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Indirect Network Effect and Spillover Effect in Food Delivery Platforms†

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I analyze how the food delivery market's indirect network effect and spillover effect influence the spread of food delivery platforms in different counties. This study finds that there is a positive local indirect network effect and a positive spillover effect in the adoption of the platform by examining the food delivery platform market in South Korea as of 2020. As food delivery platforms secure consumers who use them, more restaurants on the other side of a two-sided market adopt such platforms (indirect network effect). The spillover effect would allow other restaurants in a region to become more likely to adopt food delivery platforms if there are a greater number of restaurants in the region that use such platforms. This study contributes to the comprehension of technology diffusion and the marketing strategies of platform providers by providing empirical evidence of both effects.

Key Word: Network Effect, Spillover Effect, Food Delivery Platforms, COVID-19, South Korea
JEL Code: L81, L87, L14

I. Introduction

The platform as defined here is a two-sided market in which various participants are connected to attain economic transactions. Riders and passengers are tied by mobility platforms such as *Uber* and *Kakao mobility*, and restaurants and consumers are linked by food delivery platforms. The platform industry is a key industry in the digital economy, and its domain and influence have been growing consistently. Hence, theoretical and empirical studies that offer a better understanding of the platform market are underway. In this study, I link the local network effect and the spillover effect to explore a typical platform, in this case a food delivery platform. It is critical to comprehend platform providers' strategies regarding the spread of their

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food delivery operations.

The network effect, often known as a ‘network externality,’ is a critical feature of platforms. This implies that the platform’s value increases as its user base expands (Evans and Gawer, 2016). Network effects are classified as direct network effects or indirect network effects based on the stakeholder in the market which is affected. The term "*direct network effect*," which is synonymous with "within-group network effect," refers here to the degree to which the impact of a rise in the number of users has an impact on the efficiency of the activities of other users who are part of the same group. A positive direct network effect corresponds for instance to the spread of telephones and languages, while a negative direct network effect corresponds to congestion caused by increased numbers of cars under limited road conditions.

Indirect network effects, on the other hand, refer to how an additional increase in users has an effect on the utility of users belonging to other groups, and it is appropriate to apply indirect network effects in two-sided markets, such as platform markets. It is possible to separate different user groups, which is why this effect is also referred to as the cross-group network effect. This contrasts with the direct network effect, which cannot be separated in terms of different user groups. The indirect network effect in particular is a key feature of the platform market. Platforms compete for users in this two-sided market, and as the number of one sides’ users increases, so does the utility of the other sides’ users and, eventually, the number of both sides’ users.

Due to the fact that platforms for food delivery are also two-sided markets, there is a high probability that an indirect network effect may exist. Thus, I analyze indirect network effects in a food delivery platform market, specifically the correlation between rising consumer demand and an increase in the number of restaurants adopting food delivery platforms. The more consumers who use food delivery platforms, the more revenue restaurants can expect from such platforms. This leads to greater adoption of food delivery platforms by local restaurants, meaning that more restaurants will provide food delivery services. The indirect network effect in the food delivery platform is limited to the local area, which is a type of local indirect network effect. Customers place an order for food delivery with a restaurant in the same area, and restaurants also attempt to attract local customers. Due to this characteristic of food delivery, a food delivery platform market represents a viable means of observing indirect network effects at the regional level.

The spillover effect is another feature of the food delivery platform. With regard to delivery platforms, the spillover effect is identical to learning from others, and as more restaurants utilize them, non-adopters can readily adopt food delivery platforms. Restaurants are more likely to adopt food delivery platforms with greater confidence when they can learn about platforms from nearby restaurants. If there is a spillover effect, the new adoption rate will rise in areas with high initial adoption rates. To measure the spillover effect, the adoption rate in January of 2020, prior to the COVID-19 shutdowns, is used as the initial distribution to determine if there are regional variations in the future adoption rates of food delivery platforms.

The indirect network effect on food delivery platforms examines the impact of rising consumer demand on restaurant adoption of food delivery platforms, whereas the spillover effect on food delivery platforms examines how much the initial platform distribution influences the subsequent platform distribution. By examining these effects and the corresponding regional variations, I determine where indirect network effects and spillover effects occur and which factors are responsible for their occurrence. The year under consideration is 2020, which includes the period preceding and following the COVID-19 outbreak, an event that greatly spurred the growth of South Korea's food delivery platforms market. Between 2017 and 2019, the market for food delivery platforms more than doubled. COVID-19 expedited the growth of food delivery platform markets in 2020. Dine-in demand was partially converted to food delivery orders through delivery platforms as dine-in orders declined (Lee, 2021). The high demand for food delivery has led to a significant overall increase in the number of restaurants employing food delivery platforms. However, the rate of adoption of platforms varies from region to region.

I used market (local) level data to estimate these effects. The data contain a large number of variables, and it is possible to analyze them in various ways. For this study, I used average monthly sales, average monthly delivery sales, and the number of local restaurants for each region. Furthermore, regional variables are considered by utilizing local consumption, COVID-19 cases and average ages. My first empirical finding is that there is a local indirect network effect and a local spillover effect in the adoption of a food delivery platform. Using instrumental variables (IVs), additional control variables, and a variety of sample periods, all have a positive impact on the adoption of food delivery platforms. Considering two effects according to different restaurant categories, I also find a positive effect, but in restaurant categories where the adoption of food delivery platforms is already high, such as fried chicken, the spillover effect tends to be negative.

It is anticipated that the findings of this study have significant policy implications. As demonstrated by Lee (2021), the adoption of food delivery platforms contributes significantly to the preservation and growth of individual restaurant sales. The adoption of such platforms has a significant positive effect on total sales, particularly in small restaurants. Understanding the adoption mechanism allows one to forecast the platform provider's distribution strategy, as well as the stimulating effect of adoption.

The remaining sections of this study are as follows. Section II reviews previous studies related to indirect network effects and spillover effects. Section III introduces the data and the regression model. Section IV presents the empirical results, and Section V summarizes the contents and provides a conclusion.

II. Literature Review

There have been numerous studies of indirect network effects and spillover effects. Rysman (2004) studied indirect network effects using the Yellow pages. This platform business connects subscribers and advertisers. Advertisers maximize their profits by placing ads. He discovers that the advertising level (i.e., amount) has a positive effect on the advertising prices on the supply side and that the advertising level has a positive effect on advertisers' market share (demand) on the demand side. This indicates that users and advertisers experience a network effect indirectly. In the video game console market, Dubé, Hitsch, and Chintagunta (2010) examine the expansion of market share caused by the indirect network effect. Rysman, Gowrisankaran, and Park (2011) analyze indirect network effects in the DVD player and title markets. Furthermore, Ohashi (2003), Park (2004), and Björkegren (2019) provide evidence of an indirect network effect in a two-sided market.

Goolsbee and Klenow (2002) and Kim *et al*. (2021) examine the existence of local spillover effects of IT technology and digital platforms. Kim *et al*. (2021) analyzes the direct network effect between platform users in the *fantasy sports* platform market in the United States. Because this platform is a type of online social platform, the presence of a direct network effect has a high probability of arising in it. In particular, the existence of a local network effect can be confirmed due to the fact that it is frequently used by local friends or acquaintances. Strictly speaking, this network effect is distinct from the spillover effect, but in the *fantasy sports* market, it is challenging to distinguish between these two effects. Goolsbee and Klenow (2002) exhibit a more pronounced spillover effect. They confirmed, from a local spillover perspective, the degree to which home computers were distributed in the region in 1997. Given that it is difficult to expect a social network effect through home computers because the Internet was not widely used at the time, this case can be interpreted as diffusion through learning (spillover effect) from other computer users. Indeed, home computer ownership is more common in areas where there are high percentages of computer users. Furthermore, Keller (2002) finds a local network effect in R&D expenditure, and Jaffe *et al*. (1993) explore the mechanism of technology diffusion in US patent citations.

I contribute this study to the platform market literature on the network effect and spillover effect. There have been few empirical studies that confirm both an indirect network effect and a spillover effect, and there have been few empirical studies of the food delivery platform markets. As noted previously, there is a significant probability that both a direct network effect and a spillover effect will occur in the market for food delivery platforms, and in this market, the two effects can be separated. One effect will be overestimated if the two effects are not reflected in an empirical analysis. As a result, a study examining both effects is essential, and this study is noteworthy in that aspect.

III. Data and Model

I use proprietary credit card data provided by Shinhan Card, which covers the entire South Korean restaurant market in 2020. This dataset contains the average monthly sales of 250 regional restaurants.[1] For those that use food delivery platforms, the average monthly delivery sales and delivery orders are also included. The food delivery platforms included in this data are *Baemin* and *Yogiyo*, which have the largest market share in South Korea for food delivery platforms. As of the end of 2020, there are more than ten food delivery platforms in South Korea; however, the combined market share of the top two platforms is 99.2%, which means that they can be considered to represent the entire market.[2] Another point regarding the dataset is that it was collected from a single credit card company. As a result, there is concern that the average monthly sales and orders of restaurants for each region may be underestimated. Fortunately, this dataset can represent transactions of the

[1] The average monthly sales of restaurants for each region
[2] Korea Fair Trade Commission (2020).

entire market because the credit card company[3] provides estimated values such as total monthly sales and total monthly delivery sales, paid using credit cards, based on market share.

The data contain information at all county levels in South Korea, but the adoption rate of food delivery platforms[4] is very low in some regions. For the purpose of conducting an accurate analysis, data from 18 regions[5] are omitted from the set because the adoption rates in these regions are expected to be lower than 1% during any months in 2020.

I use twelve restaurant categories for the analysis: Korean, Chinese, Japanese, Western, other foreign, pizza, fried chicken, bakery, coffee shops, snack shops, bars, and other food business.[6] Because the dataset contains detailed information about the average monthly sales of restaurants in each category, I use that information to examine the spillover effect and the indirect network effect for each restaurant category.

The data are the monthly market (county) level and include periods prior to COVID-19 (January 2020) and during COVID-19 (since February 2020). As of January of 2020, 18.2% of restaurants in all markets had adopted food delivery platforms. In December, the adoption rate increased to 28.6% (Figure 1). In 2020, the proportion of restaurants using food delivery platforms steadily increased. There were a large number of restaurants that more recently adopted the platforms, particularly in February, August, and December (Figure 1). This is consistent with COVID-19's first, second, and third surge periods. Because COVID-19 cases and death tolls increased during these periods, the demand for food delivery appears to have soared as a result of the social distancing policies. The high demand for food delivery may have led to an increase in the adoption of food delivery platforms.

(Unit: %, count)

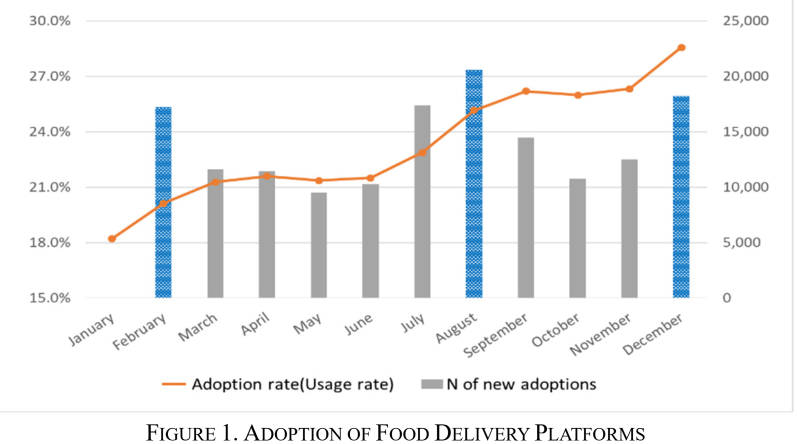

FIGURE 1. ADOPTION OF FOOD DELIVERY PLATFORMS

[3]Shinhan Inc.

[4]The adoption rate of food delivery platforms refers to the number restaurants using the platforms divided by the total number of restaurants in a region.

[5]These regions are islands and mountainous areas such as Sinan-gun, Ulleung-gun, and Yeongyang-gun.

[6]Originally, there were 16 types of restaurants, including institutional restaurants, general entertainment bars, dance entertainment bars, and catering restaurants. Due to their remarkably low adoption rate of food delivery platforms, these four restaurant categories were excluded from the analysis.

In this study, I aim to identify market factors influencing delivery platform adoption from February to August of 2020, when COVID-19 began. In February, during the first COVID-19 surge, the duration is too short to expect a local spillover effect because the shock to the market is very abrupt. In other words, too few restaurants were prepared for the use of these platforms. The number of restaurants adopting such a platform is fully reflected by August, with a continuous increase up to that point. The adoption of food delivery platforms has slowed since August of 2020 (Figure 1). This could imply that a significant number of restaurants capable of providing food delivery service had already adopted the platform. Therefore, I use the period of February-August rather than the February-December period as the baseline analysis period. While the number of restaurants using the platform grows in December when compared to August, some restaurant categories, such as fried chicken, are slow to adopt the platform. I assume in this study that there is sufficient time to examine the indirect network effect and the spillover effect, as the adoption rate of food delivery platforms increased substantially from February to August. In the appendix, the same analysis for other periods, specifically Feb-Mar and Feb-Dec, are also shown as a robustness check.[7]

According to January market statistics, the highest food delivery platform adoption rate (*adopted% (Jan)*) is 28.1%, while the lowest rate is 8.6% (Table 1). The ratio of food delivery sales to total restaurant sales in January is at least 0.04%; the maximum is 8.9% and the average is 3.5% (Ratio of Delivery Sales (Jan), Table 1). Given the low adoption rate of food delivery platforms and the low sales ratio in

TABLE 1—SUMMARY STATISTICS

Variable	Obs.	Mean	Std. Dev.	Min	Max
Adoption% (Feb-Aug)	232	0.1162	0.0592	0.0081	0.2227
Adopted% (Jan)	232	0.1368	0.0807	0.0086	0.2807
Log (Delivery orders) (Order / 1000 people)	232	5.0844	1.4178	1.0047	6.8496
Log (Consumption) (1000KRW)	11	9.7639	0.0928	9.6731	9.9984
Age	232	44.4565	4.2117	36.4000	54.5000
Population Density (N / 1000km^2)	232	0.4221	0.6034	0.0019	2.6316
COVID-19 Cases (Cases / 1000 people)	11	0.8318	1.5523	0.0089	14.9400
Sales of Restaurant using a platform (Jan, 1000KRW)	232	12,355.85	4,902.16	3,296.26	29,015.60
Average Delivery Orders (Jan)	232	102.2615	49.0873	14.393	253.7421
Ratio of Delivery Sales (Jan)	232	0.0350	0.0238	0.0004	0.0894

Note: 1) The unit of observations is a county, 2) Delivery orders are the average monthly delivery orders per 1,000 people in the region, 3) COVID-19 cases are the number of COVID-19 cases relative to the population of the region.

Source: Shinhan Inc. data in 2020; Statistics Korea, 2022; Public Data Portal (www.data.go.kr).

[7]See Appendix Table A1 (Robustness result (Period)). This clearly demonstrates that the results for different time periods (Feb-Mar, Feb-Dec) are consistent with the baseline analysis (Feb-Aug).

January, it is clear that the food delivery platform market had room to grow after January of 2020.

In addition to restaurant market statistics, general administrative statistics for each region are used. This includes each region's average age, population density, annual consumption level, and COVID-19 cases relative to the population. In an ideal scenario, regional statistical figures can be divided into 232 regions, but the annual consumption level and COVID-19 cases are added as wide-area units (eleven nationwide) due to restrictions in currently available data. Except for COVID-19 cases, 2019 statistics are used. In particular, COVID-19 cases can act as a demand shifter as a variable that controls the COVID-19-induced shift in market demand.

I use the following analysis model to determine how the indirect network effect and spillover effect affect the adoption of food delivery platforms.

$$adoption\%_c = \alpha + \beta_1 adopted\%_{c,0} + \beta_2 \log(deliveries)_{c,-1} + \gamma X_c + \delta Z_{c,-1} + u_c$$

Here, $adoption\%_c$ represents the fraction of restaurants that newly adopt a delivery platform for each county (c) between February and August (*flow value*).[8] To simplify the calculation, the adoption rate is based on the total number of restaurants in August. There is no significant change in the total number of restaurants because the number of newly opened or closed restaurants balances out between these periods.[9]

In addition, $adoption\%_c$ is influenced by two major factors. First, I define $adopted\%_{c,0}$ as the rate of adoption of food delivery platforms among restaurants in each region in January of 2020 (*stock value*) and examine its impact (Spillover effect, Figure 2). The effect of spillover considers the distribution that occurred before COVID-19. I examine how the initial distribution of platforms (platform distribution rate in January of 2020) affects the ongoing distribution after January of 2020. This is a spillover effect estimation method similar to that used by Goolsbee and Klenow (2002). They measure the spillover effect by region by taking into account the percentage of households that owned a personal computer in the preceding year. This is in contrast to Kim *et al*. (2021), who use the absolute number of users who use a *fantasy sports* platform compared to the previous year (*stock value*). Because the total number of restaurants varies by region and given that each region also differs in terms of area and population, it is necessary to standardize platform adoption in relation to the total number of restaurants. On the other hand, as Kim *et al.* (2021) demonstrate, an analysis through the absolute number of restaurants adopting platforms also needs to be carried out as part of the robustness check (Appendix Table A2).[10]

[8]Because one explanatory variable, *adopted% (January)*, is a stock variable, I regress this with a stock variable, *adopted% (August)* as a dependent variable (Appendix Table A3). The result also demonstrates the presence of a spillover effect, as the coefficient of *adopted% (January)* is greater than 1.

[9]When calculating the number of restaurants that have adopted a food delivery platform, I do not consider restaurants that have kept or closed food delivery platforms after their initial adoption. This is done because adoption is influenced by the spillover effect or the direct network effect, whereas food delivery platform discontinuation is influenced more by the business environment of the circumstances at individual restaurants.

[10]The result also demonstrates the presence of a spillover effect with a positive coefficient of the absolute

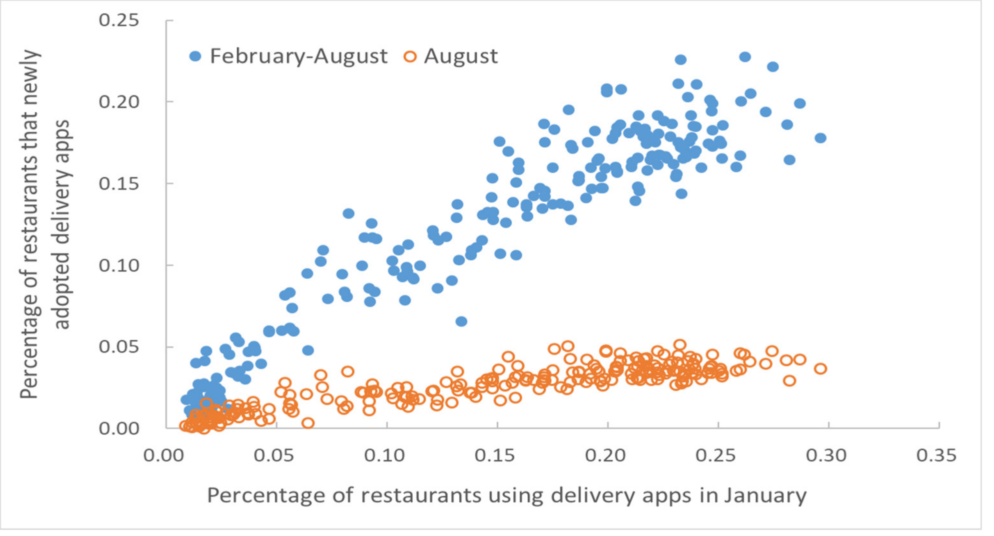

FIGURE 2. SPILLOVER EFFECT

Second, the number of food deliveries relative to the regional population from February to July ($\log(deliveries)_{c,-1}$) is used as an indirect network effect indicator.[11] In fact, the number of customers who subscribe to the delivery platform is a better indicator of the indirect network effect. However, given the current state of the delivery platform market, it is more reasonable to employ the number of active users as a variable rather than the number of subscribers because many consumers subscribe but rarely use the platform. Due to the difficulty of obtaining such variables, I propose to use the number of delivery orders per population as a proxy for the number of active users. I assume that delivery orders are proportionate to the number of active users and that a restaurant would be interested in increasing the total number of orders to maximize their profit. The global external shock caused by COVID-19 is expected to boost demand for delivered food. In fact, the number of food delivery orders nationwide remained high after January, reaching an all-time high in December (31.52 million, Figure 3). During this time, the market's increased demand for food delivery created an incentive for restaurants that did not previously provide food delivery services to adopt food delivery platforms in order to provide food delivery as a service. It is possible to observe how the number of delivery orders per 1000 people in each region influences the adoption of food delivery platforms.[12]

X_c denotes certain time-invariant variables, in this case the regional population density, average age, and annual consumption per capita in 2019. I control the characteristics of local consumption groups using these variables. Finally, $Z_{c,-1}$ is the monthly average of COVID-19 cases per unit population[13] by county from

number of restaurants adopting platforms.

[11]Monthly average of (total delivery orders in each month / regional population) for each region

[12]While an increase in consumers using food delivery platforms may be a factor in indirect network effects, more active demand for food delivery services is reflected in the number of orders, such as average deliveries relative to the population.

[13]The population unit is 1,000 people.

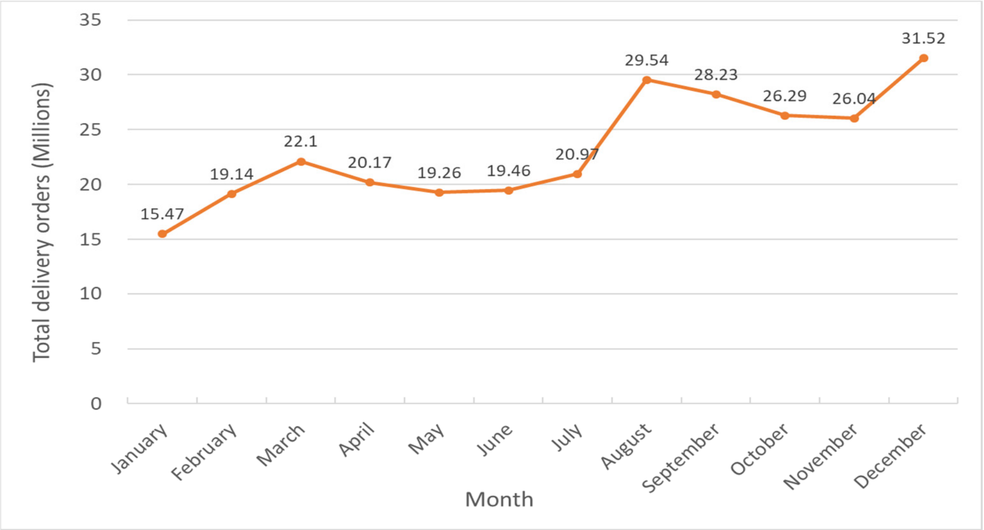

FIGURE 3. DELIVERY ORDERS

February to July. During the same time period, I assume that COVID-19 influences the adoption of food delivery platforms via an increase in food delivery service expenditures. As a result, I need a variable that can control the effect of COVID-19 by region, and COVID-19 cases play this role in the estimation.

Finally, an instrumental variables added to address the endogeneity issue between the unobserved term (u_c) and $adopted\%_{c,0}$. Because both $adoption\%_c$ (flow value between Feb-Aug) and $adopted\%_{c,0}$ (stock value on January) are related to restaurants' adoption of food delivery platforms, u_c can be correlated with $adoption\%_c$. The estimation result may be overestimated if both terms are positively correlated. I created three instrumental variables for $adopted\%_{c,0}$ by combining variables related to the delivery platform in January. The first instrument is the average sales in January by restaurants utilizing delivery platforms for each region, consisting of regional average sales including dine-in sales and delivery sales. The second is the average delivery orders in January for each region, which indicates the regional variation in delivery orders. The final instrument is the ratio of delivery sales to total sales in January for each region. I consider that these instruments are flow variables and that $adopted\%_{c,0}$ is a stock variable, which may address concerns about their validity as instruments. My argument with regard to instruments is that the accumulated adoption rate ($adopted\%_{c,0}$) is proportionate to the region's average monthly adoption rate. Since there is no unconventional shock in January, such as COVID-19, variables related to January's food delivery can be adequately reliable instruments as they correlate with the long-term average adoption rate. It is assumed, in particular, that there was no shock that generated a major regional dispersion prior to COVID-19.

These instrumental variables also satisfy the exclusion condition with the unobserved term (u_c). Because COVID-19 began in February, the food delivery variables in each region in January are not projected to effect adoption beginning in February. In the months following January, such as February and March, instruments may have an effect on the error term, but the direct effect of the instrumental variables on the error term would decline over time.

As previously stated, I examine the baseline model, and the statistical figures for variables in the regression model are shown in Table 1.

IV. Results

To begin, I present the result of the baseline specification in Table 2. The dependent variable is the percentage of restaurants that newly adopt a food delivery platform since February. The spillover effect is driven by the proportion of restaurants that employ a food delivery platform in January.[14] The indirect network is also influenced by the number of delivery orders per regional population between February and July. The first column in Table 2 is a result of an ordinary least squares estimation (OLS) that considers only two significant independent variables.[15] Both coefficients of the independent variables are statistically significant, meaning that a *one percent* increase in delivery orders per unit population is associated with a 0.0088 (*0.88 percentage points*) increase in the adoption rate of food delivery

TABLE 2—BASELINE RESULTS

Dependent variable: Adoption %	OLS (1)	OLS (2)	IV (3)	IV (4)
Adopted% (Jan)	0.564***	0.525***	0.480***	0.449***
	(0.028)	(0.034)	(0.034)	(0.041)
Log(delivery orders)	0.009***	0.006**	0.013***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Log(Consumption)		0.020		0.013
		(0.021)		(0.021)
Age		-0.002**		-0.002***
		(0.001)		(0.001)
Population Density		-0.000		0.003
		(0.004)		(0.004)
Avg. COVID-19 Cases		0.160		0.269
		(0.168)		(0.171)
Constant	-0.006	-0.109	-0.015**	-0.005
	(0.005)	(0.209)	(0.006)	(0.211)
R-squared	0.914	0.918	0.911	0.916
N	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, 3) Delivery orders are the average monthly delivery orders per 1,000 people in the region, 4) Avg. COVID-19 cases denotes the number of COVID-19 cases per 1,000 people in the region.

[14]For the spillover effect within COVID-19, I estimate the model with data between February and August in Appendix Table A4. *Adopted% (February)* is used and log (deliveries) is the average delivery orders relative to the population between March and August. This result also shows a spillover effect and an indirect network effect, but the coefficients are somewhat lower than those of the baseline result (Table 2).

[15]Indirect network effect variable and spillover effect variable.

platforms by local restaurants until August. Moreover, an increase of *one percentage points* (increase by 0.01) in the adoption rate of January will increase by 0.0056 (*0.56 percentage points*) local restaurants' adoption rate until August. It has been discovered that as the number of delivery orders per population or the adoption rate in January increases, so does the adoption rate after January.

I then include variables related to county characteristics. If column (1) in Table 2 is misspecified as a result of these variables, then both coefficients of the key independent variables should decrease or increase when those variables are added. In column (2) of Table 2, I include four covariates: log (annual consumption average, 1,000 KRW), age, population density, and COVID-19 cases per population. Similar to the first column of Table 2, both coefficients of the main variables are statistically significant while declining. Only the age variables have a significant coefficient among the added variables, and it is discovered that the platform's adoption rate decreases as the regional average age increases. COVID-19 cases per regional population have positive coefficients but are not statistically significant (*p-value*=0.595). This could result from the large monthly variation of COVID-19 cases from February to July.[16] Furthermore, as previously stated, the COVID-19 cases variable consists of eleven wide-regional units rather than 232 narrow-regional units and thus does not accurately reflect COVID-19's local effects.

Owing to simultaneity issues with estimating the spillover effect, the OLS results may be skewed. I add three instrumental variables to the adoption rate of food delivery platforms. The first-stage regression of column (3) of Table 2 yields 0.9244 *R-squared* and 177.691 *F-statistics* outcomes, indicating that the instrumental variables are positively correlated with the January adoption rate. The addition of four control variables shows that this trend also exist in column (4) of Table 2 (*F-statistics*=165.07, R^2=0.9420).

When I include instrumental variables in the analysis, the results are consistent with the previous results. In the instrumental variable estimations, the coefficients of the indirect network effect and spillover effect are both significant. Moreover, the coefficient of spillover effect is lower than in the OLS results. This means that the OLS specification resulted in an upward bias. A similar result is obtained for additional control variables, as only the age variable has a significant coefficient.

These findings indicate that the local direct network effect and the local spillover effect occur simultaneously in the adoption of food delivery platforms. The higher the delivery orders per unit population and the higher the previous adoption rate in a region, the more restaurants will adopt the platform. In addition, the average age of the region has a significant impact on platform adoption, but other regional variables such as population density, COVID-19 cases, and annual consumption per capita appear insignificant with regard to platform adoption.

Tables A1 and A2 in the appendix show alternative specification results for Table 2. The dependent variable in the baseline model is the new adoption rate up to August, and COVID-19 cases and the number of delivery orders are used from February to July. It is important that I verify whether or not the indirect network effect and the spillover effect are present in 2020, regardless of the variation in

[16]For a more accurate calculation, it is necessary to add COVID-19 cases for each month or use a monthly standardized value.

COVID-19. Columns (1) and (2) of Appendix Table A1 use adoption rates through March, while Columns (3) and (4) use adoption rates through December. The presence of a local indirect network effect and a spillover effect is demonstrated by the statistical significance of all coefficients for the key independent variables. Furthermore, the coefficient values increase from March to December. This is a natural result of the fact that the number of restaurants adopting the platforms increases in March, August, and December compared to the fixed adoption rate in January. Consequently, because delivery orders use a monthly average, the corresponding coefficient is expected to increase over time for the same reason.

Table A2 in the appendix shows the results when using the number of delivery platform user restaurants in January rather than the adoption rate of restaurants as a spillover effect variable. When each restaurant decides whether to adopt a food delivery platform, I believe that the number of restaurants using a platform in the region is just as important as the rate of adoption in the region. The coefficient of the alternative variable is also significant, and the more restaurants that already use a platform, the more restaurants that start using them. If the dependent variable is the number of adoptions, this alternative variable has little relevance. According to the findings, there will be an increase in the adoption rate of local restaurants from 0.0032 to 0.0128 in areas with 100 more delivery restaurants in January. In other words, when there are 100 more delivery restaurants, the result would be 0.3~1.3 *percentage points* higher for the adoption rate.

I have thus far analyzed spillover and indirect network effects without separating restaurants into distinct categories. I am interested in determining whether or not there are additional indirect network effects and spillover effects for each restaurant category. The availability of delivery services varies greatly depending on the type of food. The decision to adopt a food delivery service can be influenced by whether nearby restaurants in the same category provide such a service. Table 3 shows the adoption rate of food delivery by restaurant category. Fried chicken restaurants have the highest rate of delivery adoption in 2020, at 61.0 percent.[17] Korean food restaurants have a delivery platform adoption rate of 17.4 percent, which is significantly lower than that of fried chicken restaurants. In addition to fried chicken restaurants, other foreign food restaurants (60.6%), other food business (51.3%), and pizza (50.6%) have high delivery platform adoption rates. Because there is a significant difference in platform adoption rates, it is worthwhile to examine spillover and indirect network effects for each restaurant category, but the ratio of each restaurant category should also be considered. Table 3 also displays the market share of each restaurant category in terms of the number of restaurants, orders, and sales. Suppose a restaurant category's market share is too low, such as for other foreign food, Japanese food, and Western food. In such cases, the analysis results may be skewed. Therefore, these are excluded from the analysis.

There are two specifications. The first specification assumes that the spillover effect occurs through the adoption rate of restaurants in the *same category*. The second assumes that the spillover effect occurs via the adoption rate of *all categories* in a region. The adoption rate of each restaurant category between February and

[17]As of December, this is 64.8 percent.

TABLE 3—DESCRIPTIVE STATISTICS BY FOOD CATEGORY

(Unit: %)

Restaurant Category	Restaurant share based on the number of sales[1)]	Restaurant share based on sales[2)]	Restaurant share based on the number of restaurants[3)]	Proportion that use delivery platforms[4)]
Fried chicken	4.7	5.1	5.5	61.0
Other foreign food	0.3	0.3	0.2	60.6
Other food business	0.4	0.3	0.3	51.3
Pizza	10.4	5.9	4.2	50.6
Chinese food	4.3	4.9	3.4	34.8
Snack shop	4.8	2.7	3.5	34.5
Japanese food	1.9	3.9	2.3	32.6
Bakery	7.8	3.9	2.6	27.4
Western food	1.7	3.0	1.9	23.1
Coffee shop	14.1	5.1	6.1	19.9
Korean food	48.4	62.9	67.4	17.4
Other bar	1.1	1.9	2.6	10.9

Note: 1) Percentage of each food category in the total based on the number of card sales, 2) Percentage of each food category in the total based on sales amount, 3) Percentage of each food category in the total based on the number of restaurant companies, 4) Based on the number of card sales, the average percent of restaurants using delivery platforms is listed in descending order.

Source: Author's calculations based on Shinhan Inc. data in 2020.

August is the common dependent variable.[18] Both specifications for the indirect network effect factor use the average number of delivery orders per unit population.

The results of indirect network effects and spillover effects on Korean food, Chinese food, pizza, fried chicken, and coffee shops are shown in Tables 4 and 5.[19] Table 4 employs the adoption rate of platforms in the same category of restaurants as an independent variable, whereas Table 5 employs the adoption rate of platforms across categories. I employ instrumental variable estimation with various control variables, but I only report the coefficients of the two main variables in Tables 4 and 5.

Because half of the restaurants are Korean food restaurants, the result of Korean food is very similar to the result of Table 2, the baseline specification for all restaurant categories. The indirect network effect and spillover effect are generally positive in non-alcoholic beverage restaurants (coffee shops), the second largest category of restaurants, but when using the adoption rate of that category (January), the coefficient of the indirect network effect is not significant. The results for Chinese restaurants are the same, but the coefficients of the indirect network effect are insignificant in both specifications. The indirect network effect and the spillover effect appear to be significant for pizza restaurants. On the other hand, the spillover effect for fried chicken restaurants is not particularly significant. This could be due

[18]The denominator is the total number of restaurants in the same category, while the numerator is the number of delivery restaurants in the same category.

[19]Other restaurant categories are also analyzed, but invalid coefficients were found due to the limited number of restaurants in the same category. However, the overall sign of the factors is positive.

TABLE 4—RESULT BY RESTAURANT CATEGORY: SPILLOVER FROM THE SAME CATEGORY

Dependent variable: Adoption %	Korean food	Chinese food	Pizza	Fried chicken	Coffee Shops
Log(delivery orders)	0.0094 ***	0.1524	0.3145 ***	0.4950 ***	0.0329
	(0.0032)	(0.1046)	(0.1193)	(0.0995)	(0.0667)
Adopted % (Jan)	0.8418 ***	7.5288 ***	6.1832 **	0.3402	17.7125 ***
	(0.0804)	(1.1338)	(1.2051)	(0.8516)	(1.5155)
R-squared	0.9108	0.8037	0.7324	0.7063	0.7023
N	232	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5—RESULT BY RESTAURANT CATEGORY: SPILLOVER FROM ALL CATEGORIES

Dependent variable: Adoption %	Korean food	Chinese food	Pizza	Fried chicken	Coffee Shops
Log(delivery orders)	0.0093 ***	0.0813	0.7319 ***	0.6351 ***	0.2121 ***
	(0.0031)	(0.1182)	(0.0819)	(0.0826)	(0.0536)
Adopted % (Jan)	0.7063 ***	14.1480 ***	3.2754 **	-4.6468 ***	12.2695 ***
	(0.0629)	(2.3913)	(1.6564)	(1.6708)	(1.0841)
R-squared	0.9174	0.7745	0.7189	0.6765	0.7672
N	232	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

to the high usage of delivery services at fried chicken restaurants in January. Fried chicken restaurants accounted for 61.0% of delivery platform adoption in 2020, far exceeding the other restaurant categories. The proportion of delivery restaurants of fried chicken is 57.5% in January and 64.8% in December, an increase of 7.3% during the year.[20] Numerous restaurants have already adopted food delivery platforms, and further adoption of food delivery platforms is limited. This is a natural phenomenon, and even if there are spillover effects and indirect network effects, there will come a time when development is constrained and this influence will be reduced. As a result, the two effects are possible during the growth stage, but slow growth can also occur in other restaurant categories.

As previously stated, various specifications confirmed the existence of a local indirect network effect and a local spillover effect in adopting a food delivery platform. These findings also imply the possibility that a compounding effect will occur with regard to the adoption of food delivery platforms. As the number of consumers grows, so does the number of restaurants that use delivery platforms, which in turn influences other restaurants in the same region to adopt delivery platforms. Therefore, the importance of securing users on one side of the market for delivery platforms to grow is evident.

[20]Author's calculations based on Shinhan Inc. data in 2020

V. Conclusion

Using market-level data from the South Korean restaurant market, I discover evidence of local indirect network effects and local spillover effects in the adoption of food delivery platforms. This is found in spite of the possibility of a distorted result due to the COVID-19 pandemic. There has been little previous research on the existence of these two effects. In a two-sided market, an indirect network effect and a spillover effect can occur concurrently. The implication that two local effects had a positive impact demonstrates how essential it is for platform providers to attract customers successfully in the market for delivery platforms. As the number of customers who use food delivery platforms in the same area increases, more restaurants are likely to adopt a food delivery platform. This in turn encourages other restaurants in the same area to start using food delivery platforms. On the other hand, it is clear that the effect of COVID-19 had a significant impact on the development of demand in the year 2020. This is in addition to the marketing effect that the providers of food delivery platforms had.

These findings have several implications. From the perspective of a platform provider, it is possible to promote the subscription (adoption) of consumers and restaurants in a short period of time by investing heavily in areas with younger age groups during the beginning phases. Furthermore, continuing to promote these platforms in areas with a low adoption rate is optimal for expanding both markets and eventually returning a high benefit. According to this study, aggressive marketing by platform providers, such as distributing discount coupons, is the best strategy.

This study focuses on the market level and therefore mostly shows the benefits gained by food delivery platform providers. Further studies at the restaurant level would provide insight into the mechanisms that lead to restaurants adopting, maintaining and quitting the use of food delivery platforms.

APPENDIX

TABLE A1—ROBUSTNESS RESULT (PERIOD)

Dependent variable: **Adoption % (Feb-Mar)** or **Adoption % (Feb-Dec)**	IV **March** (1)	IV **March** (2)	IV **December** (3)	IV **December** (4)
Adopted% in Jan	0.1904 ***	0.1961 ***	0.5984 ***	0.4984 ***
	(0.0142)	(0.0200)	(0.0566)	(0.0657)
Log (delivery orders)	0.0021 ***	0.0013	0.0301 ***	0.0203 ***
	(0.0008)	(0.0009)	(0.0032)	(0.0033)
Log (consumption)		0.0047		0.0249
		(0.0085)		(0.0361)
Age		-0.0004 *		-0.0038 ***
		(0.0002)		(0.0010)
Population Density		-0.0025 *		0.0177 ***
		(0.0014)		(0.0062)
Avg. COVID-19 Cases		0.0007 ***		-0.0019 *
		(0.0002)		(0.0010)
Constant	-0.0009	-0.0237	-0.0486 ***	-0.0600
	(0.0023)	(0.0843)	(0.0109)	(0.3604)
R-square	0.8714	0.8861	0.8944	0.9041
N	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, 3) The variable delivery orders is the average monthly delivery orders per 1,000 people in the region, 4) The variable Avg. COVID-19 Cases is the number of COVID-19 cases per 1,000 people in the region.

TABLE A2—ROBUSTNESS RESULT (N OF DELIVERY RESTAURANTS)

Dependent variable: Adoption % (Feb-Aug)	OLS (1)	OLS (2)	IV (3)	IV (4)
N of Delivery Restaurants/100	0.0045 ***	0.0032 ***	0.0089 ***	0.0128 ***
	(0.0005)	(0.0006)	(0.0013)	(0.0027)
Log (delivery orders)	0.0262 ***	0.0172 ***	0.0159 ***	0.0131 ***
	(0.0017)	(0.0024)	(0.0033)	(0.0036)
Log (consumption)		-0.0400		-0.0629
		(0.0287)		(0.0428)
Age		-0.0039 ***		0.0012
		(0.0008)		(0.0018)
Population Density		0.0155 ***		-0.0040
		(0.0048)		(0.0087)
Avg. COVID-19 Cases		0.0014		0.0028 *
		(0.0010)		(0.0016)
Constant	-0.0398 ***	0.5707 **	-0.0101	0.5439
	(0.0071)	(0.2843)	(0.0112)	(0.4199)
R-square	0.8218	0.8422	0.7650	0.6451
N	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, 3) The variable delivery orders is the average monthly delivery orders per 1,000 people in the region, 4) The variable Avg. COVID-19 Cases is the number of COVID-19 cases per 1,000 people in the region.

TABLE A3—ROBUSTNESS RESULT (ADOPTED% (AUG) AS A DEPENDENT VARIABLE)

Dependent variable: **Adopted% (August)**	OLS (1)	OLS (2)	IV (3)	IV (4)
Adopted% (Jan)	1.181 ***	1.172 ***	1.138 ***	1.136 ***
	(0.018)	(0.021)	(0.021)	(0.025)
Log (delivery orders)	0.008 ***	0.006 ***	0.010 ***	0.006 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (consumption)		0.003		-0.001
		(0.013)		(0.013)
Age		-0.001 ***		-0.001 ***
		(0.000)		(0.000)
Population Density		-0.003		-0.001
		(0.002)		(0.002)
Avg. COVID-19 Cases		-0.061		-0.010
		(0.103)		(0.104)
Constant	-0.008 *	0.032	-0.012 ***	0.081
	(0.003)	(0.128)	(0.004)	(0.129)
R-square	0.989	0.990	0.989	0.990
N	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, 3) The variable delivery orders is the average monthly delivery orders per 1,000 people in the region, 4) The variable Avg. COVID-19 Cases is the number of COVID-19 cases per 1,000 people in the region.

TABLE A4—ROBUSTNESS RESULT (WITHIN COVID-19: ADOPTED% (FEB))

Dependent variable: Adoption % **(Mar-Aug)**	OLS (1)	OLS (2)	IV (3)	IV (4)
Adopted% (Feb)	0.542 ***	0.512 ***	0.456 ***	0.427 ***
	(0.024)	(0.029)	(0.030)	(0.036)
Log (delivery orders)	0.007 ***	0.005 **	0.012 ***	0.007 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Log (consumption)		0.026		0.016
		(0.019)		(0.020)
Age		-0.001 *		-0.002 ***
		(0.001)		(0.001)
Population Density		-0.000		0.004
		(0.003)		(0.003)
Avg. COVID-19 Cases		0.077		0.216
		(0.157)		(0.161)
Constant	-0.004	-0.178	-0.014 **	-0.047
	(0.005)	(0.195)	(0.005)	(0.198)
R-square	0.926	0.929	0.922	0.926
N	232	232	232	232

Note: 1) Numbers in parentheses are standard errors, 2) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, 3) The variable delivery orders is the average monthly delivery orders per 1,000 people in the region, 4) The variable Avg. COVID-19 Cases is the number of COVID-19 cases per 1,000 people in the region.

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