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**Spatial Interaction Between Fuel Stations
in the Hungarian Gasoline Market**

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Üzemanyagtöltő állomások közötti térbeli
kölsönhatások a magyar benzinpiacon

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I Introduction

The energy industry takes on a prominent role in nowadays challenges. As environmental considerations get increasingly important, and geopolitical conflicts challenge global supply chains, the role of energy grows significantly. Fuel industry is no exception. Olabi et al. (2021) argue that understanding this rapidly changing, transforming industry is of utmost importance.

This research aims to contribute to a deeper understanding of the fuel industry by investigating the interactions between fuel stations based on their locations. The ultimate goal is to explore how spatially related fuel stations reflect this spatial relationship in their pricing. Using the Hungarian 95-octane gasoline market, I investigate how the small stations change their prices concerning how other stations change their own prices in the area. I separate the effects by different groups of brands, inferring on effect size and persistence as a function of distance. Measuring market competition, composition, and territorial effects is out of the scope of this research, but they will be considered to avoid distortions.

Transportation expenses accounted for as much as 10% of the overall per capita expenditure among median-income consumers in 2020 in Hungary (Hungarian Central Statistical Office 2021). This large share demonstrates that the topic concerns us all on an everyday basis. Even small changes in the market have huge consequences for the society as a whole. This is one of the reasons why competition authorities are concerned with effective market competition.

Defining the appropriate market and competitors is an essential step in recognizing collusive behavior. This research helps to identify the relevant local markets the fuel stations compete in, thereby helping antitrust investigations. The results of this paper can be used to recognize cartels or to review and evaluate the effect of mergers and acquisitions on market competition. Furthermore, understanding spatial interaction between fuel stations helps urban planners and policymakers to find appropriate locations for new fuel stations.

According to Bergantino et al. (2020) and Haucap et al. (2017), the presence of small firms in the market often induces greater competition, pushing down prices in the entire market, and resulting in higher consumer well-being. In Hungary, the number of these small firms decreased in recent years (Hungarian Petroleum Association 2023a), making it even more important to understand their behavior and the way they interact with the rest of the stations. Also, these stations apply a rather

heterogeneous pricing strategy, providing a better opportunity for investigation compared to other, larger brands.

The fuel market is a widely researched area, however, it branches out to many lesser-known fields. There is research about investigating the competition between different types of stations (Haucap et al. 2017). Also, spatial interaction between fuel stations is a more developed area (Bergantino et al. 2020). But at the time of this research, there is no example of combining these two and estimating the spatial effects of different types of market participants at the same time. R. Farkas (2017) also expresses the need for further research in spatial interaction and more sophisticated market definition in the Hungarian fuel market. This paper aims to fill this gap.

In the next section, I review the related literature and summarize relevant aspects of the fuel market. In the third section, I discuss the data collection procedure and provide descriptive statistics. The empirical model is built in the fourth section. In the fifth section, I present the results. The final section concludes.

II Literature Review

1 The Hungarian retail fuel market

The Hungarian retail fuel market is characterized by large takeovers, composition changes, and, especially in recent years, several shocks. At the beginning of 2007, Agip acquired Jet while Lukoil acquired Esso stations. This gradual market concentration continued when MOL, the largest participant took over Agip in 2016 and Lukoil in 2022. The latter takeover contained an agreement between MOL and Orlen to exchange stations in Hungary and Poland to avoid excessive market power. This was necessary to meet the competition regulations of the European Commission. Further station exchanges between these two brands happened in early 2024. Due to all these changes in the past decades, a more concentrated station ownership structure formed with only a few large participants.

In contrast to large brands, small brands own one or very few stations and they exert market power only in their local market. These stations are also referred to as independent, unbranded, or white stations. From 2007, the number of small participants increased substantially. By the end

of 2008, the market was characterized by a few large brands and many small ones but almost no medium-sized (D. Farkas et al. 2009).

Between 2020 and 2023, several shocks hit the fuel industry. The Hungarian Petroleum Association (2023a), an advocacy organization established by some of the largest retailers in Hungary, points out that in these years, the fuel industry could not operate on a market basis as it has been heavily influenced by the coronavirus pandemic, geopolitical conflicts, sanctions, price ceiling, and refinery failure. They add that these events reorganized ownership structure, mainly at the expense of the number of small brands.

In these long-lasting unfavorable circumstances, the members of the Hungarian Petroleum Association sold 16.5% less 95-octane gasoline in 2023 compared to 2022 (Hungarian Petroleum Association 2023b). This negative change is less than the change in diesel, which corresponds to a decrease of 19.6%. Fuel sales are easy to account for as a particular type of fuel is technically a homogeneous product, even across different branded stations. Yet, pricing this homogeneous product brings up various components.

One group of these components is international conditions, such as the Brent crude oil price and the USD/HUF exchange rate. They play an important role when determining retail prices (Hungarian Petroleum Association (2023a); González and Moral (2023)) as they are responsible for the wholesale price. D. Farkas et al. (2009) claim that this wholesale price similarly influences different retailers and largely determines retailer price, therefore price differences between dates are well explained by wholesale price changes. As a result, the interaction of retailers with the upstream industry might have some implications on price setting.

Vertically integrated market participants have an incentive to raise wholesale prices in the hope of squeezing out other players. However, if demand for wholesale gasoline is elastic enough, raising its price generates a profit loss not only in the upstream market but overall (Gilbert and J. Hastings 2001). Multiple retailers in Hungary have one or more refineries. Most of these refineries are situated far from Hungarian markets, therefore their existence enhances competition among wholesalers to a limited extent. This implies moderate demand elasticity for wholesale gasoline. Although this market environment might enable taking advantage of vertical integration, competition authorities strictly regulate such behavior. In 2010, the Hungarian Competition Authority initiated an investigation at MOL due to possible abuse of their dominant position (Hungarian

Competition Authority 2014). A few years later, this authority investigated and fined Shell for sharing misleading information regarding their products (Hungarian Competition Authority 2015). Based on that, fuel markets are actively monitored, and the necessary measures are put in place to prevent or punish the misuse of power. Therefore, it is unlikely that vertical integration implies a competitive advantage in the retail gasoline market. This is also confirmed by D. Farkas et al. (2009), who claim that even if vertically integrated companies like MOL and OMV tend to charge higher prices in Hungary, there is no evidence that it is caused by their presence in the upstream industry.

2 Pricing components in the gasoline market

It is widely accepted that retail fuel is a homogeneous product (González and Moral (2023); Haucap et al. (2017)). Despite the homogeneous quality, the same type of fuel costs different amounts at different stations. In this subsection, I collect the factors that influence gasoline pricing besides international conditions, mentioned before. These factors are namely brand and station-specific characteristics, as well as competition, and territorial factors. Location specificities and spatial interaction will be discussed in a separate subsection.

Starting with brands, González and Moral (2023) and Haucap et al. (2017) argue that brand affiliation affects prices through brand recognition, operations efficiency, and bargaining power with the supplier. Larger brands can benefit from economies of scale, so they may bear lower costs in certain areas. In addition, brands with more stations cover a larger market, allowing them to build stronger customer loyalty. This gives larger brands a competitive advantage over smaller ones, possibly resulting in higher prices.

Some characteristics apply to stations instead of brands. Services like a car wash, shop, and canteen drive up prices (D. Farkas et al. (2009); R. Farkas (2017)). The wider the variety of services a station provides, the higher the price it usually charges, because customers care about supplementary products and services, resulting in lower price elasticity of demand for gasoline (Haucap et al. 2017).

Gasoline demand shows a high dependence on territorial factors, just like the supply. Higher population density forms a more concentrated consumer base, shifting demand upwards. GDP per capita should show the purchasing power of these consumers. Higher GDP per capita is reflected

by higher demand. On the supply side, the higher the real estate and land costs, the more costly for the stations to enter the market. The level of non-financial costs like administration or regulation barriers may also attract or deter potential entrants. González and Moral (2023) estimate the effect of competition on retail prices. They point out that the intensity of competition (the number of market participants in an area) should be considered endogenous. A local market with high demand has a potentially high price level. This attracts more participants. As more stations appear, the competition between them becomes much more fierce, pushing down prices. The opposite is happening for example in the case of high entry costs. Overall, the price level is misleadingly similar in various degrees of competition intensity. However, by controlling for these supply and demand factors, the true effect of competition intensity can be obtained. Researchers Netz and Taylor (2002) also control for these supply-demand features, while Clemenz and Gugler (2009) mention them but they are unable to address supply bias.

Territorial factors are closely related to competition intensity, but this intensity has considerable price effects on its own. Barron et al. (2004) present several theoretical models that support the idea that more market participants result in lower prices. They also find empirical evidence that higher seller density negatively correlates with prices and also with price dispersion within an area. These results are also confirmed by R. Farkas (2017) and Clemenz and Gugler (2009). Competition effects however are not fully explained by only the market concentration.

Clemenz and Gugler (2009) and Van Meerbeeck (2003) go further than the number of competitors by claiming that not only the concentration but also their composition is what impacts prices. The study carried out by Clemenz and Gugler (2009) found empirical evidence that a higher share of independent stations in the market causes lower prices. It is however not straightforward why the presence of small firms reduces prices. Pennerstorfer and Weiss (2013) identify two channels in which unbranded stations affect prices. First, with the competition effect, the sheer number and the pricing strategy of unbranded stations enhance the competition, pushing down prices in the whole market. Second, if unbranded stations are associated with inferior fuel, more unbranded stations induce lower competition among branded stations. By separating these two effects, they find that both competition and composition effects are present, with the stronger competition effect offsetting the composition effect. Therefore, ignoring the composition effect leads to underestimating the competition effect.

One more aspect of market composition is the presence of same-branded firms. Van Meerbeeck (2003) and Clemenz and Gugler (2009) found that if more stations of the same brand are present in the same local market, they tend to raise prices. Although it is not explicitly stated, the reason behind that may be that higher market share contributes to higher market power. With more stations in a local market, the particular brand can more easily assert its own interests. However, this requires a highly concentrated ownership in the local market, which might not be a common feature. This might explain why J. S. Hastings (2004) could not confirm that the share of same-branded firms in the local market raises prices. However, they found significant effects of market entries and takeovers on prices.

According to J. S. Hastings (2004), if independents on the market are replaced, competition softens, resulting in higher prices. This is especially true if the competitors have smaller market shares as they compete more intensely for non-loyal consumers than high-share competitors with a more loyal consumer base.

Newly entering stations reduce the prices of the incumbent stations. This reduction is higher the closer the new entrant is and higher if the entrant is unbranded, but these effects are not durable (Cardoso et al. 2022). From that, I can conclude that new entrants engage in price competition to attract the consumer base of the incumbent stations and price higher later when a solid consumer base is captured.

This subsection lists many factors that influence the pricing behavior of fuel stations. The next subsection is dedicated to another, widely researched factor, location.

3 Location and spatial interaction

The location of fuel stations is an important determinant of the role they play in the market. Different sites produce different conditions, so they need to be taken into account when considering station interactions. González and Moral (2023) point out that particular location types are highly preferable to establish a station. For example, locations close to airports face decreased price elasticity of demand. Highway locations are also special as consumers are willing to pay higher costs instead of going off the road, losing time and progress, therefore the stations by the highway form a separate market (Van Meerbeeck 2003).

Van Meerbeeck (2003), Haucap et al. (2017) and Banfi et al. (2005) mention that border loca-

tions are subject to fuel tourism, and they price accordingly. Fuel tourism is caused by the price difference across the national border. Price-sensitive consumers take advantage of this price difference and they are willing to cross the border to save some money as long as the station is close enough to the border. Banfi et al. (2005) claim that the stations closer than 5 kilometers from the border can be treated as border stations. In my research, I also use this 5-kilometer distance to define and treat border stations accordingly. But it is not only the distance from the border that affects the market but the market itself can be defined as an area within a certain distance.

Defining the relevant market is a key element of market regulation, policy-making, and strategy formulation by station operators. This relevant market contains those participants who may influence each other with their decisions. In the retail fuel market, this market is a specific area. All the stations have their own area they compete in, called their local market. Bergantino et al. (2020) and González and Moral (2023) defined this local market as a circle around the station with a radius of 3 kilometers, while (Haucap et al. 2017) used the distance definition of 2 kilometers. Perdiguerro and Borrell (2012) use a different approach and instead of an area, they define the local market as a 5-6 minutes drive from a station. Note that this means larger distances around better road networks. Given all the local markets of the incumbent stations, Netz and Taylor (2002) found evidence that firms choose locations for their stations in a way that minimizes spatial interaction with other stations.

Within these local markets, González and Moral (2023) claim that the closer the competitor to the station is, the more they engage in price competition, and the degree of competition is non-linear in distance. This spatial interaction depends not only on the distance but also on the brand (Yu et al. 2023).

Instead of investigating the spatial interaction of separate brands, Haucap et al. (2017) distinguish 3 groups and assign the stations into one of the three groups by the brand. The three groups are the brands with national networks and brand awareness, the brands with regional networks, and the independent stations. Brand categorization is also used by González and Moral (2023) who identified brands as either premium or non-premium brands. They found that if the closest neighbor is identified as a low-cost station, then prices substantially drop, regardless of the station affiliation.

Altogether, it can be concluded that market definition and spatial interaction in distance are in a privileged relationship. Also, brands can be categorized according to their market characteristics

to reach parsimonious modeling. The next subsection briefly summarizes the development and the main features of spatial econometric models.

4 Spatial and spatiotemporal models

Spatial models are a set of econometric models, used for estimating spatial interaction. The first comprehensive description of spatial models was provided by Anselin (1988). Using distance-based relationships between observations, he laid the foundations of spatial econometrics. Since then, the scientific community has used this model extensively, further developing it in many directions. Catania and Billé (2017) constructed a group of spatial models, integrating temporal effects. They show that dynamic spatiotemporal models are effective tools for estimating time-varying spatial dependence or time-varying, and cross-sectional heteroscedasticity.

Bergantino et al. (2020) investigated a spatial autoregressive phenomenon of fuel prices in Rome. In practice, they studied how the price charged by a station is influenced by the price of spatially related other stations at the same time period. Using cross-sectional data on fuel prices, they managed to separate the spatial effects of surrounding stations from competition and territorial effects. Competition and territorial controls capture the effect of the number and structure of competitors as well as the supply-demand characteristics of the area. However, these controls are unable to measure how the spatial dependence on price evolves with the distance between stations. Spatial econometric models solve this problem by controlling for the spatial interactions between stations. These factors recognize that the pricing behavior of a station may be also influenced by the pricing of nearby areas.

LeSage et al. (2017) also studied fuel pricing in a spatiotemporal setup. Using heterogeneous coefficients, they show that spatiotemporal methods are efficient tools to estimate spatial interaction between proximately situated fuel stations. From the point of view of my own research, one main value of this paper is the demonstration of how to study the interaction of spatial effects and brand affiliation in a panel setup.

III Data

1 Data collection

In this section, I overview the data collection and the resulting database and go through the main quantitative characteristics and trends of the Hungarian fuel market.

There is no detailed, publicly available dataset on Hungarian fuel prices that could be used for this analysis. Also, potential owners of such a dataset are not willing to share that, as it can be a major business resource. Therefore, I construct my own database by collecting and linking together fuel prices available on the Internet on a daily basis.

The website holtankoljak.hu provides current fuel price information by station and the type of fuel in Hungary. Brand affiliation and address of each station are also given. By constructing an automated web scraping algorithm, I obtained daily prices of 95-octane gasoline at more than 1,300 stations from September 2023 to January 2024. This provides altogether 132,829 price observations in an unbalanced panel database. On the 11th of November 2023, the website changed substantially, offering additional information like the days passed since the last price update of a station. On the same date, many stations were filtered out as they had already exited the market. Since the exiting stations appeared with the last reported price before that day, the panel before contains outdated price observations. Therefore, I rely on the data only after the 11th of November. This excludes the possibility of using nonexistent stations to estimate spatial effects.

Based on addresses, the location coordinates are matched to the stations. Using these coordinates and additional administrative GEO shape files, I also matched the settlement, district, and county of location to the stations as well as the distance from the national border. Based on brand affiliation and the address of the station, IDs are generated. This way, a particular station gets a different ID in case of a takeover. The web scraping algorithm with the obtained data can be accessed online through [GitHub](#).

2 Descriptive statistics

Table 1: Summay statistics of brands in Hungarian retail fuel market as of 11th November 2023. 95-octane gasoline prices are used.

Brand	Number of Stations (in Budapest)	Market Share	Mean Price	Median Price	sd. Price
Mol	457 (55)	37.06%	601.5	598.0	12.74
Shell	184 (40)	14.92%	602.4	599.9	9.04
Omv	175 (48)	14.19%	604.5	599.9	14.37
Orlen	79 (10)	6.41%	597.5	594	12.67
Mobil Petrol	47 (4)	3.81%	594.6	586.9	24.01
Oil	32 (0)	2.60%	590.9	589.9	17.19
Avia	29 (1)	2.35%	594.5	594.0	13.86
Mol Partner+	24 (0)	1.95%	591.6	591.4	19.93
Auchan	18 (3)	1.46%	575	575	0
Hunpetrol	12 (0)	0.97%	586.4	587	4.82
Other Small Brands	176 (10)	14.27%	600.2	598.0	14.24
All	1233 (171)	100%	599.0	598.0	14.66

Summary statistics of brand affiliation and prices charged are listed in Table 1. Market share is defined as the ratio of the number of stations of a company to the total number of stations. The top three stations possess a huge share, 66.18% of the market together which points to a highly concentrated market. There are other brands with considerable shares but these are much smaller ones. Prices are relatively homogeneous whereas the standard deviation of pricing has a larger range among different brands. Note that this figure includes highway stations too, where prices tend to be significantly higher.

Based on the literature, highway locations form separate markets with much higher prices. Figure 1 demonstrates the distribution of prices charged by stations including and excluding highway stations. The difference between the two plots points out that highway stations are indeed priced higher in Hungary. The rest of the stations price in a way that the corresponding density plot approaches normal distribution with a slight left skewness. In the analysis part, I use stations that are unaffected by special circumstances. These circumstances are highway location or proximity to the national border. While highway stations form separate markets and they are unlikely to have a

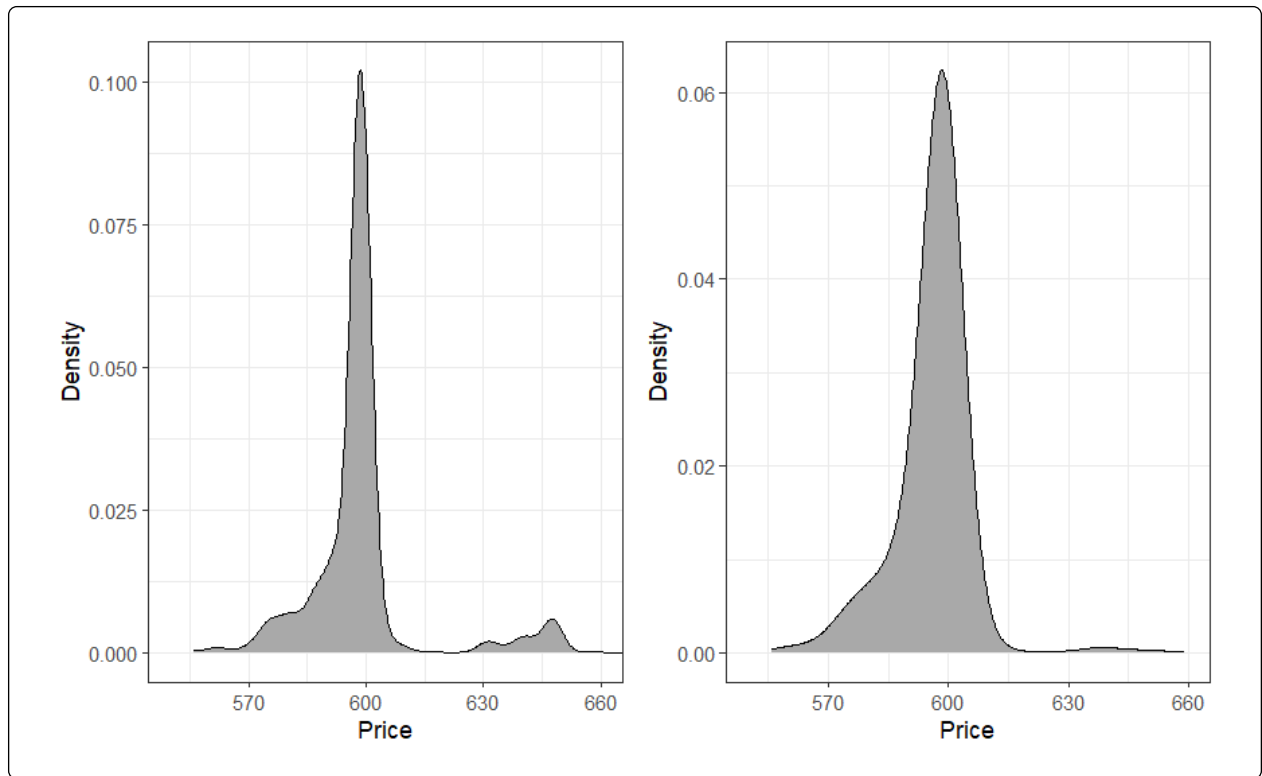


Figure 1: Distribution of fuel prices with highways (left) and without (right) on 11th November 2023. Own figure.

significant interaction with other stations, border stations are different. They are likely to have an impact on the pricing level in an area, consequently influencing firms that are not border stations but are close to those. Border stations however are being influenced by international markets because they are located close to the border. Based on the literature, this distance is set to 5 kilometers. I filter out highway stations altogether from the analysis. In the case of the border stations, I retain their spatial effect, while I exclude them from the analysis, in a way detailed in the model part.

After filtering out highway stations, I explore the pricing distribution of stations by brands in Figure 2. It can be seen that the largest stations charge relatively high, homogeneous prices. Other larger firms tend to exhibit much higher variance in prices, just like white stations.

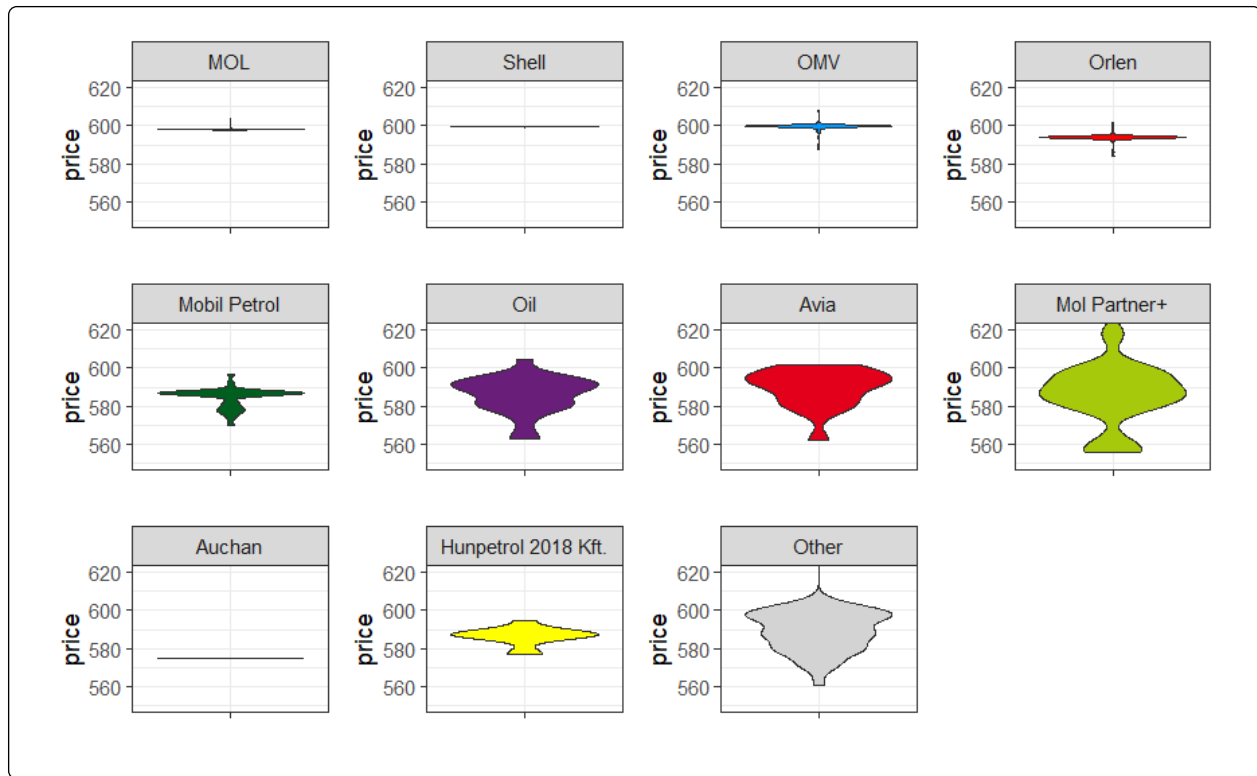


Figure 2: Distribution of fuel prices by brand on 11th November 2023. Own figure.

Based on these apparent and reasonably assumed differences in size, pricing, and brand loyalty, I split brands into three categories. I refer to the largest brands with higher prices as large premium brands due to the associated quality, the variety of services, the extensive station networks, and the higher prices. These brands are Mol, Shell, Omv, and Orlen. Although Orlen is smaller than the other three, it follows a similar pricing strategy as them and has a broad international recognition. The second group of brands are Mobil Petrol, Oil, Avia, Mol Partner+, Auchan, and Hunpetrol. The stations of these brands can take advantage of some brand recognition as they are present in many local markets. Since they have heterogeneous pricing with lower prices than the first group on average, I refer to the stations of these firms as large discount stations. The remaining brands own white stations, with less than 10 stations, most often only one or two stations.

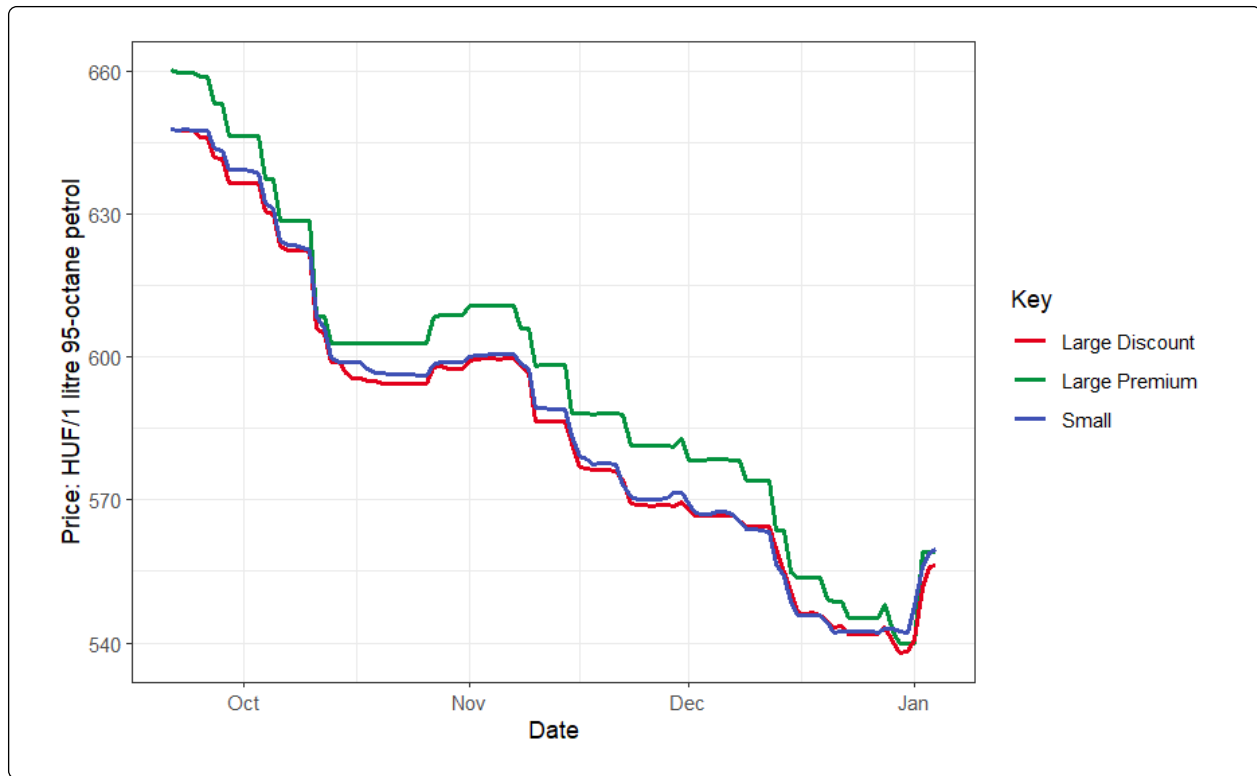


Figure 3: Fuel price trends by category excluding highway stations from 21st September 2023 to 4th January 2024. Own figure.

To demonstrate the pricing difference among the three different groups, I plot the average prices of the corresponding stations in Figure 3. It can be seen that the average prices of all the groups move together strongly. However, there are differences in the levels as large premium stations charge slightly higher than large discounts and small stations. The latter two groups have very similar pricing with more frequent small adjustments than large premium stations.

The three groups of brands and the corresponding stations behave differently, therefore treating them as separate units enables separating their effects. In the next section, I describe how to reveal the spatial interaction between these groups by building a spatiotemporal model that estimates the spatial effects.

IV Model

1 Spatial modelling

To investigate how the price level of the surrounding area affects the pricing of small stations, I developed a time and individual fixed effects spatiotemporal model. This type of model is capable of controlling for time trends and individual-specific characteristics. This way it filters out competition and territorial effects and reports spatial dependencies directly. These spatial effects are disintegrated by the three different neighbor types defined previously.

Equation (1) contains the main regression equation. Besides fixed effects, the model uses three time-variant spatial dependence factors. Each of these factors is represented by a spatially-lagged dependent variable. A factor like that is the weighted average of price changes, charged by the surrounding stations at a time. The three factors determine the average price level changes, charged by surrounding large premium stations, large discount stations, and other small stations. All three factors are station and time-specific as stations are situated at different local markets and the price structure of these local markets change in time.

$$\Delta \mathbf{P}_{\mathbf{tn}} = \alpha_s \mathbf{W}_{st} \Delta \mathbf{P}_{\mathbf{tN}} + \beta \mathbf{ID} + \gamma_t \mathbf{T} + \epsilon_t \quad (1)$$

The dependent variable $\Delta \mathbf{P}_{\mathbf{tn}}$ is the $n \times 1$ vector of change in prices in time period t , charged by small stations. It is an n element subset of all the N stations. $\mathbf{W}_{st}$ is the $n \times N$ spatial weights matrix in time period t , corresponding to the neighbor group s . The n -th row determines the N spatial weights of the particular station, namely how that station spatially interacts with all the N stations. $\Delta \mathbf{P}_{\mathbf{tN}}$ is the $N \times 1$ vector of price changes of all N stations in time t . s denotes the three groups of neighbor types: large premium, large discount, and small neighbors. Furthermore, $\mathbf{ID}$ and $\mathbf{T}$ stand for the individual and the time-fixed effects respectively, and ϵ_t is the vector of error terms at time t .

The interaction of $\mathbf{W}_{st}$ and $\Delta \mathbf{P}_{\mathbf{tN}}$ provides the spatial autoregressive term. Their product is the $n \times 1$ vector of change of spatially weighted price level charged by the neighbor group s at time t . Consequently, α_s reports how the pricing of small fuel stations reacts to the change in the surrounding price level of the neighbor group s .

2 Construction of the spatial weight matrix

Spatial weight matrix $\mathbf{W}_{st}$ is constructed in three steps. In the first step, I compute a distance matrix of stations, based on their coordinates. The values of this symmetric $N \times N$ matrix report the distance between the corresponding row and column stations. Then, I choose a distance parameter δ . This parameter defines a circle around each station which is interpreted as the relevant local market of the station. It is assumed that no station further than δ exerts any spatial effect on a chosen station. In the distance matrix, for every value above δ , I reassign the value to 0. This indicates that the spatial effect of that station pair is irrelevant.

In the second step, I create three separate matrices from the previously transformed distance matrix. Each of the three new matrices corresponds to a type of neighbor. I create the weight matrix of large premium neighbors by resetting all column values to 0, except for those columns that represent large premium stations. In the resulting $N \times N$ matrix, all rows may contain positive values, while columns contain positive values only if they correspond to large premium neighbors. I create the weight matrix of large discount stations and independent stations in a symmetrical way. As a result, the three matrices contain the distances between all stations and their relevant neighbors from group s .

In the third step, I create the spatial weights matrices from these three matrices. I row-standardize all three matrices, in a procedure described by equation (2), where d_{ij} represent only non-zero distances between station i and j . That is, for all elements of non-zero rows, I reassign their values. First, I subtract the distance from δ . Then, I divide this value by the row sum of these values. As a result, the closer stations get a higher weight, and more distant ones get lower weights. In the resulting spatial weight matrices, all non-zero rows sum up to 1 (see equation (3)).

$$w_{ij} = \frac{\delta - d_{ij}}{\sum_{j=1}^N \delta - d_{ij}} \quad (2)$$

$$\sum_{j=1}^N w_{ij} = \begin{cases} 1 & \text{if } \exists w_{ij} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall i \quad (3)$$

The resulting weights show how local neighbors contribute to the surrounding price level of a station. More neighbors mean that each of them is assigned a lower weight. Also, closer neighbors

have a higher contribution to the price level than neighbors far away, represented by higher weight. The three spatial weight matrices are created for all time periods. This enables stations to enter or exit the market and also allows for a change in ownership.

To determine how the price levels charged by different neighbor groups affect the pricing of small neighbors, I use the sample of small firms only and the corresponding rows of the spatial weight matrix. At this point, border stations are also filtered out. During the weight matrix calculation, they were present in the sample, enabling their contribution to the price level. At this point, I exclude them from the analysis. As a result, the original $N \times 1$ vector of price changes is reduced to an $n \times 1$ vector, while the $N \times N$ spatial weight matrices are reduced to $n \times N$ matrices.

By gradually increasing δ , I define larger and larger areas as the relevant market, introducing new stations that influence local price levels. In the case of low neighborhood density, adjusting δ might not introduce new neighbors. If that is the case, the surrounding price level for the station is the same for the increased δ . Therefore, estimates for larger δ might fail to capture the effects of the broader market and estimates report the effect of the price level in a smaller market. The less dense the neighbor network is, the higher the threat of overestimating the effects of that network at a broader market definition. This is likely to influence estimates of the effect of small station neighborhoods first, as that is the least dense, and the effect of large premium stations last as they have the densest network.

3 Modelling concentric rings

To overcome the issue of station network density, a possible way would be to introduce concentric rings instead of circles as the relevant market. These rings would show how particular slices of the market interact spatially with the corresponding station. The price level in a ring may be influenced by stations of neighboring rings, therefore rings should be investigated together. This comes with difficulties. There may be very few stations that have all types of neighbors in each ring. Increasing ring width can resolve the problem at the cost of losing detailed results.

In practice, the introduction of rings changes only the construction of the spatial weight matrices. Instead of assigning zero weight for all station-pair situated further from each other than δ , I assign zero weight for all station-pair that are not within a particular distance interval. All subsequent steps are identical in constructing the spatial weight matrices. Equation (4) describes the

regression equation with rings instead of circles. The lower bound of the closest interval is zero, making the first ring a circle.

$$\Delta \mathbf{P}_{\mathbf{tn}} = \alpha_{\mathbf{sd}} \mathbf{W}_{std} \Delta \mathbf{P}_{\mathbf{tN}} + \beta \mathbf{ID} + \gamma_t \mathbf{T} + \epsilon_t \quad (4)$$

Equation (4) uses different rings defined by interval d . The difference between equation (1) and equation (4) is that equation (4) uses multiple spatial autoregressive factors for the same neighbor type for all rings. Therefore, the model estimates three parameters for each ring, corresponding to the spatial effect of all three neighbor groups. The results of estimating coefficients concerning regression equations (1) and (4) are discussed in the next section.

V Results

Since the capital, Budapest has a much denser network of fuel stations, local market features and interactions here may be different from the rest of the country. Therefore, I estimate spatial effects both including and excluding Budapest. Unfortunately, Budapest alone cannot present as many fuel stations to produce meaningful results, so only the two previously mentioned scenarios can be considered.

Table 2 summarizes coefficient estimates of regression equation (1) by including and excluding Budapest. Variables *price_small*, *price_large_d* and *price_large_p* denote the effects of the spatial autoregressive terms, namely how the change in the price level of surrounding small brands, large discount brands, and large premium brands influences the pricing of small stations respectively. The market is defined as a 3-kilometer radius area. Coefficients can be interpreted as the degree how small stations react to price changes in their area.

Table 2: Estimating the effects of the price level charged by neighbors. Circular market defined by $\delta = 3km$. Clustered standard errors in brackets.

	Dependent variable: ΔP_{tn}	
	Including Budapest	Excluding Budapest
<i>price_small</i>	0.010 (0.007)	0.015** (0.005)
<i>price_large_d</i>	0.060*** (0.013)	0.043*** (0.011)
<i>price_large_p</i>	0.123*** (0.021)	0.124*** (0.021)
<i>ID_fixed_effect</i>	Yes	Yes
<i>Time_fixed_effect</i>	Yes	Yes
Within R ²	0.2182	0.2122
Observations (nt)	2035	1911
n	51	47

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

The results are obtained after filtering out the effects of individual and time-specific characteristics using fixed effects. The effect of the number of surrounding stations, their composition, the time-invariant supply-demand factors, and other individual-specific features are controlled for by the individual fixed effects. Also, the effects of Brent oil price, exchange rate changes, and other time-variant features are captured by time fixed effects. Therefore, all brand and station-specific features were filtered out, as well as the effect of territorial factors and competition through station concentration and structure. The results reflect the partial effect of spatial interaction with the market on small fuel stations, separated from other effects. Temporal lags of the spatial autoregressive terms were also tested but proved to be insignificant, meaning that effects are immediate. The lack of a price leader group is also suggested by Figure 3.

It is important to notice that all spatial autoregressive coefficients are positive, meaning that a price change in the local market induces the corresponding station to change its pricing in the same direction. In both cases, the change in the price level of large premium brands has the highest effect, two to three times as high as the effect of large discount brands.

The large discount brands demonstrate some differences between the two cases. If the stations of Budapest are also included, the effect exerted by large discount brands grows, while it declines and becomes insignificant for small stations. The reason behind that might be that market trends are dissimilar in Budapest and the rest of the country. For example, if customers in Budapest develop different levels of loyalty towards large discount brands, this can impact how small firms react to price changes in those stations. It is also possible that the composition of the three theoretical groups is different in Budapest and the rest of the country.

Based on Table 1, it is indeed the case that the distribution of brands in the large discount category is different in the two areas. Also, the number of these stations is low in Budapest, and since they have a rather heterogeneous pricing strategy, our estimates are sensitive to pricing deviations among these stations. The network density of large discount brands is higher outside of Budapest, producing estimates less sensitive to such price deviations.

Outside of Budapest, A 1 unit change in the price level of the surrounding large premium brands results in a 0.124 unit change in the pricing of the small station present in the market, in the same direction. For large discount brands and other small stations, the size of the same effect is 0.043 and 0.015, respectively. These estimations largely depend on the definition of the relevant market. By gradually increasing δ , I adjust the size of the market and obtain spatial autoregressive coefficients by the type of neighbor group. I plot the coefficients of large premium brands in Figure 4, the coefficients of large discount brands in Figure 5, and the coefficients of small brands in Figure 6.

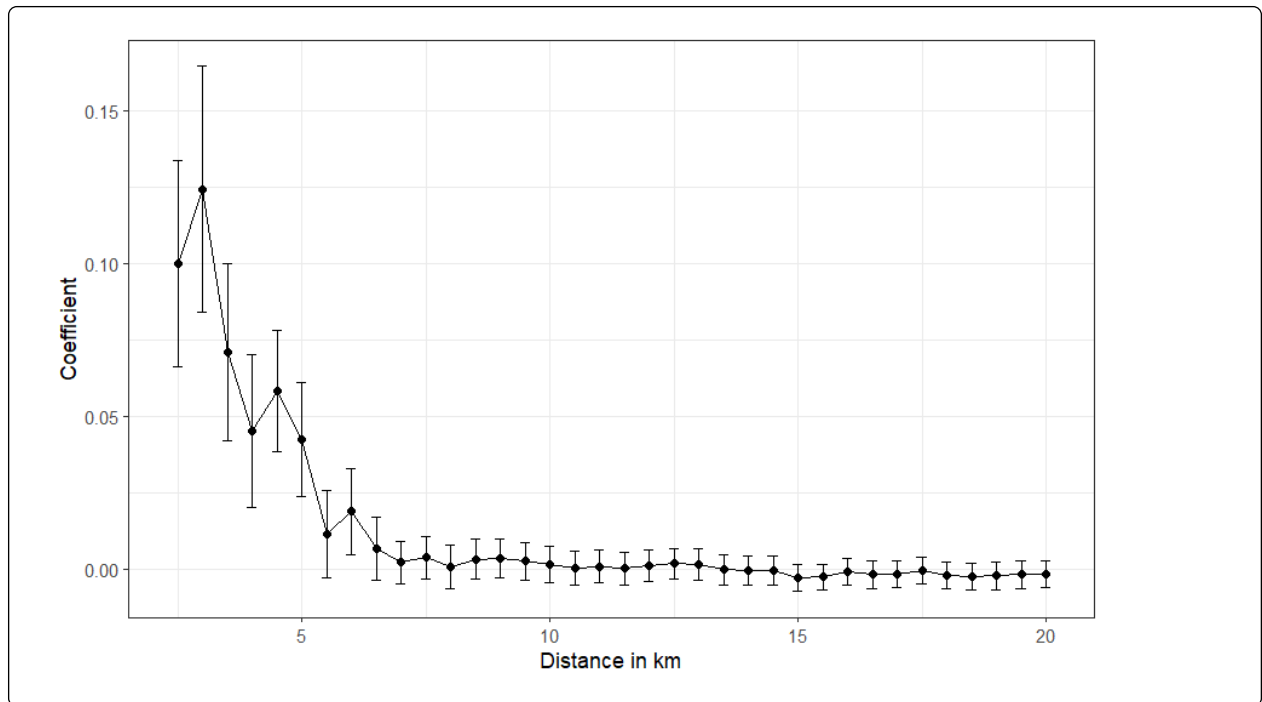


Figure 4: Coefficients of the spatial autoregressive term of large premium brands of regression (1) with various market radius, outside of Budapest. 95% confidence intervals are plotted. Own figure.

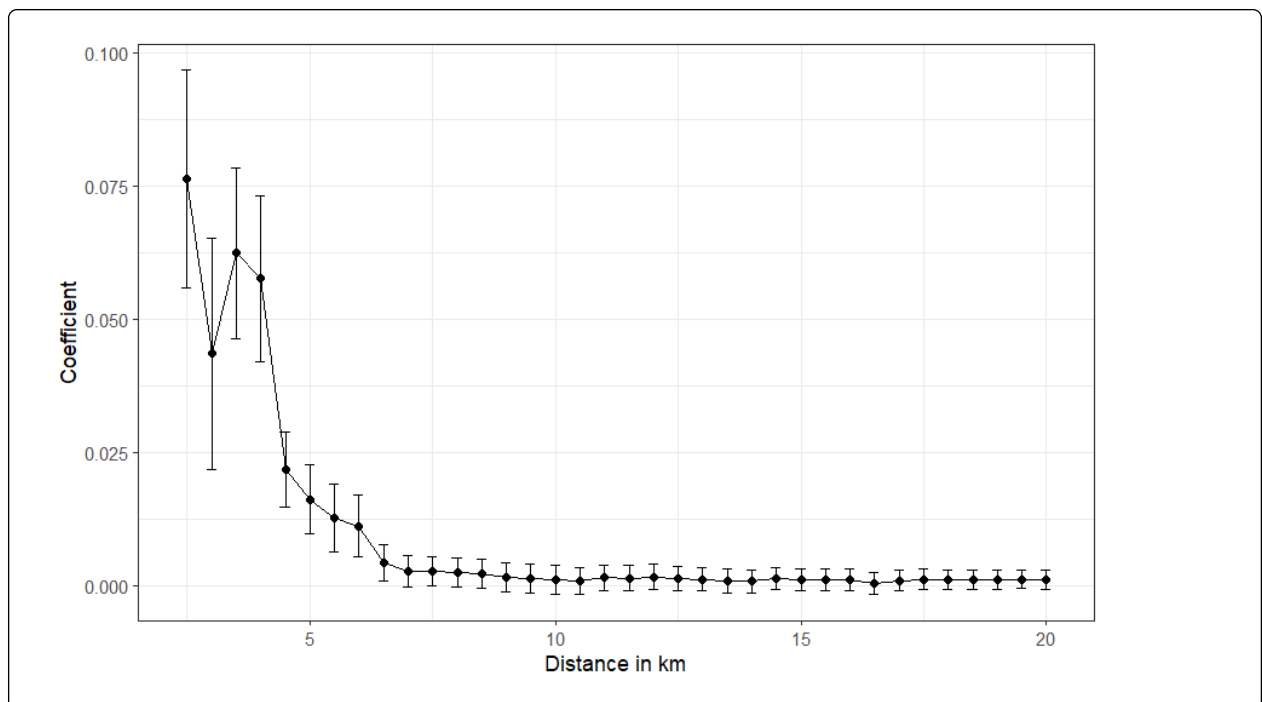


Figure 5: Coefficients of the spatial autoregressive term of large discount brands of regression (1) with various market radius, outside of Budapest. 95% confidence intervals are plotted. Own figure.

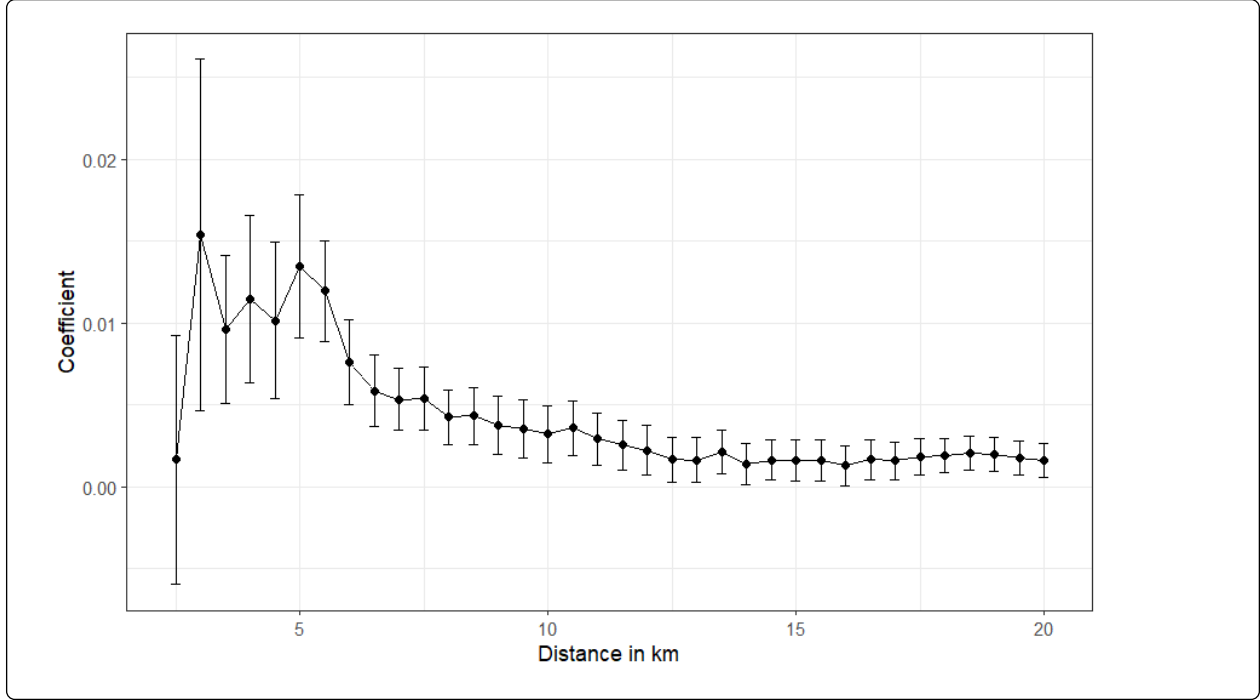


Figure 6: Coefficients of the spatial autoregressive term of small brands of regression (1) with various market radius, outside of Budapest. 95% confidence intervals are plotted. Own figure.

It can be seen that the three spatial autoregressive terms behave similarly as the market radius is increased. After initial high values, the coefficients decrease fast, converging to zero. This demonstrates that by defining a larger market, the price level of that starts to have a smaller and less significant effect on the small stations. Furthermore, the effect of large premium brands converges to zero the fastest, while the effect of the presence of small firms remains for larger distances too.

I describe the possible reason behind this phenomenon in the model part. Basically, if a neighbor group is less dense, increasing the relevant market radius rarely introduces new market participants. As a result, in a less dense network, the broader market definition sometimes might be the same as the narrower one, and defining a larger market reveals its irrelevance slowly. To test whether the long-lasting effects are attributable to a less dense network of the particular neighbor type, I estimate the spatial effects of the price levels in concentric rings instead of circles of increasing radius.

Table 3 summarizes the effects of price levels charged by stations in the surrounding rings. There are only a few stations that have all types of neighbors at various distances, therefore only two rings are constructed: one between 0 and 5 kilometers and one between 5 and 10 kilometers.

Table 3: Estimating the effects of the price level of surrounding areas on small stations, outside of Budapest, with stations having 3 or more stations in their outer ring. Concentric rings are defined with market radius 0 to 5 and 5 to 10 kilometers.

	Dependent variable: ΔP_{tn}	
	(1)	(2)
<i>price_small_0_5km</i>	0.013*** (0.002)	0.011* (0.005)
<i>price_large_d_0_5km</i>	0.016*** (0.003)	0.050* (0.025)
<i>price_large_p_0_5km</i>	0.042*** (0.10)	0.412*** (0.102)
<i>price_small_5_10km</i>		0.012 (0.007)
<i>price_large_d_5_10km</i>		0.061* (0.031)
<i>price_large_p_5_10km</i>		0.187* (0.079)
<i>ID_fixed_effect</i>	Yes	Yes
<i>Time_fixed_effect</i>	Yes	Yes
Within R ²	0.1466	0.5277
Observations ($n \times t$)	509	119
Stations (n)	15	5

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Model (1) in Table 3 is estimating the coefficients of a single ring (practically a circle) with a distance of 0 to 5 kilometers from the station. The change in the price level charged by each group in the circle positively associates with the corresponding small station. In model (2), I add a ring around this circle and estimate the effect of the price level charged in this ring, while I preserve the inner circle too. This way, I extend the market by 5 more kilometers as the ring is defined as the distance of 5 to 10 kilometers from the corresponding station. By estimating the circle and the ring in the same model, I enable different coefficients for them and prevent them from producing biased estimates in case these markets interact with each other.

It can be seen that model (2) produces larger estimates for the circle than model (1). This means

that after controlling for the outer ring, the inner circle has a larger, significant effect with the outer areas also demonstrating a positive impact in the case of large discount and large premium brands. From that, I can conclude that the closer and the more distant markets interact with each other, and disregarding larger areas will bias the effects of closer areas. Also, after controlling for the closer and the more distant markets together, it is visible that the pricing of small stations indeed has insignificant effects if they are located further away. This confirms the assumption that the small stations produce significant effects in the case of large market definitions only because their network is much less dense.

Although the magnitude of the effects is higher if both the circle and the ring are included, results should be treated with caution. The number of stations having each neighbor type in the circle and the ring is very low. Therefore, despite having significant effects, inferences can be made only on the main patterns.

These inferences are that (i) there is a positive spatial effect between the small stations and other stations in pricing, after separating other effects. If a station in the proximity of a small station changes its gasoline price, the small station changes the price in the same direction. This spatial effect (ii) has a different impact size and persistence, depending on the brands of the surrounding stations. If the neighboring station is a large premium station, the effect size is larger and more persistent. Large discount stations have similarly persistent, smaller effects, while small stations exert smaller and less persistent effects. Also, (iii) disregarding more distant stations will bias the magnitude and the persistence of these spatial effects. If stations further away are excluded, the effect size and the persistence of small stations are overestimated, while the opposite is true for large discount and large premium brands. Spatial interactions and their persistence in distance can be interpreted as the size of the relevant market and how important that market is for the small stations.

VI Conclusion

This research aimed to show how the spatial relations in the fuel market in Hungary affect small stations. There are many different sources of impact on the fuel market, which makes it difficult to identify the core reason for price changes. I separated the distortions of time trends and the change

in competition and territorial factors from the spatial effects. These spatial effects reflect that small fuel stations in the retail fuel market apply similar price changes to the changes in the price level around them. The larger the firms around them, the greater the effect and the more persistent it is as a function of distance. For small firms, the relevant large premium and large discount stations are located within a 10-kilometer radius circle with those that are closer being much more important. Also, the large premiums are more important than large discount neighbors. At the same time, the relevant, other small neighbor stations are located within a 5-kilometer radius circle around the corresponding small station.

Results are general for the Hungarian retail gasoline market excluding Budapest, where the structure of participants is different. Although the main patterns could be discovered, the exact size of the effects should be treated with reservations due to the lack of the appropriate number of observations. Also, results might alter with a different brand categorization procedure.

Overall, the main findings of this paper help regulatory and competition authorities to achieve higher consumer well-being. With spatial effects separated by brand category, a more detailed market definition helps to recognize collusive behavior and to evaluate mergers and acquisitions. Urban planners and policymakers may also find the results useful when determining optimal locations for new fuel stations.

The paper also identifies further areas for research. Instead of brand categories, investigating the interaction between separate brands might produce interesting results with accurate effect sizes. Also, decomposing this effect by exact distance rather than using price level within an area would capture a different aspect of spatial interaction, thus complementing this research. Differences between location types, such as Budapest, county capitals, and other locations, as well as the use of other fuel types, can further improve our understanding of spatial interaction.

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