

Analyzing gasoline prices in five Italian cities: Insights from social network analysis

Andrea Fronzetti Colladon^{a,*}, Giulia Verdoliva^{a,1}, Ludovica Segneri^a, Andrea G. Vitali^b

^a Department of Engineering, University of Perugia, Via G. Duranti 93, 06125 Perugia, Italy

^b Department of Enterprise Engineering, University of Rome Tor Vergata, Via del Politecnico 1, 00133 Rome, Italy

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ABSTRACT

Gasoline is an essential commodity, almost as important as food and clothing. Our research delves into the factors that could influence the consumer price of gasoline using social network analysis. Different factors influence gas stations' pricing strategies, including their location and proximity to competitors. We conducted an urban network analysis, examining the network position of nearly 700 gas stations across five Italian cities. Our findings indicate that different network positions are associated with varying gasoline prices. We discovered that centrality metrics, such as betweenness and distinctiveness, are the most informative. Our study has significant implications for managers seeking to improve their consumer pricing strategy. In addition, network analysis can support urban planning decisions, thereby fostering a sustainable environment that benefits both citizens and businesses alike.

1. Introduction

The study of gasoline prices has always been a hot topic among theoretical and applied economists for several reasons (Bergantino et al., 2020). Despite gasoline being a fairly homogeneous product, prices can vary significantly from one gas station to another. In many cases, these price differences are motivated by the degree of local competition, which is determined not only by the number of competitors but also by the geographical distribution of neighboring gas stations. Consumers tend to purchase gasoline at stations close to their residences due to the transport costs they would incur to get to other gas stations (Ardiyok, 2012; Ning & Haining, 2003). As a result, competition in the gasoline sector is highly localized, and gas stations only recognize the nearest ones as competitors (Benson et al., 1992).

The relationship between competition intensity and retail gasoline prices has been of great interest in literature. Various indicators have been used to measure the degree of competition, such as gas station density (Clemen & Gugler, 2006; Pennerstorfer, 2009) or the number of competitors (Van Meerbeeck, 2003). Some studies explored the effect of concentration measures, while others focused on the type of stations (Hastings, 2004). In recent years, there has been a growing interest in

the spatial dependence of fuel prices. Considering the concept of centrality, Firgo et al. (2015) conducted a study on the Austrian gasoline market, focusing on the city of Vienna, and found that while the prices of gas stations are more strongly correlated with the prices of central competitors, there is no evidence for a significant relationship between centrality and the level of prices. Our study extends this previous research by gathering data from multiple cities and introducing indicators from social network analysis other than degree centrality. The objective is to examine how the location of a gas station, and thus its position in the urban network, is associated with consumer gasoline prices.

Indeed, it is widely acknowledged that price competition between gas stations is heavily influenced by their location (Haucap et al., 2017; Kim, 2011), and our analysis aims to identify factors ascertained through network analysis that contribute to an enhanced comprehension of pricing strategies. Although gasoline is a homogeneous product, the brand, service facilities, and particularly the location of the gas stations are elements of product differentiation that typically exert an influence on prices (Barron et al., 2004; Clemen & Gugler, 2006; Haucap et al., 2017; Phongphanich & Shannon, 2022). Additionally, the centrality of a gas station network is easy to conceptualize and measure

* Corresponding author.

E-mail addresses: andrea.fronzeticolladon@unipg.it (A. Fronzetti Colladon), gverdoliva@bcintelligence.org (G. Verdoliva), lsegneri@bcintelligence.org (L. Segneri), vitalandgiu@gmail.com (A.G. Vitali).

¹ The first two authors contributed equally to this work and are listed in alphabetical order.

by its location within the road network (Firgo et al., 2015).

Our study focuses on five Italian cities and the network position of almost 700 gas stations. We calculated centrality metrics, including traditional ones such as degree, betweenness, and closeness centrality, as well as a more recent metric called distinctiveness centrality. We found that betweenness and distinctiveness centrality were the most informative metrics, highlighting the association between gasoline price and the urban network position of gas stations. To the best of our knowledge, this is the first study that examines a broader range of centrality metrics in urban networks and investigates the association between gas station network positions and prices. In addition, unlike previous studies focusing on road structure (e.g., Crucitti et al., 2006; Gil, 2017; Porta et al., 2009), our approach focuses on the distance between gas stations to produce a network representation of potential competitive relationships.

Our results provide important information for urban policymakers and company managers interested in improving their consumer pricing strategy. Through network analysis, managers could be more informed about pricing decisions. Our findings show that gas stations with high betweenness and distinctiveness centrality set higher gasoline prices. This discovery offers valuable insights for urban planning and resource management as well as for companies seeking to optimize their pricing strategies.

The remainder of this paper is organized as follows. Section 2 delves into the influence of retailer location on gasoline prices. Section 3 outlines the data collection methods and network construction techniques employed, along with describing centrality metrics. The results are presented in Section 4. In Section 5, we discuss the results and implications of our study.

2. How retailer location impacts gasoline price

Previous studies focused on the relationship between the intensity of competition and gasoline retail prices, measuring the degree of competition through various indicators such as station density, i.e., the number of gas stations per square kilometers (Clemenst & Gugler, 2006; Pennerstorfer, 2009; Pennerstorfer & Weiss, 2013; Van Meerbeeck, 2003), the number of competitors (Barron et al., 2004; Hosken et al., 2008), and measures of concentration such as the concentration ratio and the Herfindahl-Hirschman index (Eckert & West, 2005; Kihm et al., 2016; Sen, 2003). Numerous studies have examined the influence of competition on price. These studies not only considered the intensity of competition but also delved into the characteristics of the seller and the composition of its competitors (Balaguer & Ripollés, 2018; Chandra & Tappata, 2011; Lewis, 2008). For example, some studies argued that unbranded stations play a significant role, as their mere presence is a crucial factor in determining the dynamics of price competition (Eckert & West, 2004; Erutku & Hildebrand, 2010). Arocena et al. (2023) provided evidence of distinct competitive dynamics between branded and unbranded gas stations. They analyzed the impact of local competition on gasoline prices, highlighting how the presence of unbranded stations affects the market. Furthermore, González and Moral (2023) shed light on how premium brands can mitigate competition in their local markets, enabling competitors to charge higher prices. Similarly, Balaguer and Ripollés (2020) observed that the entry of a station belonging to the network of dominant market companies tends to result in above-average prices.

It is widely recognized that price competition among gas stations is heavily influenced by geographical location, and our analysis aims to identify the key factors that play a significant role in this competition. Alderighi and Baudino's (2015) analysis focused on the price behavior of gas stations in Italy, although limited to Cuneo, a medium-sized city in the northwestern part of Italy. This work observes how gas stations adjust their gasoline and diesel prices in response to their neighboring competitors. Kim (2011) studied how the distance between gas stations affects fuel prices. The results show that reducing the distance between

gas stations leads to higher gas prices, but only if the nearest station is within 100 m or the station with the lowest price can be reached within 200 m. Otherwise, the opposite effect is observed. Similarly, Hogg et al. (2012) conducted a study on retail gas stations in South-Eastern Queensland and discovered that the proximity of competitors influences price choices. Houde's (2012) analysis of pricing behavior in Québec City reveals that the degree of competition is not solely determined by relative distance but also by whether or not gas stations are located on a common local commuting path. This is because commuters can choose from all retailers on their usual path without incurring high costs. In contrast, people who do not commute for work typically have access primarily to gas stations near their residences.

In recent years, numerous scholars have endeavored to establish connections between urban studies and network science (Cheng et al., 2013; Derudder & Neal, 2018; Neal, 2013; Neal & Rozenblat, 2021). In general, it has been observed that studying urban networks can enhance our comprehension of cities. At the same time, urban studies have provided a valuable framework for the development and application of network analysis (B. Wang et al., 2018). Derudder and Neal (2018) identified three distinct levels of urban networks based on the type of research question being asked. These levels include micro, meso, and macro. In our study, we focus on micro-urban networks. These networks exist within cities, such as the gas station networks we will examine in our specific case. Over the years, several studies have examined the centrality of road networks in relation to dependent variables such as business density (Porta et al., 2009) and location of economic activities (Gil, 2017; Orhan, 2023).

Recent research also highlighted the importance of network centrality in pricing, with studies using Social Network Analysis techniques to represent firms as nodes connected through a network of roads and crossroads (Braid, 2013; Firgo et al., 2015, 2016). These studies showed that firms with a more central position in a spatial network have a greater impact on their competitors' prices and equilibrium prices. Challenging in this field of research is the problem of endogeneity, which some scholars solve using econometric techniques such as panel data analysis (Koh et al., 2022). For example, time and incumbent fixed effect were used to deal with non-time-varying factors. Other authors used natural or quasi-natural experiments to assess causality between industry-specific variables and gasoline prices (Pennerstorfer & Weiss, 2013). Lastly, Sen and Townley (2010) used population size as an instrumental variable to explore the relationship between market concentration and retail prices.

Firgo et al. (2015) showed that the position of a firm in the network, in relation to its competitors, determines the level of competition between them. This means that the more central a retailer is, the more intense the competition it faces – with simulation experiments suggesting that the impact of a price change by an individual gas station on equilibrium prices increases with its degree of centrality.

To address the limitations of previous research, which primarily focuses on degree as the main measure of centrality, our study seeks to introduce new indicators derived from social network analysis. It is important to note that the urban networks we construct in this study are not road networks but networks that represent relationships of potential competition between service stations, given their geographical distance. From this perspective, the nodes within these networks represent specific points (gas stations) in the urban space, while their connections represent travel distances. This approach allows us to add to the traditional understanding of urban networks by mapping relationships among competitors. The objective is to enhance our understanding of how the location and consequent urban network centrality of gas stations influence consumer prices, exploring whether social network analysis can provide valuable information to assist retailers in their decision-making processes. Specifically, we use more sophisticated metrics than degree centrality and consider other node characteristics, such as their betweenness and distinctiveness centrality, while analyzing the real networks of five Italian cities.

3. Methodology

3.1. Data collection and network construction

Using an existing database (Vitali, 2018), we considered five Italian cities for our analysis: Brescia, Florence, Milan, Naples, and Turin. This sample is interesting due to its heterogeneity, encompassing northern, central, and southern Italy locations. Furthermore, these cities vary in urban area, population, and population density,² as shown in Table 1. The database comprises data from February 2018 concerning 792 gas stations across these cities. It offers comprehensive information, including station ID, brand, and geographical coordinates. For 682 stations, average retail prices of self-service gasoline for February 2018 were also accessible. This dataset is derived from organized open data from the Ministry of Enterprise and Made in Italy. Similar studies into the relationship between gas station locations and prices relied on analogous databases that align station characteristics with gas price data, typically sourced from similar platforms (Firgo et al., 2015; Koh et al., 2022).

A network was created for each city, where nodes represent gas stations and arcs their proximity relationship.³ These arcs are weighted according to the inverse of the distance in kilometers traveled by a driver to move from one gas station to the other. Since the networks are not oriented, the weights of the arcs were determined as the inverse of the average of two weights, considering, in one case, the distance traveled by a motorist from gas station i to gas station j and, in the other case, the distance from j to i . Traveling distances were calculated using Open Street Map,⁴ considering the geographical position of each facility. We include the network graphs for all 5 Italian cities analyzed in Appendix A for illustrative purposes only. These visualizations were created using the Gephi software (Fig. A1). Furthermore, network descriptives, i.e., size, density, and Average Distance Among Reachable Pairs (ADARP), are provided in Table A1.

Each city is associated with a network of gasoline stations operating in the territory in the first quarter of 2018. To represent direct connections of each gas station (node), we chose to consider only those retailers located within a travel distance of 10 km. This choice partially differs from previous studies, including the works of Barron et al. (2004) and Remer (2016), who used the number of stations within 2.4 km as a proxy for spatial competition. Other authors, such as Clemenz and Gugler (2006), used the number of stations per square kilometer, while Haucap et al. (2017) and Bello Pintado and Contín-Pilart (2010) used the number of competitors within 2 km. However, as discussed by Hierro-Recio et al. (2020), previous research has yielded conflicting results, indicating a lack of consensus regarding the distance that

signifies spatial competition between two gas stations. Given this inconsistency in the literature, we have tested our models on additional network cuts, specifically 5 and 2.5 km, without obtaining better results. These additional findings are discussed in Section 5.

3.2. Regression model and study variables

This study examines approximately 700 gas stations located in different cities. As a result, we chose multilevel regression models to capture reductions in the residual variance of this nested structure (Nezlek, 2008).

The dependent variable used in this study is the gasoline price per liter in the self-service mode set by each surveyed gas station. The prices and master data of each gas station were obtained from the historical archive provided by the Italian Ministry of Business and Made in Italy.⁵

Concerning the independent variables, we have considered well-known centrality measures commonly used to evaluate nodes' influence and positional power in networks. Specifically, in this case, centrality metrics are used to evaluate the network position of a gas station. In this study, we refer to some of the most commonly used and widely accepted measures, including degree centrality, betweenness centrality, and closeness centrality (Freeman, 1979), and a newer metric, namely distinctiveness centrality (Fronzetti Colladon & Naldi, 2020). Considering all these metrics allows us to represent the concept of network centrality better and consider its most relevant aspects. The degree centrality of a node is defined as the number of edges connected to that node. In our case, it measures how many close competitors a gas station has.

Betweenness centrality quantifies the frequency with which a node is positioned on the shortest path between all pairs of nodes in the network, thus serving as a bridge and acquiring brokerage power (Borgatti et al., 2013). It is defined as:

$$B(i) = \sum_{j < k} \frac{g_{jk}(i)}{g_{jk}}$$

where g_{jk} represents the number of shortest network paths connecting a generic pair of nodes j and k , and $g_{jk}(i)$ represents the number of those paths that involve node i . The metric can be standardized to allow a comparison between networks of different sizes by dividing its value by $(n-1)(n-2)/2$, where n is the number of nodes in the graph. Betweenness centrality was used in urban network studies to capture the extent to which a place is a pass-through point in a trip with a different origin and final destination (Porta et al., 2009; F. Wang et al., 2014).

Closeness centrality assesses how much a node is embedded into a social network. Gas stations with higher closeness centrality are connected to their peers by shorter network paths. In simpler terms, closeness is calculated as the reciprocal of the sum of the shortest path lengths between the node and all other nodes in the graph (Freeman, 1979; Wasserman & Faust, 1994):

$$C(i) = \frac{n-1}{\sum_{j=1}^n d_{ij}}$$

where d_{ij} denotes the length of the shortest path that connects nodes i and j . Closeness has been used in urban network studies to represent the accessibility of a place (Porta et al., 2009).

Finally, the distinctiveness centrality logic gives more importance to gas stations strongly linked to other gas stations with fewer connections (Fronzetti Colladon & Naldi, 2020). These are stations that often lie in between the network core and periphery, or are peripheral. Distinctiveness is a metric that places greater value on direct connections to

Table 1
Descriptive data for the analyzed cities.

City	Area (km ²)	Population (p)	Density (p/km ²)	Mean price (€)	St. dev. (€)
Brescia	90.3	194,255	2151	1.55986	0.03089
Florence	102.4	373,991	3652	1.55973	0.08703
Milan	181.8	1,380,995	7596	1.58249	0.08254
Naples	117.3	957,571	8163	1.58894	0.10437
Turin	130.2	868,878	6673	1.59145	0.08075

² We extracted the population data from the website of the National Institute of Statistics (ISTAT) for 2018 (<https://demo.istat.it/>). Instead, the valuation of the urban area was derived from the reports published on the official websites of each respective municipality.

³ Although we only have self-service price data for 682 gas stations, all 792 gas stations were considered to construct the networks.

⁴ <https://www.openstreetmap.org/#map=5/42.088/12.564>.

⁵ <https://www.mimit.gov.it/index.php/it/open-data/elenco-dataset/carburanti-archivio-prezzi>.

loosely connected nodes rather than redundant connections to nodes already connected to many others. The concept behind this is that a node is deemed more significant if it serves to connect nodes that would otherwise be isolated or too peripheral. Therefore, a node that can bridge the gap between these loosely connected nodes and the rest of the network is considered more valuable. Distinctiveness can be defined as:

$$D(i) = \sum_{j=1, j \neq i}^n \log_{10} \frac{n-1}{h_j} I_{(w_{ij}>0)}$$

where n is the total number of nodes, and W is the set of weights associated with each edge; h_j is the degree of node j , which is a neighbor of node i . $I_{(w_{ij}>0)}$ is a function that is equal to zero if nodes i and j are not connected (i.e., if $w_{ij} = 0$), and is equal to 1 otherwise. The metric can be standardized considering its upper bound $(n-1)\log_{10}(n-1)$ to allow a comparison between networks of different sizes.

We used the SBS BI app⁶ to compute centrality metrics (Fronzetti Colladon & Grippa, 2020).

3.2.1. Control variables

Lastly, we considered several control variables. Population represents each city's average number of inhabitants, calculated in December 2018. Many previous studies used population as a proxy for fuel demand. For example, Clemenz and Gugler (2006), Firgo et al. (2015), Kihm et al. (2016), and Pennerstorfer (2009) all found a positive relationship between population density and fuel prices. In contrast, Pennerstorfer and Weiss (2013) found a negative relationship between gasoline prices and population density, indicating that gas stations located in remote areas with low population density tend to be significantly more expensive.

Furthermore, numerous studies have demonstrated a correlation between weather conditions, such as temperature and precipitation, and car usage and fuel consumption (Karlsson et al., 2012; Tsiakmakis et al., 2016). This means that the fuel consumed and the frequency of car usage can fluctuate depending on the weather. In our particular case, we considered each city's average temperature and rainfall in the time period of our analysis.

Being located on a highway or main road can also influence a gas station's price, with studies demonstrating the presence of a natural monopoly/duopoly scenario for highway gas stations (Haucap et al., 2017; Hierro-Recio et al., 2020). Accordingly, Location-MainRoad is a dummy variable equal to 1 if the station is located on a main road and 0 when located on other types of roads. Location-Highway is also a dummy variable that takes the value 1 when the station is on a high-capacity road, like a highway, and 0 when located on other types of road.

The presence or absence of a specific brand is another important factor in determining gasoline prices. This is because companies often enforce certain policies or price ranges, which can influence the pricing of gasoline at their affiliated stations (Clemenz & Gugler, 2006; LeSage et al., 2017, 2019; Van Meerbeeck, 2003). Research has demonstrated that unbranded stations can increase price competition by offering significantly lower prices. However, a high concentration of unbranded stations in a local market can also reduce price competition in the higher-quality segment of the market (Pennerstorfer, 2009). Brand is a set of dummy variables we use to identify gas station brands.

4. Results

In order to look for an association between gas station network position and gasoline price, we performed a Spearman's correlation

analysis, as presented in Table 2. The table shows the different correlation coefficients for each city (i.e., network) in our sample. We correlated gasoline prices with degree, distinctiveness, betweenness, and closeness centrality.

The correlations are significant in all cases, excluding betweenness and distinctiveness centrality for Brescia. On average, distinctiveness exhibits the highest correlation coefficients. The highest correlation between price and centrality is obtained by distinctiveness for Florence ($\rho = 0.423, p < 0.001$). These preliminary results suggest an association between gasoline prices and the urban network position of gas stations.

We extended our analysis through the multilevel regression models with fixed effects presented in Table 3. We used a multilevel linear regression as gas stations (level 1) are located in different cities (level 2). According to Nezlek (2008), this choice holds even when the intraclass correlation coefficient (ICC), i.e., the proportion of variance at level 2, is small. Indeed, we find this for our sample, where only 1.4 % of the variance is attributable to the differences in the groups (cities). We start with the empty Model 1 to show how variance is distributed across levels and find a 98.6 % residual variance. Subsequently, we include our control variables in Model 2 and obtain a level 1 variance reduction of 9.9 %. Not surprisingly, being located on a highway positively impacts prices, which are generally higher than those of gas stations located on urban roads. The nearly 100 % reduction of variance at level 2, which appears in all models, is negligible due to the very small amount of variance at this level.

In Models 3–6, we test the effect of centrality metrics. We test these measures in separate models to avoid collinearity issues because they are highly correlated. We find that the highest residual variance reduction (18.60 %) is obtained by including distinctiveness centrality in Model 4. The second highest level 1 variance reduction is when we use betweenness centrality in Model 5 (17.67 %). Once again, these results give evidence to the informative power of our urban network analysis, and in particular of the distinctiveness and betweenness centrality indicators.⁷

5. Discussion and conclusion

Compared to conventional spatial models, where firms and consumers are evenly distributed, and the exact location of a firm is insignificant (Salop, 1979), our approach provides valuable insights into additional factors that may impact pricing, thereby aiding managers in making informed managerial decisions. We argue that location choice is a crucial decision that firms must make, also affecting urban development and services offered to citizens. Our analysis demonstrates the importance of going beyond the consideration of more traditional variables (such as population density and location on a highway) in determining the selling price of gasoline. To capture the complexity of the gasoline market, we use social network analysis, which allows the addition of potentially useful information that could be integrated with that of more traditional spatial models. Our study demonstrates that centrality metrics should be considered in spatial differentiation studies to better understand gas station pricing strategies and obtain valuable insights that can aid in developing new decision support systems.

We find that betweenness and distinctiveness centrality hold greater importance than degree and closeness in the models. This suggests that gas stations positioned between other stations, whether between central and peripheral stations or at a midpoint between multiple stations, set, on average, higher prices. A high betweenness score indicates that the

⁷ We also tried principal component factor analysis to create a variable that could consider all our centrality metrics together, and another variable only considering distinctiveness and betweenness (our most significant predictors). When included in a model, these new variables are significant, but the percentage reduction in level 1 variance is no greater than that obtained using distinctiveness centrality alone.

⁶ <https://bi.semanticbrandscore.com>.

Table 2

Correlations of network centrality with gasoline price by city.

Variable	Brescia	Florence	Milan	Naples	Turin	Row average
Degree	0.339**	0.292**	0.369***	0.182*	0.307***	0.298
Distinctiveness	0.197	0.423***	0.390***	0.250**	0.251**	0.302
Betweenness	0.164	0.410***	0.374***	0.270***	0.263***	0.296
Closeness	0.339**	0.292**	0.368***	0.180*	0.307***	0.297

*** $p < 0.001$.** $p < 0.01$.* $p < 0.05$.**Table 3**

Multilevel regression models.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Population		1.79E−8*	4.95E−8***	−3.19E−8***	2.06E−8*	5.41E−8***
Temperature		0.00204	0.01639***	−0.02638***	−0.00562	0.01760***
Avg Rainfall		0.00018**	0.00022***	0.00013*	0.00019	0.00022***
Location – Highway		0.10861***	0.14185***	0.14447***	0.12300***	0.13746***
Location – MainRoad		−0.00214	0.02001	0.01042	0.01423	0.02186
Degree			0.14429***			
Distinctiveness				2.38770***		
Betweenness					14.82111***	
Closeness						0.25299***
Constant	1.57833***	1.36606***	0.97191***	1.81089***	1.44952***	0.85058***
Brand	No	Yes	Yes	Yes	Yes	Yes
Variance L2	0.0001041	4.88E−23	1.58E−23	1.72E−24	5.87E−23	2.59E−22
Variance L1	0.0072544	0.006539	0.0060837	0.005905	0.0059729	0.0060332
Variance Reduction L2		100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
Variance Reduction L1		9.86 %	16.14 %	18.60 %	17.67 %	16.83 %
Groups	5	5	5	5	5	5
N	682	682	682	682	682	682

*** $p < 0.001$.** $p < 0.01$.* $p < 0.05$.

station is situated at a crossing point or serves as a link between other distributors farther apart within the network. Having a high degree, on the other hand, indicates that the gas station is located in proximity to many other competitors, which could be a positive sign as it suggests a highly populated or particularly interesting area with high demand (Clemenzen & Gugler, 2006; Firgo et al., 2015; Kihm et al., 2016; Pennerstorfer, 2009). However, numerous competitors in the area could reduce the chances for a single distributor to establish the price (Bergeaud & Raimbault, 2020; Eckert & West, 2005; Sen, 2003). The following reasoning could be a valid justification for the results obtained in the models, particularly the fact that betweenness is more informative than degree. Similarly, the measure of distinctiveness, which may indicate numerous ties to more isolated gas stations, appears to be the most informative. A potential theoretical explanation for our findings is that fuel prices tend to be higher in areas with limited supply. The lack of demand in such areas often results in a natural monopoly/duopoly scenario, making it challenging to introduce competition into the market (Hierro-Recio et al., 2020). This situation may facilitate collusion, leading to price increases. On the other hand, gas stations located near many competitors (high degree) are characterized by not only an increased demand (Clemenzen & Gugler, 2006) but also a greater presence of competitors (Sen, 2003), which leads to a decrease in the likelihood of a single distributor setting the price unilaterally.

In partial contrast to Firgo et al. (2015), our research, conducted across multiple cities and incorporating new centrality metrics, reveals a significant relationship between centrality and price levels. This association likely arises not only from the proximity of competitors but also from various strategic and network positioning factors, as described by the newly introduced centrality metrics.

Social network analysis provides a diverse array of centrality metrics, facilitating the evaluation of various network structures. For example, networks may encompass nodes symbolizing partner countries

within a project, enabling the assessment of collaborative efforts among them (Nita et al., 2016) or bank accounts, offering insights into financial transactions susceptible to money laundering (Fronzetti Colladon & Remondi, 2017). In our specific case, we explore the association between the network positioning of gas stations and gasoline prices. In terms of work related to urban networks (Neal, 2013; Neal & Rozenblat, 2021), it is worth noting that frequently utilized metrics are degree centrality, betweenness, and closeness (Gil, 2017; Porta et al., 2009), whereas the utilization of distinctiveness appears to be relatively new. To the best of our knowledge, this is the first work to consider this additional metric to study the prices of gas stations in association with their position in the urban network.

Our results can inform urban policymakers and could support them while designing strategies for the siting of gas stations. This may be especially important in areas not yet served by gas stations or where prices are high, as informed decisions could foster competition – possibly translating into tangible benefits for citizens, such as reduced gasoline costs. It is of fundamental importance that urban planners adopt an approach that is as informed as possible to place economic activities, not only for environmental sustainability (Niță et al., 2023) but also for effective resource management. Thus effectively addressing the crucial role that gas station placement plays in meeting the future needs of communities without neglecting the strategic value that specific locations might have for businesses. It is worth noting that the decision to establish a retail outlet, like a gas station, carries significant weight, as the process of relocating such establishments is both arduous and financially burdensome (Baviera-Puig et al., 2016; Vithanage et al., 2023). Therefore, this study offers valuable insights into the factors that urban policymakers should consider.

As an additional robustness test, we conducted a sensitivity analysis to explore additional cutoff distances while building network links. For the reasons discussed in Section 3, we explored the impact of using 5 and

2.5 km as alternative thresholds. We found no improvement in results when considering the 2.5 km threshold. However, when we used the 5-km limit, we observed improved correlations for the city of Brescia. Interestingly, the correlations for the other cities worsened when this limit was applied. This could be attributed to certain characteristics of Brescia, such as its smaller population, lower density, and smaller area compared to the other cities in our sample. In an attempt to address this discrepancy, we tested additional multilevel models using a mixed approach. We employed a 5 km threshold for Brescia while keeping the 10 km threshold for the other cities. These models did not yield improved results. Findings consistently indicated that the 10-km cutoff was the most significant in reducing variance.

One limitation of our study may arise from the decision to create a non-oriented network. We did not define a source node and a destination node to avoid restricting the driver's route. However, this choice would carry the risk of disconnecting two neighboring nodes simply because the route from A to B is long, without considering that the route from B to A could be shorter. Nevertheless, we find that this issue does not arise in our sample as the differences in distances between the two directions are generally minimal and almost negligible.

Given the heterogeneity of gasoline prices among different cities and retailers in Italy, future research could test the empirical framework we have proposed considering a larger number of cities or other countries to see whether our results are confirmed. In addition, it would be interesting to consider other network centrality metrics or incorporate the average income of people living in the gas station area as a control variable in future research.

Furthermore, conducting future longitudinal studies could prove valuable in examining the influence of network evolution on prices over time. Indeed, one limitation of our study is its cross-sectional nature, which does not allow us to establish cause-and-effect relationships or address possible endogeneity issues – such as the fact that prices and the number of competitors could be simultaneously determined (Balaguer & Ripollés, 2020). However, it is important to note that the network is not expected to undergo frequent changes. Therefore, longitudinal studies should encompass time horizons spanning several years, considering events such as the opening and closing of gas stations. Here, our main

goal is to provide insights into the potential significance of a new approach and social network metrics that could prove useful in this field.

In conclusion, our findings have important implications for policy-makers and company managers interested in improving their consumer pricing strategy. We show how network analysis could be valuable in informing pricing decisions. Furthermore, the implications of this research extend to scholars studying urban networks. We propose the application of new social network analysis metrics, such as distinctiveness, in the context of the retail gasoline market. This can provide valuable insights and contribute to advancements in urban planning and understanding urban networks.

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CRediT authorship contribution statement

Andrea Fronzetti Colladon: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization. **Giulia Verdoliva:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Ludovica Segneri:** Writing – original draft, Data curation. **Andrea G. Vitali:** Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available upon reasonable request to the second author.

Appendix A

Fig. A1 shows the network graphs of the gas stations located in the five cities considered in our sample.

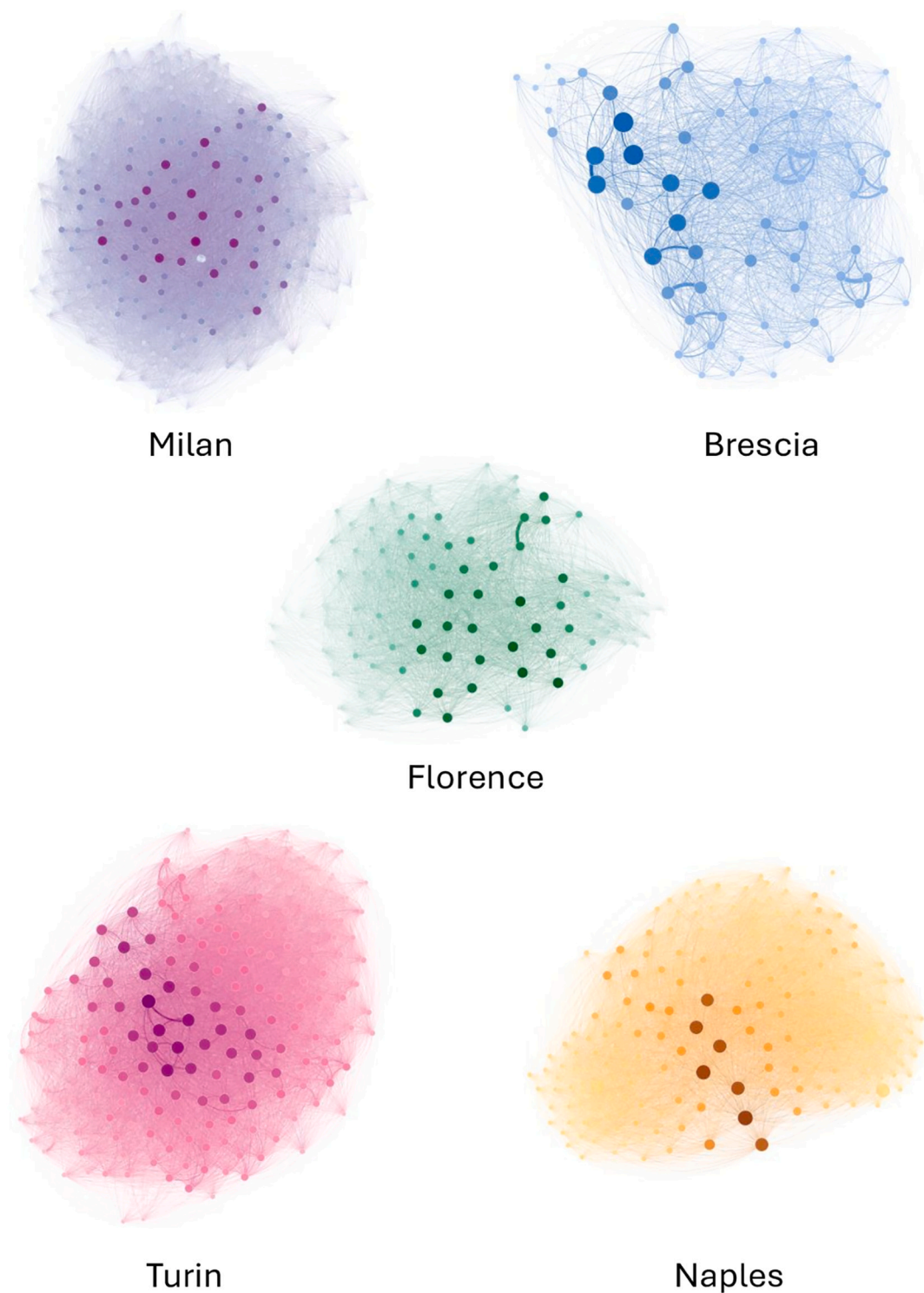


Fig. A1. Network graphs.

Table A1 provides an overview of descriptive variables for each network graph, considering size, density, and Average Distance Between Reachable Pairs (ADARP). Size refers to the number of nodes, hence gas stations, analyzed within each city, ranging from 70 in Brescia to 237 in Milan. Density, representing the ratio between existing and possible links, exhibits the highest value in Brescia (0.89) and the lowest in Naples (0.58). Additionally, the average distance between reachable pairs (ADARP) is presented, reflecting the average distances between all nodes that can be reached, directly or indirectly. Across all cases, this value remains relatively low, consistently below 1.5.⁸

⁸ This outcome also depends on the arc cutoff distance for representing the networks, as elaborated in Section 3.1.

Table A1
Network descriptives.

City	Size	Density	ADARP
Brescia	70	0.8952	1.1048
Florence	99	0.8029	1.1987
Milan	237	0.6750	1.3261
Naples	195	0.5831	1.4237
Turin	191	0.8106	1.1894

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