or time costs. Transportation costs lower the utility of the product consumed. Therefore, firms gain local market power as consumers prefer to consume near their own location. The existing theoretical and empirical literature to investigate the existence of local market power is typically based on models of localized competition in the tradition of Hotelling’s (1929) linear city and Salop’s (1979) circular city model of spatial competition.

In these models strong assumptions are made which lead to a spatial symmetry (homogeneity) of firms in a highly stylized one-dimensional market space. However, neither the assumptions about the nature of the market space nor the assumptions leading to such a symmetric distribution of firms are likely to hold in many markets, especially retail markets. In Hotelling’s and Salop’s models – and in most other spatial competition models that have evolved from these canonical models – firms are distributed equidistantly throughout the market. Spatial differentiation (or any other form of horizontal product differentiation) is therefore the same for all firms. This result arises from a uniform distribution of consumers and from the possibility of a costless relocation of firms as soon as a new store opens up or an existing one shuts down. However, the establishment (closure) of a new store is a quite costly endeavor in most situations. Thus, unless all incumbents relocate, the entry or exit of a single firm leads to an asymmetric distribution of firms in space.

Additionally, in models of localized competition, each firm is assumed to directly compete with its direct neighbors only and, due to the stylized 1-dimensional spatial structure, each firm has the same number of direct rivals. One firm competes with a neighboring firm with the same intensity as the other way around. Therefore, competition between firms is symmetric and despite being spatially differentiated the location of a particular firm is de facto irrelevant.

\footnote{This section is based on the introduction of the paper “Centrality and Pricing in Differentiated Markets: The Case of Gasoline” by Firgo et al. (2011).}
Consumers and firms are connected through a network of roads and intersections. Some firms are located at or near an intersection of roads while other firms are located somewhere along a single road. A firm located close to an intersection tends to have more directly neighboring firms – i.e. firms located at other roads leading to the same intersection – than firms located far from intersections, which have one neighbor on each side along the road at most. This nature of the market space leads to an asymmetric number of neighbors a firm directly competes with. Thus, spatial heterogeneities arise in two dimensions: First, firms differ in the distance they are located from other firms. Second, if direct competition is assumed to take place between neighboring firms only, firms differ in their number of direct competitors. The first dimension is commonly known as the degree of differentiation. I refer to the second dimension as differences in the (network) centrality of firms because analyzing competition in a spatial framework of roads and intersections implies an analysis of spatial competition in a network or on a graph.

In the theoretical literature on spatial competition, a number of studies have analyzed either the first or the second type of asymmetry. However, to my knowledge, a theoretical model that includes both dimensions of spatial heterogeneity does not exist. While a large number of empirical studies have analyzed the impact of the first dimension of spatial asymmetries on price levels for several industries, the effect of the latter – differences in the number of neighbors and thus, differences in the degree of (network) centrality – has been widely ignored in the empirical literature. The empirical literature completely lacks of investigations of the impact of network centrality on price levels and on the strategic interaction between firms.

This lack of literature is surprising considering the fact that the importance of network centrality has been widely analyzed in other disciplines such as neurobiology and psychology, in business-related fields such as transport management and operations research and, with an increasing intensity, in the literature on social networks as a consequence of their growing importance in everyday life. Networks involving social interaction are characterized by agents that are connected through friendship, acquaintanceship or professional links. The role of centrality in social networks has been recently analyzed, for instance, in the context of peer-group smoking behavior (Christakis and Fowler, 2008), and
the individual impact of scientists in co-authorship networks (Yan and Ding, 2009). In the context of industrial organization the social network literature has analyzed the influence of individuals within organizations depending on their location within the organizational structure (Brass, 1984), and the impact of centrality on firm’s innovations (Valente, 1996). Brass and Burkhardt (1992, p. 191) argue that, looking at a star-shaped network structure, most people simply declare the central node (agent) the most influential and powerful one without even asking for the context and type of network represented by the star-graph.

If strategic interaction between firms in a pricing game is considered as social interaction then it is obvious that the impact of centrality on the behavior of firms deserves more attention than it has received in the literature on spatial competition. The present thesis is a first attempt to investigate asymmetries in the strategic interaction between spatially differentiated firms arising from differences in their relative positions within the market space. Centrality is therefore not associated with a firm’s ability to access a higher level of demand, but with a firm’s location in the network (market) space relative to the locations of other firms. The following questions are to be addressed in the analysis: How does centrality influence the strategic interaction between firms in pricing? What impact does centrality have on equilibrium prices and price levels? I attempt to model the impact of centrality on firms’ pricing decisions both theoretically and empirically. The implications of the theoretical model introduced in this thesis are applied to the Austrian retail gasoline market using two different approaches. All results obtained provide evidence that the strategic interaction between suppliers is strongly related to their positions within the market.

The remainder of this thesis is organized as follows. Chapter 2 provides a review of related theoretical work on spatial competition and a short review of related empirical studies analyzing pricing in retail gasoline markets. Chapter 2 concludes with reasoning on the importance of explicitly considering centrality in the context of the existing literature. Chapter 3 introduces an extension of the so-called ‘spokes model’ by Chen and Riordan (2007) as a first theoretical approach to integrate both dimensions of spatial asymmetries discussed above. This model leads to three propositions about the impact of centrality on asymmetries in the strategic interaction between firms in pricing, on asymmetries in
the transmission of shocks, and on the impact of centrality on the price levels of firms. This asymmetric spokes model is estimated empirically for the Austrian retail gasoline market in Chapter 5. It is also applied in a more general framework analyzing the retail gasoline market of Vienna as one interconnected network in Chapter 6. Before the empirical applications are conducted, Chapter 4 discusses econometric issues that are relevant for the empirical analysis. Chapter 7 summarizes the results and discusses the policy implications that can be drawn from these results. Chapter 7 also discusses the limitations of this thesis and considerations for further research.
2 Related Literature - Pricing in Spatially Differentiated Markets

2.1 Theoretical Models

The first economist to discuss product differentiation was Piero Sraffa in 1926. Sraffa pointed out that markets are usually divided into different regions in which a seller “enjoys a privileged position whereby it obtains advantages which – if not in extent, at least in their nature – are equal to those enjoyed by the ordinary monopolist” (Sraffa, 1926, p. 545). A region is regarded as a certain range of consumer preferences that is matched best by the product offered by a particular seller.\(^2\) Hotelling (1929) adds a spatial aspect to these considerations, even though his model of a linear city, with its consumers and suppliers distributed along a horizontal axis, only serves as a “figurative term for a great congeries of qualities” (Hotelling, 1929, p. 54). Since the days of Sraffa and Hotelling, spatial economics has evolved as an entire sub-discipline of economics. Usually the literature on spatial competition is divided into two types of models. In localized competition models in the tradition of Hotelling (1929) competition takes place between neighboring firms only. In models of non-localized (global) competition in the tradition of Chamberlin (1948), every firm competes directly with all other firms in the market. This division, however, is not very fruitful for the purpose of this thesis. I rather split the theoretical literature on spatial competition into models with spatially homogeneous firms (Section 2.1.1) and models in which firms are heterogeneous in terms of their location within the market space (Section 2.1.2). These two sections discuss a selection of models that are relevant for the theoretical and/ or the empirical analysis later in this thesis. Graphical illustrations of all models are provided in Figure 1 on page 8. A detailed survey of spatial competition models is provided by Biscaia and Mota (2011).

2.1.1 Spatial Homogeneity

In his seminal paper, Hotelling (1929) analyzes the market space as a 1-dimensional line (see Figure 1(a)), the so-called linear city.\(^3\) With the assumption of a uniform distribution

\(^2\)Product differentiation can take place on a vertical (quality) and horizontal level (characteristics/space). As this thesis deals with spatial competition I will focus on models analyzing horizontal product differentiation only. For a survey of models on vertical differentiation see Martin (2004).

\(^3\)Even though Hotelling does not consider a physical line (street) but rather an axis reflecting the characteristics of a product (e.g. milk ranging from zero-fat milk to whole milk) the idea can be and has been
of consumers facing linear transportation costs along the line, Hotelling (1929) studies the equilibrium outcomes if two firms provide their products within this market space. He concludes that the equilibrium locations of firms are back-to-back at the center of the line as each firm, if not located at the center, can increase its profit by moving closer to the market center. This result is known as the principle of minimum differentiation. However, fifty years later it was proven by d’Aspremont et al. (1979) that Hotelling was incorrect: If the distance between firms is small\(^4\), firms have incentives to undercut the price of the other firm and steal all consumers from this firm. As a result d’Aspremont et al. (1979) show that a Nash-equilibrium in pure strategies does not exist in the Hotelling (1929) model, without making additional assumptions on the pricing behavior of firms. Under the assumption of quadratic rather than linear transportation costs, the authors demonstrate that a Nash-equilibrium in pure strategies exists in the so-called principle of maximum differentiation, i.e. firms locate at the opposite ends of the line.

The framework of the linear city still serves as a standard approach in modeling spatial competitions and has been modified and extended numerous times.\(^5\) The most prominent of all extensions is the circular city model by Salop (1979), which is illustrated in Figure 1(b). In this model the pricing decision of firms depends on whether they compete with their neighbors or not. If the number of firms in the market is low or if transportation costs are high, firms might act as monopolies for consumers located close-by.\(^6\) Salop assumes that relocation costs are zero and that firms chose maximum differentiation. Thus, firms are located symmetrically around the circle. As more firms enter the market, the distance between firms decreases and it might become more profitable for firms to compete for consumers with their neighboring firms on both sides of the circle. In this case, firms find themselves in a pricing game: each firm has the same number of competitors, i.e. the nearest firm on the left and on the right, irrespective of the total number of firms in the market. Thus, competition is localized.

\(^4\)In the case of symmetric locations if the distance between firms is smaller than half of the length of the line (d’Aspremont et al., 1979, p. 1147);

\(^5\)Vickrey (1964) and Salop (1979) consider a line that is curved to a circle to avoid the consequences of asymmetries implied by edges when the analysis is generalized to more than two firms. Eaton and Lipsey (1975), among others, analyze the linear city models with several different numbers of firms in the market. Anderson et al. (1997) replace the assumption of a uniform distribution of consumers by a symmetric log-concave consumer density.

\(^6\)In Salop’s (1979) model consumers have the choice between the differentiated product offered by the firms in the market and a homogeneous outside good.
In contrast to the family of models of localized competition, models of non-localized (global) competition describe markets in which each firm directly competes with all other firms in the market. Based on the seminal works of Chamberlin (1948) and Dixit and Stiglitz (1977), von Ungern-Sternberg (1991) and Chen and Riordan (2007) analyze non-localized competition in a spatial setting. In such spatial settings non-localized competition can be described as fully-connected graphs in which firms compete more or less symmetrically with one another, as depicted in Figure 1(d), 1(e) and 1(f).

von Ungern-Sternberg (1991) chooses a Pyramid-shaped market with one firm at the top and one firm in each corner of the triangular bottom of the pyramid. Consumers’ locations reflect their order of preferences. Their first preference is the firm closest to their own location. Their second preference is the second-nearest firm. The two remaining firms are located at an equidistance and reflect their least (third) preferred choice.

Chen and Riordan (2007) introduce the so-called ‘spokes model’ as “a new analytical tool for differentiated oligopoly and a representation of spatial monopolistic competition” (Chen and Riordan, 2007, p. 897). Their spokes model is a star-shaped graph with a central intersection and a number of $N \geq 2$ spokes of length $l$. The end of each spoke hosts at most one of $n$ firms in the market, thus $n \leq N$. Firms produce a horizontally differentiated product. Consumers are distributed equidistantly across the spokes network and each spoke represents different product characteristics. Consumers located on spoke $i$ have a taste for product $i$ no matter if the product is available (the spoke hosts a firm) or not. The location of a particular consumer (the distance the consumer is located from the center) reflects the strength of the preference for product $i$. The further the consumer is located from the center, the stronger is the preference for $i$ and the higher are the transportation costs (the lower is the net utility) of consuming a product different from $i$. Under the assumption of zero entry costs, the effects of entry on equilibrium prices depend on the consumers’ willingness-to-pay for the variety preferred. As the results of

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7Chen and Riordan (2007) assume that consumers only have a willingness to pay for two varieties: for the variety represented by the spoke they are located on and for a second variety which may also be either available or not. If the willingness-to-pay for these varieties is high, the entry of another firm reduces market prices. However, if the willingness-to-pay for the preferred varieties is low, new entry leads to higher prices. Therefore, the number of firms can be either too high or too low in comparison to the social optimum under free entry.
the spokes model are not of particular interest to the focus of this thesis, I will not discuss these results in more detail. However, the spatial framework of the spokes model serves as the basis for the theoretical model introduced in Chapter 3.

Figure 1: Spatial competition models at a glance

(a) Hotelling (1929)  
(b) Salop (1979)  
(c) Fik (1991b)  
(d) Chamberlin (1948)  
(e) von Ungern-Sternberg (1991)  
(f) Chen and Riordan (2007)  
(g) Braid (1989)  
(h) Fik (1991a)  
(i) Balasubramanian (1998); Bouckaert (2000); Madden and Pezzino (2011)
2.1.2 Spatial Heterogeneity

In all models presented in the section above, firms are spatially differentiated. However, they are located equidistantly throughout the market space. No firm has a locational advantage over another firm. Compared to the great number of models assuming such a spatial homogeneity of firms, only a limited number of models elaborate spatial patterns in which firms actually face different circumstances in terms of demand and competition because of heterogeneous locations.

Braid (1989) introduces a star-shaped market space similar to the spokes model by Chen and Riordan (2007), in which one firm is located at the central intersection and each spoke hosts an arbitrary and symmetrically distributed number of firms (Figure 1(g) for the case of three spokes). Unlike in Chen and Riordan (2007), all spokes are occupied by firms. In the pricing sub-game, Braid (1989) shows that the first order condition for the central firm is a function of the average prices of all neighbors of first order (i.e. the innermost firm on each spoke), while the first order condition for firms along the spokes is a function of the average price of the interior and the exterior neighbor. Formally: 

\[ p_i = f\left(\frac{1}{2n} \sum p_j\right), \]

where \( p_i \) is the price of firm \( i \) and where \( n \) is the number of adjacent neighbors of firm \( i \), with \( j = 1, \ldots, n \) and \( j \neq i \). The outermost firm of each spoke has only an interior but no exterior neighbor, and thus considers the price of one firm only. All firms except for the central and the outermost firm on each spoke find themselves in situations identical to firms in the Salop (1979) model. In the short-run analysis Braid (1989) assumes that locations are fixed. Under Braid’s assumptions equilibrium prices are the same for all firms but the profits of the firm in the center are higher. For the long run, when firm choose locations in a first stage and prices in a second stage of the game, Braid (1989) concludes that a Nash-equilibrium in locations for an intersection of more than two spokes (\( N > 2 \)) does not exist.

Fik and Mulligan (1991) analyze a linear city with five firms and a linear city with four firms which is intersected by an orthogonal road that hosts an additional firm. As in Braid (1989) firms differ in their number of neighbors. The two firms at the edges of the linear city and the firm at the orthogonal road have one neighbor. The interior firm at the intersection has three neighbors, while the other interior firm has two neighbors. The slope of the reaction function of firm \( i \) again is given by 

\[ p_i = f\left(\frac{1}{2n} \sum p_j\right). \]

Fik and Mulligan
(1991) study the equilibrium prices of firms in different combinations of individual firms’ price conjectures through numerical simulations.\(^8\) The authors find that, all other things constant, equilibrium prices decline for firms with a higher number of adjacent neighbors. The contradiction of the uniform pricing in Braid (1989) results from the difference in the spatial structure. While Braid’s (1989) market reflects a perfectly symmetric star graph, the intersection in Fik and Mulligan (1991) is not at the center of the linear city, which results in a non-symmetric star-shaped graph.

Fik (1991a) extends the framework of Braid (1989) and Fik and Mulligan (1991) and applies pricing games to networks (graphs) in general.\(^9\) An example is illustrated in Figure 1(h). Under Nash-Bertrand competition\(^10\) the profit maximizing price \((p_i)\) of firm \(i\) with \(n\) direct (adjacent) neighbors again is a function of \(p_i \equiv f(1/(2n) \sum p_j)\). As in Fik and Mulligan (1991), numerical simulations of price levels of individual firms are performed for a number of different (grid) networks and for different compositions of individual price conjectures. Fik (1991a) is unable to draw general conclusions about the price levels of central and remote firms for different network (market) structures. Price levels are found to depend on the specification of the network and on the price conjectures.

Apart from the three studies discussed in this section, theoretical considerations of spatial asymmetries are restricted to modifications of the circular city model. Fik (1991b) relaxes Salop’s (1979) assumption of an equidistant distribution of firms along the circle (Figure 1(c)). Still, the distribution of firms is symmetric in his clustered linear city. Several models (Figure 1(i)) extend the Salop (1979) model to a circular city with a city center (Balasubramanian, 1998; Bouckaert, 2000; Madden and Pezzino, 2011). Firms along the circle are considered as classical retailers (mall or high street shops), and firms in the center as direct marketers (mail delivery). While firms on the circle face localized competition with an additional neighbor in the center, the central firm finds itself in a situation of non-localized competition with all firm on the circle. For consumers, transportation costs for purchasing at a firm on the circle depend on their own and on the firm’s location. Transportation costs for purchasing at the center are the same for all consumers and can

\(^{8}\)The authors allow firms to differ in their price conjectures (near Löschian, Hotelling-Smithies (Nash-Bertrand), Greenhut-Ohta). See Greenhut et al. (1989) for details on price conjectures in spatial models.

\(^{9}\)Section 6.3 of this thesis gives an introduction into networks (graphs) and their characteristics.

\(^{10}\)Like in Fik and Mulligan (1991) price conjectures of of firms may vary individually.
be interpreted as fixed shipping costs.

### 2.2 Empirics - The Retail Gasoline Market

The retail gasoline market is the most popular retail industry subject to the empirical analysis of firms’ behavior in spatially (horizontally) differentiated markets. Besides the strategic interaction of gasoline stations, which will be the focus of the empirical analysis of this thesis, a number of other aspects of price competition have been analyzed for this industry, including the impact of the degree of differentiation on prices, market concentration, and dynamic pricing (price cycles). Clemenz and Gugler (2006, p. 292) emphasize four reasons in favor of employing this industry in the analysis of empirical issues of spatial competition:

- In terms of its physical and chemical properties, gasoline is a nearly perfectly homogeneous good.

- Due to this homogeneity, consumer preferences particularly rely on the price and on transportation costs. Therefore, in accordance with localized competition models, competition is likely to take place between neighboring gasoline stations.

- Considering the enormous entry and exit costs, the two-stage decisions often modeled – with the locational choice first, followed by (price) competition – reflect some key aspects of strategic interaction in oligopoly markets.

- Gasoline prices are well monitored and documented. Thus, comprehensive data on this retail industry are available.

The arguments of Clemenz and Gugler are supported by a Sheffield, UK household survey conducted by Ning and Haining (2003). It reveals that a great majority of consumers regard gasoline as a homogeneous product. Thus, the actual purchase decision strongly depends on the locations of and distances between consumers and firms. Therefore, firms gain local market power and have incentives to set prices strategically even if the total number of firms in the market is large. In the remainder of this chapter, some of the key findings of empirical studies on spatial price competition in retail gasoline markets are presented.\(^\text{11}\) A

\(^\text{11}\)Empirically several retail industries selling rather homogeneous products have been analyzed in terms of spatial competition using dependent variables such as prices, quality differences, the density of retailers, entry and exit decisions, market shares of different companies or franchises, etc. The analysis includes,
very comprehensive review of literature related to the retail gasoline market was recently published by Eckert (2011).

2.2.1 Strategic Interaction in Pricing

A rather small number of studies have tried to model strategic interaction in the pricing decisions of gasoline stations beyond focusing on price levels. Based on field surveys at gasoline stations, a questionnaire survey for the operators of gasoline stations, and a household survey, Ning and Haining (2003) conduct a profound analysis of the Sheffield, UK retail gasoline market. Their questionnaire survey reveals that over 80% of gasoline stations claim to consider prices of the nearest station in their own pricing decision. Also, more than 60% indicate that they consider more than one gasoline station, mostly stations located at the same or at nearby roads. Regression analysis of prices confirms not only the evidence for nearest neighbor competition, but also the evidence for competition among stations within geographically defined groups or clusters. Additionally, Ning and Haining (2003) highlight the importance of location attributes. According to their field survey, the lowest prices are being charged at sites attached to supermarkets and at stations on main roads. The authors further conclude that station characteristics (e.g. the existence of a car sale, a garage, etc.) and some demand-side variables (the number of cars and the percentage of high income households in a market) do not contribute to explaining retail price variations in their sample.

Atkinson et al. (2009) collected price data for 27 of 28 gasoline stations in Guelph, Canada, eight times per day for a period of 103 days in 2005, along with the characteristics of each station. They find that stations “tend to match (or set a small differential with) a small number of other stations” (Atkinson et al., 2009, p. 586). However, the authors point out that there is little evidence that these other stations need to be the nearest ones. They claim that responses to changes by stations of the same chain are found to be correlated to a higher degree than responses to close stations. Finally, they find asymmetries in the adjustments following price changes. While they find evidence for a ‘domino effect’ of price decreases in space, price increases are claimed to follow different patterns. More empir-

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among others, retail food (Fik, 1991b) and hamburger prices (Kalnins, 2003; Thomadsen, 2005), payoffs of motels along highways (Mazzeo, 2002) and of the video retail industry (Seim, 2006), prices of movie theaters Davis (2006), tuition fees at private U.S. universities (McMillen et al., 2007) and bank interest on borrowings (Richards et al., 2008).
Lee (2009) estimates price reaction functions of gasoline stations using a spatial autoregressive (SAR) model – as will be specified in this thesis – to confirm the findings of Ning and Haining (2003). His results for the county of San Diego, California show that gasoline stations do not only compete with the closest station. However, by using different critical radii in the spatial weights matrices of the SAR model\textsuperscript{12}, Lee (2009) finds that competition is highly localized and is strongest between stations within a 1 mile radius. A similar result – highly localized competition – is found by Pinkse et al. (2002), who estimate price reaction functions (SAR models) for the American wholesale gasoline market. Netz and Taylor (2002) and Pennerstorfer (2009) also estimate price reaction functions using SAR models, but focus on different aspects of competition in the retail gasoline market (see sections below).

\subsection*{2.2.2 Spatial Differentiation and Price Dispersion}

As mentioned above, a number of gasoline market related studies focus on the importance of spatial differentiation and station density for price levels. For the Los Angeles metropolitan area, Netz and Taylor (2002) present three measures of the intensity of competition a particular gasoline station faces: the total number of stations within a certain radius, the rate of non-major brand and independent stations within this radius, and the rate of stations of the same brand as the focal station. The authors show that the degree of differentiation (spatially and via station characteristics) increases if competition increases.

Barron et al. (2004) analyze the effect of the number of gasoline stations on local market prices for four U.S. metropolitan areas. The authors prove that a higher number of stations leads to lower average prices and lower price dispersion. They include the distance to the next rival as an indicator for the degree of spatial differentiation. However, the expected impact of spatial differentiation – decreasing prices following from a decreasing distance to rivals – is not statistically significant in most specifications. Lewis (2008) confirms the results of Barron et al. (2004) on price dispersion for the Los Angeles retail gasoline mar-

\footnote{For more details on SAR models and the spatial econometrics literature see Chapter 4.}
ket, but dividing stations into two categories, major brands and discounters/independents, Lewis (2008) finds that price dispersion is only lower if there are more competitors from the stations’s own category nearby.

Using Austrian municipality and district averages, Clemenz and Gugler (2006) observe a negative impact of station density on prices. Another finding of their paper is that station density is significantly related to the population density, but the former increases proportionally less than the latter. Most recently, the results for prices obtained by Clemenz and Gugler (2006) were confirmed by Sen and Townley (2010) for the Canadian retail gasoline market. Their analysis focuses on the impacts of outlet rationalization on retail gasoline prices. For several Canadian metropolitan areas, they find evidence that the decrease in the number of gasoline stations during the 1990s led – all other things equal – to a significant increase in retail gasoline prices.

The dimensions of horizontal/spatial and vertical differentiation are put together by Iyer and Seetharaman (2008). Using data for the St. Louis metropolitan area, they integrate both dimensions of differentiation (horizontal/ spatial and vertical) by allowing for consumer heterogeneity. The authors find evidence that the dispersion of prices charged in a local market, as well as the dispersion of quality characteristics such as brand, services, etc., are positively related to the dispersion of the per-capita income within a local market area. Additionally, they show that the dispersion is higher if stations are clustered together (minimal horizontal differentiation), which suggests that firms differentiate vertically to a higher degree when horizontal differentiation is low. This result is consistent with the standard literature on multiple dimensions of differentiation, e.g. Irmen and Thisse (1998), in which firms differentiate maximally in one dimension and minimally in all other dimensions.

Another recent study by Verlinda (2008) analyzes the extent to which local market power resulting from (spatial) differentiation contributes to the fact that retail gasoline prices rise much faster when stations’ costs (wholesale prices) increase than they fall when costs decrease, a fact that was previously detected by Borenstein et al. (1997) and confirmed in recent publications by Deltas (2008) and Alm et al. (2009). For the south of Orange County, California, the author finds evidence that effects of branding, a greater
geographic distance to rivals, and characteristics which further differentiate a station (e.g., service bays) support these asymmetries in price responses.

2.2.3 Market Concentration and the Role of Independent Stations

The work by Barron et al. (2004) and Lewis (2008) already discussed above emphasizes the effect of independent (or non-major brand) gasoline stations in a market. On the one hand, the presence of stations of this category reduces the concentration and the market share of major brand stations. This aspect is expected to increase competition. On the other hand, as Netz and Taylor (2002) point out, a higher market share of independent stations can soften price competition among branded stations, at least if consumers treat branded and unbranded gasoline as non-homogeneous products. Pennerstorfer (2009) refers to the former aspect as the ‘competition effect’ and to the latter as the ‘composition effect’ when analyzing the role of independent stations in the retail gasoline market of Lower Austria.

In a related study analyzing the Greater Los Angeles and San Diego metropolitan areas, Hastings (2004) finds evidence that the presence of independent stations in a local market reduces the average market price. However, in a recent comment Taylor et al. (2010) contradict the results of Hastings (2004) using different data covering the same period of time and the same area. They do not find a significant effect similar to the one in Hastings (2004). Also, Clemenz and Gugler (2006) add the degree of market concentration to their analysis and do not find an immediate consistent impact of market concentration on prices. However, they find that concentration has a negative influence on the density of stations, which in turn has an observable negative influence on prices. In a very recent contribution, Houde (2011) compares the effects of an increased market concentration after a merger in the Quebec metropolitan area and finds a significant increase in prices post merger.\textsuperscript{13}

Still, there is more evidence for a significant role of non-major and independent stations on market prices: Sen (2005) studies gasoline prices of eleven Canadian cities and concludes that an increase in the market share of non-major brand gasoline stations leads to lower average market prices even though prices within the group of non-major brand gasoline

\textsuperscript{13}Houde (2011) defines consumers’ locations as commuter paths rather than as fixed locations, which is the standard (single-address) approach in spatial models and also in this thesis.
stations increase due to a higher concentration in this group. On the other hand, prices of major brands decline due to a lower degree of market concentration. This decline outweighs the price increase in the former group for a negative net effect of non-major brand stations on prices. The results obtained by Pennerstorfer (2009) are different at first glance: The author also concludes that an increase in the market share of independent stations leads to lower average market prices (competition effect), but in addition shows that this increase leads to higher prices among branded stations (composition effect) due to less competition among branded stations. However, unlike Sen (2005), Pennerstorfer (2009) separates unbranded (independent) and branded stations, so non-major and major brands are assigned to the same group. Thus, the results of Pennerstorfer (2009) are not a contradiction of the results of Sen (2005). Lewis (2008) finds evidence that having a higher number of discounters and independents close-by leads to higher price dispersion among major brands.

2.2.4 Dynamic Pricing and Price Cycles

Besides the main characteristics of the retail gasoline market pointed out by Clemenz and Gugler (2006) and discussed above, this industry has another interesting feature: “Retail gasoline markets are unique in that the price for the product is broadcast for all to see, including competitors.” (Doyle et al., 2010, p.660). The transparency of prices facilitates price competition as well as collusion. Within the last years, a large number of studies have analyzed pricing behavior using price data with highly frequent observations. This data allows the study of dynamics in pricing that could not otherwise be observed.

High-frequency price data reveals two effects that are worth to be highlighted: First, there are obvious asymmetries in the time it takes until rises and declines in wholesale prices are passed-through to retail prices (recently Verliga (2008), Deltas (2008) and Alm et al. (2009) as briefly discussed above). Second, a great deal of studies find evidence for price cycles that are characterized by few substantial rises in price, each followed by a large number of small declines. This phenomenon is known as Edgeworth price cycles\(^\text{14}\). Noel (2009) shows that there is a link between the first and the second dynamic. Analyzing the metropolitan area of Toronto, the author concludes that Edgeworth cycles are one of the

\(^{14}\text{See Maskin and Tirole (1988) for details.}\)
main reasons for asymmetries in the pass-through time of changes in the wholesale price to retail prices. According to Noel (2009) these asymmetries are found to be higher if cycles are present. However, the author points out that Edgeworth cycles are not the reason for the existence of these asymmetries. Based on data on U.S. cities, Lewis and Noel (2011) compare cities with and without cycling behavior and find that cities with Edgeworth price cycles respond to changes in the wholesale prices much quicker than (similar) cities where prices do not experience such cycles (up to three times faster). They conclude that Edgeworth cycles reduce the inefficiencies of slow pass-through of cost shocks. To some degree these results seem to contradict the findings of Noel (2009), which surprisingly is not commented upon at all in Lewis and Noel (2011).

Price cycles (sticky prices) are very often associated with the absence (presence) of a dominant market leader. Based on weekly data, Noel (2007a) analyzes nineteen Canadian cities to detect higher cycling activities in cities in which a higher proportion of gasoline stations is operated by small firms. Doyle et al. (2010) confirm the relevance of market concentration to the occurrence of Edgeworth cycles. They also confirm that markets with a high concentration (i.e. markets with dominant firms) are less likely to cycle due to a facilitation of tacit collusion. However, the authors also detect that a very low concentration (i.e. markets with a large share of independents) leads to a low probability of cycling behavior. The latter aspect of these findings can be related to the findings in Noel (2007b), i.e. a new cycle (a rise in prices) is more likely to be initiated by a large firm (a firm operating many gasoline stations) than by small firms.

Apart from cycling behavior, Hosken et al. (2008) reveal that pricing behaviors differ significantly among gasoline stations. They demonstrate that, within the suburbs of Washington, DC, stations at both ends of the price range are characterized by smaller jumps in their price rankings over time than stations charging closer to the mean. In other words, stations charging very high (low) prices in one period are more like to charge very high (low) prices in other periods. Nevertheless, Hosken et al. (2008) conclude that stations change their relative prices frequently and that movements in the price ranking may be very large.
2.3 Conclusion: The Need for Real World Patterns

Both the theoretical literature and empirical studies analyzing pricing in markets with spatial competition place restrictive assumptions on the spatial patterns and on a symmetry in competition, at least implicitly. Most theoretical models are characterized by making explicit assumptions about a symmetric distribution of firms in space or by assuming a costless relocation of firms which leads to a symmetric spatial distribution of firms. In models characterized by a spatial homogeneity (see Section 2.1.1), firms are differentiated but they are ‘equally different’. Neither their own location in the market nor the location of their neighbors is relevant and competition between firms is perfectly symmetric. To maintain a symmetric distribution of firms, all incumbents must relocate as soon as one firm enters (leaves) the market. However, an asymmetric distribution of firms in space becomes most likely as soon as relocation is costly. Even if the assumption of a symmetric distribution of firms is relaxed, firms still have a symmetric number of neighbors in models assuming a one-dimensional market space, such as a line or a circle.

A symmetry in competition between firms in a spatial market resulting from a symmetric number of neighbors appears questionable in many markets, especially in traditional retail markets: Due to a complex network of roads and intersections, some locations might be considered as the center of a local market (e.g. a central square or the intersection of two major roads). Clearly, a firm located close to such central locations has more neighboring firms than a firm somewhere along a single road. Theoretical models that pick up on such considerations are rare; the few existing exceptions were introduced in Section 2.1.2 above. However, even though some of them model realistic geographical structures, such an intersection (Braid, 1989; Fik and Mulligan, 1991) or networks in general (Fik, 1991a), they still place strong assumptions on the spatial distribution of firms: They allow firms to differ in the number of neighbors but they assume firms to be distributed equidistantly and symmetrically throughout the market. Also, these models assume that one firm is located directly at the intersection of two or more lines (spokes), but they do not allow for a case in which an intersections is not occupied by a firms. In a nutshell, the existing theoretical literature on spatial competition fails to account for asymmetries that doubtlessly arise when the market space is analyzed in the context of a network of roads and intersections that characterizes many markets in which consumers must frequent the location of the
suppliers in order to consume. These asymmetries may not only be reflected in the price levels of central and less central (remote) firms, but are also likely to influence the intensity of interaction between firms. As Fik and Mulligan (1991, p. 87) put it:

“Highly accessible firms in the market have the advantage of competing for a larger share of the market and yet have the disadvantage of interacting with the greatest number of firms directly. This further complicates the nature of price competition, since the equilibrium conditions and market share are dependent upon many factors; namely (i) the number and length of network links associated with any node/firm (on an individual and aggregate basis); (ii) the relative positioning of that node with respect to all other nodes/firms in the network; (iii) the direct and indirect influences of price linkages; . . .”

While the empirical literature has analyzed the impact of spatial differentiation and other aspects of spatial competition on price levels, very few studies have model the strategic interaction between suppliers. Out of the great number of econometric works conducted on retail gasoline markets that use prices as the dependent variable, only Netz and Taylor (2002), Pennerstorfer (2009) and Lee (2009) explicitly model price reaction functions to account for strategic interaction between stations. The results presented in Netz and Taylor (2002) and Lee (2009) show the strong differences in sign, magnitude and significance of the estimated coefficients that occur if the existence of strategic interactions between gasoline stations are ignored and only price levels are estimated using standard techniques such as OLS estimation. Therefore, the empirical literature needs to model strategic interaction properly in order to obtain meaningful results. Yet, the studies explicitly modeling price reaction functions also assume a symmetric competition between firms as each study estimates only a single coefficient for the slope of the reaction functions of all firms, instead of allowing for asymmetries as a result of spatially heterogeneous firms.

The next chapter presents an extension of the spokes model by Chen and Riordan (2007) which allows for an asymmetric spatial distribution of firms. To my knowledge, this extension is the first attempt to model spatial competition in an environment in which firms differ 1) in their number of neighbors 2) in their degree of spatial differentiation, i.e. firms are neither distributed equidistantly nor symmetrically. The propositions resulting from
this model will be tested for the retail gasoline market because of the special characteristics of this market, which were discussed at the beginning of Section 2.2 above.
3 Centrality and Pricing in a Theoretical Spokes Model

The original spokes model introduced by Chen and Riordan (2007), which was briefly discussed in Section 2.1.1, is of particularly relevance in situations of non-localized competition. For instance, symmetrical competition between firms as modeled by Chen and Riordan (2007) is likely to exist in online markets, in which different retailers sell similar products, or in conventional retailing if one shop sells a number of similar products of different brands. For instance, a consumer who wants to purchase a white shirt at a department store of his choice has to decide between shirts of different brands. However, this thesis is focused on spatially differentiated markets characterized by localized competition. In such markets retailers are distributed throughout the market space, which is defined by a network of roads and intersections. Due to the spatial structure of the road network, spatial asymmetries arise in two dimensions in many (retail) markets:

1. Some firms are closer to other firms
2. Some firms have more neighboring firms than others

The first type of asymmetry has been considered theoretically by Fik (1991b) and analyzed in several empirical applications (see the discussion of related empirical literature in Section 2.2.2). Very few theoretical models (see Section 2.1.2) tackle the strong assumptions of a strictly one-dimensional space that by its nature does not allow more than one competitor on each side of a line or a circle and in which the only difference in the number of neighbors is that the outermost firms on a line have one neighbor while all other firms have two neighbors. The models in Section 2.1.2, e.g. Braid (1989), Fik (1991a) or Balasubramanian (1998), allow firms to differ in their centrality (i.e. the number of direct competitors) but again, firms are distributed symmetrically throughout a highly stylized market space.

The modified spokes model presented in this chapter is the first attempt to model competition between spatially heterogeneous firms in a framework that incorporates both dimensions of asymmetry. The market structure is simple but quite realistic for markets in which space is the main source of differentiation. Firms differ in the degree of spatial

\[15\] This chapter is based on the paper “Centrality and Pricing in Differentiated Markets: The Case of Gasoline” by Firgo et al. (2011).
differentiation, i.e. their distance to adjacent neighbors, and in the degree of network centrality, i.e. the number of neighbors. While some firms are located close to a central intersection of spokes (roads), some firms are located further off. Figure 2 shows the idea of this asymmetric spokes model in detail.

Figure 2 describes an asymmetric spokes model for $N = 4$ spokes, the central firm ($C$), and $n = 2$ remote (peripheral) firms ($R_i$), with $i = 1, ..., n$. For central and remote firms I will stick to the following notation: $C$ is the unique central firm, $R$ refers to remote firms in general, $R_i$ refers to one particular and $R_j$, with $j \neq i$, to all other remote firms. $C$ is defined as the firm closest to the market center; all other firms in the market are considered as remote firms. A number of assumptions for this model are presented in the following Section 3.1. In Section 3.2 I derive price reaction (best response) functions for central and remote firms that lead to a set of propositions, which are discussed in Section 3.4.

\[ \text{Figure 2: An asymmetric spokes model} \]

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16 The linear city model by Hotelling (1929) with $d_C \neq d_i$ is a special case of the asymmetric spokes model with $N = 2$ and $n = 1$. The star-shaped model by Braid (1989) corresponds to an asymmetric spokes model with $N = n - 1$, $d_C = 0$ and $d_i = d_j \forall i$, i.e. all spokes are occupied by a firm, the central firm is located right at the center and all remote firms are located equidistantly.
3.1 Framework and Assumptions

This section lists the assumptions of the asymmetric spokes model:

a) $N \geq 2$ spokes of standardized length $l$ are connected through a central intersection, the market center.

b) Each spoke hosts one firm at most and $0 \leq d \leq l$ is the distance a firm is located away from the center.

c) Consumers are uniformly distributed throughout the spokes network.

d) Search costs are zero. Consumers have perfect information about the utility $s_C (s_i)$ and the price $p_C (p_i)$ of the product sold by each firm.

e) Consumers face constant transportation costs $t$ per unit of distance they have to travel from their own location $x$ to the location of the firm of their choice.

f) For each consumer the net utility of consumption is strictly positive and each consumer purchases exactly one unit of the product per period, i.e. the market is covered.

g) Firms sell a spatially differentiated but otherwise homogeneous product, thus $s_C = s_i = s$.$^{17}$

h) Firms have constant marginal costs $c_C (c_i)$. Fixed costs are normalized to zero for convenience.

i) Locations of firms are fixed and there is no entry or exit.

j) There is always exactly one central firm $C$ and a finite number of $1 \leq n < N$ remote firms $R_i$ with $i = 1, 2, \ldots, n$. The central firm is the firm located closest to the market center, thus $d_C < d_i$, $\forall i$.

k) Each firm sells a strictly positive quantity and there exists a Nash-equilibrium in prices with the central firm serving consumers on empty spokes.

l) To ensure the existence of a Nash-Equilibrium a so-called Modified Zero Conjectural Variation (MZCV) behavior is assumed$^{18}$, i.e. firms do not undercut rivals’ prices to

$^{17}$With respect to the empirical applications to the retail gasoline market this assumption seems very plausible. According to a 1997 Sheffield, England household survey only 20% of respondents believe that there are quality differences between gasoline station brands at all (Ning and Haining, 2003).

$^{18}$See Eaton and Lipsey (1978) and Braid (1989) for details on the MZCV, which is also known in the literature as the ‘no mill-price undercutting assumption’.
steal consumers on empty spokes or in the hinterland of a rival. A justification of the MZCV in the setting of the asymmetric spokes model is given in Appendix A. Further, the existence of a Nash-equilibrium is assured by restricting \( N/n \leq 2 \). The necessity of this restriction is discussed in detail at the end of Section 3.2.

### 3.2 Pricing in a Nash-Bertrand Equilibrium

As illustrated by the short orthogonal lines in Figure 2 and following assumption k), the market area of \( C \) borders with all \( R_i \), but the market areas of each \( R_i \) do not border with one another as the market area of \( C \) extends its own spoke. The boundary of the market area of each firm can be identified by calculating the location of the marginal consumer, who is exactly indifferent between buying at \( C \) or at the \( R_i \) closest to him. The location of the marginal consumer is at the location \((x_i)\) where the net utility of consuming at \( C \) is equal to the net utility of consuming at \( R_i \),

\[
s - p_C - t(d_C + x_i) = s - p_i - t(d_i - x_i).
\]

(1)

The left-hand side of equation (1) describes the net utility of a consumer buying the product at \( C \). The utility \((s)\) is reduced by the price \( p_C \) and the transportation costs, which are a product of the distance the consumer has to travel to the location of \( C \) times the transportation costs per unit. The travel distance is equal to the distance the consumer has to travel to the center \((x_i)\) plus the distance \((d_C)\) that \( C \) is located from the center.\(^{19}\)

The right hand side describes the net utility of consuming at \( R_i \). As the marginal consumer \( x_i \) is located on the same spoke as \( R_i \), the distance from \( x_i \) to \( R_i \) is given by \( d_i - x_i \). Rearranging equation (1) and solving for \( x_i \) leads to

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

(2)

In other words, the locations of the marginal consumers and thus the location of the market boundaries depend on differences in the prices charged by \( C \) and \( R_i \), and on differences in the distances they are located from the center.

In modeling competition I build on a standard Bertrand-model of price competition with

\(^{19}\)Due to assumption k) the marginal consumer is always located at a spoke different from \( C \).
differentiated products. This model typically starts with the demand function, in which demand for a firm depends negatively on its own price, and positively on those of its rivals. I begin with modeling consumers’ choice, which allows me to stick to the notation above. A firm’s profit function can be denoted as the profit per unit (assumption h)) times the number of units sold, which is equal to the number of consumers purchasing the product at the respective firm (assumption f)). With the information given, the profit and reaction function of each firm can be derived. By the nature of the model, different functions must be considered for \( C \) and \( R \). The profit function of \( C \) can be denoted as follows:

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

The first term within the square brackets accounts for all consumers located at the spoke of \( R_i \) who consume at \( C \). The second term accounts for all spokes on which remote firms are absent, as consumers located along these spokes always purchase at \( C \). Inserting equation (2) into equation (3), the profit function of \( C \) can be rewritten as

\[
\pi_C = (p_C - c_C) \left[ \frac{\sum_{i=1}^{n} p_i - np_C + t \left( \sum_{i=1}^{n} d_i - nd_C \right)}{2t} + l(N-n) \right].
\] (4)

In order to obtain the price reaction function of \( C \), the first order condition of the profit function has to be derived.

\[
\frac{\partial \pi_C}{\partial p_C} = \frac{1}{2t} \left[ \sum_{i=1}^{n} p_i - 2np_C + t \left( \sum_{i=1}^{n} d_i - nd_C \right) + nc_C \right] + l(N-n) = 0
\] (5)

Rearranging terms and solving for \( p_C \) leads to the reaction function of \( C \):

\[
p_C = \frac{1}{2} \left[ \frac{\sum_{i=1}^{n} p_i}{n} + t \left( \frac{\sum_{i=1}^{n} d_i}{n} - d_C \right) + c_C \right] + tl \left( \frac{N-n}{n} \right).
\] (6)

The profit maximizing price of \( C \) increases with the average price of the \( R \) and with the ratio of spokes not occupied by remote firms. The average degree of spatial differentiation (the distance to the center) of the \( R \) increases the profit maximizing price of \( C \) while \( C \)’s own degree of spatial differentiation decreases this price. The profit maximizing price also increases with the per unit transportation costs \( t \), with the marginal costs \( c_C \) and with the
length of the spokes $l$.

As the market area of $R_i$ never exceeds its own spoke, it only borders with the market area of $C$. The profit function of $R_i$ is given by

$$\pi_i = (p_i - c_i)(l - x_i).$$

(7)

Inserting equation (2) into (7) leads to the profit function of $R_i$:

$$\pi_i = (p_i - c_i) \left( l - \frac{p_i - p_C + t(d_i - d_C)}{2l} \right).$$

(8)

The first order condition of this function is given by

$$\frac{\partial \pi_i}{\partial p_i} = l - \frac{2p_i - p_C + t(d_i - d_C) - c_i}{2t} = 0.$$  

(9)

Rearranging terms and solving for $p_i$ yields the price reaction function of $R_i$:

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

(10)

The profit maximizing price of $R_i$ increases with the price charged by $C$ and with $C$’s degree of spatial differentiation, but decreases with $R_i$’s own degree of spatial differentiation. The constant terms $c_i$, $t$ and $l$ also increase $R_i$’s profit maximizing price.

Based on the price reaction functions, the Nash-Bertrand equilibrium prices can be solved. However, the calculations of equilibrium prices would yield quite complex results with little illustrative power because of the asymmetries in the distance firms are located from the center. Thus, in a first step I calculate equilibrium prices of central and remote firms under the assumption of an equidistant distribution of the remote firms. In a second step I relax this assumption and simulate equilibrium prices for a set of different scenarios with predetermined numerical values of the key parameters.

Inserting equation (10) into equation (6) and solving for $p_C$ and $p_i$ leads to the equilibrium prices of central ($p_C^*$) and remote firms ($p_i^*$) under the assumption of $d_i = d_j, \forall j$,
with \( j = \{1, \ldots, n\} \).

\[
p_C^* = c_C + \frac{1}{3} t \left( d_i - d_C - 2l + \frac{4lN}{n} \right),
\]
\[
p_i^* = c_i + \frac{1}{3} t \left( d_C - d_i + 2l + \frac{2lN}{n} \right).
\]

Assuming \( c_C = c_i \), the difference in equilibrium prices of central and remote firms under the assumption of \( d_i = d_j, \forall j \), with \( j = \{1, \ldots, n\} \) is thus given by

\[
p_C^* - p_i^* = \frac{2t}{3} (d_i - d_C - 2l) + \frac{2Ntl}{3n},
\]

with \(-4tl/3 < 2t(d_i - d_C - 2l)/3 \leq -2tl/3\) and with \(2Ntl/(3n) > 2tl/3\), as \( N > n \).

Thus, under the assumptions of \( d_i = d_j, \forall j \), and \( c_C = c_i \), the price charged by \( C \) is higher than the price charged by \( R_i \), if and only if \( N/n > 2 - (d_i - d_C)/l \).

From the equilibrium prices \( p_C^* \) and \( p_i^* \), it is also possible to calculate the location of \( x_i \). Inserting these equilibrium prices of the equations in (11) into equation (2), the equilibrium location of the marginal consumer (\( x_i^* \)) results in

\[
x_i^* = \frac{1}{6} \left( d_i - d_C + 4l - \frac{2lN}{n} \right) > 0,
\]

as for assumption \( k \) to hold it is required that \( x_i > 0 \). Otherwise the empty spokes and central parts of occupied spokes are not served by the central firm and the profit functions in equations (3) and (7) would be wrong. From (13) it follows that in order to assure that \( x_i > 0 \), it is necessary that the condition \( N/n < 2 + (d_i - d_C)/(2l) \) is true. Note that \( N/n \leq 2 \) is a sufficient condition for \( x_i > 0 \) as \( (d_i - d_C)/(2l) > 0 \).

### 3.3 Some Numerical Simulations

An illustration of the findings about equilibrium prices if the assumption of \( d_i = d_j, \forall j \) is relaxed, can be achieved through numerical simulations. Table 1 shows the results of several numerical simulations testing the changes in prices, profits and locations of the marginal consumer if ceteris paribus changes are made in the number of spokes \( (N) \), the

\[\text{[Footnote]}\]

It is true that \(-4tl/3 < 2t(d_i - d_C - 2l)/3 \) rather than \(-4tl/3 \leq 2t(d_i - d_C - 2l)/3 \) because assumption \( j \) assures that \( d_C < d_i, \forall i \).
number of remote firms \((n)\), or the firms’ distances to the center \((d_C\) and \(d_i\)).

While \(N, n, d_C\) and \(d_i\) may vary, \(t = 1, l = 1\), and \(c_C = C_i = 0\) are held constant throughout all simulations as changes resulting from varying these parameters are not of particular interest at this point. The top section of Table 1 shows that, for \(n = 4\) and the given \(d_i\), the central firm charges the highest price in the market when \(N = 7\). If \(N\) is reduced to \(N = 6\) the number of spokes completely served by the central firm decreases from 3 to 2. This loss of consumers on an additional empty spoke makes it attractive for the central firm to gain consumers on the \(n\) spokes hosting the remote firms by lowering its price. If the number of spokes is reduced to \(N = 5\), all spokes are occupied by firms. The central firm now charges the lowest price of all firms in the market in order to steal consumers from the spokes of the remote firms. In a nutshell, the higher the number of empty spokes, which raises the demand for the central firm, the less attractive it is for this

<table>
<thead>
<tr>
<th>Firm</th>
<th>Distance</th>
<th>(x_i)</th>
<th>Price</th>
<th>Profits</th>
<th>(x_i)</th>
<th>Price</th>
<th>Profits</th>
<th>(x_i)</th>
<th>Price</th>
<th>Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>(C)</td>
<td>(d_c = 0.10)</td>
<td>1.833</td>
<td>6.722</td>
<td>1.500</td>
<td>4.500</td>
<td>1.167</td>
<td>2.722</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R_1)</td>
<td>(d_1 = 0.30)</td>
<td>0.092</td>
<td>1.817</td>
<td>1.650</td>
<td>0.175</td>
<td>1.650</td>
<td>0.209</td>
<td>0.258</td>
<td>1.483</td>
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<tr>
<td>(R_2)</td>
<td>(d_2 = 0.50)</td>
<td>0.142</td>
<td>1.717</td>
<td>1.473</td>
<td>0.225</td>
<td>1.550</td>
<td>0.196</td>
<td>0.308</td>
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<tr>
<td>(R_3)</td>
<td>(d_3 = 0.70)</td>
<td>0.192</td>
<td>1.617</td>
<td>1.307</td>
<td>0.275</td>
<td>1.450</td>
<td>0.184</td>
<td>0.358</td>
<td>1.283</td>
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<tr>
<td>(R_4)</td>
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<td>1.517</td>
<td>1.150</td>
<td>0.325</td>
<td>1.350</td>
<td>0.171</td>
<td>0.400</td>
<td>1.183</td>
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<th>(x_i)</th>
<th>Price</th>
<th>Profits</th>
<th>(x_i)</th>
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<th>Profits</th>
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<td>4.500</td>
<td>1.689</td>
<td>3.356</td>
<td>3.433</td>
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<td>-0.258</td>
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<td>3.167</td>
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<tr>
<td>(R_3)</td>
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<td>0.228</td>
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<tr>
<td>(R_2)</td>
<td>(d_2 = 1.00)</td>
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<td>1.963</td>
<td>1.975</td>
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<td>1.963</td>
<td>1.975</td>
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<th>Profits</th>
<th>(x_i)</th>
<th>Price</th>
<th>Profits</th>
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<td>1.988</td>
<td>1.975</td>
<td></td>
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<tr>
<td>(R_2)</td>
<td>(d_2 = 0.20)</td>
<td>0.019</td>
<td>1.963</td>
<td>1.926</td>
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<tr>
<td>(R_3)</td>
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<td>0.019</td>
<td>1.963</td>
<td>1.926</td>
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</table>
firm to compete for consumers at the spokes of remote firms.

The middle section of Table 1 shows that if the number of spokes is held constant \((N = 6)\) while \(n\) is reduced, at some point the price difference between central and remote firms becomes too big to assure that the marginal consumer \(x_i\) is located at the spoke of firm \(i\) but it rather moves to the spoke of \(C\). This scenario, however, is not compatible with assumption k) and leads to profit functions different from equations (3) and (7). Therefore, I impose the restriction of \(N/n \leq 2\) in assumption l) which is sufficient for assumption k) to hold, irrespective of relative differences in \(dC\) and \(d_i\).

The bottom section of Table 1 varies the absolute and relative distances of the central and remote firms. Profits for the central firm (remote firms) are higher (lower) if the remote firms are located further from the center or if the central firm is located closer to the center. However, the results remain unchanged if all firms move equally and the distances between firms do not change. Thus, the profit maximizing prices only change with changes in the relative distances \(C\) and \(R_i\) are located from the center.

### 3.4 Propositions

A comparison of the price reaction functions and the equilibrium prices of \(C\) and \(R_i\) in Sections 3.2 and 3.3 highlights the impact of centrality on firms’ pricing behavior. Three effects are worth to be highlighted:

**Proposition 1 - Centrality and asymmetric competition:** *Firms respond more strongly to price changes by a central firm than to price changes by a remote firm.* Centrality implies an asymmetry in the firms’ price reaction functions, given by

\[
\frac{\partial p_i}{\partial p_C} = \frac{1}{2} > \frac{1}{2n} = \frac{\partial p_C}{\partial p_i}, \quad \frac{\partial p_j}{\partial p_i} = 0, \quad \forall n > 1. \quad (14)
\]

The price reaction function of a remote firm \((R_i)\) in equation (10) and Figure 3 illustrates that two remote firms never compete for the same customer. A price change of one remote firm \(R_i\) thus has no direct impact on another remote firm \(R_j\). Remote firms have only one competitor, namely the central firm, and the price response of the remote firm to a change in the price of the central firm will thus be relatively strong. The central firm \(C\),
on the other hand, has \( n \) direct competitors. If \( n \) is large, a change in the price of one remote competitor will be of relatively minor importance and will trigger a relatively small price response by the central firm. Thus, the optimal price of a central firm becomes less sensitive to price changes of an individual remote firm if the number of remote firms (\( n \)) increases. The asymmetries in the price reaction functions are illustrated in Figure 3(a) and 3(b).

Figure 3: Price reaction functions of central and remote firms

Proposition 2 - Centrality and the transmission of shocks: *The impact of an individual exogenous shock*\(^{21}\) *on equilibrium prices will depend on whether the shock originates from the central or a remote firm.* The fact that centrality is associated with a larger number of direct competitors also implies that a shock by a single firm will diffuse differently if originating from a central or a remote firm, respectively. Starting from equilibrium prices, in the counterfactual experiment that the marginal costs of \( C \) change by \( \partial c_C \), the change in the price of \( C \) is \( \partial p_C = (1/2)\partial c_C \). The reaction of each \( R_i \) is equal to \((1/2)\partial p_C\) and thus \((1/2)(1/2)\partial c_C\). However, the reaction of each \( R_i \) again causes a reaction by \( C \), which again causes a reaction in the prices of every \( R_i \). The process continues until a new equilibrium is reached. The total impact of \( \partial c_C \) on equilibrium prices \((p^*_C)\) and \((p^*_i)\) is denoted in the equations in (15), and the total impact

\(^{21}\)E.g. a cost shock of one particular gasoline station after a change in the ownership (a takeover).
of \( \partial c_i \) on equilibrium prices \((p_C^\ast)\) and \((p_i^\ast)\) in the equations in (16).

\[
\frac{\partial p_C^\ast + \sum_{i=1}^{n} \partial p_i^\ast}{\partial c} = \frac{1}{2} \partial c_C + n \frac{1}{2^2} \partial c_C + \frac{1}{2^3} \partial c_C + n \frac{1}{2^4} \partial c_C + \frac{1}{2^5} \partial c_C + \ldots, \tag{15}
\]

\[
\frac{\partial p_C^\ast + \sum_{i=1}^{n} \partial p_i^\ast}{\partial c_i} = \frac{1}{2} \left( \sum_{a=0}^{\infty} \left( \frac{1}{2} \right)^{2a} + n \sum_{a=0}^{\infty} \left( \frac{1}{2} \right)^{2a+1} \right) \partial c_C, \tag{16}
\]

Assuming that \( \partial c_C = \partial c_i = \partial c \), the difference between the total impact of a shock originating from \( C \) and \( R_i \) is equal to

\[
\left| \frac{\partial p_C^\ast + \sum_{i=1}^{n} \partial p_i^\ast}{\partial c} \right| - \left| \frac{\partial p_C^\ast + \sum_{i=1}^{n} \partial p_i^\ast}{\partial c_i} \right| = \partial c n^2 - \frac{1}{2n} \sum_{a=0}^{\infty} \left( \frac{1}{2} \right)^{2a+1} > 0, \forall n > 1, \tag{17}
\]

\[
\lim_{a \to \infty} \sum_{a=0}^{\infty} \left( \frac{1}{2} \right)^{2a+1} = \frac{2}{3}. \]

**Proposition 3 - Centrality and price levels: The effect of centrality on firms’ equilibrium prices is ambiguous.** A shorter distance to the center, i.e. a more central location, increases a firm’s demand, which leads to higher prices, ceteris paribus. This effect comes from the fact that firms do not lose consumers in the hinterland of their spoke when they are located closer to the center, but \( C \) \((R_i)\) gains consumers on the spokes occupied by remote firms (on its own spoke) when it is located closer to the center. The analysis of equilibrium price levels (equation (12) and simulations in Section 3.3) shows that \( C \) charges lower prices than (some of) the remote firms if the ratio of empty spokes to firms is low. In other words, if – all other things equal – the number of remote firms increases or the number of consumers lacking nearby firms decreases, the equilibrium price of the central firm can be lower than equilibrium prices of remote firms. Therefore, no clear-cut conclusion can be drawn on differences in the price levels of central and remote firms.
3.5 Summary

In this chapter I have extended the spokes model by Chen and Riordan (2007) to allow for spatial asymmetries between firms in a sense that firms differ 1) in the number of neighbors and 2) in the distances between firms. Calculating the price reaction functions and equilibrium prices leads to three propositions about the consequences of these spatial asymmetries for the strategic interaction between central and remote firms, for price the levels of these two groups of firms, and for their role in the transmission of shocks on equilibrium prices. These propositions suggest that there are substantial differences in the role of central and remote firms in a localized competition market. The model suggests that the central firm acts like a market-leader kind of firm by the sole fact that its pricing decision affects all other firms in the market, while the influence of an individual non-central (remote) firm decreases with the number of remote firms in the market. The three propositions made in this chapter will be tested in two empirical analyses on the retail gasoline market in Chapters 5 and 6.
4 Selected Aspects of Spatial Econometrics

The main goal of this thesis is to investigate differences in the pricing behavior of firms depending on their location in a market space. As proposed in the theoretical model of Chapter 3, firms play a pricing game and consider the prices of rivals in their own pricing decision. In the firms’ price reaction functions in equations (6) and (10), the variable price appears on both sides of each of the equations. In order to test the propositions of Section 3.4, I focus on estimating price reaction functions for a sample or population of different firms rather than the price reaction function of an individual firm. If firms in a market set their prices simultaneously and conditionally upon the expected prices of other firms, then the economic problem is a spatial one from an econometric point of view (Pinkse and Slade, 2010, p. 108). The term spatial does not necessarily refer to space in the narrower sense but to a dependence of actions of an individual agent on actions of other agents. The existence of spatial dependence has a number of consequences for the econometric analysis of a problem. These consequences and the econometric specification of price reaction functions shall be discussed in the following subsections.22

4.1 Spatial Dependence and Spatial Models

The standard linear regression model23 assumes that in a sample of \( n \) observations a variable \( y \) depends on a set of \( k \) exogenous variables stored in the matrix \( X \) (including or excluding a constant) and is usually denoted as

\[
y = X\beta + \epsilon, \tag{18}
\]

\[
\epsilon \sim N(0, \sigma^2 I),
\]

where \( y \) is of dimension \( n \times 1 \) and \( X \) of dimension \( n \times k \). \( \beta \) is the \( k \times 1 \) vector of the coefficients of the exogenous variables and \( \epsilon \) is the \( n \times 1 \) vector of independent and identically distributed (i.i.d.) error terms with zero mean, \( E(\epsilon) = 0 \), and a homoskedastic variance \( \sigma^2 \), with \( E(\epsilon\epsilon') = \sigma^2 I \), where \( I \) is an \( n \times n \) identity matrix. In case of spatial dependence24

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22 As a basis for further reading in the field of spatial econometrics I recommend a recent publication by Anselin (2010) titled ‘Thirty years of spatial econometrics’. In this paper Anselin provides a comprehensive review of advances of all kinds in the field of spatial econometrics in their chronological order, from its beginning in the late 1970s to most recent findings.

23 See e.g., Greene (2008).

24 ‘Spatial dependence’ and ‘spatial autocorrelation’ are commonly used synonymously in the literature and are also used as synonyms in this thesis.
of the dependent variable \( y \) on the values of \( y \) and/or on (some variables in) \( X \) of other observations, not all relevant information determining \( y \) is included in the set of explanatory variables \( X \). The spatial dependence will enter the error term \( e_i \), which violates the assumption of i.i.d. error terms and will thus lead to an inefficiency in the variance of the coefficients estimated. Therefore, \( t \)-statistics and several tests for misspecification will be biased (Anselin and Rey, 1991, p. 113). As a consequence, the necessity of accounting for spatial dependence in the regression model arises from a statistical motivation. A violation of the assumption of i.i.d. error terms due to spatial dependence can be detected by a set of different specification tests introduced in Section 4.3 below. However, modeling spatial dependence may also be motivated economically. LeSage and Pace (2009, chap. 2) list the main motivations based on theoretical grounds for considering spatial models. These can be an expected spatial heterogeneity of observations due to regional differences or similarities, interaction and spillovers between observations in the dependent variable, externalities in the exogenous variables and diffusion in a space-time context. Depending on the nature of spatial dependence, different specifications for a correct regression model must be considered.\(^{25}\) These shall be introduced and labeled as in LeSage and Pace (2009, p. 32f).\(^{26}\)

If spatial dependence cannot be related to any observable variable but is likely to arise from an unobserved spatial heterogeneity of observations, the correct model is the so-called spatial error model (SEM):

\[
y = X\beta + u, \tag{19}
\]

\[
u = \lambda Wu + \epsilon,
\]

\[
\epsilon \sim N(0, \sigma^2 I).
\]

In the second equation of (19), \( W \) is an \( n \times n \) spatial weights matrix storing the information of the spatial relationships between the \( n \) observations. \( w_{ij} \) is different from zero if observation \( j \) is relevant for \( i \) in the determination of the spatial dependence. I stick to the term ‘neighbors’ if \( i \) and \( j \) interact and thus if \( w_{ij} \neq 0 \). Details on possible designs of \( W \) will be given in Section 4.2 below. \( \lambda \) is the coefficient of spatial autocorrelation of the

\(^{25}\) I focus on local spatial autocorrelation. For a survey of specifications modeling global spatial autocorrelation see Anselin (2003).

\(^{26}\) I deviate from LeSage and Pace (2009) by including a constant into the matrix of exogenous variables \( X \).
error terms.

In many cases, however, the value of \( y_i \) of observation \( i \) explicitly depends on the value \( y_j \) of another observation, e.g. the output or pricing decision of one firm in a duopoly depends on the price of the other firm in the market. Thus, a correct specification requires an inclusion of the values of \( y \) of other observations influencing a particular observation’s \( y \). The values of \( y \) of other relevant observations usually enter the equation as a (weighted) sum or average (Anselin and Rey, 1991, p. 113). The specification in equation (20) is known as a spatial autoregressive (SAR) model.

\[
y = \rho W y + X \beta + \epsilon, \tag{20}
\]

\[
y = (I - \rho W)^{-1}(X \beta + \epsilon),
\]

\[
\epsilon \sim N(0, \sigma^2 I).
\]

\( W y \) is the spatial lag of the dependent variable and \( \rho \) is the coefficient of spatial autocorrelation of the dependent variable. The reduced form equation in (20) shows the multidirectional character of spatial dependence. \((I - \rho W)^{-1}\) can be interpreted similarly to a Leontief-Inverse and is serves as a spatial multiplier because

\[
(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \ldots \tag{21}
\]

As a consequence all observations are connected to each other indirectly via \( W \) unless the sample consists of different ‘islands’ that do not interact with each other. In such a case \( W \) is block diagonal and interaction takes place within blocks only. With usually \(|\rho| < 1\) and with \( W \) usually being row-normalized, the influence of neighbors of higher order will become the smaller, the higher the order of neighborhood (Anselin, 2003, p. 155f).

If there is a suspicion that spatial dependence exists in both in observable and unobservable factors, a general (SAC) model including a spatial lag and a spatial error can be
applied.

\begin{align}
y &= \rho W_1 y + X \beta + u, \\
u &= \lambda W_2 u + \epsilon, \\
y &= (I - \rho W_1)^{-1} X \beta + (I - \rho W_1)^{-1} (I - \lambda W_2) \epsilon, \\
\epsilon &\sim N(0, \sigma^2 I).
\end{align}

The spatial pattern leading to a spatial dependence in \( y \) can be different from the pattern leading to spatial dependence in the error terms. Thus, \( W_1 \) may or may not be equal to \( W_2 \).

In some cases \( y \) may also depend on \( WX \), e.g. due to externalities. The specification that accounts for this extension of the SAR model is known as the spatial Durbin model (SDM)

\begin{align}
y &= \rho Wy + X \beta + WX \gamma + \epsilon, \\
y &= (I - \rho W)^{-1} (X \beta + WX \gamma + \epsilon), \\
\epsilon &\sim N(0, \sigma^2 I),
\end{align}

where \( \gamma \) is the \( k \times 1 \) vector of coefficients of \( WX \). In case \( \rho = 0 \), there is only a spatial lag of \( X \) (a so-called SLX model). Some models, e.g. the empirical models introduced in Chapters 5 and 6 of this thesis, may require more than one spatial lag. A SAR or SDM model with more than one spatial lag can be formulated as follows (LeSage and Pace, 2009, p. 52):

\begin{align}
y &= \sum_{l}^{L} \rho_l W_l y + X \beta + \sum_{l}^{L} W_l X \gamma_l + \epsilon, \\
\epsilon &\sim N(0, \sigma^2 I),
\end{align}

where \( l \leq L \) is the index of the lag and \( L \) is the total number of lags.

The actual choice of the model can be driven by theory and/or by statistics. Whether a spatial lag or a spatial error (or both) should be included in a regression model from a statistical point of view can be tested through a number of tests, which are introduced in
Section 4.3 below.

4.2 The Spatial Weights Matrix

Besides the choice of a proper model in the presence of spatial dependence, a proper design of the spatial weights matrix $W$ is also an important issue. Two main considerations have to be made: Who is directly related to whom and to what extent? Generally, $W$ is designed such that $w_{ij} \neq 0$ if $j$ is related to $i$ and $w_{ij} = 0$ otherwise.\(^{27}\) The value of $w_{ij} \neq 0$ can be either binary so that $w_{ij} = 1$ if $j$ is related to $i$, or weighted by the distance $(d_{ij})$ between $i$ and $j$.\(^{28}\) To follow Tobler’s first law of geography (Tobler, 1970) a higher weight is usually put on nearer neighbors, e.g. $w_{ij} = 1/d_{ij}$ or $w_{ij} = 1/d_{ij}^2$. Usually $W$ is row-normalized in order to facilitate the interpretation of the parameters $\rho$ and $\lambda$, and the comparability of different models (Anselin, 2002, p. 257). In a row-normalized matrix, $w^*_{ij} = w_{ij}/\sum_j w_{ij}$, and $0 \leq w^*_{ij} \leq 1$. As a consequence, $w^*_{ij} = w^*_ji$ is not a necessary condition and $W$ may become asymmetric. The main advantage of row-normalizing $W$ is that the values of the spatially lagged variable(s) can be interpreted as a (weighted) average of the value of neighboring observations (Liu and Lee, 2010, pp. 99f).

In the literature three\(^{29}\) concepts have mainly been used to account for spatial dependence between two observations $i$ and $j$:

(i) $w_{ij} \neq 0$ if $i$ and $j$ are adjacent neighbors.

(ii) $w_{ij} \neq 0$ if $j$ is located within a critical distance of $i$.

(iii) $w_{ij} \neq 0$ if $j$ is among the $k$-nearest neighbors of $i$.

While neighborhood between two observations is necessarily mutual in the adjacent neighborhood criterion (i), this is not necessarily the case in (ii) and (iii). When applying critical

\(^{27}\)Self neighborhood is usually excluded so that $w_{ii} = 0$.

\(^{28}\)Distance does not only apply to spatial distance. Also concepts of economic distance, e.g. Conley and Ligon (2002) and Conley and Topa (2002), and non-spatial distance have been used for the construction of $W$. Examples for the latter are the similarity of different brands of beer through alcohol strength (Pinkse and Slade, 2004), the proximity of juices through brand, flavor, sugar, etc. (Pofahl and Richards, 2009), and the similarity of different brands of ice cream through their volume and nutrition facts (Richards et al., 2010).

\(^{29}\)See Getis and Aldstadt (2004) for a comprehensive survey of theoretical concepts of constructing spatial weights matrices and Stakhovych and Bijmolt (2009) for a very recent literature survey on the construction of $W$. 

37
distances between observations, a mutual direct relation is only given if Euclidean distances (radii) are used. If distance is measured by the driving distance on the road, for instance, \( d_{ij} \neq d_{ji} \) may be a result of one-way streets. As for \( k \)-nearest neighborhood, if \( j \) is among the \( k \) nearest neighbors of \( i \) and \( i \) is located at a rather remote place while \( j \) is quite central and has at least \( k \) neighbors located closer to \( j \) than \( j \) to \( i \), then \( w_{ij} \neq 0 \) while \( w_{ji} = 0 \). Thus, using the criteria (ii) and (iii) an observation may directly influence another observation but not the other way around.

The choice of the criterion and the calculation of the weights depends on the context of research but, as Anselin (2002, p. 257) puts it, the “specification of the weights matrix is a matter of some arbitrariness . . . ”. A construction of \( W \) through an adjacent neighborhood is most likely preferred when observations are regions like districts or countries.\(^{30}\) When observations are points in space, e.g. the locations of firms, mostly criteria (ii) or (iii) are applied. Anselin (2002, p. 258) argues that, in case of

“a high degree of heterogeneity in the spatial distribution of points or in the areas of regions, there may be no satisfactory critical distance. In those instances, a ‘small’ distance will tend to yield a lot of islands (or, unconnected observations). Also, a distance chosen to ensure that each unit has at least one neighbor may result in an unacceptably large number of neighbors”

for other observations. Thus, in case of a heterogeneous spatial distribution, the construction of \( W \) using a \( k \)-nearest neighborhood constraint may be preferable.\(^{31}\)

### 4.3 Tests for Spatial Autocorrelation

As discussed in Section 4.1, spatial dependence leads to misspecification if ignored. The literature provides a number of tests for the \( H_0 \) of no spatial dependence against the \( H_1 \) of spatial dependence (diffuse tests) or spatial dependence including suggestions about a proper specification (focused tests). The following paragraphs provide a summary of the most common tests of spatial dependence as discussed by Anselin et al. (1996) and Florax and de Graaff (2004).

\(^{30}\)For a recent example see Becker et al. (2009) who analyze a SAR model of corruption on a country level.

\(^{31}\)See Pennerstorfer (2009) for a recent contribution using different critical distances to estimate spatial error autocorrelation in retail gasoline prices and Lambert et al. (2010) for a recent empirical application of a \( k \)-nearest neighbor spatial weights matrix to the locational choice of start-up firms.
4.3.1 Moran’s I

The diffuse Moran’s I (Moran, 1950) tests the $H_0$ of no spatial dependence against the $H_1$ of spatial dependence based on the OLS residuals of the model $y = X\beta + \epsilon$. The test statistic $I$ is equal to

$$ I = \frac{n}{S} \times \frac{\epsilon' W \epsilon}{\epsilon' \epsilon}, \quad (25) $$

where $n$ is the number of observations, $S$ is the sum of all elements of $W$ and $\epsilon$ is the $n \times 1$ vector of the OLS residuals.\(^{32}\) A popular interpretation of the coefficient $I$ is that it reflects the coefficient of spatial autocorrelation ($\rho$). However, Anselin (1988b, p. 102) points out that this interpretation is not correct. As illustrated in equation (25), $I$ is equivalent to a regression of $W\epsilon$ on $\epsilon$ and thus (loosely speaking) reflects the extent to which the spatially lagged error terms $W\epsilon$ can be explained by the actual error terms $\epsilon$. $\rho$, however, reflects the extent to which a variable can be explained by a spatially lagged variable. For the case discussed here, this would be equivalent to a regression of $\epsilon$ on $W\epsilon$ rather than a regression of $W\epsilon$ on $\epsilon$. Though $I$ is not a good means of measuring $\rho$, especially if $\rho$ is not close to zero (Li et al., 2007), it can be used to detect spatial dependence, however, without the possibility of drawing a specific conclusion other than its existence.

The expected value $E$ of $I$ in case of no spatial dependence is $E(I) = 1/(n - 1)$. The statistical inference for Moran’s $I$ test can be based on $z$-values under the assumption of normality or other assumptions (Florax and de Graaff, 2004, p. 35f). In a standard normal distribution (see e.g. Greene (2008, pp.991f)), $z_I$ is equal to

$$ z_I = \frac{I - E(I)}{SD(I)}, \quad (26) $$

where $SD(I)$ is the standard deviation of Moran’s $I$ from its expected value.

4.3.2 LM Tests

As a diffuse test, Moran’s $I$ can be used to detect spatial dependence but it does not direct towards a specific alternative specification (Florax and de Graaff, 2004, pp. 37). Thus, in order to test whether a spatial lag or a spatial error model is more appropriate, tests that

\(^{32}\)Note that in case of a row-normalized $W$ with row-sums equal to one, $n/S$ is also equal to one, as $S = n \times 1$ (Florax and de Graaff, 2004, p. 35).
focus on either spatial model are necessary. A set of LM tests using the residuals ($\epsilon$) and the variance $\sigma^2 = \epsilon'\epsilon/n$ of an OLS regression model as denoted in equation (18) and with $W_1 = W_2 = W$, where $W_1$ ($W_2$) is the spatial weights matrix for the spatial lag (error)$^{33}$, tests the $H_0$ of no spatial dependence (i.e., $\rho = 0, \lambda = 0$) against the alternative hypothesis defined by each LM test.$^{34}$ All LM tests introduced here are asymptotically distributed as $\chi^2_1$. The LM-error test ($LM_\lambda$) was introduced by Burridge (1980), and tests the $H_0$ of no spatial autocorrelation against the alternative hypothesis defined by each LM test.

All LM tests introduced here are asymptotically distributed as $\chi^2_1$. The LM-error test ($LM_\lambda$) was introduced by Burridge (1980), and tests the $H_0$ of no spatial autocorrelation against the alternative hypothesis defined by each LM test.

$$LM_\lambda = \frac{(\epsilon'W\epsilon/\sigma^2)^2}{T},$$

(27)

with the trace expression $T = tr [(W' + W)W]$. Alternatively, there is a so-called ‘robust’ version of the LM error test ($LM^*_\lambda$) introduced by Bera and Yoon (1993) testing the same $H_1$ including a nuisance parameter $\rho$ which may or may not be zero.

$$LM^*_\lambda = \frac{[\epsilon'W\epsilon/\sigma^2 - T(nJ)^{-1}\epsilon'Wy/\sigma^2]^2}{T \left[1 - T(nJ)^{-1}\right]},$$

(28)

with

$$J = \frac{1}{n\sigma^2} \left[(WX\beta)'M(WX\beta) + T\sigma^2\right],$$

(29)

where $n$ is the number of observations and $M = I - X(X'X)^{-1}X'$, with $I$ being an identity matrix of dimension $n \times n$. $LM^*_\lambda$ also tests whether there is a spatial dependence in the error, but in contrast to $LM_\lambda$ is robust to the existence ($\rho \neq 0$) or absence ($\rho = 0$) of a spatial lag.

LM tests also exist for the $H_1$: $\rho \neq 0$ under the assumption that $\lambda = 0$ for the classical LM-lag test ($LM_\rho$) as introduced by Anselin (1988a), and for a ‘robust’ version ($LM^*_\rho$) that is robust to the existence ($\lambda \neq 0$) or absence ($\lambda = 0$) of a spatial dependence in the error terms. The robust version ($LM^*_\rho$) of this test was also introduced by Bera and Yoon

$^{33}$See Anselin et al. (1996) for the case of $W_1 \neq W_2$.

$^{34}$The tests here are introduced as in Anselin et al. (1996, p. 83f) using a slightly different notation which is consistent with the notation of equations (19) to (23) above.
\[ \text{LM}_\rho = \frac{[\epsilon' W y/\sigma^2]^2}{nJ}, \] (30)

and

\[ \text{LM}_\rho^* = \frac{[\epsilon' W y/\sigma^2 - \epsilon' W \epsilon/\sigma^2]^2}{nJ - T}. \] (31)

The literature provides guidelines on how to proceed if there is a presumption of spatial dependence. The classical approach to test the correct specification in case of spatial dependence using the \( \text{LM}_\rho \) and \( \text{LM}_\lambda \) test can be formulated as follows (Florax et al., 2003, p. 561):

1. Estimate the linear model \( y = X\beta + \epsilon \) using OLS.

2. Test the \( H_0 \) of no spatial dependence against an omitted spatial lag using the \( \text{LM}_\rho \) test and against spatially autoregressive errors using the \( \text{LM}_\lambda \) test.

3. If neither \( \text{LM}_\rho \) nor \( \text{LM}_\lambda \) show significance, estimate the initial OLS specification as in step 1.

4. If \( \text{LM}_\rho \) is significant but \( \text{LM}_\lambda \) is not (\( \text{LM}_\lambda \) is significant but \( \text{LM}_\rho \) is not), estimate a SAR (SEM) model.

5. If both tests reject the \( H_0 \) of no spatial dependence, estimate the model for which the LM test shows a higher significance. In case \( \text{LM}_\rho > \text{LM}_\lambda \) estimate a SAR model. If, however, \( \text{LM}_\lambda > \text{LM}_\rho \), estimate a SEM specification.

The robust tests \( \text{LM}_\rho^* \) and \( \text{LM}_\lambda^* \) can be used instead of the classical versions \( \text{LM}_\rho \) and \( \text{LM}_\lambda \). Florax et al. (2003, p. 562) suggest a hybrid strategy using both the classical and the robust LM-tests using \( \text{LM}_\rho^* \) and \( \text{LM}_\lambda^* \) instead of the classical versions in step 5. Using Monte Carlo simulations Florax et al. (2003) compare the approach of using the classical with the approach of using the robust LM-tests. Their key finding is that the classical strategy slightly dominates the robust one in power and accuracy. However, the results also suggest that for large sample sizes and/or high degrees of spatial dependence both approaches (asymptotically) yield the same results.

Besides these econometric guidelines in finding a proper specification, there may also be reasons for choosing either a SAR or a SEM model based on economic theory. If the spatial
lag itself is of particular interest as a variable, which is clearly the case in the estimation of reaction functions of interacting firms, a spatial lag has to be included by necessity.

4.4 Consequences of Spatial Autocorrelation

While autocorrelation in time series is unidirectional (a time trend) and can be controlled for by adding lagged variables in a linear regression model, (spatial) autocorrelation in a cross-section is more complicated and multidirectional due to feedback effects (Pinkse and Slade, 2010, p. 111). The price level in time period $t$ is likely to depend on the price level of period $t-1$, but not the other way around. However, the characteristics and decisions of a firm $i$ can affect a nearby firm $j$ and the characteristics and decisions of firm $j$ can affect firm $i$. In other words, if I interact with my neighbors and my neighbor interacts with his neighbors, then there will be feedback effects of my action as I am my neighbor’s neighbor. While an omitted spatial lag will always lead to biased estimates, the omission of a spatial error will not lead to a bias in the estimates but to inefficiency and thus to a bias in various test statistics (Anselin and Rey, 1991, pp. 113f). The following Section 4.4.1 shows the inconsistency of OLS estimates in case of spatial autocorrelation of the dependent variable. Section 4.4.2 introduces alternative estimation techniques that properly account for spatial dependence.

4.4.1 Ordinary Least Squares

The purpose of this section is to show why the multidirectional character of spatial autocorrelation leads to biased and inconsistent OLS estimates. In contrast to autocorrelation in time series, the inclusion of a spatial lag will still lead to biased OLS estimates, irrespective of a potential correction of the error correlation through the inclusion of the lag. The following paragraphs are adopted from Anselin (1988b, p. 58). However, the notation deviates from Anselin (1988b) to be consistent with the sections above. The case shall be demonstrated using the pure spatial autoregressive model

$$y = \rho Wy + \epsilon. \quad (32)$$

The spatial lag shall be denoted as $y_L = Wy$. Even if there are no exogenous regressors, the effects can be illustrated without a loss of generality. The OLS estimate for the
Coefficient $\rho$ is denoted as $r$ and is equal to

$$r = (y_L'y_L)^{-1}y_L'y.$$  \hspace{2cm} (33)

If $y$ from equation (32) is substituted into equation (33), it can be rewritten as

$$r = \rho + (y_L'y_L)^{-1}y_L'\epsilon,$$  \hspace{2cm} (34)

as the term $\rho y_L'y_L(y_L'y_L)^{-1}$ cancels down to $\rho$. The OLS estimate $r$ only equals the true $\rho$ if the second term on the right hand side of equation (34) cancels down to zero. This, however, is only the case if there is no spatial correlation and thus only if $\rho = 0$.

In contrast to time series, the expected value $E[y_L'\epsilon] \neq 0$ even if the residuals are not autocorrelated. As follows from equation (32), $y = (I - \rho W)^{-1}\epsilon$ and $y_L = W y = W(I - \rho W)^{-1}\epsilon$. Thus, $E[y_L'\epsilon] = E[[W(I - \rho W)^{-1}\epsilon]'\epsilon]$, which again is only zero if $\rho = 0$. Also, the OLS estimator will be inconsistent as the probability limit ($\text{plim}$) for $y_L'\epsilon$ will be non-zero unless $\rho = 0$ because $\text{plim} n^{-1}(y_L'\epsilon) = \text{plim} n^{-1}\epsilon'W(I - \rho W)^{-1}\epsilon$, which will only equal zero if $\rho = 0$.

To summarize the last paragraphs, except for the case of $\rho = 0$, the OLS estimator will lead to biased and inconsistent parameters even if a spatial lag is included into the model.\footnote{Lee (2002) shows that in some cases OLS can be consistent if each unit has a very small spatial impact on other units but is influenced aggregately by a large number of other units. In the usual case of rather sparse spatial weights matrices, however, OLS will be inconsistent. In case of a purely spatial autoregressive model $y = \rho W y + \epsilon$ OLS will never lead to consistent estimates (Lee, 2002).} In case of $\rho = 0$ with residual autocorrelation ($\lambda \neq 0$) the OLS estimator will not be biased but inefficient (Anselin, 1988b, pp. 108f). Thus, approaches other than OLS must be applied in order to obtain unbiased and efficient estimates. In the next section the Maximum Likelihood approach will be introduced as a convenient and common estimation technique for spatial models.
4.4.2 Maximum Likelihood Estimation

Maximum Likelihood (ML) estimations are popular in empirical applications of spatial models. In general, ML is popular because of its large sample properties. The estimators are consistent, asymptotically efficient and asymptotically normal (Greene, 2008, chap. 16.4). Anselin (1988b, p. 63) introduces a log-likelihood function for a SAC model that additionally accounts for heteroskedasticity in the error terms. Based on this function, Lacombe (2004, p. 114) forms a log-likelihood function for a SAR model with two spatial lags. LeSage and Pace (2009, p. 53) describe the log-likelihood function (\( \ln L \)) for the SAC model as follows:

\[
\ln L = -\frac{n}{2} \ln (\pi \sigma^2) + \ln |A| + \ln |B| - \frac{\epsilon^T \epsilon}{2\sigma^2}, \\
\epsilon = B (Ay - X\beta), \\
A = I - \rho W_1, \\
B = I - \lambda W_2.
\] (35)

Here \( n \) is the number of observations and \( \sigma^2 \) is the (homoskedastic) variance of the residuals. The model can also be implemented with \( W_1 = W_2 = W \). The values for \( \rho, \lambda, \sigma^2 \), and the coefficients of \( \beta \) that maximize the log-likelihood function in (35) can be estimated in an iterative process in which (\( \ln L \)) is concentrated using software such as MATLAB. In case of a SAR model (\( \lambda = 0 \)), the log-likelihood function (35) is simplified to

\[
\ln L = -\frac{n}{2} \ln (\pi \sigma^2) + \ln |A| - \frac{\epsilon^T \epsilon}{2\sigma^2}, \\
\epsilon = (Ay - X\beta), \\
A = I - \rho W,
\] (36)

as illustrated in LeSage and Pace (2009, p. 47). In case of the inclusion of a spatial lag of \( X \) (SDM model), \( X\beta \) is replaced by \( Z\delta \) where \( Z = [\iota \ X \ WX] \), \( \iota \) is a vector of ones and \( X \) is the matrix of explanatory variables excluding the constant. \( \delta \) is the vector of the coefficients to be estimated and includes the constant, as well as the coefficients of \( X \) and

\[\]
For an application of multiple spatial lags in a SAR, SDM or SAC model the simple modification $A = (I - \sum_{l} \rho_l W_l)$ in the log-likelihood function (35) becomes necessary (Lacombe, 2004, p. 114).

Alternatives to the Maximum Likelihood approach in spatial models are two-stage least squares estimates (2SLS) via instrumental variables (IV), generalized methods of moments (GMM), or Bayesian models.

4.5 The Spatial Multiplier

The feedback effects that occur in situations of spatial dependence have already been discussed in Section 4.1. Section 4.5.1 illustrates the total impact of a shock (change) in the dependent variable of one observation on the dependent variables of all observations. Section 4.5.2 shows how the direct impacts of changes in the exogenous variables on the dependent variable multiply through the spatial multiplier, and presents a method to calculate the total impacts of exogenous variables that also include indirect (feedback) effects.

4.5.1 Shocks in the Dependent Variable

The inverse $(I - \rho W)^{-1}$ as in equation (20) can be interpreted as a multiplier in the change of the value of an observation’s variable. If there is a spatial lag, a change in the dependent variable $y_i$ of observation $i$ directly causes a change in the dependent variable $y_j$ of a neighboring observation $j$. This reaction by observation $j$ again causes a direct reaction by observation $i$ and so on. Assuming an equilibrium before the shock, the adjustment process continues until a new equilibrium is reached. Let $G$ be an $n \times n$ matrix with

\[
G = (I - \rho W)^{-1},
\]

then the element $g_{ij}$ reflects the total change in the value of $y_i$ following a change in $y_j$.

In the $1 \times n$ vector $s$ of the column-sums of $G$, the value of $s_j = \sum_i g_{ij}$ is the sum of

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38 The SLX model $y = X\beta + WX\gamma + \epsilon$ can be estimated via OLS because neither $W$ nor $X$ are endogenous.

39 Lacombe (2004) is one of very few empirical examples for a SAR model with multiple spatial lags. Other examples include Kalnins (2003) and McMillen et al. (2007). Recent theoretical advances in the specification of higher order SAR models come from Hays et al. (2010), and Lee and Liu (2010).

40 See Lee (2007a) or Kelejian and Prucha (2010) for recent advances in spatial 2SLS and GMM models and LeSage and Pace (2009, chap. 5) for an introduction into Bayesian spatial econometric models.
changes in the values of the dependent variable $y$ of all observations following a change in $y_j$ by one, including the initial change itself. In making use of this multiplier one can for instance compare the impact of different observations in a sample on equilibrium prices and relate the findings to proposition 2 in Section 3.4, i.e. differences in the transmission of individual shocks due to differences in the position within the market space.

### 4.5.2 Direct, Indirect and Total Effects

Similarly to $y_j$, a change in the value of an exogenous variable $x_{jr}$ of $j$, with $r = \{1, 2, \ldots, k\}$, where $k$ is the number of exogenous variables in $X$, can have an impact on $y_i$. In an SDM specification a change in the value of an exogenous variable of $j$ has a direct effect on $y_i$ through the lagged $WX$. However, if there is a lagged dependent variable, there will also be an effect of $x_{jr}$ on $y_i$, even in the SAR model. This effect is of an indirect nature and takes place via the effect of a change in an exogenous variable of $j$ on $y_j$. Because the change in $j$’s dependent variable has a direct effect on $i$, the impact of $x_{jr}$ on $i$ is indirect.

Formally, in the data generating process of the SAR model

$$y_i = \rho W y + X \beta + \epsilon,$$

the column vector $c$ containing the row sums of $(I - \rho W)^{-1} (I \beta_r)$ reflects the total effect on $y_i$ for each of the $n$ observations, if all observations change their value of the $r$-th exogenous variable by the same amount. To obtain the average total effect of $r$ on $y$ if all observations change the value by the same amount, the sum of the elements in $c$ has to be divided by the number of observations $n$. Similarly, the row vector $s$ containing the column sums of $(I - \rho W)^{-1} (I \beta_r)$ reflects for each observation $j$ the total effect on all $n$ observations resulting from an individual change in the value of $r$ by observation $j$. The average total effect of a change in the $r$th variable from an observation is the sum of total effects over all observations (the sum of all elements in $s$) divided by $n$.

The direct impact of a change in $i$’s own value of the exogenous variable $x_{ir}$ on $y_i$ is given by

$$\frac{\partial y_i}{\partial x_{ir}} = [(I - \rho W)^{-1} (I \beta_r)]_{ii}.$$  

41The remaining paragraphs of this subsection are taken from Le Sage and Pace (2009, pp. 34-38) but are applied to a SAR model instead of a SDM model to keep the illustration simpler.
The average direct effect of the $r$th exogenous variable on $y$ is the trace of $(I - \rho W)^{-1} (I \beta_r)$ divided by $n$. The average indirect effect of an exogenous variable is the difference between the average total effects and the average direct effects. The average total effects, and thus also the indirect effects, can be calculated from the coefficients obtained from the estimates of the underlying model using software such as MATLAB.\textsuperscript{42} For a row-normalized $W$ the average total effect of the $r$th exogenous variable on $y$ is equal to $(1 - \rho)^{-1} \beta_r$.

\textsuperscript{42}For technical details and computational issues see LeSage and Pace (2009, chap. 4.9).
5 Centrality and Pricing in an Empirical Spokes Model: An Application to the Austrian Retail Gasoline Market

5.1 Introduction

The asymmetric spokes model presented in Chapter 3 leads to three propositions about the pricing behavior of firms in spatially differentiated markets. These are, in a nutshell, 1) firms respond more strongly to price changes by a central firm than to price changes by a remote firm; 2) the impact of individual exogenous (cost) shocks on market prices depends on the centrality of the station(s) inducing the shock; 3) there is no clear-cut effect of centrality on price levels. In the remainder of this thesis, these propositions are tested in two empirical applications to the Austrian retail gasoline market using data on the geographical locations of the complete population of gasoline stations in Austria collected by the company Catalist in August 2003. Using the GIS software ArcGIS, the geographical coordinates of each gasoline station are located and plotted on a map. The routing tool WiGeoNetwork by WiGeoGIS calculates the driving time from each gasoline station to all other gasoline stations within a critical distance (time) in ArcGIS. These spatial data are merged with station level pricing data and regional data (see Section 5.5). The empirical application in this chapter is a ‘literal’ translation of the theoretical asymmetric spokes model to an empirical econometric version.

At the beginning, some very important considerations must be taken into account not only about the definition of local markets, but especially about the definition of a unique center for each market which properly meets the criteria of the center in the theoretical model. Also, finding an econometric specification to test the propositions made in Section 3.4 is quite a complex issue. Finally, while the results of the empirical asymmetric spokes model presented in this chapter mainly confirm the theoretical model, this empirical version of the model is associated with a number of strong assumptions and very little room to check the robustness of the results. Because of these limitations the propositions of

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43Earlier versions of this chapter were presented as “Pricing with asymmetric spatial competition: Evidence from the retail gasoline market” by Firgo et al. (2010b) at the 4th World Conference of the Spatial Econometrics Association (SEA) in Chicago in June 2010, and as “Pricing in spatially differentiated markets with central and peripheral firms: The retail gasoline market” by Firgo et al. (2010a) at the EBES 2010 Conference - Athens in October 2010.

44For company details see http://www.catalist.com.
Chapter 3 are tested in an additional empirical application in Chapter 6.

This chapter is organized as follows: Section 5.2 discusses different concepts and definitions of local markets in the literature and describes how local markets are defined in this empirical study. Section 5.3 illustrates how, once local markets have been defined, market centers as well as central and remote firms are identified. Section 5.3 also gives information on how centrality or remoteness is stored in spatial weights matrices and how this information enters the econometric model. Section 5.4 introduces the econometric model, while Section 5.5 describes the data used and provides some descriptive statistics. Section 5.6 discusses the econometric results and simulates the impacts of individual shocks on market prices based on these results. Finally, Section 5.7 concludes this first empirical part and discusses the shortcomings of this approach, which leads to the second empirical application in Section 6, which relaxes some assumptions and analyzes the theoretical asymmetric spokes model in the more general context of networks and network centrality.

5.2 Definitions of Local Markets

The asymmetric spokes model presented in Chapter 3 describes a local market with a simple spatial structure: An arbitrary number of roads intersect in a single central intersection. The firm located closest to this intersection is considered to be the central firm; all other firms are considered as remote firms. No firm is located in the hinterland of another firm and no spoke leads to another intersection.

The empirical literature mainly provides two approaches to model localized competition in retail markets. In the first approach researchers assume that each firm marks the center of its own radial market and that the markets of neighboring firms may overlap. As a consequence the industry becomes one big interconnected network in which competition between firms takes place within a certain radius. Radii can be defined by Euclidean distances (Shepard, 1991; Netz and Taylor, 2002; Barron et al., 2004; Lewis, 2008; Pennerstorfer, 2009) or by driving distance (Hastings, 2004). This radial approach has been mainly used to analyze the impact of spatial differentiation, i.e. the distance to nearby firms, on price levels. However, the asymmetric spokes model rules out overlapping and
interacting markets that arise in this radial approach.\footnote{Kalnins (2003) and Pennerstorfer (2009) use Thiessen Polygons (see Dale (2005) for detailed information) to construct non-overlapping markets for each firm in which a firm’s location marks the centroid of its market. In this approach competition is assumed to take place between adjacent polygons only. This approach is also not applicable for the present analysis because it also leads to an interconnected network of polygons which cannot be broken down into isolated markets.}

The second approach to defining local markets seeks to delimit markets by geographical or political units. The number or density of firms within one census tract (Pinkse et al., 2002), zip-code (Clemenz and Gugler, 2006), municipality (Asplund and Sandin, 1999) or county (Clemenz and Gugler, 2006; Verlinda, 2008) has been used as a variable measuring the intensity of competition. This approach has the advantage of a clear-cut definition of what is considered a local market and which firms belong to it. Furthermore, different political or geographical units can be used to test the robustness of the results obtained (Clemenz and Gugler, 2006). However, such units cannot be used to identify local markets in the present case for two reasons. First, in most cases these units are likely to result in local market areas that are too big to describe the spatial structure of the asymmetric spokes model. Second, what is usually considered as the center of such a unit (e.g. a main square of a town or the biggest town in a county) does not meet the requirements of a market center in the asymmetric spokes model.

Apart from these two main approaches, two studies use different ways of defining local markets. Ning and Haining (2003) treat gasoline stations located on the same road and nearby stations of intersecting roads as the same local market, which is “a somewhat subjective classification” (Ning and Haining, 2003, p. 2147). Pinkse et al. (2002) construct local wholesale gasoline markets via nearest-neighbor-relations. They connect each observation to its spatially nearest neighbor and assign all stations to the same local market as long as they are connected through nearest-neighbor-relations. Figure 4 illustrates the definition of local markets by Pinkse et al. (2002). Each arrow in Figure 4 indicates a nearest-neighbor-relation between two stations. The arrow from observation $k$ to observation $i$ indicates that $i$ is $k$’s nearest neighbor. The bidirectional arrow between $i$ and $j$ implies that $i$ and $j$ are mutually nearest neighbors. As long as firms are connected through arrows they share a common market. As there is no nearest-neighbor-relation between $k$ and $l$, they belong to different markets.
I follow the approach by Pinkse et al. (2002) because it leads to local markets that best match the market structure of the asymmetric spokes model. The markets delimited this way are small, ranging from 2 to 16 gasoline stations. Table 2 reports the distribution of stations per local market for the Austrian retail gasoline market. A total of 761 local markets are delimited. 241 of the 761 local markets identified (31.67%) consist of two stations only. Markets with three and markets with four stations account for about 40%

Table 2: Distribution of the number of gasoline stations per local market

<table>
<thead>
<tr>
<th># of Stations</th>
<th>Freq.</th>
<th>Ratio</th>
<th>Cumm.</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>241</td>
<td>0.3167</td>
<td>0.3167</td>
</tr>
<tr>
<td>3</td>
<td>176</td>
<td>0.2313</td>
<td>0.5480</td>
</tr>
<tr>
<td>4</td>
<td>151</td>
<td>0.1984</td>
<td>0.7464</td>
</tr>
<tr>
<td>5</td>
<td>93</td>
<td>0.1222</td>
<td>0.8686</td>
</tr>
<tr>
<td>6</td>
<td>42</td>
<td>0.0552</td>
<td>0.9238</td>
</tr>
<tr>
<td>7</td>
<td>27</td>
<td>0.0355</td>
<td>0.9593</td>
</tr>
<tr>
<td>8</td>
<td>12</td>
<td>0.0158</td>
<td>0.9750</td>
</tr>
<tr>
<td>9</td>
<td>9</td>
<td>0.0118</td>
<td>0.9869</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>0.0013</td>
<td>0.9882</td>
</tr>
<tr>
<td>11</td>
<td>5</td>
<td>0.0066</td>
<td>0.9947</td>
</tr>
<tr>
<td>12</td>
<td>3</td>
<td>0.0039</td>
<td>0.9987</td>
</tr>
<tr>
<td>16</td>
<td>1</td>
<td>0.0013</td>
<td>1.0000</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>761</strong></td>
<td><strong>1.0000</strong></td>
<td></td>
</tr>
</tbody>
</table>
of all markets. 75% of all local markets include less than 5 stations. However, about two thirds of all gasoline stations are operating in markets with more than three stations. More than 40% of all stations belong to markets with more than four stations and 17% of stations belong to markets with more than six stations.

5.3 Center and Periphery

Now that local markets have been delimited, further considerations have to be made regarding the definition of a center for each of these markets (section 5.3.1) and about the translation of these considerations into the econometric specification (section 5.3.2) of the model.

5.3.1 The Market Center – A Median Location Problem

The definition of a proper market center is a complex issue. In schematic diagrams like Figure 2 and Figure 4, there is only one intersection in each market that can be naturally treated as the market center. However, many of the 761 real world markets that were delimited show spatial patterns that are more complex in terms of the locations of stations and/ or in terms of the structure of the road network. The former problem implies that, for example, two or more stations can be located at the same road (spoke), which is excluded by assumptions in the theoretical model. The latter problem, a road system more complex than in the theoretical model, implies that there may be more than one intersection in a local market or some roads might be connected through several intersections. Thus, many markets lack a “natural” center identifiable at a single glance.

Figure 5 plots a local market in a rural area of Lower Austria as an example. The light blue (purple) lines mark primary (secondary) roads. Minor roads are not illustrated. The winding gray lines mark the borders of municipalities. There are two major criteria for a proper market center in the present setting. First, it has to be located on the road network and not somewhere off the road. Thus, space is reduced to a graph. Second, it has to be a unique point located on this graph. In a seminal paper Hakimi (1964) provides a graph-

46Markets with only two stations have to be excluded from the empirical analysis. See Section 5.3.1 for a detailed discussion. These 241 markets times 2 stations per market account for 17% of the population of 2,814 gasoline stations in Austria.
Hakimi (1964) describes the task of finding an optimum location for a switching center in a telephone interconnection system, in which the “problem is to find the exact location of the switching center [...] such that, say, the total length of the wires is a minimum” (Hakimi, 1964, p. 450). While Hakimi names this location the absolute median of a graph, his concept has been generalized to so-called $p$-median location problems, where $p$ is the number of points on a graph satisfying an optimization problem similar to Hakimi (1964). The definition of the market center as the 1-median location is straightforward and meets the criteria for a market center. It is the point at which the sum of distances on the road network to all gasoline stations in the market is minimized, thus

$$\min d_C + \sum_{i=1}^{n} d_i,$$

where $d_C (d_i)$ is the distance the central (a remote) station is located away from the center. All distances calculated in this empirical application measure distance in terms of driving

---

47 See Tansel et al. (1983) for more details on $p$-median location problems.
time (in minutes). Using driving time rather than driving distance has the main advantage of considering differences in speed limits. Ignoring differences in speed limits would lead to a substantial bias in the measurement of distance, especially because the data used covers urban as well as rural areas.

In Figure 5, the black dot and the two white dots are the three gasoline stations operating in the local market plotted. The three-digit number (601) refers to the index number of the local market. The four-digit numbers are the index numbers of the individual gasoline stations. The market center is located at the pinpoint of the red pin. The black dot is the central gasoline station, as it is located closer to the center than all other stations (the white dots).

For each market the location of the market center had to be calculated manually using ArcGIS and the routing tool WiGeoNetwork.\footnote{At this point I would like to thank Mathias Knapp and Dimitri Kudrnofsky for their calculations.} For this purpose, in each market a number of pins are set exactly to and close to locations that look like potential median location points at first glance. The distances to all gasoline stations in the same local market are calculated for each of these pins. In a second step, a number of pins are set very close to each other around the pin with the lowest sum of distances in the first step. Finally, the pin with the lowest sum of distances in the second step is chosen as the market center, as it is the 1-median location of the local market.

In some markets a unique median location does not exist. For example, in a market with two gasoline stations, all points between these two stations are median location points. The same logic applies to the two innermost stations in markets with any even number of stations as long as they are located along the same road. All of these markets must be excluded from the analysis. However, neither of these exceptions present a market structure that is described by the asymmetric spokes model. Having a number of local markets, a center for each market and the distances of gasoline stations to the market center (and thus the division between central and remote stations) is all the information required to set up the econometric specification of the asymmetric spokes model.
5.3.2 Spatial Weights Matrices for Central and Remote Gasoline Stations

This section provides a numerical example of how local markets and the information on central and remote stations are stored in spatial weights matrices, which were discussed in Section 4.2. Let us store the structure of the two markets schematically illustrated in Figure 4 in the matrix $W$. Assume that the letters $i$ to $n$ attributed to every gasoline station in Figure 4 correspond to the lines and rows of $W$, where $w_{ij} = 1$ if $i$ and $j$ belong to the same market, and $w_{ij} = 0$ otherwise. Then,

$$W = \begin{pmatrix}
0 & 1 & 1 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 1 & 0
\end{pmatrix}.$$ 

It can be easily noticed that, due to the delimited local markets, $W$ is block-diagonal.\(^{49}\) As pointed out by Anselin (2002, p. 259), a block diagonal structure in $W$ does not allow for high order neighborhood and contiguity across higher order levels. In other words, space is broken into a number of islands where interaction only takes place within an island but not across islands. Thus, a shock emanating from agents at one island does not diffuse in space except for the own island. Anselin (2002, p. 259) further points out that in a row-normalized block-diagonal weights matrix the effect of each neighbor will approach zero if the number of neighbors in the group (block) becomes large in a row-normalized $W$ matrix, as $w_{ij} = 1/n_g$, where $n_g$ is the number of units in group (block) $g$. Therefore, “in the limit, the weights matrix becomes effectively zero, eliminating the effect of the spatial correlation” Anselin (2002, p. 259). Lee (2007b, p. 335) also raises concerns about the (weak) identification of interaction effects in large non-interacting groups. However, he concludes that identification is not a problem if the sizes of groups vary sufficiently. In the present empirical model, the groups (local markets) are rather small and vary in their size. Therefore, the block diagonal structure of $W$ is not expected to weaken the identification

\(^{49}\)Empirical applications using block diagonal matrices in economics are sparse but some work has been done in the field of new social economics and social interaction models. See Lee et al. (2010) for a short review.
of the spatial effects.

At this point it is worth mentioning the works of Lee (2007b) and Lin (2010). Lee (2007b) theoretically and Lin (2010) empirically suggest de-group-meaning the values in \( y \) and \( X \) in the setting of a block diagonal \( W \) matrix with non-interacting groups to account for unobservable group specific effects.\(^{50}\) It is important to notice the strategy of de-group meaning that, however, is not feasible in the present analysis. Markets are too small and each member of a market has direct links to all other members in the market through \( W \). As an example: In a market of three stations, the own de-group-meaned price must depend negatively on the de-group-meaned price of the other two stations by definition, as the own de-group-meaned price is the deviation from the average of the own and the other two prices. If the own price is below the average, the price of at least one other neighbor has to be above average. Therefore, there has to be a negative direct impact of rivals’ de-group-meaned prices on the own de-group-meaned price and the true effects (an expected positive impact of rivals’ prices) cannot be identified. De-group-meaning in a SAR model only works if the links in \( W \) are sparse compared to the group size (Lin, 2010, p. 835).

Matrix \( W \) above describes the neighborhood relations of Figure 4 but does not yet contain any information about centrality and periphery. Remember that three different and asymmetric types of interaction are considered in the theoretical asymmetric spokes model of Chapter 3:

1. How do remote stations influence central stations (\( R \rightarrow C \))?
2. How do central stations influence remote stations (\( C \rightarrow R \))?
3. How do remote stations influence other remote stations (\( R \rightarrow R \))?

In Figure 4 station \( i \) (first row/column in \( W \)) and station \( m \) (fifth row/column in \( W \))

\(^{50}\)For this purpose a group matrix \( J_g \) of dimension \( n_g \times n_g \) is constructed for every group \( g \), where \( n_g \) is the number of members \( n \) in group \( g \), so \( J_g = I_{n_g} - \frac{1}{n_g} l_g l_g' \). Here, \( I_{n_g} \) is an identity matrix of dimension \( n_g \times n_g \) and \( l_g \) is a \( n_g \times 1 \) unit vector. Lee (2007b) and Lin (2010) include the block-diagonal matrix \( J \) into their original SAR model. \( J \) is of dimension \( gn_g \times gn_g \) and contains all \( g \) groups. Thus, \( Jy = \rho JW y + JX \beta + J \epsilon \), and \( \hat{y} = \rho JW \hat{y} + \hat{X} \beta + \hat{\epsilon} \), where \( \hat{y}, \hat{X} \) and \( \hat{\epsilon} \) are the de-group-meaned values of the original variables in \( y \), \( X \) and \( \epsilon \). Both authors analyze the more general specification of a spatial Durbin model (SDM) but the lags of the exogenous variables are not of interest for the present analysis and can be omitted.
are the central stations. All other stations are considered as remote. To include this information in the analysis and to identify these three types of interaction, $W$ has to be split into the three matrices

$$W^{R\rightarrow C} = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}, \quad W^{C\rightarrow R} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix},$$

$$W^{R\rightarrow R} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}.$$

In matrix $W^{R\rightarrow C}$ the element $w_{ij}^{R\rightarrow C} = 1$ if $i$ is a central and $j$ is a remote station of the same market. In matrix $W^{C\rightarrow R}$ the element $w_{ij}^{C\rightarrow R} = 1$ if $i$ is a remote and $j$ is the central station of the same market. Finally, in $W^{R\rightarrow R}$ the element $w_{ij}^{R\rightarrow R} = 1$ if $i$ is a remote and $j$ is another remote station of the same market. Further, it follows that $W^{R\rightarrow C} + W^{C\rightarrow R} + W^{R\rightarrow R} = W$.

### 5.4 Econometric Specification

As it is the aim of this empirical analysis to estimate price reaction functions of central and remote gasoline stations, I estimate a spatial autoregressive (SAR) model as discussed in detail in Chapter 4. This model contains the prices of rivals on the explanatory side of the equation as a so-called spatially lagged dependent variable. The spatial information is stored in the matrix $W$. The data covers a total of 23 time periods, 22 of which can be included into the estimation. The sample is analyzed as a repeated cross-section with time period fixed effects rather than as a real panel because the data is extremely unbalanced due to missing data in the dependent variable (price). For each period, a market
is only included into the estimation if information is available on the prices of all gasoline stations in the market. Unfortunately, this requirement substantially reduces the number of markets included in the estimation.\footnote{For details on the data and descriptive statistics see Section 5.5.} However, having prices of all stations in a market is necessary for two reasons: First, due to the split of \( W \) into the three sub-matrices \( W^{R\rightarrow C} \), \( W^{C\rightarrow R} \) and \( W^{R\rightarrow R} \), missing data (and thus dropped observations) might result in all-empty rows if they are not intended to be all-empty.\footnote{Note that the all-zero rows in \( W^{R\rightarrow C} \) for remote observations and the all-zeros rows in \( W^{C\rightarrow R} \) and \( W^{R\rightarrow R} \) for central observations are not a problem because the explanatory variables include a dummy which is equal to one if the observation is a central gasoline station and zero otherwise. See Getis and Aldstadt (2004) and Aldstadt and Getis (2006) for details on consequences of all-zero rows in \( W \).} Second, I want to analyze how the influence of a single gasoline station changes with the number of stations per market. Including observations with missing data would lead to a bias in the number of stations per market. For example, if there are four stations in the market but data is only available for three of them, the market would have to be treated either as a market of three stations or a market of four stations overweighting a single station.

After cleaning out markets with missing data for each period, individual coefficients can be estimated for markets with different numbers of stations. As a result of this reduction, no markets with more than 6 stations remain in the sample. On the one hand, this fact is bad news as markets with a relatively large number of stations are excluded from the analysis. On the other hand it is also good news because it limits the complexity of the econometric model and improves the presentability of the results.

I start out with a basic model assuming symmetric competition between all stations in a market, irrespective of their centrality. This model corresponds to the usual empirical approach of analyzing spatial competition and does not pay attention to the spatial heterogeneity of firms. This model is used as a benchmark for the econometric estimation of the asymmetric spokes model. The benchmark model is given by

\[
y = \sum_{m=3}^{6} \rho_m W_m y + X \beta + Z \gamma + \epsilon. (40)
\]

\( y \) is the vector of prices, \( m \) indicates the number of stations in the market, \( \rho_m \) are the coefficients of spatial autocorrelation and reflect the slopes of the price reaction functions
of gasoline stations in markets with different numbers of stations. For example, $\rho_3$ is the expected mean slope of the price reaction function of stations in markets with three stations. The weight matrices of different time periods are connected to a single block diagonal matrix $W$ of dimension $N \times N$, with $N = \sum_{t=1}^{22} n_t$, where $n_t$ is the number of observations in period $t$. $X$ is of dimension $N \times k$ and contains $k$ exogenous variables including a constant and some interaction terms of exogenous variables with a dummy variable set equal to one if an observation is a central gasoline station. These interaction terms are included to test for differences in the intercept of the price reaction functions of central and remote stations if differences can be expected from the theoretical model. Observations of different periods are added to $X$ vertically. $\beta$ is the $k \times 1$ vector of coefficients of the exogenous variables. $Z$ is a $N \times f$ matrix of $f$ fixed effects dummy variables and $\gamma$ is the $f \times 1$ vector of coefficients of the fixed effects. Finally, $\epsilon$ is a vector of i.i.d. errors.

Matrix $W$ is then split into the three matrices $W^{R\rightarrow C}$, $W^{C\rightarrow R}$ and $W^{R\rightarrow R}$ as discussed in the previous Section 5.3.2 to test differences in the pricing behavior of central and remote gasoline stations:

$$y = \sum_{m=3}^{6} \rho^{R\rightarrow C}_m W^{R\rightarrow C}_m y + \sum_{m=3}^{6} \rho^{C\rightarrow R}_m W^{C\rightarrow R}_m y + \sum_{m=3}^{6} \rho^{R\rightarrow R}_m W^{R\rightarrow R}_m y + X\beta + Z\gamma + \epsilon. \quad (41)$$

The model now has a total of 12 spatial lags that are to be interpreted as follows: $\rho^{R\rightarrow C}_3$ is the expected price change by a central gasoline station as a response to a price change of one unit by one remote gasoline station in a market of three stations. In the same way, $\rho^{C\rightarrow R}_4$ is the amount a remote station is expected to react to a price change by the central station in a market of four stations. While the theoretical model predicts positive values decreasing in $m$ for $\rho^{R\rightarrow C}_m$ and positive constant values for $\rho^{C\rightarrow R}_m$, $\rho^{R\rightarrow R}_m$ should not significantly differ from zero following the theoretical model.

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53The reason for including these interaction terms already into the benchmark model that does not consider asymmetries between central and remote gasoline stations may seem strange at first glance but facilitates the comparability of the fit of this model with the asymmetric spokes model in equation (41). An exclusion of these interaction terms from the benchmark model did not result in significant changes in the slope parameters.

54Note that the spatial weights matrices in (41) are not row-normalized because different matrices are used for observations with different numbers of neighbors.
5.5 Data and Descriptive Statistics

As already discussed briefly in the introduction of this chapter, the data on gasoline stations covers the entire population of gasoline stations in Austria as of August 2003. The company Catalist\textsuperscript{55} collected a comprehensive set of data including stations’ postal addresses, geographical coordinates, brands, ownership, numerous characteristics such as opening hours, services in addition to refueling, quality indicators, size, visibility, traffic and other information on the facilities. The variables selected from the Catalist data for this empirical analysis are summarized in Table 4 on page 64 and discussed below.

The Catalist data are merged with information on prices and addresses on a station level collected by the Austrian Chamber of Labor (Arbeiterkammer) between October 1999 and March 2005. Every three months, prices were collected within one to three days nationwide for a total of 23 points in time, 22 of which are used in the estimations. One of the periods does not contain enough observations to be included for reasons discussed below. Table 5 on page 67 summarizes the number of observations per period. The price data covers about 60\% of all gasoline stations, but prices are not available for all of these stations for every period. In addition to observations eliminated because they belong to markets with two stations only\textsuperscript{56} or because of an absence of a unique market center, a market is eliminated from the sample in period \( t \) if price information of at least one station in the market is not available in \( t \). Especially for markets with many stations, the probability of having price information available for every station is quite low. As a result, no markets \( \geq 8 \) stations can be included in the estimation, and the few remaining markets with 7 stations have to be excluded for technical reasons.\textsuperscript{57} A total of 92 markets can be included in the repeated cross-sectional analysis, for a total of 783 markets observed. Markets with 3 stations are observed 392 times (50\% of the sample), markets with 4 stations 254 times (32\%), markets with 5 stations 94 times (12\%), and markets with 6 stations 43 times (6\%). The 92 markets cover a total of 343 different gasoline stations. Each of these stations/markets appears in the sample 8.5 times on average (with a median of 7).

\textsuperscript{55}See http://www.catalist.com for company details.

\textsuperscript{56}In these markets the asymmetric spokes model does not apply (see Section 5.3.1).

\textsuperscript{57}Sufficient data on markets with 7 stations is not available for every period. Due to the construction of individual \( W \) matrices for markets of different numbers of stations, an inclusion of these markets would have resulted in a \( W \) matrix with all-empty blocks in periods where no markets with 7 stations are available.
Additionally, some regional data provided by the Austrian Statistical Office (Statistik Austria) on a municipality level are added to the data set. These data include numbers on commuting behavior, population density, tourism, and the share of alpine surface and woods, in order to model regional and local differences in demand and costs. The data set also includes prices of business premises provided by the Austrian Chamber of Commerce (Wirtschaftskammer) on a district level to further approximate differences in stations’ costs.

5.5.1 Price, Spatial and Regional Variables

Table 3 provides some descriptive statistics and definitions of the dependent variable, spatial and regional data. The average sample mean of prices (variable PRICE) of one liter of diesel is 75.6 Euro cents.\(^5^8\) The lowest price (61.9) was collected in 03/2002, the highest (92.0) in 12/2004. Using the information on the locations of gasoline stations, the distances between gasoline stations and the distances to the market center were calculated in ArcGIS using a routing tool provided by WiGeoNetwork. C is a dummy variable set equal to one if an observation is a central gasoline station. Central stations account for 26.82\% of the sample. DIST TO CENTER measures the driving time in minutes, from a gasoline station to the center of the market it is assigned to. This distance ranges from zero (station is located at the market center) to 23.6 minutes, with a mean of 2.46 minutes. Even though the data covers urban and rural regions, the variance in the driving time to the center is quite low – a standard deviation of 3.66 minutes – as markets tend to be very local. The interaction term C*DIST TO CENTER measures DIST TO CENTER for central stations. It is equal to zero if an observation is not a central station. Thus, the estimated coefficient of C*DIST TO CENTER describes the deviation of the expected impact of changes in the distance to the center if a station is central, from the impact of changes in the distance of all non-central (remote) stations, which is remaining in the coefficient of DIST TO CENTER. C*AV DIST REMOTE is the average driving time of all remote stations to the market center for central observations. If an observation is a remote station, this variable is equal to

\(^5^8\)I am using prices on diesel rather than gasoline as more prices are available for diesel. Using the smaller number of price information available for regular or Super / Eurosuper gasoline, the sample would shrink to a unfeasibly small size. However, unlike in North America diesel-engined cars are very common in European countries. Within the time period analyzed in this study the share of cars with diesel engines increased steadily to more than 50\% of all cars in 2005 (Statistik Austria, 2006).
Table 3: Descriptive statistics - price, spatial and regional data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Min</th>
<th>Std.Dev.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRICE</td>
<td>Price of 1 liter of diesel in Euro cents</td>
<td>75.5998</td>
<td>61.9000</td>
<td>6.4229</td>
<td>92.0000</td>
</tr>
<tr>
<td>C</td>
<td>Dummy variable set equal to one if the station is central</td>
<td>0.2682</td>
<td>0.0000</td>
<td>0.4431</td>
<td>1.0000</td>
</tr>
<tr>
<td>DIST TO CENTER</td>
<td>Distance a station is located from the center</td>
<td>2.4679</td>
<td>0.0000</td>
<td>3.6600</td>
<td>23.6400</td>
</tr>
<tr>
<td>C*DIST TO CENTER</td>
<td>DIST TO CENTER if the obs. is a central station</td>
<td>0.0710</td>
<td>0.0000</td>
<td>0.2254</td>
<td>2.7200</td>
</tr>
<tr>
<td>C*AV DIST REMOTE</td>
<td>Avg. distance of remote stations to center if obs. is a central station</td>
<td>0.8594</td>
<td>0.0000</td>
<td>2.3968</td>
<td>3.1367</td>
</tr>
<tr>
<td>(1-C)*DIST CENTRAL</td>
<td>Distance of market’s central station to center if obs. is a remote station</td>
<td>0.1942</td>
<td>0.0000</td>
<td>0.3334</td>
<td>2.7200</td>
</tr>
<tr>
<td>(1-C)*AV DIST REMOTE</td>
<td>Avg. distance of the other remote stations to center if obs. is a remote station</td>
<td>1.9766</td>
<td>16.2500</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>COMMUTERS</td>
<td>Ratio of incoming plus outgoing commuters to population of a municipality in percent</td>
<td>35.0372</td>
<td>11.4818</td>
<td>13.8360</td>
<td>110.7596</td>
</tr>
<tr>
<td>TOURISM</td>
<td>Number of touristic overnight stays in the municipality in the month observed+</td>
<td>105,345.0000</td>
<td>0.0000</td>
<td>223,714.9000</td>
<td>836,698.0000</td>
</tr>
<tr>
<td>LOW TOURISM</td>
<td>Equal to one if TOURISM is n/a (report optional if overnight stays per year &lt; 1,000)</td>
<td>0.1551</td>
<td>0.0000</td>
<td>0.3621</td>
<td>1.0000</td>
</tr>
<tr>
<td>POP DENSITY</td>
<td>Population density per square kilometer on a municipality level</td>
<td>1,262.8060</td>
<td>4.1657</td>
<td>2,534.8730</td>
<td>18,153.5200</td>
</tr>
<tr>
<td>PREMISES</td>
<td>Average price for business premises per square meter on a district level+</td>
<td>116.4591</td>
<td>0.0000</td>
<td>69.5982</td>
<td>280.8000</td>
</tr>
<tr>
<td>N/A PREMISES</td>
<td>Equal to one if PREMISES is n/a</td>
<td>0.0288</td>
<td>0.0000</td>
<td>0.1672</td>
<td>1.0000</td>
</tr>
<tr>
<td>ALPS+WOOD</td>
<td>Ratio of alpine areas plus forests to total surface of the municipality in percent</td>
<td>38.3456</td>
<td>0.0000</td>
<td>26.3590</td>
<td>87.2362</td>
</tr>
</tbody>
</table>

# of observations: 2,920

* Missing values replaced by zeros
zero. On the other hand, \( (1-C)\times{AV\,DIST\,REMOTE} \) 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. \( (1-C)\times{DIST\,CENTRAL} \) is only different from zero if an observation is a remote station. The value reflects the distance the central station of the market a remote station is assigned to is located away from the center.

All of these distance-based variables are also found in the theoretical asymmetric spokes model. From the theoretical model I expect a negative impact of \( DIST\,TO\,CENTER \) and \( C\times{DIST\,TO\,CENTER} \) on prices, but a positive impact of \( C\times{AV\,DIST\,REMOTE} \) and \( (1-C)\times{DIST\,CENTRAL} \). These expected negative impacts result from a loss of consumers when moving further away from the center. The positive impacts result in an increase in the (average) distance between the central and remote stations and thus leads to a higher degree of market power. \( (1-C)\times{AV\,DIST\,REMOTE} \) should not have a significant impact as remote stations do not compete with each other in the theoretical model.

Three variables are included to approximate differences in local demand. \( COMMUTERS \) is the ratio of incoming plus outgoing commuters in a municipality over the population of the municipality in percent. \( TOURISM \) is the number of touristic overnight stays per municipality in the month observed. The high numbers in the mean and variance are mainly driven by a few big cities like Vienna and various touristic villages in the Alps. Municipalities with more than 1,000 touristic overnight stays have to report the numbers to the Austrian Statistical Office. For municipalities with less than 1,000 overnight stays reporting is voluntary. For municipalities not reporting their numbers, the data are missing (15% of the sample). As the missing values depend on their own value and not on the value of the dependent variable (PRICE), they can be considered as ‘missing at random’ (Greene, 2008, pp. 61ff). Observations (completely) missing at random can be either deleted from the sample or transformed by the ‘modified zero-order regression’. In such a regression missing values are replaced by zeros. For each variable containing missing values, new dummy-variables are generated that are equal to one if the value is missing for the observation, and zero otherwise. This approach is more efficient than dropping an observation, but does lead to a measurement error. However, as Greene (2008, p. 63) points out, the bias is likely to be very small if, among other things, the proportion of
missing data is small. Also, given the far-reaching consequences of deleting observations for the whole sample through the spatial interdependence of observations – deleting a few observations would imply deleting the entire market to which an observation belongs – deleting observations with missing data is not feasible due to the high level of inefficiency involved. Therefore, the dummy variable LOW TOURISM is set equal to one if TOURISM is missing and set to zero otherwise. POP DENSITY is used to account for differences in the degree of urbanization on a municipality level.

PREMISES is the district’s average price for business premises per square meter and is included to approximate local differences in costs. For some districts no data on prices for business premises are available. These values are again ‘missing at random’ because whether they are missing or not depends on the location (district) but not on gasoline prices. Missing values are again replaced by zeros and the dummy N/A PREMISES controls for the missing values, which account for only 2.8% of the observations. ALPS+WOOD is included as an additional proxy for local differences in costs. It contains the share of alpine surface and woods of a municipality’s total surface and serves as an indicator for the remoteness of a municipality and the accessibility of refineries. This variable is also included as a cost proxy in Clemenz and Gugler (2006).

### 5.5.2 Site Characteristics

**Table 4: Descriptive statistics - site characteristics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>True</th>
<th>Inf n/a</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Description</td>
<td>Freq</td>
<td>Share</td>
</tr>
<tr>
<td>BRANDED</td>
<td>Equal to one if station is branded</td>
<td>2,489</td>
<td>85.24%</td>
</tr>
<tr>
<td>DEALER OWNED</td>
<td>Equal to one if station is owned by the dealer</td>
<td>869</td>
<td>29.76%</td>
</tr>
<tr>
<td>HIGHWAY</td>
<td>Equal to one if station is located on a highway</td>
<td>33</td>
<td>1.13%</td>
</tr>
<tr>
<td>SERVICE</td>
<td>Equal to one if station offers attendance service</td>
<td>693</td>
<td>23.73%</td>
</tr>
<tr>
<td>SIZE &gt; 2000</td>
<td>Equal to one if facility surface is &gt; 2,000m²</td>
<td>981</td>
<td>33.60%</td>
</tr>
<tr>
<td>TRAFFIC GOOD</td>
<td>Equal to one if road-traffic at site is heavy</td>
<td>2,060</td>
<td>70.55%</td>
</tr>
</tbody>
</table>

# of observations: 2,920
Missing values replaced by zero
Dummy variables created for each variable with missing data; Dummy equal to one if data n/a

59 For more details on missing data see the textbook by Little and Rubin (2002).
Out of the multitudinous variables offered by Catalist, only a few main site characteristics are selected as controls because the impact of different site characteristics on prices are not of particular interest in this study. The variables included in the estimations are illustrated and described in Table 4. Pennerstorfer (2008, 2009) includes a multitude of these variables into his analysis of the Austrian retail gasoline market, but finds that only a few of them have significant impacts on prices. However, the author does find a strong impact of brands on prices: His results show that 9 out of 10 brands operating in Austria charge significantly higher prices than unbranded stations. Only the prices of one minor brand are not significantly different from unbranded stations. For reasons of efficiency, different brands are therefore subsumed in the variable BRANDED. Branded stations account for 85% of observations in the sample. Some of the branded stations are not owned by the respective company but by the dealer operating under licence of a brand. The share of dealer-owned (variable DEALER OWNED) stations in the sample is 30%. While unbranded (independent) stations are assumed to set prices independently, the degree of self-government in pricing decisions of individual branded stations is unclear. Experts expect that at least the major brands decide on prices centrally, but, as Pennerstorfer (2008, p. 69) puts it, there is no evidence.

Some other station characteristics that are likely to raise consumer demand are included in the estimation: Gasoline stations located along a highway (HIGHWAY) are expected to charge higher prices as consumers on a highway face high search costs and high transportation costs when leaving the highway for refueling. The dummy variable TRAFFIC GOOD is equal to one if traffic at the location of a station is considered heavy by Catalist and is included as a proxy for differences in stations’ demand. Stations offering attendance service (SERVICE) and large stations (SIZE > 2000) may be considered as qualitatively superior, as fueling does not have to be done by oneself in the former case and the waiting time is likely to be lower in the latter case.

For some stations one or several site characteristics are missing in the Catalist data. However, correlations with brands, regions etc. did not show any significant patterns for the missing values in Pennerstorfer (2008, pp. 74ff). Thus, the missing values can be considered as ‘missing completely at random’ (Greene, 2008, p. 61). The fraction of
missing values is very small for all of these variables as illustrated in Table 4 (between 2.4% and 7.8%) and the variables are not of particular interest for this study. Thus, for reasons of efficiency observations with missing data are again included in the sample applying the ‘modified zero-order regression’ with dummy variables controlling for originally missing values, which are replaced by zeros.\textsuperscript{60}

### 5.5.3 Fixed Effects

In addition to variables on space, regional/local and site characteristics, some fixed effects are included in the model. Dummies for the different time periods are included to control for the substantial shifts in crude oil prices over time. The distribution of observations over the 22 time periods is illustrated in Table 5. The last period is left out in the estimation as a reference group. Further, fixed effects are included for markets with different numbers of stations since the number of competitors may have an impact on price levels, which is not captured by the slope parameters of stations’ price reaction functions. As depicted in Table 5, 40\% (35\%) of all observations belong to markets of three (of four) stations. Markets with five or six gasoline stations account for about 25\%. Markets with three stations are left out as a reference group.

Table 5 also illustrates the fixed effects for Austria’s nine federal states, which are characterized by a general increase in income and price levels from east to west. The relative majority (25\%) of the observations are located in the federal state of Lower Austria (Niederösterreich). The states of Burgenland, Upper Austria (Oberösterreich) and Vorarlberg each account for less than 2\% of all observations.

### 5.6 Results and Discussion

#### 5.6.1 Tests for Spatial Dependence

Section 4.3.2 introduced a number of tests to detect spatial dependence in the data. A diffuse test for the pure existence of spatial dependence is the so-called Moran’s $I$ test. The (robust) LM-Lag and LM-Error tests are used to test whether the data used have the characteristics of a spatial lag or a spatial error process, if spatial dependence is detected

\textsuperscript{60}For HIGHWAY and TRAFFIC GOOD the missing values affect exactly the same observations. Thus, a single dummy variable is sufficient to control for missing values of both variables.
Table 5: Descriptive statistics - fixed effects

<table>
<thead>
<tr>
<th>Variable</th>
<th>Freq.</th>
<th>Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time period</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pd0406</td>
<td>91</td>
<td>3.12%</td>
</tr>
<tr>
<td>pd0409</td>
<td>86</td>
<td>2.95%</td>
</tr>
<tr>
<td>pd0412</td>
<td>87</td>
<td>2.98%</td>
</tr>
<tr>
<td>pd0503*</td>
<td>80</td>
<td>2.74%</td>
</tr>
<tr>
<td>pd0003</td>
<td>161</td>
<td>5.51%</td>
</tr>
<tr>
<td>pd9910</td>
<td>167</td>
<td>5.72%</td>
</tr>
<tr>
<td>pd9912</td>
<td>159</td>
<td>5.45%</td>
</tr>
<tr>
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<td>5.45%</td>
</tr>
<tr>
<td>pd0007</td>
<td>157</td>
<td>5.38%</td>
</tr>
<tr>
<td>pd0109</td>
<td>105</td>
<td>3.60%</td>
</tr>
<tr>
<td>pd0111</td>
<td>111</td>
<td>3.80%</td>
</tr>
<tr>
<td>Gasoline stations per market</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pd0010</td>
<td>98</td>
<td>3.36%</td>
</tr>
<tr>
<td>pd0012</td>
<td>105</td>
<td>3.60%</td>
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<td>3.49%</td>
</tr>
<tr>
<td>pd0106</td>
<td>95</td>
<td>3.25%</td>
</tr>
<tr>
<td>pd0109</td>
<td>105</td>
<td>3.60%</td>
</tr>
<tr>
<td>pd0203</td>
<td>181</td>
<td>6.20%</td>
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<td>5.55%</td>
</tr>
<tr>
<td>pd0209</td>
<td>176</td>
<td>6.03%</td>
</tr>
<tr>
<td>pd0212</td>
<td>202</td>
<td>6.92%</td>
</tr>
<tr>
<td>pd0306</td>
<td>107</td>
<td>3.66%</td>
</tr>
<tr>
<td>pd0309</td>
<td>210</td>
<td>7.19%</td>
</tr>
<tr>
<td>pd0312</td>
<td>186</td>
<td>6.37%</td>
</tr>
<tr>
<td>Federal state</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pd0403</td>
<td>92</td>
<td>3.15%</td>
</tr>
<tr>
<td>pd0412</td>
<td>87</td>
<td>2.98%</td>
</tr>
<tr>
<td>pd0503*</td>
<td>80</td>
<td>2.74%</td>
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<tr>
<td>pd0003</td>
<td>161</td>
<td>5.51%</td>
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<tr>
<td>pd9910</td>
<td>167</td>
<td>5.72%</td>
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<tr>
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<td>159</td>
<td>5.45%</td>
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<tr>
<td>Gasoline stations per market</td>
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<td>pd0010</td>
<td>98</td>
<td>3.36%</td>
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<td>pd0012</td>
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<tr>
<td>pd0503*</td>
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<td>2.74%</td>
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<tr>
<td>Federal state</td>
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<tr>
<td>pd0109</td>
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<tr>
<td>pd0111</td>
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<tr>
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</tr>
<tr>
<td>Federal state</td>
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<tr>
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<td>3.60%</td>
</tr>
<tr>
<td>pd0111</td>
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</tr>
<tr>
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</tr>
<tr>
<td>pd0412</td>
<td>87</td>
<td>2.98%</td>
</tr>
<tr>
<td>pd0503*</td>
<td>80</td>
<td>2.74%</td>
</tr>
</tbody>
</table>

* Left out as a reference group

# of observations: 2,920

at all. Table 6 shows the results of the tests for spatial dependence using the OLS residuals of the regression $y = X\beta + \epsilon$ based on the variables presented in Section 5.5 and the spatial weights matrix $W$ discussed in Section 5.4. The results of this OLS estimation are reported in specification [5] of Table 16 in Appendix B.

Table 6: Tests for spatial dependence

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>z-Stat.</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran’s I</td>
<td>0.7713</td>
<td>46.0670</td>
<td>0.0000***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$-Stat.</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM-Lag</td>
<td>2264.0000</td>
<td>0.0000***</td>
</tr>
<tr>
<td>LM-Error</td>
<td>2314.6000</td>
<td>0.0000***</td>
</tr>
<tr>
<td>Robust LM-Lag</td>
<td>1.4445</td>
<td>0.1612</td>
</tr>
<tr>
<td>Robust LM-Error</td>
<td>51.9639</td>
<td>0.0000***</td>
</tr>
</tbody>
</table>

# of obs.: 2,920; *** 1%, ** 5%, * 10% significance level
$\chi^2$: df = 1

The value of the Moran’s $I$ test statistic is significantly different from zero. Thus, the null-hypothesis of no spatial dependence has to be rejected and a simple OLS regression of $y = X\beta + \epsilon$ leads to biased (SAR process) or inefficient (SEM process) estimates of $\beta$. While the high coefficient of Moran’s $I$ (0.77) indicates a high level of spatial dependence, it does not give a hint on whether a spatial lag or a spatial error model should be estimated.
from a statistical point of view. This question is addressed by the Lagrange Multiplier (LM)-tests also reported in Table 6.

The LM-Lag and the LM-Error tests are both significantly different from zero. The value of the LM-Error tests is slightly higher than the value of the LM-Lag test but both values are quite high. The robust LM-Lag (LM-Error) test allows for a spatial correlation in the error terms (dependent variable) while testing for a spatial correlation in the dependent variable (error terms). While the robust LM-Error test is highly significant, the robust LM-Lag test is not. Thus, the robust LM-Tests recommends a SEM specification over a SAR model, while the regular LM-test does not. However, this recommendation is motivated from a purely statistical point of view. As the main goal of this study is to estimate price reaction functions, a spatial lag – and thus a SAR model – is the preferred specification from a economically motivated point of view. Table 16 in Appendix B provides the estimates of a SEM model (specification [6]) and a SAR model (specification [7]) using $W$ to account for spatial autocorrelation in the error terms and the dependent variable, respectively. A comparison of the two specifications illustrates the robustness of the results in terms of significance and positive/ negative signs with respect to these two different specifications. Therefore, I stick to the SAR model as the main specification.

5.6.2 Results of the Maximum Likelihood Estimations

The main results of the ML-estimates of prices are reported in Table 7. Specification [1] represents the benchmark model of equation (40) and does not consider asymmetries in the competition between central and remote stations. The coefficients $\rho_m$ estimated for $W_{my}$ reflect the reaction to a price change of one competitor in the market under the assumption of a symmetric competition between stations. The coefficient of 0.3261 for $\rho_3$ can be interpreted as follows: In markets with three stations, a station is expected to change its price by 0.33 cents if one of the two other stations in the market change their price by one cent. The impact of one station on the prices of competitors decreases steadily as the number of stations in a market increases in specification [1]. In markets with four (five) stations, the expected reaction to a price change of one cent by one competitor is equal to 0.22 (0.17) cents. In markets with six stations, a price change by one station leads to an
expected reaction by other stations of 0.13 cents.

The results in specification [1] are estimated under the assumption that the reaction functions of stations are symmetric with respect to both their own and the rivals’ locations in the market. Specifications [2] to [4] relax the assumption of a symmetric competition by stations and test for the asymmetries proposed by the theoretical asymmetric spokes model of Chapter 3. The likelihood ratio test statistics at the bottom of Table 7 favor specification [2] over specifications [3] and [4]. Thus, I will focus on discussing the main results for the coefficients of specification [2]. The slope parameters of the reaction functions of specification [2] reveal that competition in markets with three stations seems to be quite symmetric. Remote stations have the same impact on central stations as the other way around. Also, remote stations seem to interact with one another with the same intensity. The $t$-test based statistics of Table 8 confirm that there is no significant asymmetry in the competition between central and remote stations in markets with three stations. The same applies to markets with four stations. The coefficients for the slope parameters do not significantly differ from those of the benchmark model in specification [1] and are between 0.21 and 0.24. The $t$-tests reported in Table 8 also reject the asymmetry implied by the asymmetric spokes model for markets with four stations.

The existence of an asymmetric competition described by the asymmetric spokes model, however, becomes apparent when taking a closer look at the parameters for markets with five and six stations. The reaction of remote stations to a price change of one cent by the central station increases to a change of 0.53 cents in markets with five stations, while the reaction of the central station (remote stations) to a remote station (another remote station) decreases to 0.16 (0.05). In markets of six stations, the reaction of remote stations to the central station is 0.37 while it is only 0.07 to another remote station. The reaction of the central station to a remote station is equal to 0.12. Thus, for markets with 5 and 6 stations, the central station becomes a much more important reference in pricing. The asymmetry is confirmed by the $t$-tests in Table 8, in which the null-hypothesis of symmetric (identical) coefficients is rejected at a 99% significance level for markets with five and six stations.

The coefficients of specification [2] are very robust in size and significance with respect to the changes made in specification [3] and [4]. Further, Table 7 only reports the results referring to the main propositions of this thesis. The complete estimation results including all control variables are reported in Table 14 and 15 in Appendix B.
Table 7: Estimates of gasoline prices in the empirical spokes model

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>[1]</th>
<th>[2]</th>
<th>[3]</th>
<th>[4]</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \rho_3 )</td>
<td>0.3261</td>
<td>63.1889***</td>
<td>0.3205</td>
<td>51.3948***</td>
</tr>
<tr>
<td>( \rho_4 )</td>
<td>0.2180</td>
<td>60.0520***</td>
<td>0.3202</td>
<td>10.4689***</td>
</tr>
<tr>
<td>( \rho_5 )</td>
<td>0.1710</td>
<td>50.4335***</td>
<td>0.2136</td>
<td>47.3359***</td>
</tr>
<tr>
<td>( \rho_6 )</td>
<td>0.1322</td>
<td>33.7559***</td>
<td>0.2428</td>
<td>9.2115***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow C} )</td>
<td>0.3156</td>
<td>43.0588***</td>
<td>0.3105</td>
<td>51.3948***</td>
</tr>
<tr>
<td>( \rho_{C \rightarrow R} )</td>
<td>0.3330</td>
<td>10.1115***</td>
<td>0.3302</td>
<td>10.4689***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow R} )</td>
<td>0.3328</td>
<td>10.8469***</td>
<td>0.3284</td>
<td>10.8176***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow C} )</td>
<td>0.2210</td>
<td>37.8511***</td>
<td>0.2092</td>
<td>15.3416***</td>
</tr>
<tr>
<td>( \rho_{C \rightarrow R} )</td>
<td>0.2393</td>
<td>8.0303***</td>
<td>0.2288</td>
<td>9.2115***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow R} )</td>
<td>0.1649</td>
<td>25.8326***</td>
<td>0.1670</td>
<td>41.8240***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow C} )</td>
<td>0.5342</td>
<td>508.2663***</td>
<td>0.5509</td>
<td>528.8856***</td>
</tr>
<tr>
<td>( \rho_{C \rightarrow R} )</td>
<td>0.0529</td>
<td>153.3454***</td>
<td>0.0466</td>
<td>133.8640***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow R} )</td>
<td>0.1185</td>
<td>13.0787***</td>
<td>0.1322</td>
<td>30.7012***</td>
</tr>
<tr>
<td>( \rho_{R \rightarrow C} )</td>
<td>0.3731</td>
<td>5.6716***</td>
<td>0.3131</td>
<td>4.9365***</td>
</tr>
<tr>
<td>( \rho_{C \rightarrow R} )</td>
<td>0.0785</td>
<td>4.9800***</td>
<td>0.0900</td>
<td>5.6935***</td>
</tr>
<tr>
<td>C</td>
<td>0.3770</td>
<td>2.9065***</td>
<td>2.9808</td>
<td>2.4326**</td>
</tr>
<tr>
<td>STATIONS_4</td>
<td>-0.2721</td>
<td>-0.3610</td>
<td>0.8848</td>
<td>0.9539</td>
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<tr>
<td>STATIONS_6</td>
<td>-1.3788</td>
<td>-0.9660</td>
<td>-2.3271</td>
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<tr>
<td>C*STATIONS_4</td>
<td>0.2473</td>
<td>1.6195</td>
<td>3.6436</td>
<td>1.9775**</td>
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<tr>
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<td>-0.3644</td>
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<td>-0.4749</td>
<td>-0.1914</td>
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<tr>
<td>C*STATIONS_6</td>
<td>0.4249</td>
<td>1.5124</td>
<td>4.8746</td>
<td>1.2191</td>
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<tr>
<td>DIST TO CENTER</td>
<td>0.0455</td>
<td>4.2388***</td>
<td>0.0425</td>
<td>3.9686***</td>
</tr>
<tr>
<td>C*DIST TO CENTER</td>
<td>-0.3535</td>
<td>-2.2473**</td>
<td>-0.3847</td>
<td>-2.4621***</td>
</tr>
<tr>
<td>C*AV DIST REMOTE</td>
<td>0.0831</td>
<td>3.1748***</td>
<td>0.0822</td>
<td>3.1592***</td>
</tr>
<tr>
<td>(1-C)*DIST CENTRAL</td>
<td>0.1036</td>
<td>0.9544</td>
<td>0.0548</td>
<td>0.5040</td>
</tr>
<tr>
<td>(1-C)*AV DIST REMOTE</td>
<td>0.0323</td>
<td>2.3505**</td>
<td>0.0345</td>
<td>2.5322**</td>
</tr>
<tr>
<td>Regional &amp; Site Char.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Federal State F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Period F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( \ell )</td>
<td>-4,795.2371</td>
<td>-4,774.3487</td>
<td>-4,778.0722</td>
<td>-4,832.1812</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>2.4084</td>
<td>2.3638</td>
<td>2.3684</td>
<td>2.3955</td>
</tr>
<tr>
<td>LR-Test (p-value)</td>
<td>7.4470</td>
<td>(0.0589)*</td>
<td>108.2180</td>
<td>(0.0000)***</td>
</tr>
</tbody>
</table>

\# of obs.: 2,920; *** 1%, ** 5%, * 10% significance level

+ H1: Specification [2]
Table 8: Testing symmetric vs. asymmetric competition using $t$-tests

<table>
<thead>
<tr>
<th>$H_0$: $\bar{X} = \mu$</th>
<th>[2]</th>
<th>[3]</th>
<th>[4]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_3$</td>
<td>1.4221</td>
<td>0.8906</td>
<td>0.9399</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_3$</td>
<td>0.2107</td>
<td>0.1301</td>
<td>0.6679</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_4$</td>
<td>0.2205</td>
<td>0.0786</td>
<td>0.3048</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_4$</td>
<td>0.5097</td>
<td>0.9750</td>
<td>0.3127</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_5$</td>
<td>0.7832</td>
<td>0.9425</td>
<td>0.8972</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_5$</td>
<td>0.8260</td>
<td>0.6462</td>
<td>0.0821</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_5$</td>
<td>0.9492</td>
<td>0.9914</td>
<td>0.5767</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_5$</td>
<td>345.5981***</td>
<td>364.7534***</td>
<td>382.5020***</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_5$</td>
<td>342.0462***</td>
<td>357.7189***</td>
<td>350.7275***</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_6$</td>
<td>1.5125</td>
<td>0.0006</td>
<td>0.7135</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_6$</td>
<td>3.6613***</td>
<td>2.8517***</td>
<td>3.4363***</td>
</tr>
<tr>
<td>$\rho_{C-R}^{C-R} = \rho_6$</td>
<td>3.4057***</td>
<td>2.6701***</td>
<td>2.9922***</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_6$</td>
<td>0.0031</td>
<td>0.0295</td>
<td>0.1942</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_6$</td>
<td>0.8148</td>
<td>0.8567</td>
<td>0.5762</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_6$</td>
<td>39.1853***</td>
<td>44.7594***</td>
<td>48.4631***</td>
</tr>
<tr>
<td>$\rho_{R-C}^{R-C} = \rho_6$</td>
<td>5.7545***</td>
<td>4.5835***</td>
<td>5.4418***</td>
</tr>
</tbody>
</table>

# of obs.: 2,920; *** 1%, ** 5%, * 10% significance level

stations in all specifications.\(^{62}\)

In the theoretical asymmetric spokes model of Chapter 3, it was argued that centrality does not only affect the strategic interaction in a pricing game, but also has an impact on price levels, albeit this impact can be either positive or negative. The value of $C$ – a dummy variable equal to one if a gasoline station is considered central, and zero otherwise – is significantly different from zero. In specification [1] the expected price of central stations is 0.38 cents higher than the price of remote stations, ceteris paribus. However, this difference increases to 1.69 (2.98) in specification [2] ([4]) when central and remote stations are modeled more explicitly through spatial lags. I also test the impact of the number of stations in the market on price levels – as competition might tighten with an increasing number of stations – and find that prices in markets with more than four stations (STATIONS_5 and STATIONS_6) are lower than in the reference group of markets with three stations, but the effect is significant for markets with five stations only. Additionally, I interact centrality and the number of stations in specifications [1] and [2] but I do not find robust results confirming that centrality increases the pressure put on price levels if

---

\(^{62}\)The fact that $\rho_{R-C}^{R-C} = \rho_5$ and $\rho_{R-C}^{R-C} = \rho_6$ are not rejected by the $t$-tests in Table 8 does not weaken these results because for the central gasoline station competition with remote stations does not change compared to the assumption of symmetric competition in specification [1]. In either case the central station’s competitors are all the remote stations in the market. Thus, the role of remote stations remains unchanged from the perspective of the central station.
the number of competitors (neighbors) increases.\textsuperscript{63}

The theoretical asymmetric spokes model further suggests that a decrease in centrality, i.e. a greater distance from the center, leads to lower equilibrium prices for both central and remote stations. However, DIST TO CENTER indicates that the prices of remote stations are expected to increase by 0.04 cents if the driving time to the center increases by one minute, which contradicts the theoretical model. The coefficient of C\*DIST TO CENTER can be interpreted in the sense that an increase in the distance to the center of a central station by one minute of driving time is expected to lead to a price that is 0.38 cents lower than the price change resulting from an increase in the distance to the center by one minute for the group of remote stations.\textsuperscript{64} Thus, the net effect of an increase in the distance to the center for central stations by one minute is equal to $0.04 - 0.38 = -0.34$ cents. It is a common theoretical and empirical finding (see Chapter 2) that an increase in spatial differentiation (i.e. an increase in the distance to rivals) increases prices. C\*AV DIST REMOTE indicates that prices of central stations are expected to increase by 0.08 cents if the average distance of remote stations to the center increases by one minute. Also, the prices of remote stations increase by 0.03 if the distance of other remote stations to the center increases by one minute (variable (1-C)*AV DIST REMOTE). This fact contradicts the theoretical model, but is not very surprising given the empirical results, which show a significant interaction between remote stations. On the other hand, a change in the distance the central station is located from the center does not seem to affect the prices of remote stations, as (1-C)*DIST CENTRAL is not significantly different from zero.

5.6.3 The Impact of Individual Shocks of Central and Remote Gasoline Stations

This section tests for asymmetries in the total impact on equilibrium prices following a price change by an individual gasoline station. According to proposition 2 of Section 3.4, an individual cost shock, e.g. due to a takeover, of a single central station has a stronger effect on equilibrium prices of a local market than a shock of the same magnitude coming from a remote station. The existence of asymmetries in the strategic interaction between central and remote stations has already been discussed based on the \textit{t}-tests in Table 8

\textsuperscript{63}Specifications [3] and [4] leave out these interaction terms to check and confirm the robustness of the coefficients of the market size variables STATIONS\_4 to STATIONS\_6.

\textsuperscript{64}Through the interaction term C\*DIST TO CENTER the coefficient of DIST TO CENTER reflects the coefficient for remote stations only.
above. These point estimates, however, only capture the direct effects (see Section 4.5) of a price change. Starting from equilibrium prices in a local market, an increase in the price of one station will raise prices of all direct competitors. Following these reactions, the direct competitors of these direct competitors (and therefore also the station which originally changed the price) again will adjust their prices. The process stops when a new price equilibrium is reached. Assuming symmetric competition in specification [1] of Table 7, the average impact on prices of all stations in a local market is independent of whether the shock emanates from the central or a remote station. However, as confirmed by the results of this analysis, remote stations are more sensitive to the price of the central station than to the price of other remote stations in markets with more than four stations.

For any local market of \( h \) stations three matrices \( H_1, H_2 \) and \( H_3 \) of size \( h \times h \) similar to \( W^{R-C}, W^{C-R} \) and \( W^{R-R} \) are defined, but for one representative local market only. The element \( i, j \) of matrix \( H_1 \) \( (H_2) \) \( [H_3] \) is equal to one if \( i \) is the central and \( j \) a remote station \( (i \) is a remote and \( j \) the central station) \( [i \) and \( j \) are remote stations], and zero otherwise. \( \Delta p_C \) is the shock coming from the central station and \( \Delta p_i \) the shock coming from a remote station. Both vectors are of dimension \( h \times 1 \) and can be written as

\[
\Delta p_C = \begin{pmatrix}
1 \\
0 \\
0 \\
\vdots
\end{pmatrix}, \quad \Delta p_i = \begin{pmatrix}
0 \\
1 \\
0 \\
\vdots
\end{pmatrix}.
\]

Without loss of generality I assume that the central station \( C \) is represented by the first element of both vectors and that the price change by a remote station \( (R_i) \) comes from the station represented by the second element of \( \Delta p_i \). The change in equilibrium prices, \( \Delta p^* \), is a \( h \times 1 \) vector and is given by:

\[
\Delta p^*_C = (I_h - \sum_{v=1}^{3} \rho_v H_v)^{-1} \Delta p_C,
\]

\[
\Delta p^*_i = (I_h - \sum_{v=1}^{3} \rho_v H_v)^{-1} \Delta p_i.
\]

\( I_h \) is the identity matrix of dimension \( h \) and \( \rho_v \) are the spatial autoregressive coefficients

The average increase in equilibrium prices in a local market is denoted as $\Delta p^*_C$ ($\Delta p^*_i$) if the price shock comes from a central (remote) station and is equal to the sum of the elements of $\Delta p^*_C$ ($\Delta p^*_i$) divided by $h$. $\Delta p^*_C/\Delta p^*_i > 1$ indicates that the average impact of a shock coming from $C$ is higher than the average impact of the same shock emanating from $R_i$, which would confirm the existence of asymmetries in the impact on local market prices.

A bootstrap simulation technique\textsuperscript{65} is used to account for the uncertainty of the parameter values of the point estimates of the econometric model. Each parameter is drawn randomly from a normal distribution with the mean and the standard errors of the $\rho$s of specification [2]. Repeating this process 10,000 times I can derive a probability distribution instead of point estimates. The median (solid line) and the 99% and 95% confidence interval (dashed lines) are illustrated in Figure 6. The horizontal line at a value of 1 illustrates the case of symmetric competition and serves as a reference.

\textbf{Figure 6: Asymmetric vs. symmetric impacts of shocks}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{asymmetric_vs_symmetric.png}
\caption{Asymmetric vs. symmetric impacts of shocks}
\end{figure}

Figure 6 compares the ratio $\Delta p^*_C/\Delta p^*_i$ based on the simulation results to the symmetric case of $\Delta p^*_C/\Delta p^*_i = 1$ for markets with different numbers of stations. Again, a symmetric impact cannot be rejected in markets with three and four gasoline stations. However, in markets with more than four stations the central station has a higher impact than a remote

\textsuperscript{65}See Cameron and Trivedi (2005) for an introduction.
station on equilibrium prices of a local market. In markets with five and six stations the impact of an individual shock induced by the central station on equilibrium prices becomes more than twice the size of the impact of a shock by a remote station.

Figure 7: The impact of shocks on equilibrium prices of remote stations

As the $t$-tests in Table 8 on page 71 reveal, the impact of one remote station on the central station decreases proportionally with the number of remote stations in the market. Figure 7 illustrates the difference in the impact of a shock coming from the central and a remote station, respectively, on the equilibrium prices of remote stations. Again, the solid line indicates the mean and the dashed lines the 90% confidence intervals. As in all tests asymmetries in the influence of central and remote stations have to be rejected for markets with three and four stations but are significant in markets with five and six stations. The total change in equilibrium prices of a remote station following a price change of one cent by the central or another remote station is about 0.75 cents including all feedback effects in markets with three stations. The impact of one remote stations on other remote stations decreases steadily to 0.27 in markets with five and to 0.24 in markets with six stations. The total change in equilibrium prices of remote stations following a price change of the central station by one cent increases to about 1.1 cents in markets with five and to 0.8 cents in markets with six stations. The wide confidence interval in markets with 6 stations is a result of the ‘large’ standard errors of the point estimates of $\rho^C_{6 \rightarrow R}$ and $\rho^R_{6 \rightarrow R}$ compared to the other parameters used in this simulation. The results obtained in this
simulation confirm the existence of asymmetries between central and remote stations, also for the transmission of individual shocks, but again only for markets with more than four stations.

5.7 Summary and Conclusion

In this chapter I have tested the implications and propositions of the asymmetric spokes model in an empirical application to the Austrian retail gasoline market. I have specified a spatial autoregressive model that accounts for and tests asymmetries in the strategic interaction in pricing between central and remote gasoline stations. I have delimited a number of local markets and have estimated the model for markets with three to six gasoline stations. While I cannot reject the symmetry in competition that is typically presumed in the theoretical and empirical analysis of spatial price competition in markets with few stations, I find significant evidence that the central station becomes the key reference in pricing in markets with more than four gasoline stations. Even though I find that remote stations compete with other remote stations as well, the econometric results confirm that the price set by the central station serves as the main reference price for remote stations in markets $> 4$ stations. Simulations based on the econometric results show that, with an increasing number of stations in the market, the influence of the central stations on equilibrium market prices also increases relative to the influence of remote stations. Further, the econometric results provide evidence, that central gasoline stations charge higher prices than remote stations.

This chapter provides an empirical model that follows the theoretical asymmetric spokes model introduced in Chapter 3 as closely as possible. Clearly, this empirical model has its limitations. Local markets have to be defined in order to assign a market center and a central gasoline station to each market. Using nearest-neighbor-relations as a delimiter for local markets may appear somewhat arbitrary, but leads to markets that are localized enough to reflect the spatial patterns of the theoretical model. However, in this approach markets are islands. Interaction takes place between stations within one market but cannot occur between markets per definition. Even if a station of one market is relatively close to a station of another market compared to another station of its own market, competition is assumed to take place indirectly between the two stations of the same market but not
between the two stations of the different markets. A weakness of this empirical model is the binary division of stations into central and remote. The real world patterns often reflect spatial structures that are more complex than the simple star-shaped graph representing the theoretical spokes model. For instance, there might be several intersections within one local market or several stations might be located along the same spoke (road). Thus, there might exist a group of stations that are neither purely central nor purely remote as assumed in this model but rather ‘semi-central’ or ‘semi-remote’. In these cases the binary distinction between central and remote stations appears problematic.

The assumptions necessary for the empirical approach testing the asymmetric spokes model in this chapter leave very little space for checking the results for their robustness apart from the robustness checks made in the specifications presented in Section 5.6.2. No alternative measures of centrality nor alternative concepts of the market center are available. To account for the limitations of this empirical approach, I opt for a more general approach in Chapter 6 below, which forms the second empirical part of this thesis. The policy implications of the findings of the present empirical analysis and ideas for further research are discussed in detail in Chapter 7 together with the findings of the analysis presented in Chapter 6.
6 Centrality and Pricing in the Retail Gasoline Market of Vienna: A Network Approach

6.1 Introduction and Motivation

The asymmetric spokes model introduced in Chapter 3 is a simple model leading to clear-cut propositions about the pricing behavior of central and remote firms in spatially differentiated markets. The empirical application of the asymmetric spokes model to the Austrian retail gasoline market in Chapter 5 demonstrated that a market’s central gasoline station serves as the main reference for remote stations in markets with more than four stations and that the influence of an individual remote station declines steadily with the number of stations in the market. However, the empirical framework in Chapter 5 is subject to several strong assumptions and leaves very little room for modifications to check the robustness of the findings. These limitations were already discussed in detail in Section 5.7.

This chapter allows for more complex spatial patterns and regards the market as one big network of firms rather than assuming non-interacting local markets. The empirical framework relaxes some of the strong assumptions made in the empirical model of Chapter 5 and provides a more general analysis of pricing in the context of spatial differentiation and firms that are heterogeneous in their degree of centrality. The chapter is organized as follows: Section 6.2 introduces a theoretical extension of the asymmetric spokes model. An introduction into the characteristics of networks and network centrality in general is given in sections 6.3 and 6.4. Section 6.5 describes how the concept of networks and network centrality are applied to the retail gasoline market of Vienna. Section 6.6 discusses the econometric specification. Section 6.7 provides information on the data used. The results are presented and discussed in Section 6.8. Finally, Section 6.9 concludes the analysis.

6.2 An Extended Asymmetric Spokes Model

The theoretical asymmetric spokes model introduced in Chapter 3 describes a simple spatial pattern in which one firm is regarded as the central firm and all other firms as remote firms. However, the real world data very often show patterns that are much more complex, e.g. markets with several intersections, or several firms along the same road (spoke). Thus,

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66This chapter, except for the theoretical extension of the asymmetric spokes model, is based on the paper “Centrality and pricing in differentiated markets: The case of gasoline” by Firgo et al. (2011).
the dichotomy of central and remote firms sometimes appears inaccurate. In this chapter I modify one of the key features of the asymmetric spokes model, i.e., several firms can be located along the same spoke as illustrated in Figure 8. In this figure $C$ again indicates the unique central firm as the firm closest to the market center. $R_i^m$ indicates a remote firm of order $m_i$, with $m_i = \{1, \ldots, M_i\}$, where $M_i$ is the number of remote firms located at spoke $i$, with $i = \{1, \ldots n\}$, where $n$ is the number of spokes hosting remote firms. Thus, firm $R_2^1$ is the first (innermost) remote firm of $M$ remote firms located at spoke 2. The dashed lines in Figure 8 imply that there may be an arbitrary number of additional remote firms along this dashed line that are omitted in the illustration. Under the same assumptions as in section 3.1, there are now three categories of firms: 1) The central firm $C$ with $n$ neighbors, 2) semi-remote firms $R_i^m$, with $m_i < M_i$, which have two neighbors, and 3) remote firms $R_i^M$, which represent the outermost remote firm of their spoke and have one neighbor only. $d_i^m (d_C)$ is the distance $R_i^m (C)$ is located from the center and $x_i^m$ with $m > 1$ ($m = 1$) is the distance the marginal consumer is located from the center who is exactly indifferent between purchasing the product at $R_i^{m-1}$ or at $R_i^m$ (at $C$ or at $R_1^1$). $l$ is the standardized length of the spokes.
The profit function $\pi_C$ and the profit maximizing price $p_C$ correspond to $\pi_C$ and $p_C$ in the original asymmetric spokes model of Chapter 3:

$$\pi_C = (p_C - c_C) \left[ \sum_{i=1}^{n} x_i^1 + l(N - n) \right], \quad (42)$$

$$p_C = \frac{1}{2} \left[ \sum_{i=1}^{n} p_i^1 \right] + t \left( \frac{\sum_{i=1}^{n} d_i^1}{n} - d_C \right) + c_C + tl \left( \frac{N - n}{n} \right), \quad (43)$$

where $c_C$ are constant marginal costs, $N$ is the total number of spokes in the market, $p_i^1$ is the price of $R_i^1$ and $d_i^1$ is the distance $R_i^1$ is located from the center. Finally, $t$ are the constant per unit transportation costs.

Semi-remote firms of order $m_i < M_i$ have two neighbors. Their profit function ($\pi_{i}^m$) and profit maximizing price ($p_{i}^m$) are equal to

$$\pi_{i}^m = (p_{i}^m - c_{i}^m) \left( x_{i}^{m+1} - x_{i}^m \right), \quad (44)$$

$$p_{i}^m = \frac{1}{2} \left[ \frac{p_{i}^{m-1} + p_{i}^{m+1}}{2} \right] + t \left( \frac{d_{i}^{m-1} + d_{i}^{m+1}}{2} - d_{i}^m \right) + c_{i}^m, \quad \forall 1 \leq m < M, R_i^0 = C. \quad (45)$$

Thus, the price reaction function of a ‘semi remote’ firm is a function of the prices of and distances to its two neighbors. These firms correspond to firms in the circular city model by Salop (1979) that was discussed in Section 2.1.1, except for the fact that they are not necessarily distributed equidistantly along their spoke.

Finally, the profits ($\pi_{i}^M$) and the profit maximizing price ($p_{i}^M$) of the outermost remote firm of a spoke correspond to the ones of remote firms in the original asymmetric spokes model of Chapter 3:

$$\pi_{i}^M = (p_{i}^M - c_{i}^M) \left[ l - x_{i}^M \right], \quad (46)$$

$$p_{i}^M = \frac{1}{2} \left[ p_{i}^{M-1} + t \left( d_{i}^{M-1} - d_{i}^M \right) + c_{i}^M \right] + tl. \quad (47)$$

If the slopes of the reaction functions are compared, the differences in the impact of
central, semi-remote and remote firms on pricing decisions becomes obvious:

\[ \frac{\partial p_i}{\partial p_C} = \frac{1}{4}, \forall M_i > 2; \quad \frac{\partial p_i}{\partial p_M} = \frac{1}{2}, \forall M_i = 1. \]  \quad (48)

\[ \frac{\partial p_C}{\partial p_{i+1}} = \frac{1}{2n}, \forall m_i = 1; \quad \frac{\partial p_{i+1}}{\partial p_{i-1}} = \frac{1}{4}, \forall 2 \leq m_i \leq M_i - 2; \quad \frac{\partial p_M}{\partial p_{i+1}} = \frac{1}{2}, \forall m_i = M_i - 1. \]

The equations in (48) show that remote firms react more strongly to their semi-remote or central neighbors than semi-remote or central firms react to remote firms. Also, semi-remote firms react more strongly to central firms than central firms react to semi-remote firms if \( n \geq 3 \). This finding is very interesting in the context of the empirical results of the original asymmetric spokes model discussed in Chapter 5, in which a significantly stronger impact of central firms on pricing was only found in markets with more than four firms.

In comparison to the original asymmetric spokes model of Chapter 3, the impact of a firm on the pricing decision of another firm does not only depend on the centrality of the firm itself, but also on the centrality of the respective other firm. The reaction to price changes by the central firm are different for semi-remote and remote firms. Also, the impact of price changes by semi-remote firms are different for central, remote or other semi-remote firms. Thus, a clear-cut trichotomy of central, semi-remote and remote gasoline stations similar to the dichotomy of central and remote stations in the empirical analysis of Chapter 5 does not seem to be a very appropriate alternative for the empirical approach in this chapter. Thus, instead of dividing firms into three groups and repeating the empirical analysis of Chapter 5, I will opt for a different approach to testing the hypotheses of the asymmetric spokes model by considering a firm’s own position (centrality) within the market (network of firms), but also the position (centrality) of their neighbors. Therefore, the market is not split into several isolated sub-markets but treated as a single interconnected network. To analyze the impact of centrality on pricing, I assign specific degrees of centrality to each gasoline station based on different measures of network centrality. The following sections present some basic information on networks and the measures of network centrality that are applied in this analysis.
6.3 Neighborhood and Degree in Networks

In many (retail) markets, as discussed throughout this thesis, firms and consumers are scattered in space and are connected through a system of roads and intersections. Clearly, when plotted schematically, such markets reflect networks. The firms are the network’s nodes and the system of roads and intersections are the links (edges) between firms, which can be defined by adjacency, critical distances or critical numbers, i.e. the criteria also used for the construction of spatial weights matrices (see Section 4.2). Networks have been analyzed extensively in various fields of science. The theory of graphs is an entire discipline within mathematics dedicated to the analysis of networks. Social networks are a major field of research in sociology and psychology. Economic research is actually dealing with networks as well, if the units of interest are connected and interacting, even if they are not perceived as networks by the researcher. This section presents some concepts and characteristics of networks that are of special interest for the empirical analysis in this chapter.

The neighborhood relations stored in matrix $W$ of Section 4.2 describe a network with a set of $n$ nodes (firms). In case of binary ‘yes/no’ neighborhood, $w_{ij} \in \{0, 1\}$, with $w_{ij} = 1$ if $i$ and $j$ are neighbors and if $i \neq j$. Thus, $w_{ij} = 1$ indicates a direct link between the nodes $i$ and $j$. Goyal (2009, p. 10ff) presents a number of different types of networks and discusses their characteristics. Out of those, Figure 9 selects networks that represent some of the models introduced in Section 2.1.

67The term ‘graph’ is used synonymously for ‘network’.
The number of links merging in a node is equivalent to the node’s number of direct neighbors. This number is the node’s so-called ‘degree’ \((d)\). The connections (links) between two nodes in the networks described in Figure 9 can be illustrated in a network matrix \((G)\) similar to a spatial weights matrix (see Section 4.2) based on the adjacency of observations.

\[
G_a = \begin{pmatrix}
0 & 1 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0
\end{pmatrix}, \quad
G_b = \begin{pmatrix}
0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0
\end{pmatrix}, \quad
G_c = \begin{pmatrix}
0 & 1 & 1 & 1 \\
1 & 0 & 1 & 1 \\
1 & 1 & 0 & 1 \\
1 & 1 & 1 & 0
\end{pmatrix},
\]

83
$$G_d = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}, \quad G_e = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}.$$

Figures 9(a), 9(b) and 9(c) describe networks in which every node has the same number of neighbors. These networks are illustrated in the respective matrices $G_a$, $G_b$ and $G_c$. The number of neighbors is equal to one in a degree 1 network, equal to two in the degree 2 network and equal to $n - 1$ in the complete network. The theoretical models in Section 2.1.1 reflect these symmetrical types of networks. In a degree 1 network as depicted in Figure 9(a), nodes can only be connected to pairs because in all other networks at least one node would have a degree $d \geq 2$. Thus, a degree 1 network is divided into several sub-networks that are not connected to one another, which results in a block diagonal matrix ($G_a$). An economic degree 1 network is described by Hotelling (1929) and is the special case of $n = 2$ in the spokes model by Chen and Riordan (2007). Figure 9(b) describes a network in which each node is of degree 2. The circular city model by Salop (1979) is a degree 2 network. The symmetric spokes model by Chen and Riordan (2007) is described in Figure 9(c). All nodes are connected to all other nodes, which is the characteristic of a ‘complete network’. This completeness is reflected in the adjacency matrix $G_c$, in which all elements off the main diagonal are equal to one.

A star network as in Figure 9(d) consists of an arbitrary number of links which intersect in a single node at the center of the star. In the star network all nodes have a degree of 1 except for the central node, which has a degree of $n - 1$. Some of the spatial competition models presented in Section 2.1.2 have the characteristics of a star network. Although it appears similar to a star network, the asymmetric spokes model introduced in this thesis (Section 3) has to be interpreted in a slightly different way. As the central firm may be located off the central intersection there are links not only from the central to all remote nodes (firms), but also between remote nodes. Thus, strictly speaking, the asymmetric spokes model in Chapter 3 reflects a complete network. However, in terms of the market area of each firm, the asymmetric spokes model has the characteristics of a star network. The market area of the central firm is adjacent to the market areas of all other (remote) firms while the market area of each remote firm is adjacent to the market area of the central firm.
firms only. In a line network as depicted in Figure 9(e), there are also two different groups of nodes. The two outermost nodes have a degree of one; all other interior nodes have a degree of two. A line network is analyzed by Fik and Mulligan (1991) (see Section 2.1.2).

In the matrices $G_a$ to $G_e$ above, an element in these matrices is equal to one if two nodes are directly connected and zero otherwise. Thus, all links between nodes are assumed to have the same length, which implies that adjacent nodes are distributed equidistantly. Networks with a binary adjacency of 0 and 1 are referred to as ‘unweighted’ networks. All theoretical models presented in Chapter 2, except for Fik (1991b), are unweighted networks. In the asymmetric spokes model of Chapter 3, however, the assumption of an equidistant distribution of nodes is relaxed. Thus, the length of a link between two nodes can have any positive value. Networks of this kind are known as ‘weighted’ networks. In a weighted network two nodes are closer the lower the length of the link between the two nodes (Jackson, 2008, p. 21).

In all theoretical models presented so far, connections have been symmetrical in the sense that $g_{ij} = g_{ji}$. However, in some networks the possibility of an asymmetric situation of $g_{ij} \neq g_{ji}$ may occur. For example, in a network of roads there might be a one-way street between two nodes. Thus, the direct connection (link) between the two would be true in one direction but not in both. If $g_{ij} = g_{ji}$ is true for all nodes, the network is ‘undirected’. If $g_{ij} \neq g_{ji}$ occurs at least once, the network is ‘directed’ (Jackson, 2008, p. 21).

Some very helpful characteristics of a network can be detected by using adjacency matrices like $G_a$ to $G_e$. One very important feature of a matrix $G$ storing information on the links of a network is its ability to measure a node’s centrality within a network. The following Section 6.4 discusses some aspects of network centrality that are crucial to the empirical analysis in this chapter.

6.4 Network Centrality

Information on the centrality of a node within a network structure can be of interest in many cases. It might be helpful to identify a ‘key’ person within a social network, to find...
the most central position for a new hospital within the road network, or to identify a central firm in a spatial market. However, how to measure centrality properly mainly depends on the subject of research. The following types of centrality and their interpretation are considered most prominently in the literature (Jackson, 2008, pp. 37f):

1. **Degree centrality**: How connected is a node within a network?
2. **Closeness centrality**: How easily can a node reach all other nodes in a network?
3. **Betweenness centrality**: How important is a node as a connection between other nodes?
4. **Neighbors’ characteristics centrality**: How important is a node depending on the importance of its neighbors?

The first three types of centrality and a measure for each type were proposed in a seminal paper by Freeman (1979). The latter type of centrality is measured by concepts based on the former three. Degree centrality simply counts the number of direct connections a node has, but does not necessarily give any information about the importance of node. For the decision about where to construct a hospital in a city network, it is rather crucial that the hospital is easily accessible by all citizens. The concept of closeness centrality measures the longest distance a node \( i \) is located from any other node in the network, which thus detects a concept of centrality relevant for these kind of questions. The node with the highest closeness-centrality in a network is the network’s median location.\(^6^9\) Betweenness centrality measures how many shortest paths from every node \( j \) to any other node \( k \) pass through a particular node \( i \), which may be of particular interest for the maintenance of a technical network or for the flow of information as nodes with a high betweenness centrality are important for the connection of different parts of a network. All of these centrality measures can be standardized so that their values range from zero to one. Based on the measure of degree centrality, a node’s influence on the total network not only depends on its own centrality, but also on the centrality of adjacent nodes. In a network matrix \( G \) the total impact (see Section 4.5.2) of a particular node on the entire network highly depends on the connectivity of adjacent nodes directly linked to the focal node. Thus, the total importance of a node with a relatively high degree of centrality may be smaller compared

\(^6^9\)The concept of the median location was used to define the center of local markets in the empirical analysis of Chapter 5 of this thesis.
to a node with a relatively lower degree centrality if the adjacent nodes of the former have a relatively lower degree centrality compared to the latter. A number of measures based on the degree of a node look at the total impact of one node on the entire network.\textsuperscript{70}

Even though degree centrality only measures one aspect of centrality, it is the concept that best meets the criteria of measuring centrality in the context of a localized spatial competition model. Localized competition is defined through competition in the market space between adjacent firms, which are equivalent to adjacent nodes in a network. The theoretical propositions made in Section 3.4 are related to the number of direct competitors (neighbors). Thus, a criterion measuring a firm’s centrality in the market (network) in this analysis should be based on the concept of degree centrality.

\subsection*{6.4.1 Degree Centrality in Unweighted and Weighted Networks}

The concept of degree centrality ($dc$) is similar to the degree of a node. In unweighted networks the degree centrality of node $i$ is equal to

$$
dc_i = \sum_{j=1}^{n} g_{ij}, \quad g_{ij} \in \{0, 1\}. \quad (49)
$$

In small networks or networks with a high degree of connectivity, a standardized version of degree centrality can be useful. The standardized degree centrality of node $i$ is equal to $dc_i^* = dc_i / (n - 1)$, which is the ratio of the actual degree of a node to the maximum degree possible in a network of $n$ nodes. Due to the standardization it follows that $0 \leq dc_i^* \leq 1$. Thus, the standardization helps to facilitate the interpretation and comparability of the centrality of individual nodes. However, for networks characterized by low degrees of connectivity and/ or a high number of nodes, $dc_i^*$ may become unfeasibly small for most nodes.

In a weighted network the links between nodes may be of different lengths or different weights. While a higher weight of a link indicates a higher importance, a greater length indicates a greater distance between nodes, which usually implies a lower weight. In either case $w_{ij}$ is not binary as in an unweighted network, but may have any nonnegative value.

\textsuperscript{70}For a recent survey of modifications and extensions of the centrality measures introduced by Freeman (1979) see Borgatti and Everett (2006).
Thus, degree centrality in a weighted network \((wdc)\) is equal to

\[
wdc_i = \sum_{j=1}^{n} g_{ij}, \quad g_{ij} \in \{\mathbb{R}_{\geq 0}\}.
\] (50)

### 6.4.2 Degree Centrality in Directed Networks

In directed networks, links between nodes are not necessarily reciprocal. Thus, the numbers of outgoing and incoming links of a node are not necessarily the same. For social networks, Opsahl et al. (2010, p. 247) interpret the out-degree of a node as the node’s degree of activity as it counts the number of links emanating from a node. The in-degree is interpreted as a proxy for the node’s popularity as it counts the number of links leading to the node. In a directed network \(G\) is not symmetric; thus, \(g_{ij} \neq g_{ji}\) is true at least for one pair of elements. If \(g_{ij} \neq 0\) indicates a link from \(i\) to \(j\), then

\[
d_{c_{\text{out}}} = \sum_{j=1}^{n} g_{ij}
\] (51)

measures the out-degree centrality of node \(i\) and

\[
d_{c_{\text{in}}} = \sum_{i=1}^{n} g_{ij}
\] (52)

measures the in-degree centrality of node \(j\), with \(g_{ij} \in \{0, 1\}\) in unweighted and \(g_{ij} \in \{\mathbb{R}_{\geq 0}\}\) in weighted directed networks.

Translated into the context of centrality in a pricing game, the out-degree counts the number of strategically relevant neighbors a particular firm has, while the in-degree measures the number of firms of which a particular firm is a relevant neighbor.

### 6.4.3 Closeness Centrality

Closeness centrality \((cc)\) measures centrality in terms of a node’s closeness to all other nodes in the network. Thus, the closeness centrality of node \(i\) is given by

\[
cc_i = \left[ \sum_{j=1}^{n} d(i,j) \right]^{-1}
\] (53)
where \( d(i, j) \) is the (shortest path) distance between nodes \( i \) and \( j \). In an unweighted network, \( d(i, j) \) is the number of links it takes to get from \( i \) to \( j \). In a weighted network, \( d(i, j) \) is the sum of weights attributed to each link it takes to get from \( i \) to \( j \). To compare networks of different sizes, Freeman (1979, p. 226) again suggests a standardized version \((cc^*)\) of \( cc \):

\[
cc^*_i = \left( \frac{\sum_{j=1}^{n} d(i, j)}{n-1} \right)^{-1}
\]

(54)

In large networks with a low degree, \( \sum_{j=1}^{n} d(i, j) \) becomes very large. \( \sum_{j=1}^{n} d(i, j) = \infty \) for every single node if the graph is unconnected, i.e. at least one node (a group of nodes) is (are) not connected to at least one other node (a group of other nodes) (Freeman, 1979, p. 226).

### 6.5 The Retail Gasoline Market of Vienna as a Network

Unlike in the empirical analysis of Chapter 5, the analysis in this chapter is reduced to the metropolitan area of Vienna, which is the largest urban area available, as the network approach chosen requires a rather homogeneous spatial structure that would not be given if rural areas are included. I treat the Viennese retail gasoline market as a network of stores that are connected through a system of roads. Therefore, the information on geographical coordinates of the gasoline stations are linked to the road network and the distances between nearby stations are calculated using the GIS-software ArcGIS and the routing tool WIGeoNetwork. Distance is measured in driving time (minutes) rather than driving distance as the latter does not contain information on speed limits and may thus be an inaccurate measure of consumer transportation costs, which are mainly time costs.

An exact application of the existing graph theoretical measures of centrality and a transformation of the network of roads and gasoline stations into a graph is not feasible for the following reasons: First, there are two types of graph theoretical nodes in the network, namely gasoline stations and intersections of roads. However, only gasoline stations shall be treated as ‘real’ nodes, and intersections shall not. Second, roads reflect the links between nodes (stations) in this network, but stations are never located exactly on a road, but at a varying distance next to them. Therefore, the network of roads, intersections and
gasoline stations has to be transformed into a network in which gasoline stations are the only nodes and the links between these nodes reflect a neighborhood relation relevant for strategic interaction. A link is the schematic illustration of the shortest path between two gasoline stations on the road network, which may include intersections of roads that are not illustrated in the link.

Freeman (1979) argues that a proper measure of centrality must attain its maximum value in the center of a star-shaped graph, which is the most centralized of all graphs. I adopt the measures of degree centrality ($dc$), weighted degree centrality ($wdc$) and closeness centrality ($cc$) discussed in Section 6.4 so they match with the definition of the network and comply with Freeman’s criterion for centrality measures.

### 6.5.1 Construction of the Network

In constructing the network of gasoline stations in Vienna, I start with the locations of gasoline stations, which are the nodes of the network. Thus, I start with an unconnected graph of 273 gasoline stations. Next, a link is added from node $i$ to node $j$ if $j$ is among the $H$-nearest neighbors of $i$ in terms of driving time from $i$ to $j$. As this neighborhood relation is not necessarily reciprocal, the graph is directed. $H$ links originate from every node; thus, all nodes have the same out-degree $H$. Therefore, all measures of centrality have to be based on a node’s in-degree, which is the number of links leading to a node (Jackson, 2008, p. 29). Figure 10 illustrates a simple example of how the network is constructed. The set of previously unconnected nodes in Figure 10(a) are connected based on first and second nearest neighborhood ($H = 2$) in Figure 10(b). An arrow indicates a directed link,

---

71 $i$ is not necessarily among the $H$-nearest neighbors of $j$ just because $j$ is among the $H$-nearest neighbors of $i$. 

---
while lines without arrows indicate an undirected (reciprocal) link. The numbers reflect
the distance between two nodes (the length of the link). The arrows from \(A\) to \(B\) and \(C\)
indicate that \(B\) and \(C\) are the two nearest neighbors of \(A\), but that \(A\) is among the two
nearest neighbors of neither \(B\) nor \(C\).

Any network can be transformed into a matrix. Let \(G\) of dimension \(m \times m\) reflect a
network of \(m\) nodes. The element \(g_{ij} = 1\) if there is a link from node \(i\) to node \(j\). In the
present case, \(g_{ij} = 1\) if station \(j\) is among the \(H\)-nearest neighbors of station \(i\) and \(g_{ij} = 0\)
otherwise. In a next step \(G\) is split into \(H\) matrices \(G_h\), with \(h = 1, \ldots, H\), so matrix \(G_h\)
reflects a \(h\text{-th}\)-nearest neighborhood relation, and \(G = \sum_{h=1}^{H} G_h\). For the example in Figure
10, the network with \(H = 2\) can be expressed by

\[
G = \begin{bmatrix}
0 & 1 & 1 & 0 \\
0 & 0 & 1 & 1 \\
0 & 1 & 0 & 1 \\
0 & 1 & 1 & 0
\end{bmatrix}, \quad G_1 = \begin{bmatrix}
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{bmatrix}, \quad G_2 = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0
\end{bmatrix},
\]

so \(G = G_1 + G_2\). Based on the matrix \(G\) and the matrices \(G_h\), the different measures
of centrality are applied to the retail gasoline market of Vienna in order to evaluate the
importance of centrality for the pricing decisions of gasoline stations.

### 6.5.2 Measuring Degree Centrality

The degree centrality (\(dc\)) of station \(j\) in network \(G\) is given by

\[
dc_{Hj} = \sum_{h=1}^{H} \sum_{i=1}^{m} g_{hij},
\]

where \(g_{hij} = 1\) if station \(j\) is the \(h\text{-th}\)-nearest neighbor of station \(i\) and \(g_{hij} = 0\) otherwise.

Thus, as \(G = \sum_{h=1}^{H} G_h\), the degree centrality of station \(j\) is simply the sum of all elements
in column \(j\) of matrix \(G\). In the example above \(dc_{H=2} = [0 3 3 2]\) for the nodes \(A, B, C\)
and \(D\). As mentioned above, I am interested in the stations’ in-degree of centrality, as the
out-degree is equal to the sum of all elements of row \(i\) in matrix \(G\), which is the same \((H)\)
for all nodes.
6.5.3 Measuring Weighted Degree Centrality

A generalization of degree centrality is suggested by Opsahl et al. (2010) for the case of weighted networks. Following the authors I define the weighted degree centrality ($wdc$) as

$$wdc_{Hj} = \sum_{h=1}^{H} \sum_{i=1}^{m} (H - h + 1)g_{hi},$$

(56)

Unlike in the simple degree centrality $dc$, $wdc$ puts a higher weight on closer neighbors. For the present analysis there are two options for weighting the degree: either by the distance between neighbors or by their order. Weighting by distance has the disadvantage of internalizing differences in the density of gasoline stations. Stations in regions with a higher density would be weighted differently from stations in regions with a lower density. Differences in the density, however, are not of particular interest in this analysis. Thus, I weight the degree by the order of the $H$-nearest neighbors. The nearest neighbor of station $i$ is stored in matrix $G_1$ and is weighted by $H - 1 + 1 = H$. The second nearest neighbor of $i$ is stored in $G_2$ and weighted by $H - 2 + 1 = H - 1$, etc. In the example of $H = 2$ above, node $B$ is the nearest neighbor of one node ($C$), which accounts for a weight of $2 \times 1$ and the second-nearest neighbor of two nodes ($A$ and $D$), which accounts for a weight of $1 \times 2$. Therefore, $wdc_2 = 4$. Thus, in the above example $wdc_2 = [0 \ 4 \ 6 \ 2]$.

6.5.4 Measuring Closeness Centrality

An additional measure of centrality is ‘closeness centrality’ ($cc$), which relies on the closeness of a node to all other other nodes in the network. I adopt this measure of centrality; However, it is necessary to make a few changes in the original measure proposed by Freeman (1979) as the retail gasoline market of Vienna is a very large network characterized by a relatively low connectivity due to the restriction of $H$ out-degrees per node. As a consequence, $cc$ in equation (53) and the standardized version $cc^*$ in equation (54) become very small for all nodes and are not feasible measures of centrality. Thus, I modify this centrality measure by measuring the closeness of a station $j$, if it is among the $H$-nearest neighbors of another station $i$ relative to the closeness of $i$’s remaining $(H - 1)$-nearest neighbors. Closeness centrality $cc$ is the sum of the relative closenesses\footnote{I am interested in the relative closeness rather than in the absolute closeness because absolute closeness is highly correlated with the density of stations, which may well vary across space.} over all nodes of
which \( j \) is a neighbor:

\[
cc_j = \sum_{i=1}^{m} \left[ \frac{g_{ij}w_{ij}}{\sum_{j=1}^{m} g_{ij}w_{ij}} \right].
\]  
(57)

In equation (57) the element \( w_{ij} \) is the squared inverse driving time from node \( i \) to node \( j \) stored in the spatial weights matrix \( W \). In the numerical example above and \( W \) based on the squared inverse driving time, \( W \) is equal to

\[
W = \begin{bmatrix}
0 & (1/4)^2 & (1/3)^2 & (1/5)^2 \\
(1/4)^2 & 0 & (1/1)^2 & (1/3)^2 \\
(1/3)^2 & (1/1)^2 & 0 & (1/2)^2 \\
(1/5)^2 & (1/3)^2 & (1/2)^2 & 0
\end{bmatrix}.
\]

The above measure of ‘closeness centrality’ requires the row normalized version \( G^{cc} \) of the Hadamard product \( G^{cc} = G \odot W \), which is equal to

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

The closeness centrality (cc) of node \( j \) is the sum of weights it has as a neighbor of \( m \) stations, which corresponds to the sum of column \( j \) over all rows \( i \) in the transformed network matrix \( G^{cc} \). Therefore, in the present analysis, closeness centrality has to be interpreted as another approach to weight the degree centrality of a node. For this numerical example, \( cc_2 = [0.000 1.4677 2.2323 0.3000] \).

6.6 Econometric Specification

6.6.1 The Spatial Weights Matrix

For the empirical analysis of this chapter, I use several specifications of the spatial weights matrix \( W \) as proposed by Anselin (2002, p. 259), to check the robustness of the results and to compare the fit of different specifications. The first question in specifying \( W \) is how to

\(^{73}\)For a detailed description of the construction of \( W \) in this analysis see Section 6.6.1.
define neighborhood (see Section 4.2). In their survey Ning and Haining (2003) conclude that a great majority of gasoline stations not only consider the price of the closest station, but also the prices of other nearby stations. A critical cut-off distance is used rather than a critical number of k-nearest neighbors because the area analyzed is a rather homogeneous urban region. Therefore, I do not force stations into a constraint of an identical number of neighbors.

The critical distance is defined as 5 minutes of driving time for the main specifications of $W$, but to check the robustness of the results I also set the value to 10 minutes. Both values are somewhat arbitrary but are similar to critical distances used in previous studies analyzing retail gasoline markets in urban areas. André and Hammarstroem (2000, p. 327f) find that the average speed in urban areas in Europe is between 20 and 30 km/h. Therefore, a driving time of 5 (10) minutes corresponds to a distance of 1.67 to 2.5 (3.33 to 5) kilometers. In the literature on competition in retail gasoline markets in metropolitan areas, values of 0.5 to 2 miles (0.8 to 3.2 kilometers) were used to model competition (Shepard, 1991; Netz and Taylor, 2002; Ning and Haining, 2003; Barron et al., 2004; Hastings, 2004; Verlinda, 2008; Lee, 2009). In general, the shorter the critical distance chosen, the higher the number of observations with zero neighbors within this critical distance. These observations are unconnected and result in all-zero rows in $W$, i.e. observations which are not influenced by neighbors. All-zero rows are not feasible when the main goal of the analysis is the estimation of reaction functions. A larger critical distance increases the number of observations with at least one neighbor, but may increase the number of neighbors included as relevant to an unfeasibly large number for many observations.

Finally, the weights of neighboring stations have to be defined. According to Tobler’s first law of geography (Tobler, 1970), nearby neighbors – all other things equal – are more important than neighbors further away. Therefore, for $w_{ij} \neq 0$ stations are weighted by the (squared) inverse of the driving time from station $i$ to station $j$.

---

74Except for Hastings (2004) and Lee (2009), who use the driving distance on the road, all studies use Euclidean radii.
6.6.2 The Centrality Matrix

It is important to notice that the construction of the spatial weights matrix $W$ already accounts for centrality to some degree, although only implicitly. Central observations in a network are connected to a higher degree and thus appear in $W$ more often than less central observations. The sum of appearances in the $W$ matrix itself is closely related to some centrality measures based on the total effects of the spatial multiplier $(I - \rho W)^{-1}$. Thus, a simple spatial autoregressive model using $W$ already puts a higher weight on more central observations. However, $W$ alone does not reveal the differences in the impacts of centrality on pricing decisions of rivals. Thus, to analyze the impact of centrality on both the level of prices and price reactions by rivals, the three different measures of centrality elaborated above enter the econometric model through the centrality matrix $C$ of dimension $m \times m$. $C$ is diagonal, with the element $c_{ii}$ equal to the value of the respective centrality measure calculated for observation $i$. $C$ is calculated for each centrality measure and for different values of $H$. I set $H = 5$ for the main specifications, but I also experiment with different values for $H$ to check the robustness of the results.

6.6.3 The Spatial Autoregressive Model

The modified asymmetric spokes model suggests that the pricing decisions of station $i$ are influenced not only by $i$’s own degree of centrality, but also by the degree of centrality of neighboring stations. The specification of the empirical model, which accounts for both effects, is given by the following spatial autoregressive (SAR) model:

$$y = \rho_1 Wy + \rho_2 WCy + X\beta + \gamma C_\iota + \epsilon.$$  

In equation (58) $y$ 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 $W$ and $C$ are of dimension $M \times M$. $W$ is the block diagonal spatial weights matrix containing $t$ blocks of dimension $m_t$, where $m$ is the number of observations in period $t$. $C$ is a diagonal matrix with the element $c_{ii}$ measuring the degree of centrality of station $j$. To facilitate the interpretation of the spatial autoregressive parameter $\rho_1$ ($\rho_2$), $W$ ($WC$) is row-normalized in order to obtain a spatially weighted (spatially and centrality weighted) average price of rivals. The parameter

---

75 See Friedkin (1991) for a survey of centrality measures based on the spatial multiplier.
estimate of $\rho_1$ measures the (spatially weighted) price interaction between neighboring stations (i.e. the slope of the price reaction function). An asymmetry in price adjustment between neighboring rivals is captured by the parameter $\rho_2$. A positive parameter estimate of $\rho_2$ implies that prices respond more strongly to price changes by central stations, as suggested by the modified spokes model. $X$ is an $M \times k$ matrix of $k$ explanatory variables including a constant and $\beta$ is the $k \times 1$ vector of coefficients of the exogenous variables in $X$. $\iota$ is an $M \times 1$ unit vector and $\gamma$ measures the impact of centrality on a station’s price level. Finally, $\epsilon$ is the $M \times 1$ vector of i.i.d. error terms. For the econometric analysis I estimate the reduced form of equation (58) using the maximum likelihood estimator described in Chapter 4.

6.7 Data and Descriptive Statistics

The empirical analysis is based on the same data as in Chapter 5 above. The data was 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 location (and other characteristics) of all 273 gasoline stations in Vienna. Using data from ArcData Austria and the ArcGIS extension WIGeoNetwork, the geographical location of each gasoline station is linked to information on the Viennese road system. This allows the generation of accurate measures of distance (driving time) as well as the neighborhood relations between all gasoline stations in the network of roads. The following sections provide some descriptive statistics of the centrality measures (Section 6.7.1) and of the other variables used in the econometric analysis (Section 6.7.2). Variables on location characteristics were collected by the company Catalist. Information on demography and commuting behavior is obtained from the Austrian Statistical Office (Statistik Austria). Prices for business premises, which are used to approximate differences in the costs of gasoline stations, are provided by the Austrian Chamber of Commerce (Wirtschaftskammer).

For company details see http://www.catalist.com.
6.7.1 Centrality Measures

Table 9 reports the descriptive statistics for the centrality measures of gasoline stations in Vienna, which were discussed in detail in Section 6.5. I set $H = 5$ in the main specifications, but I also set $H = 2$ and $H = 10$ to check the robustness of the results with respect to the construction of the network. The measure of degree centrality ($dc$) ranges from 0 to 21, with a mean of 5.26 for $H = 5$. This means that a station is among the five nearest neighbors of other stations around five times on average. The standard deviation indicates that stations with a high degree of centrality relative to the maximum of 21 are scarce. The weighted degree centrality ($wdc$) has a mean of 15.24 and a maximum of 55; the measure of closeness centrality ($cc$) has a mean of 0.98 and a maximum of 3.22. The values for $cc$ indicate the sum of weights a station has as a neighbor of other stations in the spatial weights matrix $W$ based on the neighborhood criterion $H$.

<table>
<thead>
<tr>
<th>Centrality ($H$)</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$dc$ (5)</td>
<td>5.256</td>
<td>3.712</td>
<td>0.000</td>
<td>21.000</td>
</tr>
<tr>
<td>$wdc$ (5)</td>
<td>15.242</td>
<td>10.663</td>
<td>0.000</td>
<td>55.000</td>
</tr>
<tr>
<td>$cc$ (5)</td>
<td>0.982</td>
<td>0.660</td>
<td>0.000</td>
<td>3.220</td>
</tr>
<tr>
<td>$dc$ (2)</td>
<td>1.960</td>
<td>1.575</td>
<td>0.000</td>
<td>7.000</td>
</tr>
<tr>
<td>$wdc$ (2)</td>
<td>2.934</td>
<td>2.394</td>
<td>0.000</td>
<td>13.000</td>
</tr>
<tr>
<td>$cc$ (2)</td>
<td>0.976</td>
<td>0.770</td>
<td>0.000</td>
<td>4.020</td>
</tr>
<tr>
<td>$dc$ (10)</td>
<td>10.982</td>
<td>7.740</td>
<td>0.000</td>
<td>42.000</td>
</tr>
<tr>
<td>$wdc$ (10)</td>
<td>58.700</td>
<td>39.967</td>
<td>0.000</td>
<td>216.000</td>
</tr>
<tr>
<td>$cc$ (10)</td>
<td>0.992</td>
<td>0.618</td>
<td>0.000</td>
<td>3.140</td>
</tr>
</tbody>
</table>

The variations of $H$ to $H = 2$ and $H = 10$ show that the distribution of $dc$ and $wdc$ remains constant relative to the mean compared to the values for the preferred $H = 5$. The variance in $cc$ increases (decreases) proportionally to the mean if $H$ is set to ten (two). The correlations between the different centrality measures and for different values of $H$ are reported in Table 10. The correlation of $dc$ and $wdc$ for the same value of $H$ is between 0.96 and 0.97, while the correlation of $cc$ and $dc$ ($wdc$) ranges from 0.85 to 0.9 (0.86 and 0.96). The correlation between the same measure of centrality for different measures of $H$ is slightly lower, but above 0.75 for all and above 0.8 for most pairs. Also, the correlation of different measures for different values of $H$ is always higher than 0.74 and higher than 0.8 in most cases.
Table 10: Correlation of the centrality measures

<table>
<thead>
<tr>
<th></th>
<th>dc (5)</th>
<th>wdc (5)</th>
<th>cc (5)</th>
<th>dc (2)</th>
<th>wdc (2)</th>
<th>cc (2)</th>
<th>dc (10)</th>
<th>wdc (10)</th>
<th>cc (10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dc (5)</td>
<td>1.000</td>
<td>0.975</td>
<td>0.865</td>
<td>0.806</td>
<td>0.830</td>
<td>0.801</td>
<td>0.890</td>
<td>0.955</td>
<td>0.814</td>
</tr>
<tr>
<td>wdc (5)</td>
<td>0.975</td>
<td>1.000</td>
<td>0.878</td>
<td>0.887</td>
<td>0.899</td>
<td>0.863</td>
<td>0.890</td>
<td>0.958</td>
<td>0.820</td>
</tr>
<tr>
<td>cc (5)</td>
<td>0.865</td>
<td>0.878</td>
<td>1.000</td>
<td>0.762</td>
<td>0.810</td>
<td>0.880</td>
<td>0.843</td>
<td>0.881</td>
<td>0.960</td>
</tr>
<tr>
<td>dc (2)</td>
<td>0.806</td>
<td>0.887</td>
<td>0.762</td>
<td>1.000</td>
<td>0.961</td>
<td>0.900</td>
<td>0.766</td>
<td>0.829</td>
<td>0.699</td>
</tr>
<tr>
<td>wdc (2)</td>
<td>0.830</td>
<td>0.899</td>
<td>0.810</td>
<td>0.961</td>
<td>1.000</td>
<td>0.956</td>
<td>0.850</td>
<td>0.885</td>
<td>0.743</td>
</tr>
<tr>
<td>cc (2)</td>
<td>0.801</td>
<td>0.863</td>
<td>0.880</td>
<td>0.900</td>
<td>0.956</td>
<td>1.000</td>
<td>0.839</td>
<td>0.865</td>
<td>0.819</td>
</tr>
<tr>
<td>dc (10)</td>
<td>0.890</td>
<td>0.890</td>
<td>0.843</td>
<td>0.766</td>
<td>0.850</td>
<td>0.839</td>
<td>1.000</td>
<td>0.977</td>
<td>0.855</td>
</tr>
<tr>
<td>wdc (10)</td>
<td>0.955</td>
<td>0.958</td>
<td>0.881</td>
<td>0.829</td>
<td>0.885</td>
<td>0.865</td>
<td>0.977</td>
<td>1.000</td>
<td>0.865</td>
</tr>
<tr>
<td>cc (10)</td>
<td>0.814</td>
<td>0.820</td>
<td>0.960</td>
<td>0.699</td>
<td>0.743</td>
<td>0.819</td>
<td>0.855</td>
<td>0.865</td>
<td>1.000</td>
</tr>
</tbody>
</table>

6.7.2 Price, Location Characteristics and Fixed Effects

The descriptive statistics for the variables used in the estimations are reported in Table 11. The total number of observations is 3,051 within 22 time periods. Table 11 reports the descriptive statistics for this sample rather than for the cross-section of 273 gasoline stations because the frequency of appearances in the sample varies highly across stations.\(^{77}\)

The mean price of one liter of diesel\(^{78}\) over all time periods is 75.5 cents, with a standard deviation of 6.4. The lowest price observed is 62.4 cents, the highest one 92.9 cents. Price variations are higher over time than across space.

The centrality measures are again plotted in this table for the main specifications using $H = 5$ because the distribution in the repeated cross-section deviate from the distribution of the cross-section reported in Table 9. However, these deviations are quite small. Table 11 also reports the descriptive statistics for the location characteristics included in the estimations as controls. DISTANCE NEXT measures the driving time to the nearest neighbor in minutes. This variable reflects the degree of spatial differentiation indicated by the distance to the center in the theoretical model. The mean driving time to the nearest neighbor is 1.67 minutes. Four stations do not have neighbors within five minutes of driving time. These stations are excluded from the sample as five minutes is the cut-off distance in the spatial weights matrix $W$.\(^{79}\) The variables on the share of commuters

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\(^{77}\)A number of stations cannot be included into the estimations at all due to a total absence of price data.

\(^{78}\)As in the first empirical analysis of Chapter 5 prices of diesel are used rather than prices of gasoline because much more price observations are available for diesel prices. The share of diesel-engined cars was about 50% of all cars in Austria in 2005 (Statistik Austria, 2006).

\(^{79}\)For technical reasons stations are excluded from the sample for period $t$ if prices in $t$ are unavailable for all neighbors within the cut-off distance. To check the robustness of the results, the model is also estimated using a cut-off distance of ten minutes of driving time. This increases the sample from 3,051 to 3,188 observations.
Table 11: Descriptive statistics for the main specifications

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Std. Dev.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRICE</td>
<td>75.515</td>
<td>62.426</td>
<td>6.449</td>
<td>92.900</td>
</tr>
</tbody>
</table>

**Centrality measures**

<table>
<thead>
<tr>
<th>Centrality measures</th>
<th>Mean</th>
<th>Min</th>
<th>Std. Dev.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEGREE (dc)</td>
<td>5.915</td>
<td>0</td>
<td>3.399</td>
<td>17</td>
</tr>
<tr>
<td>WEIGHTED (wdc)</td>
<td>16.897</td>
<td>0</td>
<td>9.675</td>
<td>47</td>
</tr>
<tr>
<td>CLOSENESS (cc)</td>
<td>1.136</td>
<td>0</td>
<td>0.561</td>
<td>3.137</td>
</tr>
</tbody>
</table>

**Location characteristics**

<table>
<thead>
<tr>
<th>Location characteristics</th>
<th>Mean</th>
<th>Min</th>
<th>Std. Dev.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>DISTANCE NEXT</td>
<td>1.668</td>
<td>0.050</td>
<td>0.980</td>
<td>4.680</td>
</tr>
<tr>
<td>COMMUTERS</td>
<td>43.897</td>
<td>34.942</td>
<td>5.680</td>
<td>78.071</td>
</tr>
<tr>
<td>log POP DENS</td>
<td>8.495</td>
<td>7.196</td>
<td>0.804</td>
<td>10.127</td>
</tr>
<tr>
<td>log PREMISES</td>
<td>0.167</td>
<td>0</td>
<td>0.373</td>
<td>5.638</td>
</tr>
<tr>
<td>TRAFFIC</td>
<td>0.768</td>
<td>0</td>
<td>0.210</td>
<td>1</td>
</tr>
<tr>
<td>DEALER</td>
<td>0.210</td>
<td>0</td>
<td>0.334</td>
<td>1</td>
</tr>
<tr>
<td>SERVICE</td>
<td>0.287</td>
<td>0</td>
<td>0.053</td>
<td>1</td>
</tr>
<tr>
<td>SMALL</td>
<td>0.011</td>
<td>0</td>
<td>0.167</td>
<td>1</td>
</tr>
</tbody>
</table>

**Dummies for missing at random variables**

<table>
<thead>
<tr>
<th>Dummies for missing at random variables</th>
<th>Mean</th>
<th>Min</th>
<th>Std. Dev.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>MISS PREMISES</td>
<td>0.167</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>MISS OWNER</td>
<td>0.033</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>MISS SERVICE</td>
<td>0.011</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

**Fixed effects**

<table>
<thead>
<tr>
<th>Fixed effects</th>
<th>Mean</th>
<th>Min</th>
<th>Std. Dev.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brands</td>
<td>9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Periods</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

# of observations: 3,051

* missing values replaced by zeros
COMMUTERS, population density (POP DENS) and the average prices for factory premises (PREMISES) are collected on a district level. TRAFFIC is a 0/1 dummy variable set equal to one if traffic at the site is considered heavy by Catalist. DEALER (SERVICE) [SMALL] is a 0/1 dummy set to one if the station is owned by the dealer rather than the company (offers attendance service) [has a ground surface of less than 800 square meters].

For some districts the prices of premises are unavailable, and so is the information on ownership, attendance service and size for some stations. For each of these variables, a 0/1 dummy variable is created (variables with the prefix MISS) which takes the value of one if the information is unavailable. Table 11 illustrates that the share of missing values is very small (16.7% for PREMISES and less than 6% for the other three variables with missing data). Stations with missing values are included because the missing values can be considered to be (completely) missing at random.80

I further include brand fixed effects for the nine brands operating gasoline stations in Vienna. Unbranded (independent) stations are left out as a reference group. The major brands BP (26%), OMV (12%) and Shell (10%) account for nearly half of the stations in the sample. 21% of stations in the sample belong to the group of unbranded stations. It is worth pointing out that no significant correlation can be detected between brands and the centrality of stations but (major) brand stations are likely to charge higher prices (Pennerstorfer, 2008, 2009). I also control for shifts in price levels due to shifts in crude oil prices by including a dummy variable for each time period (with the first period left out as a reference group).

6.8 Results and Discussion

6.8.1 Tests for Spatial Dependence

In the econometric analysis, different specifications of the spatial weights matrix $W$ are used for two reasons. First, the use of several weights matrices allows a comparison of the fit of each matrix, and further allows one to find the ‘best’ specification of $W$. Second, the different specifications can be used to test the robustness of the results with respect to the construction of neighborhood. Table 12 reports the tests for spatial dependence for

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80See Little and Rubin (2002) for details on missing data.
four different specifications of $W$. The tests use the residuals of the OLS estimation of the model in equation (58) assuming $\rho_1 = \rho_2 = 0$.

The spatial weights matrix $W$ is modified by two main characteristics: On the one hand I vary the cut-off distance by including neighbors within five and ten minutes of driving time. An increase from five to ten minutes increases the sample size. However, the number of neighbors included also increases and for some stations the number of neighbors becomes quite large. In these cases the weights of individual stations become very small due to the row-normalization of $W$. Also, as the density of $W$ increases, the variance in $Wy$ decreases as $Wy$ converges to the sample mean. As a result, a rather dense matrix $W$ decreases the explanatory power of the spatial lag.

On the other hand I also vary the weight of individual neighbors by using the (single) inverse and the squared inverse of the driving time between stations. The squared inverse puts a higher weight on closer neighbors than the single inverse, which becomes relevant if the number of neighbors is high and the matrix is row-normalized. Table 11 shows that all tests confirm the existence of spatial dependence on a 99% significance level. The coefficient of Moran’s $I$ is higher for the 5 minutes cut-off distance and for the squared inverse of driving time. The values of the $LM$-$Lag$ and the $LM$-$Error$ tests are of similar size for all specifications of $W$, the robust versions of these tests diverge to a higher degree but are still highly significant. The $LM$-$Lag$ tests are higher than the $LM$-$Error$ tests only for $W$ based on a five minutes cut-off distance and the squared inverse of the driving time.

<table>
<thead>
<tr>
<th>Critical Distance (Inverse)</th>
<th>Moran’s $I$</th>
<th>$LM$-$Error$</th>
<th>$LM$-$Lag$</th>
<th>$LM$-$Error$ Robust</th>
<th>$LM$-$Lag$ Robust</th>
</tr>
</thead>
<tbody>
<tr>
<td>5min (Squared)</td>
<td>Statistics</td>
<td>0.552</td>
<td>1407.848</td>
<td>1428.252</td>
<td>28.144</td>
</tr>
<tr>
<td></td>
<td>$p$-value</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>5min (Single)</td>
<td>Statistics</td>
<td>0.505</td>
<td>1744.230</td>
<td>1718.973</td>
<td>62.558</td>
</tr>
<tr>
<td></td>
<td>$p$-value</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>10min (Squared)</td>
<td>Statistics</td>
<td>0.456</td>
<td>1931.478</td>
<td>1923.394</td>
<td>59.440</td>
</tr>
<tr>
<td></td>
<td>$p$-value</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>10min (Single)</td>
<td>Statistics</td>
<td>0.339</td>
<td>3412.470</td>
<td>3130.482</td>
<td>312.345</td>
</tr>
<tr>
<td></td>
<td>$p$-value</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
</tbody>
</table>

The spatial weights matrix $W$ is modified by two main characteristics: On the one hand I vary the cut-off distance by including neighbors within five and ten minutes of driving time. An increase from five to ten minutes increases the sample size. However, the number of neighbors included also increases and for some stations the number of neighbors becomes quite large. In these cases the weights of individual stations become very small due to the row-normalization of $W$. Also, as the density of $W$ increases, the variance in $Wy$ decreases as $Wy$ converges to the sample mean. As a result, a rather dense matrix $W$ decreases the explanatory power of the spatial lag.
as weights. However, it is the economic motivation of the analysis to model price reaction functions of gasoline stations. Therefore, I model a spatial lag model rather than a spatial error model in all specifications. $W$ is based on the five minutes cut-off distance and the squared inverse is chosen as the preferred spatial weights matrix.

6.8.2 Results of the Maximum Likelihood Estimations

The main regression results of the econometric model are illustrated in Table 13. This table only reports the results for the key variables. A discussion and tables of the results of the control variables are available in Appendix C (Table 17 and 18). This appendix also provides evidence for the robustness of the results with respect to a number of variations in the spatial weights matrix $W$ and the centrality measures.

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 SAR models conducted on the retail gasoline market (Netz and Taylor, 2002; Pennerstorfer, 2009), I find a positive parameter estimate of $\rho_1$, which is significantly different from zero at the 1%-level. A gasoline station reacts to a spatially weighted average price increase by all relevant neighbors of 1 cent with a price increase of 0.632 cents per liter in this benchmark model, irrespective of the neighbors’ centrality.

Columns [2] - [4] report parameter estimates of the asymmetric model using the three different measures of centrality introduced above. The inclusion of centrality significantly improves the explanatory power of the models: a likelihood ratio ($LR$)-test clearly rejects the restricted benchmark 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] in favor of model [4], which uses closeness centrality at the 10%-level of significance.

The parameters estimating the impact that centrality has on price levels are positive and very small, but only significant at the 10%-level for the weighted degree centrality (variable WEIGHTED) in model [3]. In the theoretical model it was argued that centrality – measured as the distance to the market center – increases prices, ceteris paribus, but that no
Table 13: Results of the maximum likelihood estimations

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Centrality</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_1$</td>
<td>0.632</td>
<td>0.013***</td>
<td>-0.044</td>
<td>0.114</td>
</tr>
<tr>
<td>$\rho_2 (dc)$</td>
<td>0.680</td>
<td>0.113***</td>
<td>0.504</td>
<td>0.119***</td>
</tr>
<tr>
<td>$\rho_2 (wdc)$</td>
<td>0.504</td>
<td>0.119***</td>
<td>0.263</td>
<td>0.129**</td>
</tr>
<tr>
<td>$\rho_2 (cc)$</td>
<td>0.263</td>
<td>0.129**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>18.223</td>
<td>1.735***</td>
<td>17.101</td>
<td>1.748***</td>
</tr>
<tr>
<td>DEGREE (dc)</td>
<td>0.010</td>
<td>0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WEIGHTED (wdc)</td>
<td>0.005</td>
<td>0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLOSENESS (cc)</td>
<td>-0.060</td>
<td>0.057</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Locational characteristics: yes
Brand fixed effects: yes
Time period fixed effects: yes

$\ell$ = -4,428.272
$\sigma^2$ = 1.851

p-value ($\chi^2$, 2): 0.000

# of observations: 3,051; *** significant at 1%, ** significant at 5%, * significant at 10%;
Centrality measures based on $H = 5$;
Construction of $W$: Squared inverse of driving time to neighbors within 5 minutes driving time;
general conclusions can be drawn about centrality and price levels. The positive effect of centrality on the level of prices in the theoretical model results from the demand enhancing effect of an increase in centrality. Since the empirical models reported in Table 13 control directly for differences in consumer demand by including several locational characteristics, centrality does not turn out to have a significant impact on prices levels in most of the estimations.

Centrality, however, does have a significant impact on the strategic pricing interactions between competitors. As reported in columns [2] - [4] of Table 13, the parameter ($\rho_2$) estimating the impact of centrality through $WC_y$ is positive and significantly different from zero at the 1%-level (5%-level) for $dc$ and $wdc$ (for $cc$). The intensity of the pricing interaction clearly increases with the centrality of neighbors. A particular gasoline station reacts more strongly to prices of a central competitor than to prices of a remote one.

For $WC_y$ with $C$ based on degree centrality ($dc$) and weighted degree centrality ($wdc$) the slope parameter ($\rho_1$) that does not account for the neighbor’s centrality loses its significance if the slope parameter accounting for centrality ($\rho_2$) is included. It remains significant if closeness centrality ($cc$) is applied as a centrality measure. The identification of the slope parameters might be weaker in specification [2] and [3] than in specification [4] because the correlation between $W_y$ and $WC^{dc}_y$ ($WC^{wdc}_y$) is higher than the correlation between $W_y$ and $WC^{cc}_y$.\textsuperscript{81} Specifications [5] to [7] of Table 17 in Appendix C report the results for a set of specifications based on a spatial weights matrix for $WC_y$, which weights neighbors binary (0/1) rather than by distance. In these specifications the coefficients of $\rho_2$ are of similar size as in specification [4] (about 0.2) and significant on a 99% significance level. These alternative specifications improve the identification but are likely to underestimate the effect of centrality because it is rather unlikely that the ‘true’ spatial weights matrix $W$ is based on binary instead of distance based weights. All specifications of Table 13, and Tables 17 and 18 in Appendix C show positive and highly significant effects of centrality on the slope parameter of stations’ price reaction functions.

\textsuperscript{81}Anselin (2001, p. 117) points out that the inclusion of multiple spatial weights matrices sharing common elements may lead to identification problems but does not provide an alternative solution.
6.8.3 The Impact of Individual Shocks on Equilibrium Prices

It is important to note that the parameter estimates of $\rho_1$ and $\rho_2$ only account for the direct response of prices to price changes of neighboring stations. To address the third implication of the asymmetric spokes model, i.e. the effect of centrality on the transmission of individual shocks to the general price level, it must be considered that each price change also triggers feedback effects to and from all neighbors in the market. Starting with equilibrium prices, a shock in costs of a focal station $i$ will not only change $i$’s own price, but also the prices of its first-order (direct) 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 of individual shocks on equilibrium prices, I use the values of $\rho_1$ and $\rho_2$ of specification [2] of Table 13, which is the model with the best fit according to the value of the concentrated log-likelihood function $\ell$. To account for the uncertainty of the parameter values estimated, I use a bootstrap simulation technique similar to the simulation in Chapter 5. Each parameter is drawn randomly from a normal distribution with the mean and the standard deviation obtained from regression [2]. $\rho_1$ and $\rho_2$ are normalized so they sum up to $\rho_1$ of specification [1] for each draw. This assumption is justified as I cannot reject the restriction that $\rho_1$ in specification [1] is significantly different from $\rho_1 + \rho_2$ in specification [2]. Figure 11 shows the effects of a price change (e.g. due to a takeover) by one particular gasoline station. The total impacts (including all feedback effects) are depicted on the vertical axis on the left; the centrality of the gasoline station is depicted on the horizontal axis (based on $dc$ for $H = 5$). The distribution of the degree of centrality ($dc$) in the population of gasoline stations in Vienna is plotted on the vertical axis on the right.

According to Figure 11(a), an exogenous cost shock which triggers a price increase of 1 cent by 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 stations) 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 gasoline station with a degree centrality of 3 (in case of a central station with a degree centrality of 8). Similarly, Figure 11(b) shows that a price increase of 1 cent by a gasoline station with a degree centrality of 3 (5) [8] leads to

82The simulations are based on the cross-section of all 273 gasoline stations in Vienna as the simulation does not require the actual price data.
Figure 11: The total impact of shocks on equilibrium prices by centrality

(a) Total impact on the initiator of the shock

(b) The aggregated total impact on all other gasoline stations
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 the neighbors of more stations, to be relatively closer to other stations, and are thus more influential in how they affect neighboring stations.

6.9 Summary and Conclusion

This chapter analyzes the retail gasoline market in the metropolitan area of Vienna. I test an extension of the theoretical asymmetric spokes model of Chapter 3 in a network approach which allows for a calculation of different measures of network centrality for each gasoline station rather than a restrictive binary division into central and remote stations. The results show a positive and significant impact of centrality on the slope of the price reaction function of neighboring gasoline stations. There is evidence that the slope of a station’s price reaction function increases with the centrality of its neighbors. It is worth noting that these findings are not an artifact of the specific functional form used to measure spatial competition or the degree of centrality. Several modifications in the measures of centrality as well as different functional forms for the measure of localized competition (different specifications of \( W \)) prove the robustness of the results. Furthermore, a large number of explanatory variables are used as controls. The results provide evidence for the importance of the location within a spatially differentiated market relative to other firms/stores, when the market space is characterized by a network of roads and intersections. Implications of these results, shortcomings of the models and some suggestions for further research are discussed in detail in Chapter 7.
7 Policy Implications, Outlook and Conclusions

7.1 Summary and Policy Implications

In this thesis I have introduced an asymmetric spokes model to account for spatial asymmetries among firms in markets with localized competition. The theoretical approach provides a simple spatial framework that allows for the identification of differences in the pricing behavior of central and less central (remote) firms. Only a few theoretical models have analyzed spatial competition in the context of spatially heterogeneous firms, i.e. firms that differ in their number of neighbors or in the distance they are located from their neighbors. The novelty of this theoretical approach is that it is – at least to my knowledge – the first attempt to model spatial competition including both of these aspects. Additionally, the framework of the spokes model allows for leaps in firm’s demand through consumers located on unshielded empty spokes.

Analyzed as a Nash-Bertrand pricing game, this theoretical model suggests that 1) a remote firm is more sensitive to the price set by a central firm than vice versa, that 2) the impact of an individual (cost) shock of the central firm has a stronger aggregated impact on equilibrium market prices than an individual shock of a remote firm and that 3) no general statements can be made on differences in the price levels of central and remote firms. On the one hand a firm located close to a central intersection (considered as the market center) has more neighbors with which to compete for consumers than a remote firm. On the other hand a central firm faces a higher demand than remote firms. The question of whether central firms charge lower or higher prices in the asymmetric spokes model depends on the ratio of demand (number of spokes) to firms in the market.

In two empirical applications the implications of the theoretical model are tested for the retail gasoline market using data on the geographical locations of gasoline stations, the road network, station level prices, and station and local (regional) characteristics. Price reaction functions of gasoline stations are estimated applying spatial autoregressive (SAR) models. The first empirical approach seeks to transform the theoretical model into an empirical one as closely as possible. For this purpose, the Austrian retail gasoline market is divided into numerous local sub-markets. A center is defined for each local market and
within each market stations are divided into one central and a number of remote stations. The econometric results of this approach illustrate that 1) in local markets with more than four stations, the central station serves as a main reference in the pricing decision, while in markets with less than five stations asymmetries in the slopes of the price reaction functions cannot be detected; 2) The total impact of an individual shock on equilibrium emanating from a central gasoline station is more than twice as high as the impact of the same shock coming from a remote station in markets with more than four stations; 3) Prices charged by central gasoline stations are significantly higher than prices of remote stations, ceteris paribus; Unfortunately the data used restricts the analysis in this empirical approach to local markets with three to six stations only.

To address the limitations of the first empirical application, I opt for a more general analysis of the role of centrality in a spatial market. The retail gasoline market of the Vienna metropolitan area is transformed into a network of gasoline stations based on neighborhood relations between stations, again calculated by the actual driving distance (time) between the stations. Using this network structure three different measures of network centrality, which are standard tools in the literature on (social) networks, can be calculated for each gasoline station. This approach also allows a wide range of checks for robustness of the results with respect to different measures of centrality, different functional forms of localized competition and different distance-based weights of rivals’ prices. The results confirm that gasoline stations are more sensitive to prices set by more central stations than by rather remote stations, and that the impact on equilibrium prices increases with a station’s centrality. However, the results obtained in this approach only find a weak positive impact of centrality on the price levels of stations.

The literature on industrial organization typically identifies asymmetries in the strategic interaction between firms as leader-follower relations in the context of time (e.g. Stackelberg leadership). The price leader changes its price first and the followers react to the price change by adopting their own prices after observing the price change. The asymmetric spokes model puts price leadership in a spatial context, as the results obtained in this thesis provide strong evidence for the fact that central suppliers serve as a stronger reference in the pricing decisions of other suppliers than remote suppliers.
In line with previous research I find that the degree of spatial differentiation (i.e. the distance to the next neighbor) increases prices, ceteris paribus. This result also confirms the findings of previous research on (parts of) the Austrian gasoline market conducted by Clemenz and Gugler (2006) and Pennerstorfer (2009). Clemenz and Gugler (2006) interpret the positive significant impact of the distance to rivals on prices as evidence against collusive behavior because it is the effect predicted by models of price competition.

While the locations of firms are ‘equally different’ and symmetric in models that follow the tradition of Salop (1979), the results obtained in this thesis clearly reject assumption of a symmetric competition between firms in space, at least for the industry studied. These findings have several important implications for policy makers. I have shown that a firm is able to gain a relatively higher importance in the strategic pricing decisions of other firms not only due to a higher market share or due to technological or cost advantages, but also through its position within the market space relative to other firms. Obtaining central (key) positions in a spatially differentiated market may lead to an increase in the market power of a firm. Therefore, it is insufficient to only consider the number of stores (stations) operated by the same firm to evaluate its market power, but also the positions of these stores relative to stores operated by other firms and independent retailers. A firm operating a smaller number of stores at central locations may have more market power than a firm operating a larger number of stores at rather remote locations.83

Therefore, unlike in the Salop (1979) model, not only the decision whether to enter the market or not becomes an important decision, but also the decision where to locate in the market. Firms, however, can increase their market power not only through the establishment of a(nother) new store, but also by a takeover of individual stores or another firm (brand). Simulations based on the econometric results obtained in this thesis have shown that a shock from an individual gasoline station due to a takeover has a much higher aggregated effect on equilibrium market prices if the station taken over is located at a central position than if the takeover affects a rather remote station. Thus, the asymmetries in space and competition are of great importance for policy makers and antitrust authorities.

83Note again, that in this thesis centrality is not related to demand but to the location relative to other firms in the road network.
evaluating mergers and acquisitions. The impact of a merger or an acquisition on market prices and social welfare strongly depends on the locations of the stores involved. If the stores acquired are at rather central (remote) locations, a takeover has strong (little) effects on social welfare. If the abandoning (closure) of individual stores in order to reduce the market concentration is a condition for the approval of a merger or acquisition – as was the case in Germany, for instance, when BP took over E.ON/ARAL in 2001 (Bundeskartellamt, 2001) – antitrust authorities should consider the centrality of relevant stations.

### 7.2 Ideas for Future Research

The research conducted in this thesis is a first attempt to highlight the importance of spatial centrality in differentiated markets if space is analyzed as a network of roads and intersections. The theoretical as well as the empirical approaches are subject to several limitations. In the theoretical model the locations of firms are fixed. Thus, the theoretical analysis can be interpreted as a short-run analysis, with price being the only strategic variable. However, as illustrated in a numerical example, the profits of the central firm can be much higher than the profits of remote firms. Thus, in the long run firms may have incentives to move towards the center and a Nash-equilibrium in locations may not exist.\(^{84}\)

An important extension of the asymmetric spokes model to a long-run analysis would be that firms decide about locations in a first stage and about prices in a second stage of the game.

The spokes model in the original version by Chen and Riordan (2007), as well as the modified version in this thesis, assumes a uniform distribution of consumers in space. As the market space equals the road network in this thesis, the assumptions of a uniform distribution of consumers and an address model with fixed consumer locations are somewhat counterfactual. Most recently Houde (2011) provides a theoretical framework in which consumer locations are defined as commuter paths. The author shows the “distribution of gasoline sales within the market is shown to be poorly correlated with the distribution of local population, and significantly more so with the distribution of work commuters” (Houde, 2011, p. 37). The strategic decisions of firms in such a framework not only depend on the structure of the road network, but also on the distribution of consumers. Relaxing

\(^{84}\)Braid (1989) points out the absence of a Nash-equilibrium in locations for a spatial model similar to the spokes model (see Section 2.1.2).
the assumption of a uniform distribution of consumers results in two types of centrality: 1) centrality as the relative position in the network, i.e. the number of neighbors or the degree of a firm, as subject to the analysis in this thesis; 2) centrality measured by the closeness and access to demand hot spots (e.g. a main commuter path or highway). The present empirical analysis controls for differences in the price levels due to differences in consumer demand by including variables on population density, the share of commuters in the population and a dummy variable for heavy traffic at the location of a station. However, the access to roads with a high level of demand may also have an impact on the strategic interaction between firms. Therefore, it would be an interesting extension of the network approach to measure centrality also by the distance to roads or intersections with a heavy traffic. Such an approach would allow one to disentangle the effects of ‘relative’ centrality measured by the location within a network kind of space and ‘absolute’ centrality measured by the distance to demand hot spots, not only on price levels but also on the strategic interaction between firms.

The theoretical analysis can be further extended to more complicated spatial patterns and to graphs in general. In a recent working paper Soetevent (2010) introduces an algorithm to calculate the locations of marginal consumers, profit maximizing prices and profits in a pricing game with two firms for any kind of graph and for any given pair of firm locations. In principle his analysis can be extended to scenarios with more than two firms, but such an extension raises computational issues. Through dynamic simulations Soetevent (2010) demonstrates that small changes in the location of one firm may have far-reaching consequences for the pricing behavior of both firms in certain spatial structures. Stable equilibria may convert into Edgeworth price cycles and vice versa if one firm changes its location. The work of Soetevent (2010) is motivated by the question of why some gasoline stations engage in price cycles and why some do not. The author concludes that, apart from circumstances favoring or limiting incentives to engage in cycles that were discussed in Section 2.2.4 of this thesis, the positions of gasoline stations within the market space may be an important factor for the phenomenon of price cycles. The role of centrality can also be analyzed in the context of this phenomenon and related to the findings of Atkinson et al. (2009), who associate price leadership in Edgeworth cycles with stations of certain brands. It would be interesting to analyze whether central stations are more (less) likely
to be the first stations to change prices and whether centrality plays a different role in price increases than in price decreases. However, only highly frequent pricing data allow for a sequential and dynamic analysis of the impact of centrality. The quality of the data on prices and the lack of highly frequent data, of course, is a shortcoming of the present empirical work and restricts the analysis to static games. Eckert and West (2004, p. 271) point out that monthly or weekly data are not enough to detect the dynamics of pricing in retail gasoline markets. Since August 2, 2011, gasoline stations in Austria are legally obligated to frequently report prices change to the federal authorities (Republic of Austria, 2011a,b). This creates a unique data base for future research on the Austrian retail gasoline market, which is of great value, not only for research on pricing in spatially differentiated markets.
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Appendices
A Justification of the Modified Zero Conjectural Variation Assumption

This section serves as an illustration of why the Modified Zero Conjectural Variation (MZCV) assumption is justified in the asymmetric spokes model of Section 3. In order to facilitate the analysis, but without a loss of generality, I assume that all remote firms are located equidistantly at distance \(d_R\) from the center, that the length of a spoke is normalized to \(l = 1\) and that marginal costs are normalized to \(c = 0\). Assuming Nash-Bertrand equilibrium prices, \(R\)'s demand is equal to \(1 - x\) and the demand for \(C\) equals \(N - n + nx\). Further, I denote \(d = d_R - d_C\). The profits of \(C\) (\(R\)) in the Nash-Bertrand equilibrium, \(\pi^N_C\) (\(\pi^N_R\)), and the location of the marginal consumer \((x^N)\) are given by

\[
\pi^N_C = \frac{((d - 2) nt + 4N)^2 t}{18n^2},
\]

\[
\pi^N_R = \frac{((d - 2) nt + 2N)^2 t}{18n^2},
\]

\[
x^N = \frac{1}{6} \left( 4 + d - \frac{2N}{n} \right) > 0.
\]

In general, \(R\) might be able to increase its profit by undercutting \(p_C\) at the market center. However, even if it is profitable for \(R\) to undercut \(C\) in a first step, it will do so if and only if \(C\) is not expected to respond to the undercutting by undercutting \(R\) again to gain back the extra demand lost to \(R\). In the counterfactual experiment that one firm \(R\) undercuts the Nash equilibrium prices of all other firms by setting its price to \(p^U_R\), the profits \((\pi^U_R)\) of this firm are given by:

\[
\pi^U_R = (p^N_C - t (d - 2x^U)) \left( N - n - x^U + (n - 1)x^{UR} \right),
\]

\[
x^U = \frac{(p^U_R - p^N_C + td)}{2t} < 0,
\]

\[
x^{UR} = \frac{(p^N_R - p^U_R)}{2t} > 0,
\]

where \(x^U\) \((x^{UR})\) corresponds to the location of the marginal consumer at the spoke of \(C\) (of the other remote firms). \(\max \pi^U_R\), s.t. \(x^U < 0\), leads to two solutions: \(\pi^U_{R_1} = f(p^U_{R_1})\) for \(\frac{4n - 2N}{-n + 3n^2} < d \leq 1\) or \(N = 2n\), and \(\pi^U_{R_2} = f(p^U_{R_1})\) for \(0 < d \leq \frac{4n - 2N}{-n + 3n^2}\) and \(N < 2n\). While
\[ \pi_R^U > \pi_R^N \] is always true under the conditions leading to \( \pi_R^U, \pi_R^U > \pi_R^N \) if and only if

\[
n(n(-4 - d(14 + d) + 2(-2 + d)(1 + d)n) + 4(7 + d + (4 + d)n)N) < 4(1 + 4n)N^2. \quad (61)
\]

The profit of \( C \) sticking to the Nash equilibrium price \( p_C^N \) when being undercut is equal to \( \pi_C^U = p_C^N(1 + x^U) < \pi_C^N \). \( C \) may increase its profit again by undercutting \( R \) to \( \pi_C^U \) determined by

\[
\pi_C^U = (p_R^U + t(d - 2x^UC)) \left( N - n + x^UC + (n-1)x^UCR \right),
\]

\[
x^UC = \frac{p_R^U - p_C^U + td}{2t} > 0,
\]

\[
x^UCR = \frac{p_R^N - p_C^U + td}{2t} > 0,
\]

if and only if \( \pi_C^U > \pi_C^U \). Inserting \( p_R^U \) and \( p_R^U \), respectively, for \( p_R^U \) into (62), max \( \pi_C^U \), s.t. \( x^UC > 0 \) leads to \( \pi_C^U > \pi_C^U \) unconditionally true for \( p_R^U = p_R^U \) and to \( \pi_C^U > \pi_C^U \) for \( p_R^U = p_R^U \) if and only if

\[
4(-2 + d)^2 n^4 + 8\sqrt{(n(4 + d - 3dn) - 2N)^2}N + 8nN(3 + 4N) +
\]

\[
n^2 (3d(4 + d) - 16(11 + 2d)N + 64N^2) + 2dn\sqrt{(n(4 + d - 3dn) - 2N)^2} >
\]

\[
2(-2 + d)n^3(20 + 5d - 16N) + 4n\sqrt{(n(4 + d - 3dn) - 2N)^2} + 12N^2.
\]

These results imply that for \( 0 < d \leq \frac{4n - 2N}{n + 3N} \) and \( N < 2n \), an attempt by any firm \( R \) to undercut \( C \) will result in an undercutting by \( C \) as a response. For \( \frac{4n - 2N}{n + 3N} < d \leq 1 \) or \( N = 2n \), \( R \) can increase its profits by undercutting \( C \) if inequality (61) holds but the undercutting will again result in an undercutting by \( C \) as a response if inequality (63) holds. However, it can be proved that (63) holds if (61) holds. Thus, in either case \( C \) will respond to an undercutting of \( R \) by undercutting \( R \) again.

The paragraphs above imply that an undercutting by \( R \) leads to a tit-for-tat response by \( C \). A concept to calculate the highest prices that can be set by \( C \) and \( R \) that guarantees each firm that it will not be undercut by a rival, are the so-called undercut-proof equilibrium prices (Morgan and Shy, 2000; Shy, 2007). The undercut-proof equilibrium price is the highest price each firm can set which guarantees the other firms higher profits if they
do not undercut their rivals than the profits they would gain in case of undercutting (ignoring rivals responses to the undercutting). Morgan and Shy (2000) apply the concept of the undercut-proof equilibrium, among other scenarios, to the Hotelling (1929) linear city model. The concept of undercut-proof equilibrium prices can also be adopted to the asymmetric spokes model. Assume that two firms are located along a linear city of length $l = 1$. A firm which serves the consumer at the center (at location $1/2$) receives a premium $Z$ additional to the demand on the linear city. This premium $Z$ can be interpreted as the additional demand a firm receives in the asymmetric spokes model if it serves consumers located on empty spokes and on spokes occupied by other firms. Firm $C$ is located left of the market center at distance $0 < a \leq 0.5$ from the left end of the line. Firm $R$ is located right of the center at distance $0 \leq b < a$ from the right end of the line. As $b < a$, firm $C$ is located closer to the center and is thus regarded as the central firm. For simplicity I assume that marginal costs are normalized to zero ($c = 0$), and thus all prices are to be interpreted as net of marginal production costs. A consumer located at $x$ is indifferent between purchasing the product at $C$ or at $R$ if the net utility of buying at $C$ (left hand side of equation (64)) is equal to the net utility of buying at $R$ (right hand side of equation (64)).

$$s - p_C - t(x - a) = s - p_R - t(1 - b - x).$$

(64)

The location of this marginal consumer $x$ is given by

$$x = \frac{1}{2} + \frac{td + p_R - p_C}{2t},$$

(65)

$$d = a - b,$$

where $d$ corresponds to the difference in the distance to the center between $C$ and $R$, and can be interpreted similarly to $d_R - d_C$ in the asymmetric spokes model. The highest price $C$ can set without making it profitable for $R$ to undercut $C$ at the center and receive $Z$ is given by

$$\pi_R = p_R (1 - x) \geq (p_C - t(d)) (1 - x + Z).$$

(66)

The highest price $R$ can set without making it profitable for $C$ to undercut $R$ at the center and receive $Z$ is given by

$$\pi_C = p_C (x) \geq (p_R + t(d)) (x + Z).$$

(67)
Substituting (65) into (66) and (67), and solving (66) and (67) as equations leads to the undercut-proof equilibrium prices $p_{UPE}^C$ and $p_{UPE}^R$, and to the location of the marginal consumer in the undercut-proof equilibrium ($x_{UPE}$).

\[
\begin{align*}
    p_{UPE}^C &= \frac{td(1 + z(3 - d + 2z))}{2(1 + z)^2}, \\
    p_{UPE}^R &= -\frac{td(1 + z(3 + d + 2z))}{2(1 + z)^2}, \\
    x_{UPE} &= \frac{1 + (1 - d)Z}{2 + 2Z}.
\end{align*}
\]  

(68)  

(69)

Under the assumption of transportation costs normalized to unity ($t = 1$), a graphical solution of the undercut-proof equilibrium is given in Figure 12. Obviously, unless $d = 0$

Figure 12: Undercut-proof equilibrium prices

implies $a = b$ ($d_C = d_R$), and/or $t = 0$, each case is ruled out in the asymmetric spokes model by assumption, $p_{UPE}^R < 0$ while $p_{UPE}^C > 0$. This means that the highest price that guarantees $R$ not being undercut at the center by $C$ is negative and leads to a loss, while the highest price $C$ can set without being undercut at the center by $R$ is positive and thus leads to positive profits.

All the results in this section indicate that starting a price war by undercutting $C$ is
not profitable for $R$ as $C$ makes higher profits when matching the undercutting of $R$ than when accepting $R$’s undercutting. Further, unlike $R$, $C$ still earns positive profits in the undercut-proof equilibrium. In a nutshell, undercutting $C$’s gross consumer price (including consumer transportation costs) at the market center does not increase $R$’s profits. Undercutting will start a price war which completely erodes the profits of $R$ because $C$ will match any undercutting, which drives $p_R$ down to zero (marginal costs).
# B Complete Estimation Results of Chapter 5

## Table 14: Complete regression results of Chapter 5 part I

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## Table 15: Complete regression results of Chapter 5 part II

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### Additional Variables

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- STATIONS_5
- STATIONS_6
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- (1-C)*DIST TO CENTER
- AV DIST REMOTE
- (1-C)*AV DIST CENTRAL
- COMMUTERS
- logTOURISM
- logPOP DENSITY
- logPREMISES
- ALPS+WOOD
- TRAFFIC GOOD
- BRANDED
- DEALER OWNED
- SIZE > 2000
- HIGHWAY
- SERVICE
- LOW TOURISM
- N/A PREMISES
- N/A OWNERSHIP
- N/A HIGHWAY TRAFFIC
- N/A SIZE
- N/A SERVICE
- Federal State F.E.
- Time Period F.E.

### Statistical Significance

- **: 1%
- ***: 0.1%
- *: 5%

# of obs.: 2,920; 1%, 5%, 10% significance level

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Time Period F.E. Yes

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C Complete Estimation Results of Chapter 6

The estimates for the different measures of centrality have already been analyzed in Chapter 6. This section provides a description of the modifications of the basic specifications to check the robustness of the results, as well as an interpretation of the estimation results of some other variables used in the empirical specifications. The complete estimation outputs are plotted in Tables 17 and 18.

C.1 Robustness Checks

In addition to the specifications [1] to [4] listed in Section 6.8.2, some more specifications were made using a critical distance of 5 minutes in the construction of \( W \), and the squared inverse distances for the weights of the elements in \( W \). Specifications [5] to [7] show the results if the centrality matrix \( C \) is interacted with a binary weights matrix \( W \) based on unweighted 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 (\( \rho_2 \)) solely accounts for the centrality of neighbors but not for the relative distances to these neighbors. Thus, it is not surprising that the share of the slope of the reaction function relying on the centrality of neighbors is smaller in specifications [5] to [7] compared to specifications [2] to [4]. However, the coefficients are still positive and significantly different from zero and identification may be stronger compared to specifications [2] to [4] because of the alternative construction of \( W \) in \( WCy \). The likelihood ratio tests reject the benchmark model in specification [1] in favor of each of the respective alternative hypotheses (specifications [5] to [7]).

I also check the robustness of the results with respect to the construction of the network matrix \( G \), which determines a station’s centrality. In specification [8] ([9]) \( H \) is set to \( H = 2 \) \((H = 10)\). The slope parameter of \( \rho_2 \) in specification [8] is much smaller (but still significant) than in specifications [2] and [9], but \( H = 2 \) seems to be an extremely narrow criterion to construct the network \( G \). The coefficient in [9] is very similar to the coefficient in [2] and is 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].

The robustness of the results are also checked with respect to the construction of \( W \). In
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<td>Dependent variable</td>
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<td>PRICE</td>
<td>PRICE</td>
<td>PRICE</td>
<td>PRICE</td>
<td>PRICE</td>
</tr>
<tr>
<td>Critical distance in W</td>
<td>5 min</td>
<td>5 min</td>
<td>5 min</td>
<td>5 min</td>
<td>5 min</td>
<td>5 min</td>
<td>5 min</td>
</tr>
<tr>
<td>Inverse of distance in W</td>
<td>Squared</td>
<td>Squared</td>
<td>Squared</td>
<td>Squared</td>
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<tr>
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<td>dc</td>
<td>dc</td>
<td>dc</td>
<td>dc</td>
<td>dc</td>
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<td>( \rho_1 )</td>
<td>0.632</td>
<td>0.013***</td>
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<td>0.114</td>
<td>0.130</td>
<td>0.120</td>
<td>0.370</td>
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<tr>
<td>( \rho_2 ) (dc)</td>
<td>0.680</td>
<td>0.113***</td>
<td>0.213</td>
<td>0.033***</td>
<td>0.504</td>
<td>0.119***</td>
<td>0.202</td>
</tr>
<tr>
<td>( \rho_2 ) (wdc)</td>
<td>0.504</td>
<td>0.119***</td>
<td>0.202</td>
<td>0.034***</td>
<td>0.263</td>
<td>0.129**</td>
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<td>( \rho_2 ) (cc)</td>
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<td>0.057 **</td>
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<td>0.008</td>
<td>0.005</td>
<td>0.003*</td>
<td>0.006</td>
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<td>0.177</td>
<td>0.029***</td>
<td>0.188</td>
<td>0.029***</td>
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<td>0.012</td>
<td>0.006**</td>
<td>0.014</td>
<td>0.006**</td>
<td>0.013</td>
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<tr>
<td>( \log POPDENs )</td>
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<td>-0.026</td>
<td>0.043</td>
<td>-0.018</td>
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<td>( \log PREMISEs )</td>
<td>0.177</td>
<td>0.057**</td>
<td>0.170</td>
<td>0.069**</td>
<td>0.161</td>
<td>0.069**</td>
<td>0.197</td>
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<tr>
<td>( \log )</td>
<td>0.010</td>
<td>0.008</td>
<td>0.013</td>
<td>0.008</td>
<td>0.005</td>
<td>0.003*</td>
<td>0.006</td>
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<td>yes</td>
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</table>

*** 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 W matrix containing zeros and ones only instead of distances;
Table 18: Complete regression results of Chapter 6 part II

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<tr>
<td>Critical distance in W</td>
<td>5 min</td>
<td>5 min</td>
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<td>10 min</td>
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<tr>
<td>Inverse of distance in W</td>
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<td>Single</td>
<td>Single</td>
<td>Squared</td>
<td>Squared</td>
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<tr>
<td>Centrality (H)</td>
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<td>0.243</td>
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</table>

*** significant at 1%, ** significant at 5%, * significant at 10%; LR-tests of the respective nested specification without centrality (H₀) against the particular H₁;
specifications [10] and [11] the inverse of the driving time is used instead of the squared inverse to determine the weights in $W$. The coefficients hardly change compared to the equivalent basic models in [1] and [2]. Finally, specifications [12] and [13] show the results if a critical distance of 10 minutes of driving time is used instead of 5 minutes for the construction of $W$. A 10 minutes radius raises the number of observations from 3,051 to 3,188, as stations with no neighbors within 5 minutes are dropped from the sample in specifications [1] to [11]. On the other hand, for many stations the number of neighbors included in $W$ using a 10 minutes radius increases to an unfeasibly high number. Using a 10 minutes radius slightly raises the slope of the reaction function. The $LR$-Test again rejects the benchmark model ignoring centrality in favor of the extensions.

C.2 More Details on the Estimation Results

In line with previous empirical findings in spatially differentiated markets, I 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.\textsuperscript{85}

To approximate demand and cost in the different districts of Vienna, I use the variables COMMUTERS, log POPDENS and log PREMISES. An increase in the rate of commuters in a district by ten percentage points is expected to directly increase the price by 0.12 to 0.15 cents. These results are interesting in a sense that commuters increase the per capita demand for gasoline/diesel on the one hand, but on the other hand have lower search costs than the average consumer because they frequently observe prices along their commuting paths. The positive sign of the coefficient indicates that the demand effect outweighs the search cost effect. The results are significant and robust in all specifications. The population density (log POPDENS) in a district, however, does not have a significant impact on prices. The variable log PREMISES accounts for differences in costs across districts. An increase in the price for business 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

\textsuperscript{85}I only report and interpret the estimates of the direct impact of the explanatory variables. The total effects include the direct effects and feedback effects due to spatial dependence and are equal to $(1 - \rho_1 - \rho_2)^{-1}\beta$. See LeSage and Pace (2009) for details.
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.

\[\text{zero in all specifications.}\]