Spatial differentiation in food service pricing: an explorative study with web-scraped data

RESEARCH ARTICLE

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Abstract

Food delivery applications have grown rapidly in recent years, fueled by increasing consumer demand for convenience and prepared foods. Previous studies on what factors encourage consumers to use delivery platforms rely largely on survey data, likely due to the lack of availability of restaurant or industry level data. Utilizing web-scraping techniques to collect restaurant level data from one of the biggest delivery applications in South Korea, Yogiyo, this study conducts an analysis on spatial market structure of the restaurant business. Through restaurant level data, market expansion, changes in the number of restaurants to order from, and changes in prices across regions with delivery application are considered. Analysis suggests that the average number of orderable restaurants increased from a nearby 2.3 restaurants to distant 13.5 restaurants with customers willingly paying for delivery fees according to distance via the delivery application. As the restaurant delivery market becomes spatially more competitive with an additional 13.5 restaurants, it is found that aggregate prices totaled with food prices and delivery fees from two restaurants in different locations converge to serve the customers between the two restaurants. In addition, the increased degree of competition due to increased number of restaurants leads the aggregate prices to decrease by between 5.13 and 7.56\%, depending on regional characteristics.

Keywords: food delivery, food economics, network analysis, restaurant business, spatial competition, web scraping

JEL codes: D22, D43, L11, Q13

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1. Introduction

The global food delivery market size reached US$ 106.1 billion in 2021 (IMARC, 2021a) and it is expected to grow at a CAGR (Compounded Annual Growth Rate) of 11.44% over the period 2022 through 2027, reaching US$ 223.7 billion (IMARC, 2021b). The food service industry has undergone substantial changes recently with the rapid growth in innovative food delivery applications on smartphones. An increasing number of consumers and restaurant owners have adopted use of delivery applications/platforms for convenience and profit improvement, respectively.

Almost half the population of South Korea is using delivery applications to order food from restaurants for delivery (MobileIndex, 2022a). South Korea has a food delivery marketplace which is valued at almost 10 times what it was just four years ago (Statistics Korea, 2022a). According to the Statistics Korea (2022a), the size of the food service delivery market, where the top three delivery platforms account for more than 90%, is estimated to be US$21.4 billion in 2021. Recently social distancing due to the COVID-19 pandemic limits mobility of people to dine out, inducing rapid delivery platform growth over the past two years under the pandemic (Statistics Korea, 2022b).

The rapid growth of delivery applications has brought many changes in the restaurant industry. For example, consumers have more options for ordering diverse foods as restaurants may expand their geographical service areas to more distant customers. As markets develop monopolistic delivery platforms could potentially seek to charge higher delivery fees to consumers and/or higher commissions to restaurants which could lead to higher menu prices if such costs are passed along (Global Competition Review, 2022; Korea JoongAng Daily, 2021a). In addition, more competition among restaurants, which possibly benefits consumers, may place pressure on small restaurants’ thin profit margins. Extended delivery to distant destinations leads to longer travel time of food, bringing food safety concerns into the topic of food delivery (CDC, 2022).

To the authors’ best knowledge, there has not been much economic research on changes in the market structure of the restaurant markets/food delivery service industries induced by the rise of food delivery applications. Because online food delivery is an emerging phenomenon, most of the existing studies analyzed consumer behavior or attitude based on psychological, marketing, and communication standpoints, but not market structure based on economic knowledge. Previous studies have examined consumers’ intention of adopting online food delivery services (Gunden et al., 2020; Hwang et al., 2019; Hwang and Kim, 2021; Okumus et al., 2018; Ray et al., 2019; Wang and Scrimgeour, 2021). Another group of existing studies are about consumers’ motivation to use delivery applications (Jiang et al., 2023; Novita and Husna, 2020; Ray et al., 2019; Tandon et al., 2021) and to return to the applications (Alalwan, 2020). A few published studies have estimated consumers’ willingness to pay (WTP) for the delivery application service (Hwang et al., 2020), examined rate of satisfaction (Alalwan, 2020; Cho et al., 2019; Kumar and Shah, 2021; Meena and Kumar, 2022; Shah et al., 2023; Zhao and Baeao, 2020). However, existing literature largely lacks a market structure approach, indicating the findings of this study may contribute to providing a new insight for the online food delivery industry.

One reason for the lack of empirical research on restaurant businesses with delivery platforms may be the lack of availability of restaurant level data. Historically, data have been collected mainly through surveys of consumers/customers. But recently a new data collection technique in online space, called web scraping, to collect data from online retailers or social media platforms (Jung, 2021; Cavallo, 2020; Cavallo and Rigobon, 2016) has become popularized. Three recent studies constitute exceptions to the use of survey data to study restaurants, namely Cheng et al., (2021), Correa et al. (2019), and Williams et al., 2020, and they used web-scraping or mining for data collection for restaurant businesses. Correa et al. (2019) in their analysis of the relationship between actual delivery time and restaurants’ performance use web-scraping and other online data sources such as Facebook and Google Maps API. Correa et al. (2019) scraped key performance indicators such as consumer review comments of fast-food providers from a Colombian online...
food delivery platform. They also generated information on traffic conditions by utilizing the location of the restaurants obtained from Facebook and travel time from Google Maps API. Traffic conditions were found to have exerted no practical effects on transaction volume and delivery time fulfillment, even though early deliveries showed a mild association with the number of comments provided by customers after receiving their orders at home (Correa et al., 2019). In addition, Cheng et al. (2021) and Williams et al. (2020) studied consumer attitudes toward restaurants or online food delivery by scraping comments from App store reviews, online communities, blogs or media. Recent analyses on food products have used web-scraping to facilitate data collection on product data, including reviews (Etumnu et al., 2020).

However, few studies have used web-scraping to collect menu prices, delivery fees, restaurant locations from delivery applications. This study utilizes web scraping for collecting data in restaurant businesses, including item names, prices, delivery fees, possible delivery regions, and exact restaurant locations with addresses that are available from online delivery applications in South Korea. Compared to consumers survey data for expenditures on food service or food away from home, web scraping has several benefits. First, web-scraping collects information from all the restaurants registered in the delivery application with detailed attributes of restaurants and dishes, such as exact locations of restaurants with address, menu prices, all deliverable destinations and differentiated delivery fees, etc. On the other hand, consumer surveys provide such information only on purchased dishes from chosen restaurants, which limits generalization of analyses and insights. Second, web scraping allows precise data collection from literal descriptions from the application while consumers surveys rely on respondents’ recollecting activities and/or experiences. That being said, web-scraped data provides high quality datasets with reduced possibility of missing or mis-specified information.

To the best of authors’ knowledge, this study is the first to research market structure in the restaurant markets with food delivery services using data amassed from delivery applications, thus exploiting web scraping and network analysis to examine relations across regions. Conducting network analysis with scraped data including geographical information of restaurants allows the authors to investigate spatial market structure of restaurant businesses, allowing insights into how restaurants facing different market condition adjust their pricing strategies. The primary objectives of this study are (1) applying methods of data collection (web scraping) and analyzing technique (network analysis) for investigating market structure of the restaurant business and (2) providing empirical research about online delivery platform and market structure of the restaurant business utilizing the big data scraped.

2. Conceptual background

2.1 Changes in delivery industry with the appearance of delivery applications

Seoul, the capital city of South Korea and home to 20% of the total country’s population, is composed of 25 administrative districts called “Gu”, with 467 legal-status subdivisions called “Dong” (Figure 1). The average area of 25 districts is 24 km², ranging from 10 to 47 km² (Seoul Open Data, 2021). Boldly estimating, 5 km (3–7 km) may be a maximum distance of delivery inside districts from edge to edge which takes up to 15–20 minutes delivery time. Furthermore, the average area of 467 subdivisions is 1.43 km², ranging from 0.23 to 12.68 km² (Seoul Open Data, 2021). The maximum distance from edge to edge is 1.2 km (0.5–3.6 km), taking up to 3–5 minutes delivery time.

Restaurants on delivery applications generally provide information about delivery regions at the subdivision level, thus it is assumed by authors that delivery markets are generally defined as a single subdivision but

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1 Web-scraping has been extensively used for other research topics such as retail prices (Cavallo, 2020), inflation (Cavallo and Rigobon, 2016), food price now/forecasting (Macias et al., 2022), etc., but not for geographical market structure in restaurant businesses from delivery applications.
also sometimes including neighboring subdivisions depending on precise restaurant locations. In South Korea, delivery costs used to be absorbed by restaurant owners and customers did not pay ‘delivery fees’ before delivery applications came into play in the restaurant industry in early 2010 (Kim, 2009). Restaurant owners hired part-time delivery drivers or riders, most of whom used to earn almost minimum wage. Given the limited geographical scope in which delivery was available, there was less competition among restaurants in localized markets due both to the delivery-related costs that restaurant owners were responsible for and degrading food quality with longer delivery times, limiting arbitrage.

Now delivery fees, which are passed on to customers, have been introduced through delivery applications. The non-trivial delivery fees have incentivized independent professional delivery drivers or riders, who are encouraged to deliver to farther locations than the restaurants did previously. These non-trivial delivery fees have spurred more restaurant options for consumers to order from through the expanded delivery market boundaries.²

Restaurant’s menu prices are not determined solely by the direct costs of food product inputs and preparation costs, such as ingredients, electricity, and gas. Rather, menu prices are also influenced by non-food product economic factors, such as residential versus commercial/business regions impacting rent costs and/or average incomes of customers within a given geography. Thus, it is possible that ordering a food item from a restaurant located in another subdivision is cheaper than ordering a comparable food item from a restaurant located in a subdivision where customers are staying.

Delivery fees incurred in South Korean delivery applications are based on uniform-delivered pricing with multiple zones addressing subdivisions in this study (Baedal Minjok, 2022). All customers within a subdivision are charged the same delivery fee irrespective of their specific locations within that subdivision. However,

² There is a minimum total amount due at checkout to use delivery service in South Korea and it varies from restaurant to restaurant. That being said, in this study, only orders qualified for delivery service by meeting the minimum total amount due are considered, as explained in the Methods section.
delivery fees vary by subdivision depending on distance from restaurants. Figure 2 illustrates conceptual description of changes in market boundaries. Figure 2 describes the market structure and its changes based on uniform-delivered pricing. Before the delivery platform came into play, restaurant 1 with higher price \( P_1 \) circumscribes its market up to the distance \( D^{10} \) serving a customer while restaurant 2 with lower price \( P_2 \) covers up \( D^{20} \) to not serving the same customer in the middle. Two restaurants serve separate markets on their own depending on their transportation cost. With the advent of delivery application service, however, market boundaries for both restaurants expand to more distant regions, competing for customers along the whole lines in Figure 2. Delivery fees in the regions where restaurants are located are \( t_1 \) and \( t_2 \), uniform inside their own zones. Higher delivery fees will be charged to farther regions. For example, \( t_2 \) will be charged to customers in the region of restaurant 1 if they order food from restaurant 2, and vice versa. In Figure 2, therefore, two restaurants compete for the customer in the middle who faces a higher aggregate price from its local restaurant 1 than the one from distant restaurant 2. Thus, it may be possible for either of the restaurants to adjust prices to serve customers and “win the competition” for the customer. This potential for competition in new ways not previously available prior to the development of today’s food delivery marketplace motivates this timely study.

2.2 Delivery platform industry in South Korea

Delivery platforms in South Korea have experienced substantial growth over the past 10 years. The proportion of food deliveries requested through delivery applications compared to direct phone calls to restaurants has been increasing from 22% in 2019 to 45% in 2021 (Korea Rural Economic Institute, 2019, 2021). According to Statistics Korea (2022), the industry has increased from KRW 2.4 trillion (US$ 1.9 billion) in 2017 to KRW 17.3 trillion (US$ 14.1 billion) in 2020. There are around 10 delivery applications in the South Korea delivery industry: Baemin, Yogiyo, Coupang Eats, WMPO, Baedaltong, KakaoTalk Delivery, Naver Delivery, etc. Of the applications, the top three, Baemin (59.7%), Yogiyo (23.8%) and Coupang Eats (15.2%), account for 98.7% of the total delivery market (MobileIndex, 2022a).

Despite the effort of KFTC to keep the market competitive, there are still complaints about high delivery fees from customers and high commissions from restaurants. On average, the delivery fee is 3394 KRW (2.71 US$ with currency rate as of 7 March 2022) (Ministry of SMEs and Startups, 2021) and commission charged on restaurants is 12–15% of the total restaurant bill (Korea JoongAng Daily, 2021b).

Anecdotally speaking, restaurants may have two countervailing effects with delivery applications: (1) burden of commission and (2) market expansion. Consequences of the expansion of delivery applications on consumers and restaurants themselves have not been examined so far due mostly to unavailability of restaurant level
data. In order to fill this gap, this study exploits web-scraping and network analysis to examine impacts of delivery applications on market structure of restaurant businesses as a first attempt.

3. Methodology

The objectives of the study are (1) to investigate the spatial market structure patterns of restaurant businesses and related food delivery and (2) examine the impact of the degrees of competition on food prices based on data collected with web-scraping. In investigating degrees of competition in spatial markets, major factors that differentiate products and services should be related to geographical attributes such as distance, travel times and/or transportation cost. Attributes other than geographical features should be similar or close to homogeneous across products. With that being said, this study examines the spatial price structure of the Jajangmyeon business.

3.1 Jajangmyeon market in South Korea

In this study, an item called Jajangmyeon\(^3\) has been chosen as the product of study; it is a noodle dish topped with black bean sauce, diced pork, and vegetables and it was selected because it is relatively homogeneous in ingredients, taste, quality, and portion sizes across restaurants. However, prices vary across restaurants based not only on ingredients and restaurant operating costs, but also on regional characteristics such as income levels, zoning classification (residential, commercial and industrial zones), and rents in different subdivisions/districts. In addition, delivery fees charged to consumers increase as the distance between restaurant and subdivision where consumers place an order from increases.

There were 4805 restaurants (which is about 5.5% of total restaurants) selling Jajangmyeon in Seoul in 2019 (Statistics Korea, 2021a) servicing a total population of 9.6 million in the same year (Statistics Korea, 2021b). Table 1 summarizes the status of the Jajangmyeon market in Seoul and Figure 3 illustrates the number of Jajangmyeon restaurants and potential market size in the number of populations per restaurant across individual districts (Statistics Korea, 2021a).

Most people in Korea enjoy Jajangmyeon and it is known for “We deliver even to a boat in the middle of the ocean”, which means it is delivered universally not only to closed indoor places like billiards, but also to wide open outdoor places such as parks, riversides, and the top of the mountains. Providing that 4595 out of 4805 restaurants serving Jajangmyeon are owned by individuals (Statistics Korea, 2021a), each of them is presumably practices their own pricing strategies. In addition, Statistics Korea has Jajangmyeon Price Index as another method for estimating Consumer Price Index (CPI) over time (Statistics Korea, 2022a). As Figure 4 shows, the Jajangmyeon Price Index moves along with CPI just as Housing Rent does. Therefore, it is suggested that Jajangmyeon can be a relevant food item for this research because it is a relatively homogeneous product and its price reflects the economic situation.

<table>
<thead>
<tr>
<th>The number of Jajangmyeon restaurants at district level</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population per Jajangmyeon restaurants at district level</td>
<td>2041</td>
<td>1320.28</td>
</tr>
</tbody>
</table>

\(^3\) Introduction of Jajangmyeon and recipes are available at Korean Bapsang (2020).
Figure 3. Status of Jajangmyeon restaurants in Seoul. (a) The number of restaurants. (b) Population per restaurant.
3.2 Data collection and analysis

Overall analysis of this study is comprised of three steps: (1) data collection: extraction of Jajangmyeon restaurants data from a delivery application exploiting web scraping, (2) network cluster analysis: identification of clusters and attractor nodes of Jajangmyeon restaurants through Markov Cluster Algorithm (MCL) and (3) price analysis: analysis of spatial price patterns and impact of degrees competition on prices. The following Figure 5 shows the framework of the study.

3.3 Web scraping of delivery platform

Web scraping allows authors to collect and process a large amount of data from online spaces using an automated process, as opposed to previously when a manual effort was needed. Web-scraping is,
therefore, a more efficient way to collect online data than the traditional copy and paste method (Nylen and Wallisch, 2017).

This study scraped Jajangmyeon restaurant data from the Yogiyo delivery application. We chose Yogiyo for two reasons: (1) technical availability of web-browser-based interface and (2) popularity. Unlike other delivery applications in Korea, Yogiyo provides a web-browser-based interface which enables web-scraping to collect data from the platform. Baemin which is the top delivery application in Korea does not utilize a web-browser-based interface, preventing researchers from web-scraping data on the platform. Second, Yogiyo is the second-largest delivery application in Korea and accounts for approximately 22% of the total delivery application market (Nielson Korea Click, 2020). However, this analysis is not about how oligopolistic delivery applications exercise their market shares on restaurants by charging higher commission fees. Rather, this is about pricing strategies of restaurants registered within delivery applications. That being said, examining restaurants’ pricing strategies in one of the leading delivery applications may provide economic insights representing strategic behaviors in restaurant businesses as well as online delivery markets in Korea.

The Octoparse platform (https://service.octoparse.com/ecommercedata), which offers customizable scraping engines and platforms, was used for web-scraping in this analysis. Three stages of data collection using Octoparse were conducted in this study: (1) searching available Jajangmyeon restaurants based on addresses at subdivision level, (2) extracting the data of such information as menus of searched Jajangmyeon restaurants and (3) inserting restaurant data into the database if the restaurant has Jajangmyeon on their menu. Detailed information about the web-scraping process is described in Section A2 in the Appendix.

3.4 Network cluster analysis

Network cluster analysis decomposes a network into a sub-network based on connections between nodes. The traditional subdivision-based spatial market boundaries might have been expanded by delivery application introduction. This potential expansion of market boundaries might have then altered spatial market structure. Thus, this study identifies sub-networks of delivery on a delivery application to specify altered market boundaries, and to analyze the spatial market structure.

This study uses MCL algorithm for network cluster analysis. MCL is an unsupervised cluster analysis algorithm for networks, which is based on the simulation of random walks in a network (Van Dongen, 2000). MCL has been applied in various types of big-data-based network identification research because of its speed and simplicity. For example, MCL was used to identify flight sub-networks from global flight networks (Xu et al., 2017) and researcher networks (Chandrasekharan et al., 2021).

The MCL algorithm starts with the construction of the Origin-Destination matrix. It then alternates the Origin-Destination matrix by iterating three steps: scaling, expansion, and inflation (Van Dongen, 2000). Scaling is the process that constructs the Markov matrix, which shows the probability of transition, by matrix normalization process. The expansion step takes the power of the Markov matrix using the matrix product. This step spreads connections to new vertices and also enhances connections to reachable vertices. In other words, the expansion step enhances within-cluster connection by increasing paths between the two nodes in the same cluster. Then, inflation is conducted by raising each matrix entry to power of over one. The inflation step will inflate entries over one, while deflating entries less than one. Therefore, the effect of the inflation step is to make strong connections stronger and weak connections weaker. These steps are repeated until the matrix becomes an idempotent Markov matrix, which will not have any further change through expansion and inflation. The rows with one or more positive elements are interpreted

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4 The raw data scraped is available upon request. In addition to the Octoparse platform, the data is currently being scraped with the Python selenium code that authors created.
as clusters. Each cluster has a star-like form, with one attractor in the center and has connections from all participant nodes. Thus, attractor nodes can be interpreted as the local center of networks. Figure 6 shows an example results of the MCL algorithm.

3.5 Price analysis

It is hypothesized that the delivery application has changed the spatial pricing structure by expanding Jajangmyeon restaurants’ reach to neighboring subdivisions. Two analyses were conducted: (1) correlation test and (2) econometric analysis. First, correlations were explored to discern relationships among the price of Jajangmyeon and additional Jajangmyeon restaurants by delivery apps to explore the prospect of significant relationships between average local price and differences in price between the average local price and the average delivery application prices, $P_{\text{average delivery application price}} - P_{\text{average local price}}$. We define the average local price as average aggregate price totaled food item price and delivery fees of restaurants in the subdivisions where the restaurants are located. The average delivery application price is defined to be the average aggregate price available from the delivery application accounting for the restaurants both in subdivisions where the restaurants are located and in neighboring subdivisions. If the difference is positive (negative), the average delivery application price is higher (lower) than the average local price. The test is based on the following hypothesis:

$$H_0: r = 0, H_1: r \neq 0$$

The $P$-value is calculated based on the $t$-value, which is calculated by the following formula:

$$t = \frac{r \sqrt{n-2}}{\sqrt{1-r^2}}$$

where $n$ is the number of connected sub-divisions. If the correlation coefficient is negative, it suggests a convergence in price suggesting the negative relationship between local prices and delivery application prices and more competition in the restaurant business.

If the negative relationship is found (it is found as is described in the results section), it suggests that there may be more competition, which motivates to progress to econometric analysis to examine the impact of degrees of competition on the prices with other related economic factors controlled. The number of local

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**Figure 6.** Example of MCL cluster analysis process (own representation).
restaurants (which are located in the subdivisions where customers stay) and of delivery restaurants (which are located in the neighboring subdivisions) in each subdivision are chosen as independent variables. The number of delivery restaurants from the neighboring subdivisions are the independent variables of interest, because it can be seen as a proxy for the increased competition as they are additions of restaurants from neighboring subdivisions led by the introduction of delivery applications. The basic regression equation for this study is as follows:

\[
\log y_{in} = \beta_0 + \beta_1 \text{local}_{in} + \beta_2 \text{delivery}_{in} + \beta_3 \text{population}_{in} + \epsilon_{in} \tag{1}
\]

where \( y_{in} \) is the average price of Jajangmyeon in subdivision \( i \) in network \( n \). \( \text{local}_{in} \) is the number of local restaurants in subdivision \( i \) in network \( n \), is the number of additional delivery \( \text{delivery}_{in} \) restaurants entering from the neighboring subdivisions with deliveries available, \( \text{population}_{in} \) is the population in subdivision \( i \) in network \( n \), representing market size.

Considering heterogeneities varying across individual districts and/or subdivisions in Seoul, such as zoning attributes or market boundaries of Jajangmyeon delivery, a certain fixed effect should be considered. In each network, prices may exhibit heterogeneity, along with an attractor, serving as the network’s central point. That being said, subdivisions linked by the same Attractor node can be classified to a single homogeneous market and network information analyzed from network cluster analysis is added to serve as fixed effect variables. The extended model aims to analyze price variations across these networks as below:

\[
\log y_{in} = \beta_0 + \beta_1 \text{local}_{in} + \beta_2 \text{delivery}_{in} + \beta_3 \text{population}_{in} + \beta_4 \text{attractor}_{in} + \sum_n \gamma_n \text{network}_{in} + \epsilon_{in} \tag{2}
\]

where \( \text{attractor}_{in} \) is a dummy variable for whether subdivision \( i \) is a network attractor, and \( \text{network}_{in} \) is a dummy variable for which network that subdivision \( i \) falls in.

The study further extended the model to analyze heterogeneous effects of competition across different network by including interaction terms between network dummy and number of delivery restaurants. The extended equation can be described as follows:

\[
\log y_{in} = \beta_0 + \beta_1 \text{local}_{in} + \beta_2 \text{delivery}_{in} + \beta_3 \text{population}_{in} + \beta_4 \text{attractor}_{in} + \sum_n \gamma_n \text{network}_{in} + \sum_n \delta_{in} \text{delivery}_{in} \cdot \text{network}_{in} + \epsilon_{in} \tag{3}
\]

The effects of competition change by delivery application can be identified by \( \beta_2 + \sum_n \delta_{in} \text{network}_{in} \). This means that the effects of the number of delivery restaurants from the neighboring subdivision may vary for each network.

4. Results and Discussions

4.1 Geographical information of the market based on the collected data

This study collected 1088 Jajangmyeon restaurants’ information on the Yogiyo delivery application from July 2021 to August 2021, accounting for approximately 39% of the total Jajangmyeon restaurants in Seoul. Figure 7 shows the locations of Jajangmyeon restaurants from which information was collected.

The collected data shows that there are on average 2.27 Jajangmyeon restaurants per subdivision, the average Jajangmyeon price as 6715 KRW (5.11 US$ with currency rate as of 2 January 2024), and the average delivery fee as 1552 KRW (1.18 US$ with currency rate as of 2 January 2024).\(^5\) Thus, the average aggregate Jajangmyeon price is 8267 KRW (6.30 US$), of which delivery fee accounts for a non-trivial 19%.

\(^5\) The delivery fee was initially averaged at the restaurant level, then the total average delivery fee was calculated.
The delivery boundary shows that on average individual Jajangmyeon restaurants deliver to seven subdivisions with an average delivery distance is 1.46 km, which is close to the average radius one subdivision (which is 1.2 km). The delivery boundary is used to generate the Origin-Destination matrix by counting the number of restaurants that can deliver from one subdivision to the other subdivision. Figure 8 illustrates the Origin-Destination network of delivery distance to delivery destination (Figure A2 in the Appendix further shows kernel density of delivery distance to delivery destination). Variations of network across districts reflect two market attributes: (1) the number of subdivisions in a single district and (2) the number of restaurants.

The network in Figure 8 indicates two distinct aspects of Origin-Destination lines. There are thin but many lines in the central and midwest regions while thick but a smaller number of lines in other regions. Such dense districts as Jongno-gu, Jung-gu were older historical districts developed around 100 years ago with lots of small subdivisions with narrow and mediocre road conditions. On the other hand, other districts such as Gangnam-gu and Seocho-gu were developed relatively recently less than 30 years ago with wider and well-paved road conditions.
Historical urban areas around the central and mid-west districts have complex thin lines with restaurants connecting lots of subdivisions. For example, subdivisions of old historical urban areas have 61.31 connected subdivisions on average, but each connection has 1.15 restaurants on average. On the other hand, the younger modern urban areas encompassing southern districts have simpler thick lines with many restaurants connected across a few subdivisions. Average numbers of connected subdivisions in the young and modern urban areas are 6.41 and each connection has 3.53 restaurants. The results suggest that the market has been expanded more in the older historical urban areas, resulting in a rise in spatial competition after delivery applications came into play in Jajangmyeon food service.

4.2 Cluster analysis

The cluster analysis identified 9 clusters (9 different colors of dots) and 13 attractor nodes. Figure 9 shows identified clusters and their attractor nodes. Clusters illustrate nodes representing subdivisions connected for deliveries and the identified clusters are almost equivalent to the union of 2 to 4 administrative district units. Since administrative districts are usually separated by geographical barriers, like streams or railroads, delivery clusters are similar to the administrative districts and separated by the river, as expected. Attractor nodes show local centers in clusters and the 13 identified attractor nodes are denser population or denser restaurant areas than their neighbors.

4.3 Changes in the number of orderable restaurants

Traditionally, people ordered Jajangmyeon within their own subdivision. From the collected data, only 2.3 restaurants are available to order from in individual subdivisions if delivery applications are not considered (Figure 10). Figure 11, however, illustrates that the Jajangmyeon can be ordered from 13.5 additional Jajangmyeon restaurants from the neighboring subdivisions through the delivery application. Thus, the results

![Figure 9. Jajangmyeon delivery clusters and attractor nodes.](image-url)
Figure 10. Number of restaurants based on address of restaurants.

Figure 11. Number of orderable restaurants on delivery applications.
show the expansion of consumer choices in the Jajangmyeon market, potentially leading to more competition among restaurants, although expanding competition to include both food and delivery prices/costs.

4.4 Changes in the price by delivery apps

The average local price, which is the average aggregate price for foods item and delivery fees of restaurants in the subdivisions where the restaurants are located, is illustrated in Figure 12. Figure 13, on the other hand, displays the average delivery application price, which is the average aggregate price available from the delivery application accounting for the restaurants both in local subdivisions where the restaurants are located and in neighboring subdivisions.

The results present a converging pattern of the Jajangmyeon prices with delivery applications. Restaurants with higher local prices reduce prices in farther and more competitive regions to absorb more customers while restaurants with lower local prices have some room to raise prices (but still lower than other competing restaurants) to increase profits. Figure 14 illustrates the relationship between average local price and differences in price between the average local price and the average delivery application prices, $P_{\text{average delivery application}} - P_{\text{average local price}}$. If the difference is positive (negative), the average delivery application price is higher (lower) than the average local price. Prices around the subdivisions with higher average local prices decreased with the introduction of delivery applications, while the ones in subdivisions with lower average local prices increased. A negative relationship between price difference and average delivery application price was found (Figure 14). Based on the correlation analysis, the Pearson correlation coefficient is $-0.82$ and the $p$-value is 0.000, indicating the negative correlation is statistically significant. Thus, the results suggest a convergence in price, the negative relationship between local prices and delivery application prices, and more competition in the restaurant business.

![Figure 12. Average local price.](image-url)
Figure 13. Average delivery app price.

Figure 14. Relationship between the average local price and the price difference between local and delivery application.
This study estimated the three econometric models to analyze the effects of increased competition by delivery restaurants on Jajangmyeon prices. Model (1), the basic model, only includes the number of delivery restaurants as a measure of competition. The extended models, model (2) and (3), also includes the network dummy variables to control market characteristics and interaction terms between the number of delivery restaurants and the network dummy variables to control heterogeneity of the network effect on price impact of delivery restaurants.

The estimation results of the models are presented in Table 2. The results of Model (1) suggest that the number of delivery restaurants has a negative effect on Jajangmyeon prices. This means that an increase in the number of delivery restaurants in a local subdivision, more competitive markets, leads to a decrease in the average price of Jajangmyeon. One more restaurant in a local subdivision decreases prices by 0.24%. However, an increase in the number of restaurants in the neighboring subdivisions has a statistically insignificant (positive) impact on price. Considering the potential heterogeneity of delivery networks, it is worth investigating further through Models (2) and (3).

The results of Model (2) suggest that the effects of increased competition by local restaurants are heterogeneous by network. In particular, the negative effect of the number of local restaurants on Jajangmyeon prices is stronger in networks 2, 3 and 4 and competition impact both in local and delivery restaurants are all negative albeit it is not statistically significant. As there is one more restaurant in the overall markets (local and neighboring subdivisions), Jajangmyeon price goes down by 0.22% (0.10% from a local restaurant and 0.12% from a delivery restaurant). Considering there are on average 15.8 restaurants in the local and neighboring subdivisions, prices are expected to decrease by 2.97% (15.8×0.22%) with increased competition from restaurants located in neighboring subdivisions.

Model (3) adds interaction terms between the number of delivery restaurants and network further addressing heterogeneity of network in the impact of competition on prices. An additional restaurant in a local subdivision decreases the price by 0.12% and one in neighboring subdivisions decreases the price by 0.07% (Table 2). In addition, if the delivery restaurants are located in the three networks 6, 7 and 8, the price impact of an additional single restaurants is a further decrease by 0.34% (if located in network 6), 0.31% (if located in network 7) and 0.49% (if located in network 8) (Table 2). The overall reduction in prices each additional delivery restaurant ranges from 0.38% to 0.56%. Given that there are 13.5 restaurants in neighboring subdivisions the price reduction ranges from 5.13% (13.5×0.38%) to 7.56% (13.5×0.56%). Networks 6, 7 and 8 are old-developed areas, which have small sub-divided areas and not well-paved roads (recall Figure 8). As is described in Figure 8, such subdivisions have shorter delivery distances with more competing restaurants. This makes the local markets more competitive so that local Jajangmyeon restaurants in these networks face more competition from distant delivery restaurants in neighboring subdivisions, which used to not be the case before the delivery application came into the market.

Figure 15 illustrates the aggregated results of the model (3) and the negative effect of the number of delivery restaurants on Jajangmyeon prices more significant in network 6, 7 and 8 (Table 2 and Figure 15). Overall, the findings of this study suggest that delivery applications have had a substantial impact on the spatial pricing structure. In addition, this study highlights that impacts of delivery applications on restaurant markets and pricing may differ by characteristics of a given area.

5. Conclusion

The introduction of delivery applications has brought changes to the food service industry. Delivery applications charge customers delivery-related costs, and thus, change spatial market structure. As more people now use delivery applications, the importance of delivery application-induced market structure changes becomes more significant.
### Table 2. Results of the regression analysis

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>No. of local restaurants</strong></td>
<td>-0.0024** (0.0011)</td>
<td>-0.0010 (0.001)</td>
<td>-0.0012 (0.001)</td>
</tr>
<tr>
<td><strong>No. of delivery restaurants</strong></td>
<td>0.004 (0.0009)</td>
<td>-0.0012 (0.0008)</td>
<td>-0.0007 (0.003)</td>
</tr>
<tr>
<td><strong>Population density (×1000 people/km²)</strong></td>
<td>-0.003 (0.047)</td>
<td>0.014 (0.039)</td>
<td>0.028 (0.042)</td>
</tr>
<tr>
<td><strong>Attractor of the network</strong></td>
<td>-0.020 (0.018)</td>
<td>-0.012 (0.018)</td>
<td></td>
</tr>
<tr>
<td><strong>Network dummy variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 2</strong></td>
<td>-0.047** (0.019)</td>
<td>-0.062 (0.045)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 3</strong></td>
<td>-0.059*** (0.017)</td>
<td>-0.054 (0.039)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 4</strong></td>
<td>-0.036* (0.020)</td>
<td>-0.081* (0.045)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 5</strong></td>
<td>0.042** (0.019)</td>
<td>0.046 (0.042)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 6</strong></td>
<td>0.037** (0.016)</td>
<td>0.084* (0.045)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 7</strong></td>
<td>0.018 (0.016)</td>
<td>0.062 (0.047)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 8</strong></td>
<td>0.072*** (0.019)</td>
<td>-0.024 (0.047)</td>
<td></td>
</tr>
<tr>
<td><strong>Network 9</strong></td>
<td>0.068*** (0.016)</td>
<td>-0.078* (0.043)</td>
<td></td>
</tr>
<tr>
<td><strong>Interaction terms</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 2 × No. of delivery restaurants</strong></td>
<td>0.0015 (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 3 × No. of delivery restaurants</strong></td>
<td>-0.0004 (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 4 × No. of delivery restaurants</strong></td>
<td>0.004 (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 5 × No. of delivery restaurants</strong></td>
<td>-0.0003 (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 6 × No. of delivery restaurants</strong></td>
<td>-0.0034 (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 7 × No. of delivery restaurants</strong></td>
<td>-0.0031 (0.003)</td>
<td></td>
<td></td>
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<tr>
<td><strong>Network 8 × No. of delivery restaurants</strong></td>
<td>-0.0049 (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Network 9 × No. of delivery restaurants</strong></td>
<td>0.0007 (0.003)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in parentheses.

***p < 0.01, **p < 0.05, ***p < 0.1.
This paper analyzed delivery-application-induced market structure changes using web-scraped data and network analysis. Compared with traditional data collection methods, web-scraping can provide more detailed price and delivery boundary information at the individual restaurant level. Web-scraping data facilitated addressing subdivision level spatial market structure changes by cluster and price analysis, but additional analyses are possible in other contexts.

Cluster and price analysis of this study suggests that the number of orderable restaurants has increased by spatial market expansion with the advent of delivery applications. In addition, there was a negative correlation between the average local price and the average price difference between local price and delivery application price, suggesting a converging pattern of Jajangmyeon prices. After the delivery application came into the marketplace, the price increased in low local price areas, while high local price areas experienced the opposite. This may suggest that additional competition might have led the Jajangmyeon price to converge with delivery applications. In addition, the increased competition reduces the Jajangmyeon prices by between 5.13 and 7.56% depending on regional characteristics. The negative correlation and price reduction was more apparent in more competitive historical urban areas than in less competitive modern urban areas. Given the rapid changes experienced in many urban areas due to pandemic-related disruptions, less frequenting of commercial districts, and more consumption taking place at home, the prospect of changes in spatial competition of restaurants traditionally servicing smaller regions within a city is of particular interest.

5.1 Limitations and future research

The results of this study suggest that delivery applications may render food service markets more competitive. However, this analysis does not provide insight about individual restaurant’s performance in terms of changes in revenue and profit, nor changes in consumers’ welfare. Web-scraping can scrape only visible or accessible information on websites (for example prices, but not quantity sold) which limits the range of research that could be conducted.
Despite the limitation of the techniques, one of the major benefits of web-scraping is large-scale data collection which can be used to lessen information asymmetry and make markets more efficient. Datasets do not usually stand alone, but are often used in analysis with other data sources for context and to enrich the depth of the analysis. The main purpose of the current study is to demonstrate the potential of using a method of online data collection and network analysis for conducting market research on restaurant businesses.

There are a variety of concerns arising from growth in food delivery options, including the potential for the use of ghost kitchens and/or lack of direct knowledge of restaurant practices. To the best of the authors knowledge, there are not specific concerns of this nature for the product of interest in this study, but this concern has been raised in other settings and for other products.

References


Appendix

A1. Plots

Figures A1 and A2 show the kernel density plot of Jajangmyeon price, delivery fee and total order cost and the kernel density of delivery distance to destination, respectively. The kernel density shows the distribution of Jajangmyeon price and total order cost are right skewed, and delivery fee has two peaks at 0 and 3000 KRW (2.43 US$ with currency rate as of 7 March 2022), reflecting the current reality that many restaurants still do not charge a delivery fee on the delivery application.

Figure A3 illustrates the relationship between the minimum local price and the minimum delivery application price. The minimum delivery prices of 129 out of 213 subdivision areas (60%) are less than the minimum local prices. Therefore, the results empirically show the possibility of an increase in spatial competition.
Figure A1. Kernel density plots of Jajangmyeon price, delivery fee and total price.

Figure A2. Kernel density of delivery distance to destination.

Figure A3. Comparison of the minimum local prices and the minimum delivery application prices.
A2. Web-scraping process

The Jajangmyeon data is collected through web-scraping following the four steps below.

Process 1: Search orderable restaurants by the representative addresses of subdivisions (Figure A4).

Process 2: Click Chinese restaurant to see only Chinese restaurants (figure A.5)

Process 3: Click each restaurant to collect menu and restaurant information (Figure A6).

Process 4: Collect menu, prices, and restaurant information (Figure A7).

The web-scraping process is implemented for all representative addresses and corresponding Chinese restaurants. Algorithm A1 shows how the loop is implemented.

Process 5: Jajangmyeon data processing

This study identified jajangmyeon restaurants and menu by using menu names with following three rules (Figure A8). Through the data processing process, the study has identified 1088 chinese restaurants with ordinary jajangmyeon menu.

- Rule 1. Include jajangmyeon (자장면 or 짜장면) in the menu
- Rule 2. Exclude premium jajangmyeon (ex. Tofu, beef jajangmyeon)
- Rule 3. Exclude combo menu (ex. jajangmyeon with sweet sour pork)

```
for all representative addresses in the list do:
  set representative addresses as delivery destination address, then search Chinese restaurants
  (process 1 and 2)
for all listed Chinese restaurants in the page do:
  click restaurants and access the menu and detailed information page (process 3)
  collect all menus name, price, and detailed restaurant information (process 4)
```

Figure A4. Search orderable restaurants.

Figure A5. Filter the results as Chinese restaurants.
Figure A6. Click each restaurant.

Figure A7. Collect menu and restaurant information.
Figure A8. Data processing process.