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Who Benefits from Food Delivery Platforms? The Heterogeneous Effects of Platforms on Restaurant Sales*

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Abstract

We quantify the heterogeneous impact of food delivery platforms on sales amounts at the restaurant level, using novel credit card transaction data from 2020 that cover the entire universe of Korean restaurants during the COVID-19 pandemic. Our instrumental-variable regression demonstrates the use of platforms increases a restaurant's monthly sales revenue by approximately 1,545 USD. Furthermore, we demonstrate the impact is particularly large on small restaurants. The bottom-decile restaurants experience a 97.6% increase in total sales revenue from platforms. Our findings show that small firms—not just 'superstar' firms—can be the main beneficiaries of technological advancements, depending on industry characteristics.

Keywords: food delivery platforms; online shopping; food delivery; COVID-19
JEL Codes: L81, L83, L10

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1 Introduction

The proliferation of online platforms has provided customers with a convenient and flexible means of purchasing goods and services without needing to physically visit brick-and-mortar stores, offering greater convenience and flexibility. Food delivery platforms are no exception to this trend. In the US, the delivery market has experienced significant growth, doubling from 2018 to 2019 and more than doubling during the COVID-19 pandemic (Ahuja et al., 2021). However, the impact of this shift on the performance of firms has yet to be fully understood and requires empirical investigation. Specifically, determining the extent to which a firm's sales revenue changes when adopting food delivery platforms, compared with relying solely on non-platform sales, is an empirical question that may vary depending on the firm's characteristics. The answer to this question would be of interest to a range of audiences, including business owners considering adopting online platforms and policymakers concerned about market and welfare implications.

We quantify the influence of online platforms on the total sales of restaurants in the Korean restaurant industry during the COVID-19 pandemic, where consumers have multiple options for ordering food: platform orders, and non-platform options such as on-premises dining. The key challenge in establishing the true influence of food delivery platforms is distinguishing the true influence from restaurant- and regional-level heterogeneity. Endogeneity may arise if platform adoption is correlated with factors specific to the restaurant, region, or time period. To address potential endogeneity issues, we employ an instrumental-variable regression with a rich set of fixed effects. We leverage novel credit card transaction data that cover the entire universe of South Korean restaurants in 2020 and control for both restaurant- and regional-level time-varying fixed effects using restaurant-level and regional-time-level variations. We also utilize an instrumental variable to account for potential restaurant-level time-varying heterogeneity. Our panel-data structure allows us to use the lagged food-delivery-platform indicator as an instrument for the food-delivery-platform indicator. This instrument is relevant because the cost of continuing to use the platforms is lower than the cost of adopting them, which usually involves fixed adoption costs. We consider this instrument exogenous: after controlling for both restaurant and county-food type-month fixed effects, the residual shocks may not be highly serially correlated. We show our main results remain robust when using an alternative instrument—the lagged proportion of competitors adopting platforms—and when estimating Callaway and Sant'Anna (2021)'s dynamic difference-in-differences model.

We demonstrate that online food delivery platforms have a substantially positive impact on restaurants' total sales, particularly small restaurants and Chinese restaurants. We find using food delivery platforms increases a restaurant's monthly sales revenue by 1,931,556 KRW (approximately 1,545 USD). In the absence of COVID-19 cases, the effect would be 1,665,237 KRW (approx. 1,332 USD). Furthermore, we show the bottom-decile restaurants tend to benefit more from using food delivery platforms in terms of log sales, with a 97.6% increase in total sales revenue, where deciles are measured by the total sales in January 2020. This effect is approximately 11 times greater than the effect on the top-decile restaurants and three times greater than that on median restaurants. The limited variation in the effect in terms of raw total sales explains why small restaurants experience large percentage increases in sales, given their smaller sizes. We also demonstrate that the impact of food delivery platforms is most substantial in Chinese restaurants, with a monthly sales increase of 5,211,786 KRW (approx. 4,169 USD). This finding could be attributed to the fact that Chinese restaurants typically serve food that is well suited for delivery, but they had lower levels of food-delivery-platform adoption. Nevertheless, interpretations of these outcomes should be made with caution. Our analysis is limited to the data from 2020, a period significantly impacted by the COVID-19 pandemic. To draw more definitive conclusions, it would be beneficial to have a dataset that spans a broader time frame.

Our paper is the first to quantify the heterogeneous influence of food delivery platforms on restaurant-level sales, using restaurant-level transaction data that cover the entire universe of restaurants in a country during the COVID-19 pandemic. Our extensive restaurant-level data allow us to identify the restaurant-level heterogeneous impact of food delivery platforms. Previous literature, often limited to data from a single firm or aggregated at the market level, has assessed the impact of introducing an online shopping channel, but has not identified potentially heterogeneous effects by firm characteristics due to data limitations. We, however, leverage detailed restaurant-level transaction data to identify heterogeneous impacts of platform use by restaurant characteristics, such as restaurant size and the type of food served. Our findings show that small firms—not just 'superstar' firms—can be the main beneficiaries of technological advancements, depending on industry characteristics. To the best of our knowledge, this distributional influence of platforms on market outcomes has not been analyzed before.

We contribute to the extant literature on the relationship between online and offline shopping (Goolsbee, 2001; Gentzkow, 2007; Prince, 2007; Brynjolfsson et al., 2009; Forman et al., 2009; Avery et al., 2012; Pozzi, 2013; Duch-Brown et al., 2017; Wang and Goldfarb, 2017; Collison, 2020; Li and Wang, 2020; Relihan, 2022; Shriver and Bollinger, 2022) and the impact of the COVID-19 pandemic on restaurant performance (Lee and Chun, 2022; Sedov, 2022; Raj et al., 2023). Pozzi (2013) uses data from a single retail chain in the supermarket industry and demonstrates limited cannibalization and an increase in total sales following the introduction of an online shopping service. Collison (2020) estimates market-level influences of food delivery platforms on sales using market-level data. Li and Wang (2020) use mobile-device location tracking data to estimate the effect of platforms on restaurant visits. Lee and Chun (2022) use data from the same provider as ours to estimate the differential impact of the pandemic on restaurants that utilized food delivery platforms compared with those that did not. Raj et al. (2023) use order-level data from a food delivery platform, Uber Eats, to investigate the impact of the pandemic on the number of platform orders.

The rest of the paper is organized as follows. Section 2 reviews the restaurant industry and food delivery platforms in Korea. Section 3 introduces the data. Section 4 describes the regression model and results. Section 5 provides discussions on our empirical results, and section 6 concludes.

2 Restaurant Industry and Food Delivery Platforms[1]

Restaurants vary in terms of their offerings, including on-premises dining, food delivery, and take-out services. Korean restaurants, which primarily serve Korean food, heavily rely on on-premises dining, accounting for 88.4% of their total sales in 2020. On the other hand, other types of restaurants have much lower proportions of on-premises dining, with 55.4% for Chinese restaurants, 21.5% for pizza, hamburger, and sandwich restaurants, and 25.6% for chicken restaurants. Korean and Chinese restaurants are generally less likely to use independent delivery service providers, with only 11.3% of Korean and 23.2% of Chinese restaurants utilizing them. By contrast, 61.8% of pizza, hamburger, and sandwich restaurants and 61.6% of chicken restaurants use such providers (Lee et al., 2021). This finding suggests that although Chinese restaurants typically serve food that is well suited for delivery, they prefer to handle delivery in-house instead of using third-party independent delivery providers. Note Chinese restaurants are unique in that until the 1970s, they were the only international food restaurants that delivered food. They typically serve Korean-Chinese cuisine, such as *Jajangmyeon* and *Jjamppong* (Yang, 2005).

The food-delivery-platform markets in the US and other countries are largely dominated by a few major players. South Korea, however, has one dominant platform, *Baemin,* although more than 20 food delivery platforms are currently operating in the country. As of December 2020, *Baemin* held a market share of 84.6%, with Yogiyo coming in second with a market share of 14.0% (Wise App Retailer, 2021).

The major players in the food-delivery-platform market include platform companies, participating restaurants, delivery drivers, and consumers. The dominant business model in this market is the "marketplace model," which accounted for 96.5% of all *Baemin* orders as of August 2020 (Baemin, 2020). Under this model, the platform acts as an intermediary between the restaurant, rider, and consumer. Once a consumer places a food delivery order, the platform notifies the restaurant. If the order is accepted, a delivery driver is assigned for delivery. This driver may be employed directly by the restaurant or provided by independent delivery service providers.[2] By contrast, the "own delivery model" involves platforms directly hiring drivers and providing delivery services. In this model, the platform handles the entire delivery process, from receiving the order to delivering the food to the customer.

The costs associated with using food delivery platforms consist of delivery costs and platform fees. Delivery costs are paid to the delivery driver and usually range from 2,000 to 4,000 KRW (approximately 1.6 to 3.2 USD), with an average delivery cost of 3,556 KRW (approx. 2.8 USD). Only 4.4% of the restaurants report their delivery costs exceed 5,000 KRW (approx. 4 USD) (Lee et al., 2021). The cost is usually shared between restaurants and consumers. Each restaurant

[1] A more extensive discussion can be found in Lee (2021).

[2] As of 2021, three major independent delivery service providers were present: Barogo, Logiall (also known as "Saenggakdaero"), and Vroong.

can determine its portion of the delivery cost, with the consumer paying the remaining amount. Normally, the consumer pays more than half of the delivery cost, although some restaurants may ask consumers to pay the entire amount. Furthermore, the platform operator charges platform fees. In 2020, *Baemin,* which holds a dominant position in the food-delivery-platform market, charged the majority of the restaurants a fixed monthly fee of 80,000 KRW (approx. 64 USD) per listing (Baemin, 2020).[3]

The preferred method for ordering food delivery varies among different age groups. Younger populations are more accustomed to food delivery platforms, with the percentage of people using these platforms as their primary method of ordering food ranging from 49.8% among those in their 20s to 25.5% among those in their 40s. However, only 11.2% of those in their 50s answered food delivery platforms as their primary method of ordering food, and none of those aged 70 or older did so (Lee et al., 2020).

3 Data

We study the impact of food delivery platforms on the total sales of restaurants, as well as the potential heterogeneity in this impact. We use the total sales as the primary dependent variable to evaluate the sales performance of the restaurants. To explore potential heterogeneity in the effect, we examine whether the impact of platforms varies depending on observable characteristics of a restaurant and its location. For the analysis, we combine restaurant-level credit card transaction data with location-characteristics data.[4]

We use credit card transaction data provided by Shinhan Card, which is the largest credit card company in South Korea, with a 21% market share in 2020 (Financial Supervisory Service, 2022). The data include all credit card transactions made at Korean restaurants through the credit card company in 2020. Data are weighted to represent national credit card usage accurately, including transactions from other issuers.[5] Note that cash payments constitute a modest share of overall transactions, accounting for approximately 8% of delivery transactions in 2020, and 16.4% and 15.6% of all offline transactions in restaurants and cafes in 2019 and 2021 (Bank of Korea, 2020, 2022; Barogo, 2022). For each restaurant, we observe a unique restaurant identifier, total and platform prepaid

[3]A restaurant has the option to purchase multiple listings and would be listed multiple times accordingly. It may also choose to pay a fixed proportion (6.8%) of the total sales. However, the latter option is only suitable for small restaurants, because it becomes unprofitable for the restaurant if its total sales exceed approximately 1.2M KRW ($\approx 80,000/6.8\%$ or 940 USD).

[4]Additionally, we conduct a supplementary analysis where we use net sales as the dependent variable. This variable deducts the primary variable costs associated with using food delivery platforms, enabling us to assess the extent to which a restaurant benefits from using these platforms. The derivation of this variable can be found in Appendix Section A.

[5]Shinhan Card provides a product line for all customer segments, from luxury to basic credit cards, and thus, no systematic selection in expenditures is evident. Expenditures using Shinhan Card each month correlate highly with total credit transactions across all credit cards and the retail sales index; the correlation coefficients are 0.97 and 0.92, respectively.

sales, and the number of total and platform prepaid orders per month, respectively.[6] Detailed information on a restaurant, including county-level location (*si-gun-gu* in Korea) and Korean standard industry classification (KSIC) code indicating the main type of food served (11 types), is also provided. Certain types of restaurants, such as cafeterias, catering services, and drinking places, are excluded from the analysis.

We consider three location-level characteristics: the number of COVID-19 cases per 100,000 people, the proportion of high-income individuals, and the proportion of the population aged 20-49. To calculate per-capita COVID-19 cases, we divide the province-month-level COVID-19 cases by the province population as of 2020 (Statistics Korea, 2020; Ministry of Health and Welfare, 2021). To determine the percentage of high-income individuals, we use the proportion of individuals in the county who did not receive the COVID-19 subsidy in 2021: the South Korean government only offered the subsidy to individuals who did not meet the income threshold. As such, 14.0% of the household did not receive the subsidy (Ministry of the Interior and Safety, 2021). Table 1 reports summary statistics.

Table 2 shows the number of restaurants, the average total sales, and the proportion of food-delivery-platform usage for 11 types of food served based on the KSIC. In addition, we also provide four categories for further analysis in section 4: Korean food, fast food, Chinese food, and other. In this paper, "fast food" refers to the restaurants that serve pizza, hamburgers, sandwiches, and chicken. As of January 2020, fast food restaurants showed high proportions of food-delivery-platform usage, ranging from 46.1% (pizza, hamburgers, sandwiches) to 57.0% (chicken). By contrast, Chinese food restaurants had low platform usage at 28.2%. Notably, both fast food and Chinese food restaurants were highly likely to have remained in business in 2020, at 80.6% (fast food) and 79.3% (Chinese food), respectively. In December 2020, all restaurant types demonstrated an approximate 10 percentage point increase in platform adoption compared to January 2020. However, most experienced a decrease in average sales. Appendix Figure A.5 illustrates the trend of average total sales and the percentage of food-delivery-platform usage over time, indicating a steady increase in the percentage of food-delivery-platform usage over time.

Figure 1 shows summary statistics by restaurant size as of January 2020, highlighting substantial variations not only in total sales but also in platform utilization and survival rates. Restaurant size is determined by their total sales in January 2020. The bottom-decile restaurants had average total sales of 321,545 KRW (approximately 257 USD) in January 2020. By contrast, the top-decile restaurants had average total sales of 53,506,135 KRW (approximately 42,805 USD), which is over 160 times higher than the average for the smallest restaurants. Figure 1 also indicates a positive association between average total sales and the proportion of restaurants using food delivery platforms. It also shows the proportion of the restaurants that maintained their business in 2020.

[6] Platform prepaid sales and orders are those processed through *Baemin* and *Yogiyo,* the two leading online delivery platforms in South Korea, which together accounted for 98.6% of the market share as of December 2020 (Wise App Retailer, 2021).

Table 1: Summary statistics

Panel A: Restaurant-level data

	Mean	Std.Dev.
Total sales	10,578.758	17,194.409
Net sales	10,387.459	17,051.482
Using platforms	0.234	0.423
Observations	7,626,223	
Number of restaurants	802,012	

Panel B: County-level data

	Mean	Std.Dev.
COVID-19 cases per 100,000 people	7.701	17.282
% of high-income individuals	0.129	0.080
% of populations aged 20-49	0.385	0.077
Observations	3,000	
Number of counties	250	

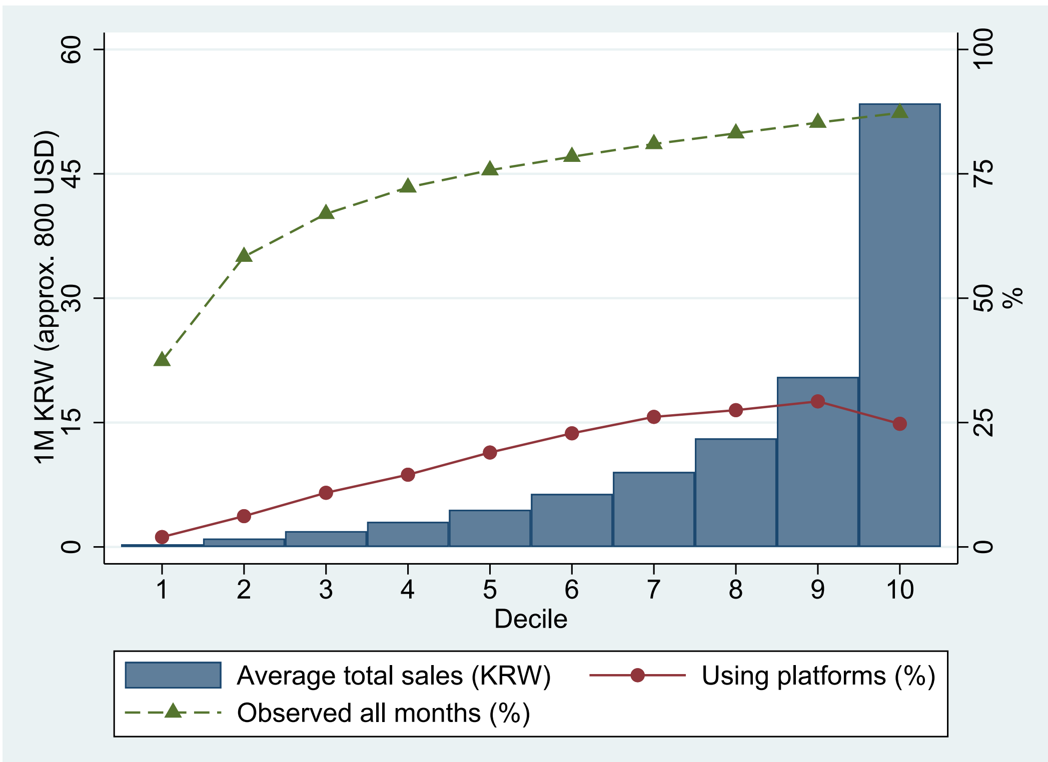
Notes: Panel A and Panel B use restaurant-month and county-month as their units of observation, respectively. In Panel A, sales were measured in 1,000 KRW (approximately 0.8 USD). “Net sales” refer to the total sales after deducting estimated delivery costs, which are the primary variable costs associated with using food delivery platforms; see Appendix Section A for derivation. “Using platforms” stands for the proportion of restaurant-months with positive platform sales. Total sales and orders are winsorized at the top 0.1% level by month. In Panel B, “COVID-19 cases per 100,000 people” are the cases in the province in which the county is located. "% of high-income individuals" represents the proportion of individuals in the county who did not meet the income threshold and therefore did not receive the COVID-19 subsidy in 2021.

Table 2: Summary statistics, by the main type of food served

	January 2020					Increases from Jan to Dec 2020	
	Observations, #	Observations, %	Average total sales, 1K KRW	Using platforms, %	Observed all months, %	Average total sales, 1K KRW	Using platforms, %p
A. Korean food	441,835	0.700	10,746.342	0.127	0.699	–3,145.026	0.095
B. Fast food	61,047	0.097	11,960.118	0.523	0.806	–812.454	0.067
Pizza, hamburgers, sandwiches	26,141	0.041	14,699.920	0.461	0.807	–847.658	0.063
Chicken	34,906	0.055	9,908.289	0.570	0.806	–878.625	0.073
C. Chinese food	22,267	0.035	16,074.693	0.282	0.793	–1,644.820	0.108
D. Other	106,507	0.169	12,423.175	0.202	0.778	–2,444.503	0.130
Japanese food	14,949	0.024	18,827.259	0.246	0.758	–3,206.904	0.154
Western-style food	12,618	0.020	18,491.361	0.166	0.676	–6,349.730	0.134
Other international food	1,298	0.002	19,624.138	0.518	0.761	–5,339.607	0.146
Confectionery stores	16,666	0.026	15,644.130	0.205	0.808	2,091.058	0.114
Snack food ("bunsik")	22,194	0.035	8,371.181	0.283	0.825	–782.184	0.105
Non-alcoholic beverages	36,905	0.058	8,592.456	0.125	0.777	–3,436.568	0.140
Other	1,877	0.003	10,277.393	0.382	0.805	4,609.974	0.217
Total	631,656	1.000	11,334.223	0.183	0.726	–2,694.824	0.103

Notes: The unit of observation is a restaurant-month. Total sales were measured in 1,000 KRW (approximately 0.8 USD). "Using platforms" stands for the proportion of restaurant-months with positive online sales. "Observed all months?" indicates restaurants observed across all months in the sample period.

Figure 1: Percentages of platform usage and those observed all months, by decile



Notes: The unit of observation is a restaurant-month observed in January 2020. "Decile" categorizes a restaurant's total sales in January 2020 into deciles. Average total sales were measured in 1,000,000 KRW (approximately 800 USD). "Using platforms (%)" stands for the proportion of restaurant-months with positive online sales. "Observed all months (%)" indicates the proportion of restaurant-months observed across all months in the sample period.

Only 37.4% of the bottom-decile restaurants managed to remain open in 2020, while 87.3% of the top-decile restaurants continued their business throughout the year. They suggest that adopting food delivery platforms could potentially increase both total sales and the probability of survival. Appendix Figure A.6 presents size-specific summary statistics for December 2020.

4 Results

4.1 Regression model

We use the following empirical model to investigate the relationship between food delivery platforms and sales:

$$y_{it} = \beta_1 \text{Platforms}_{it} + \beta_2^{'} x_{it} \times \text{Platforms}_{it} + \alpha_i + \gamma_{j(i),k(i),t} + \varepsilon_{it}, \tag{1}$$

where Platforms_{it} is an indicator variable that equals 1 when restaurant i has positive platform sales during month t. α_i and γ_{jkt} are restaurant and county-type-month fixed effects, respectively, where $j(i)$ is the county in which restaurant i is located and $k(i)$ maps restaurant i to the main type of food served. When x_{it}, the observable characteristics of a restaurant i are not controlled for, β_1 measures the effect of food delivery platforms on the restaurant's total sales revenue. When $x_{it} \times \text{Platforms}_{it}$ is also included, $\beta_1 + x_{it}^{'}\beta_2$ captures the heterogeneous effects of platforms. Our primary dependent variable y_{it} is the total sales revenue across the platform and other channels.

We note that the effect of platform adoption includes both direct influences—stemming from the adoption of platforms—and indirect effects that result from subsequent changes within a firm. A direct effect can be seen when a restaurant adopts a platform without altering any other aspect of its business structure. Indirect effects may arise if the restaurant finds it profitable to modify its operations, such as tailoring its food offerings to be more delivery-friendly. Upon the adoption of platforms, its profit-maximizing choices might also change. Therefore, the total impact of platform adoption may be considered inclusive of these indirect influences.

We use instrumental-variable regression to address potential endogeneity issues in identifying our key parameter β_1, which represents the average influence of food delivery platforms on sales. Endogeneity can arise if a restaurant's decision to adopt food delivery platforms is correlated with other restaurant-level time-varying unobserved factors affecting sales revenue. For example, if a restaurant experiences a negative shock to sales during a month and decides to adopt food delivery platforms to alleviate the situation, the coefficient of the delivery-platform variable could be biased downwards, because the variable and error term would be negatively correlated.

To address this issue, we consider two instruments. First, we use the lagged food-delivery-platform indicator, $\text{Platform}_{i,t-1}$, as an instrument. The instrument is relevant because a restaurant that has already adopted the platform is more likely to continue using it than those who have never used it; the cost of continuing to use the platforms is lower than the cost of adopting them, which usually involves fixed adoption costs. The exogeneity of the instrument would hold if error terms are not serially correlated; this necessitates that the error term, which might influence a restaurant's decision to adopt the platform, to be independent over time. The exogeneity assumption could be compromised if a restaurant, having suffered a negative shock at the restaurant-month level ε_{it}, adopted platforms to mitigate such revenue losses and yet suffers a subsequent negative shock $\varepsilon_{i,t+1}$ due to possible serial correlation in the error term. However, this assumption is unlikely to be overly strong because the error term of regression equation (1) only represents residual restaurant-level time-varying shocks after controlling for both restaurant fixed effects α_i and county-type-month fixed effects γ_{jkt}.[7]

For robustness checks, we employ an additional instrumental variable: the lagged proportion of competitors adopting platforms. This leave-one-out variable calculates the proportion of competitors using platforms within the same county-type in the previous month, excluding the adoption status of the corresponding restaurant. The relevance of this instrument hinges on whether a restaurant's decision to adopt platforms is influenced by its rivals' adoption decisions. The instrument is considered exogenous if it is uncorrelated with the error term ε_{it}, which represents restaurant-month-specific non-platform sales. The exogeneity assumption is valid if non-platform sales of a restaurant and platform sales of competitors are not closely substitutable. If they are close substitutes, a competitor's decision to adopt the platform could increase its sales and simultaneously decrease the non-platform sales of the corresponding restaurant, represented by a negative shock in ε_{it}. Although this assumption cannot be directly tested, it appears plausible given that it is unlikely for a substantial number of consumers to frequently switch between placing platform orders at one restaurant and choosing non-platform on-premises dining at another.

In the following subsection, we present robustness check results when each instrument is used in isolation. When including $x_{it} \times \text{Platforms}_{it}$, $x_{i,t-1} \times \text{z}_{it}$, where z_{it} denotes the instruments under consideration, are also employed as additional instruments.

Additionally, in our preferred specification discussed below, we consider the subset of the restaurants observed across all months in the sample period to account for the potential sample selection bias resulting from restaurant entry or exit. The exogeneity assumption may also be challenged if a restaurant's decision to enter or exit is correlated with unobserved factors that also affect total sales revenue. If a restaurant remained in business regardless of its revenue, or if the decision to remain in business were made randomly, we would then obtain an unbiased estimate of the effect of platforms from the full dataset. However, the restaurants with lower sales revenue are more likely to exit the market due to low profits, resulting in non-random attrition; the restaurant-months with higher sales revenues are more likely to be observed. Therefore, we limit our analysis to restaurants that were continuously observed throughout the entire sample period.

For additional robustness checks, we employ the dynamic difference-in-differences model by Call-

[7] Robustness-check results in Panel B of Appendix Table A.7 show our main results remain robust when we use longer lags as instruments. This finding implies the instrument exogeneity assumption, which posits no serial correlation in the error term, is valid. If there were bias in the instrumental variable estimates, using longer lags would likely lead to reduced bias since their correlation with the error term would decrease.

away and Sant'Anna (2021). This model accounts for treatment effect heterogeneity and dynamics by allowing for variations in treatment effects by the timing of treatment and over different time periods. Its principal advantage lies in its accurate event-study design, which allows for analysis of both immediate and prolonged increases in total sales following platform adoption. We exploit the differential timing of adoption as a source of variation.[8] Restaurants that have discontinued platform use at any time, or those not observed across all months in the sample period, are excluded from the analysis.

4.2 Effect of food delivery platforms on total sales

Table 3 reports restaurant-level regressions of total sales on the use of food delivery platforms. We find the adoption of online food delivery platforms leads to an increase in total sales revenue. Column (1) reports the ordinary least-squares (OLS) result, which suggests a positive correlation between food delivery platforms and total sales. The result indicates the total sales appear to increase by 4,688,362 KRW (approximately 3,751 USD) after adopting food delivery platforms.

The panel-data structure allows us to control for both restaurant-level time-invariant fixed effects and county-food type-level time-varying fixed effects. In column (2), we report a moderate effect of food delivery platforms on total sales revenue. The within-restaurant effect of food delivery platforms on total sales is 1,261,059 KRW (approx. 1,009 USD), which is substantially smaller than the OLS estimate.

Column (3) reports the instrumental-variable regression results using the lagged food-delivery-platform indicator as an instrument, indicating the use of food delivery platforms increases total sales revenue by 2,479,685 KRW (approx. 1,984 USD). Consistent with our intuition, the regression coefficient is estimated to be larger than that without an instrument, indicating the fixed-effects regression results in column (2) are downward biased.[9]

The exogeneity assumption may be challenged if a restaurant's decision to enter or exit is correlated with unobserved factors that also affect total sales revenue. To account for potential sample-selection issues, we limit our analysis to restaurants that were continuously observed throughout the entire sample period. In column (4), which is our preferred specification that uses instrumental-variable regression on these restaurants, the estimated effect on total sales is smaller than in column (3). We find the adoption of food delivery platforms is estimated to increase total sales revenue by 1,931,556 KRW (approx. 1,545 USD).[10]

[8] Appendix Figure A.5 indicates a steady increase in the percentage of food-delivery-platform usage over time.

[9] To use the lagged food-delivery-platform indicator as an instrument, a restaurant-month must be observed for at least two consecutive months. This fact explains why column (3) of Table 3 has fewer observations than column (2). The fixed-effects model that uses the same set of observations as column (3) still produces downward-biased estimates. Robustness-check results are available on request.

[10] This finding may be attributed to the potential variation in time-varying market-level shocks, which could also depend on the size of the restaurant. Columns (3) and (4) of Appendix Table A.5, which include county-type-month-size fixed effects instead of county-type-month fixed effects, indicate the estimates are similar to the estimate in column (4) of Table 3, as well as those in Panel B of Appendix Table A.5, which exclude top-decile restaurants. Moreover,

Table 3: The effect of food delivery platforms on total sales

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Platforms}_{\text{t}}$	4,688.362***	1,261.059***	2,479.685***	1,931.556***	2,278.262***	1,932.241***
	(40.395)	(15.598)	(35.587)	(41.076)	(117.960)	(41.051)
Restaurant FE		X	X	X	X	X
County-type-month FE		X	X	X	X	X
IV regression?			X	X	X	X
Observed all months?				X	X	X
First stage						
$\text{Platforms}_{\text{t-1}}$			0.440***	0.461***		0.460***
			(0.001)	(0.001)		(0.001)
$\text{Comp\_platforms}_{\text{t-1}}$					–6.016***	–0.200***
					(0.351)	(0.053)
Observations	7,626,223	7,626,223	6,708,671	5,042,796	5,042,195	5,042,195

Notes: The dependent variable is total sales, measured in 1,000 KRW (approximately 0.8 USD). The unit of observation is a restaurant-month. "(t-1)" represents the lagged variable. "Type" represents the Korean Standard Industry Classification (KSIC) codes that indicate the main types of food served in the restaurant. "Observed all months?" indicates restaurants observed across all months in the sample period. Columns with the first-stage regression results indicate the first-stage regression results, where "Platforms" is the dependent variable of the regression and its lagged variable and the lagged proportion of competitors adopting platforms, $\text{Comp\_platforms}_{\text{t-1}}$, are used as instruments. Standard errors in parentheses are clustered at the restaurant level. Significance levels are *5%, **1%, and ***0.1%.

Column (5) presents the results of an instrumental-variable regression using the lagged proportion of competitors adopting platforms as an instrument. It indicates a more substantial impact of platforms than column (4), with an increase in total sales by 2,278,262 KRW (approx. 1,823 USD). We note that two different instruments, each hinging on a completely different instrument assumption, lead to the same sign and similar magnitude. We consider this to be suggestive evidence of the validity of our instruments. Column (6) reports the two-stage least-squares (2SLS) regression results, utilizing both aforementioned instruments, yielding an estimated effect of 1,932,241 KRW (approx. 1,546 USD), which aligns closely with the estimate from column (4).

In Appendix Table A.6, we also consider net sales as a dependent variable. It is obtained by subtracting delivery costs, which are the primary expenses incurred by the restaurant when using food delivery platforms, from the total sales revenue. This dependent variable serves as a more conservative measure, because it accounts for the possibility that the total sales may increase while the sales amount net of delivery costs may remain unchanged. This scenario may arise if all consumers merely switch from other options, such as on-premises dining and takeout orders, to platform-delivery orders from the same restaurant. Appendix Table A.6 shows using food delivery platforms leads to a considerable increase in a restaurant's net sales revenue. In column (4), which is our preferred specification using instrumental-variable regression on the restaurants observed throughout the entire period, the estimated effect on net sales is 1,448,104 KRW (approx. 1,158 USD). The results suggest restaurants are highly likely to benefit from adopting food delivery platforms.

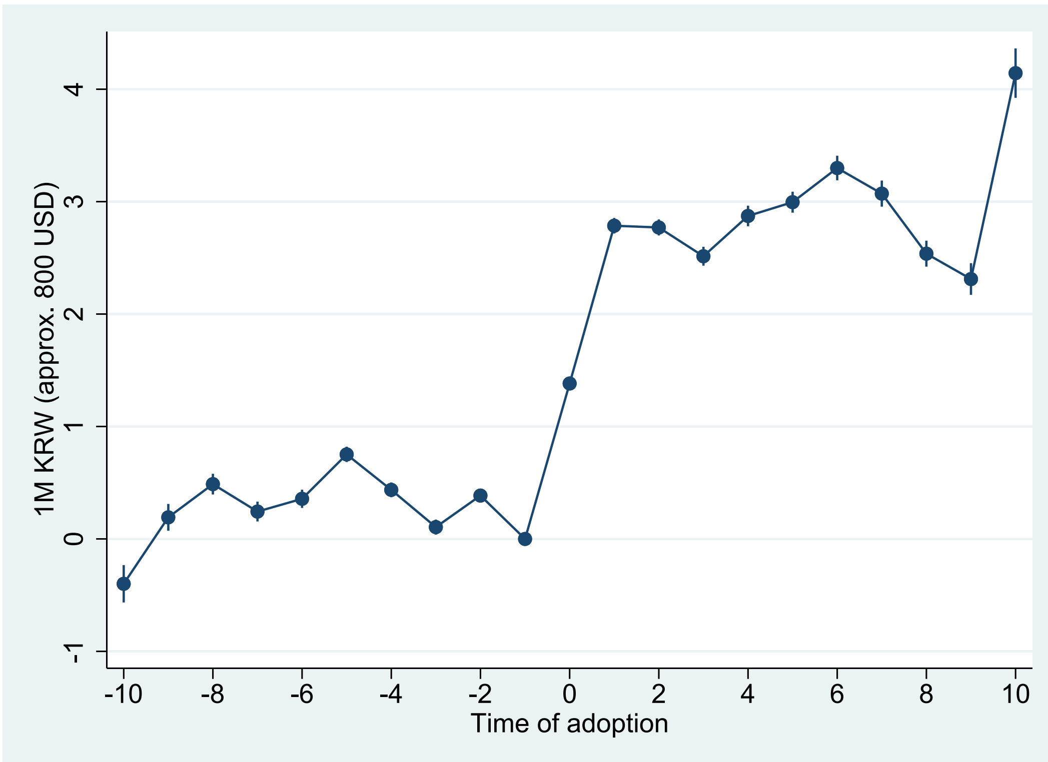
Figure 2 displays the dynamic effect of food delivery platforms on total sales, utilizing Callaway and Sant'Anna (2021)'s dynamic difference-in-differences model, where county-type fixed effects are included as covariates. The estimates reveal the dynamic effects following adoption, with moderate fluctuations observed from the first to the ninth month. The effect at the tenth month, however, appears to be as an outlier.[11] Notably, the average treatment effect, which is statistically significant at the 1% level, is 2,036,420 KRW (approx. 1,629 USD), which aligns closely with the preferred estimate of 1,931,556 KRW (approximately 1,545 USD) in column (4) of Table 3. It indicates that our instrumental variable estimate remains robust when considering potential dynamic effects.

Several remarks are in order regarding our results. First, our estimates are based on Korean data in 2020, which differs from other studies in terms of the country and time period. Specifically, the COVID-19 pandemic may have affected our results. We note that fully separating the effects of the platforms from the pandemic's is notably challenging. However, Panel A of Appendix Table A.7 suggests the impact of food delivery platforms does not differ substantially at least within the duration of our sample. Notably, the estimated effects are even more similar to each other, after

the estimates become robust to the exclusion of restaurants that were not observed in all time periods. The models in Appendix Table A.5 account for potential variations in county-type-month shocks across different restaurant sizes, which are likely relevant because the dependent variable, raw total sales, exhibits substantial variations and has a right-skewed distribution (see Figure 1).

[11]Note that the effects at the tenth month before and after adoption are based exclusively from restaurants that adopted platforms in February 2020 and December 2020, respectively. Gathering data over a longer period could provide a more accurate assessment of the dynamic effects of platform adoption.

Figure 2: The dynamic effect of food delivery platforms on total sales



Notes: The figure displays the dynamic impact of food delivery platforms on total sales by the timing of adoption. Callaway and Sant'Anna (2021)'s dynamic difference-in-differences model is estimated. The Y-axis stand for the regression estimates for the effect of food delivery platforms on total sales, with a vertical line indicating the 95% confidence interval of each regression coefficient. Specifically, for $t \geq 0$, each point denotes the average effect of platforms initially adopted t months ago, across all restaurants that have ever used platforms for at least t months; these represent the event-time average of the group-time average treatment effects on the treated (ATT), as suggested by Callaway and Sant'Anna (2021). A similar representation applies for $t < 0$, with coefficients normalized so that the effect is zero at $t = -1$. The dependent variable is total sales, measured in 1,000 KRW (approximately 0.8 USD). Restaurants that have discontinued platform use at any time, or those not observed across all months in the sample period, are excluded from the analysis. The analysis uses the never-treated group as a control and employs an outcome regression difference-in-differences estimator to determine the group-time average treatment effect. The model includes county-type fixed effects as covariates. The regression estimates are rescaled for ease of visualization.

accounting for the possibility that the impact could vary based on the number of COVID-19 cases. We further investigate the heterogeneous impacts of platforms depending on the COVID-19 cases and other observable restaurant characteristics in Section 4.

Second, Panel B of Appendix Table A.7 shows our main results do not substantially differ when we use longer lags as instruments. This result implies the assumption of instrument exogeneity, which posits no serial correlation in the error term, is likely valid, because longer lags are less prone to exhibit serial correlation with the error term (Murray, 2006). Furthermore, we find quantitatively similar results in the additional robustness checks results: the instrumental-variable regression results using the lagged proportion of competitors adopting platforms as an instrument (column (5) of Table 3) and the event-study analysis results (Figure 2).

Thirdly, in considering effects on total sales including cash transactions, our estimated effects are likely conservative and underestimated because our data only include credit card transactions. However, the overall effect accounting for cash transactions is not expected to be substantially different from our estimates. As discussed in Section 3, cash transactions constitute a minor portion of total sales and even less prevalent for delivery sales, a primary service offered by platforms.

Fourthly, the effect of platforms on total sales at the restaurant level is generally greater than at the market level. Our restaurant-level estimates account for both the market expansion effect of platform sales, which includes customers switching from "outside options" such as self-cooking or meal kits, and the business stealing effect of platform sales, which involves poaching customers from competitor restaurants. Quantifying the exact magnitudes of the market expansion and business stealing effects is beyond the scope of the paper.

Note a couple of remarks regarding the regression results using net sales as the dependent variable. First, we consider the total delivery costs, comprising not only the amount paid by consumers but also the portion paid by the restaurant. The latter is usually not explicitly stated when a consumer places an order. Thus, this variable serves as an excellent metric for evaluating whether a restaurant benefits from platforms as it deducts the total estimated delivery costs. Second, platform fees are unlikely to exert a significant impact on the net-sales variable. As discussed in section 2, *Baemin* — which dominates the food-delivery-platform market — charged a fixed monthly fee per listing in 2020, the year covered by our data. Although some measurement errors may exist in our net sales variable, we find the results remain robust when a more conservative measure of per-order delivery costs, namely, 5,000 KRW (approximately 4 USD), is used (the results are available on request).

4.3 Heterogeneous effects of food delivery platforms

We examine whether the influence of food delivery platforms on sales varies by observable characteristics of restaurants and their locations. For this purpose, we interact the observed characteristics with a food-delivery-platform indicator. Table 4 shows the effect of food delivery platforms increases with the number of COVID-19 cases and that Chinese restaurants experience more substantial ef-

Table 4: The heterogeneous effects of food delivery platforms on total sales

	(1)	(2)	(3)	(4)
$\text{Platforms}_{\text{t}}$	1,665.237***			
	(43.100)			
$\text{Platforms}_{\text{t}}$ $\times$COVID-19 cases	14.602***		14.668***	14.636***
	(0.830)		(0.832)	(0.833)
$\text{Platforms}_{\text{t}}\times$Korean food		1,691.574***	1,466.062***	1,465.550***
		(62.559)	(63.904)	(66.629)
$\text{Platforms}_{\text{t}}\times$Fast food		1,959.489***	1,815.064***	1,826.154***
		(110.362)	(110.657)	(111.966)
$\text{Platforms}_{\text{t}}\times$Chinese food		5,211.786***	5,016.297***	5,010.185***
		(249.327)	(249.676)	(249.192)
$\text{Platforms}_{\text{t}}\times$Other		1,555.171***	1,336.766***	1,331.337***
		(83.499)	(83.985)	(85.300)
$\text{Platforms}_{\text{t}}\times$Metropolitan cities		228.837**	118.928	67.115
		(82.852)	(83.000)	(83.970)
$\text{Platforms}_{\text{t}}\times${% of high-income individuals}				29.927
				(68.401)
$\text{Platforms}_{\text{t}}\times${% of population aged 20-49}				100.870
				(56.087)
Restaurant FE	X	X	X	X
County-type-month FE	X	X	X	X
IV regression?	X	X	X	X
Observed all months?	X	X	X	X
Observations	5,042,796	5,042,796	5,042,796	5,042,796

Notes: The dependent variable is total sales, measured in 1,000 KRW (approximately 0.8 USD). The unit of observation is a restaurant-month. "COVID-19 cases" are the number of COVID-19 cases per 100,000 people in the province in which the county is located. "Fast food" is defined by the Korean Standard Industry Classification (KSIC) codes that indicate pizza, hamburgers, sandwiches, chicken, and other international foods as the main types of food served. "Korean food," "Chinese food," and "Other" restaurants are defined similarly. "% of population aged 20-49" and "% of high-income individuals" are county-level variables and are standardized to facilitate easy comparison of estimates across different models. Instrumental-variable regression uses the lag of food delivery platforms interacted with observable characteristics of a restaurant as instruments. "Observed all months?" indicates restaurants observed across all months in the sample period. Standard errors in parentheses are clustered at the restaurant level. Significance levels are *5%, **1%, and ***0.1%.

fects. Column (1) shows a one-unit increase in COVID-19 cases per 100,000 people would increase a restaurant's total sales by 14,602 KRW (approx. 12 USD). In the absence of COVID-19 cases, the effect of food delivery platforms would be 1,665,237 KRW (approx. 1,332 USD). Columns (2)-(4) reveal that food delivery platforms have a greater impact on Chinese restaurants, with a potential increase of 5,211,786 KRW (approx. 4,169 USD). However, Table 4 does not provide conclusive statistical evidence on whether the impact on fast food restaurants is greater than that on Korean restaurants. In column (2), the effects on Korean and fast food restaurants exhibit no statistically significant difference from each other at the 1% significance level. Furthermore, column (4) also demonstrates that the impact of platforms does not vary based on other location-level characteristics, such as affluence and the young population, who are familiar with food delivery platforms.

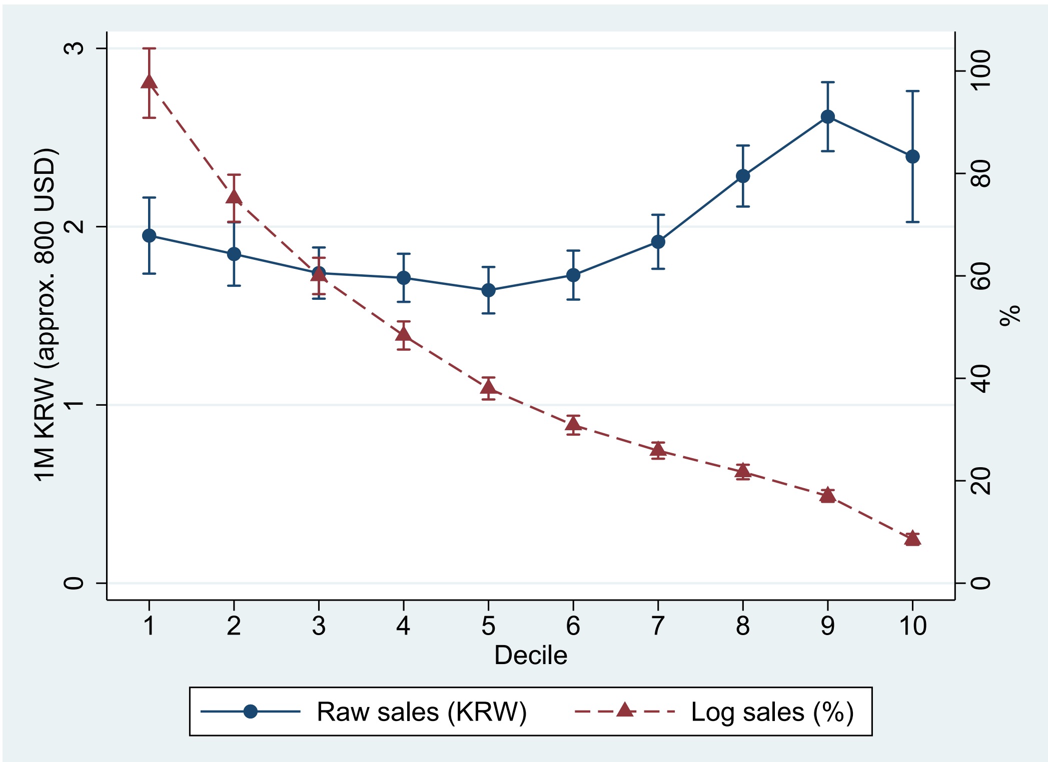
We also investigate whether the effect of platforms varies by restaurant size, as determined by its total sales in January 2020. For this purpose, we interact decile indicators with a food-delivery-platform indicator. Figure 3 reveals small and large restaurants tend to benefit more from the platforms in terms of raw total sales, but the variation in effects is somewhat limited. The effects of platforms on the bottom- and top-decile restaurants are 1,949,848 KRW (approx. 1,560 USD) and 2,393,333 KRW (approximately 1,915 USD), respectively. However, when measuring the percentage increase in total sales, the smallest restaurants benefit the most from adopting platforms. Total sales for restaurants at the bottom decile are estimated to increase by 97.6%. This impact is approximately 11 times greater than the effect on the top-decile restaurants, which is 8.6%, and 3 times greater than that on fourth- and fifth-decile restaurants, which are 38.0% and 30.9%, respectively. As shown in Figure 1, restaurant size varies greatly across restaurants. Due to the limited variation in the effects of platforms on raw total sales, the smallest restaurants substantially benefit from food delivery platforms when considering the percentage increase in sales.

Figure 4 shows that, irrespective of restaurant size, food delivery platforms have a larger impact on Chinese restaurants than on the other types of restaurants. In the right panel of Figure 4, none of the 95% confidence intervals of the regression coefficients, which represent the additional impact of platforms on Chinese restaurants by decile, includes zero, indicating all of them are statistically significant at the 5% significance level. This finding strengthens the results presented in Table 4 that the impact of platforms is larger on Chinese restaurants, because they benefit uniformly from platforms across restaurants of all sizes. Furthermore, this impact is particularly pronounced for the top-decile restaurants. Appendix Figure A.7 shows the impact of platforms does not differ uniformly across Korean, fast food, and other restaurants.

5 Discussions

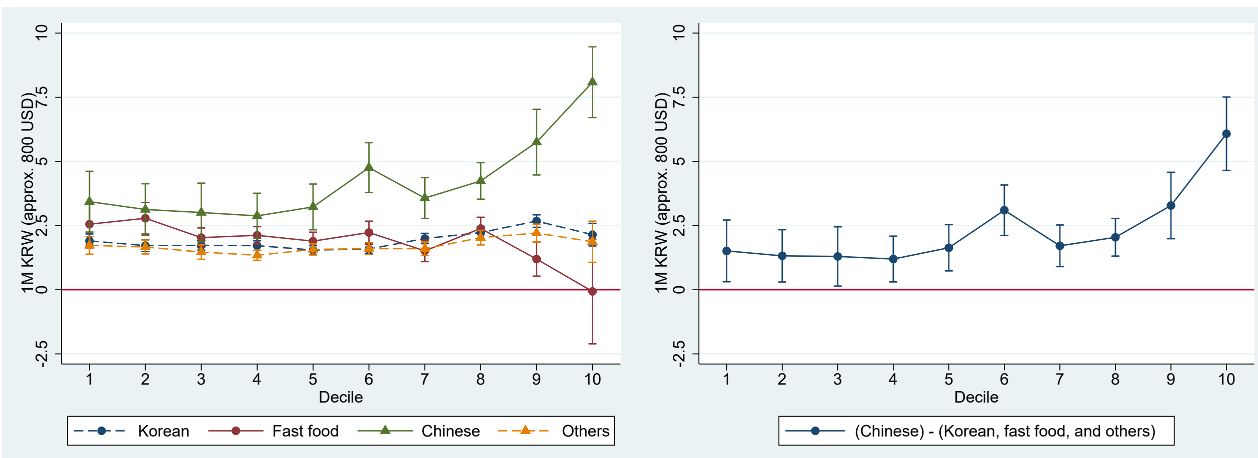
Our findings indicate that small-sized businesses can reap substantial benefits from digital platform technologies. While a detailed exploration of the mechanisms behind this impact is beyond the scope of the paper, we conjecture that food delivery platforms decrease consumers' search and travel

Figure 3: The effect of food delivery platforms on raw and log total sales, by decile



Notes: The figure displays the impact of food delivery platforms on raw and log total sales by decile, respectively. Each point represents the corresponding decile on the X-axis; for instance, decile 1 refers to the effect on the restaurants in the 0%-10% quantile. The quantiles are determined from the restaurant sales distribution as of January 2020. The left and right Y-axis stand for the regression estimates for the effect of food delivery platforms on raw and log total sales, respectively, with a vertical line indicating the 95% confidence interval of each regression coefficient. The dependent variables are raw total sales and the logarithm of total sales plus 1 (log total sales). Sales were measured in 1,000 KRW (approximately 0.8 USD). Both regression models include restaurant fixed effects and county-type-month-size fixed effects. Only restaurants observed in all months of 2020 are included in the analysis. The lag of food delivery platforms interacted with decile indicators are used as instruments for food-delivery-platform indicators. The regression estimates are rescaled for ease of visualization.

Figure 4: The effect of food delivery platforms on total sales, by decile and type



Notes: The left panel displays the impact of food delivery platforms on raw total sales by decile and type. The right panel demonstrates the additional impact of platforms on Chinese restaurants compared with the other types of restaurants. Each point represents the corresponding decile on the X-axis; for instance, decile 1 refers to the effect on the restaurants in the 0%-10% quantile. The quantiles are determined from the restaurant sales distribution as of January 2020, and therefore, they do not vary across restaurant types. The Y-axis stands for the regression estimates for the (additional) effect of food delivery platforms on total sales, with a vertical line indicating the 95% confidence interval of each regression coefficient. The dependent variable is raw total sales, measured in 1,000 KRW (approximately 0.8 USD). The regression model in the left panel estimates the effect of food delivery platforms by decile type, whereas the model in the right panel estimates the additional impact on Chinese restaurants by decile. Both models include restaurant fixed effects and county-type-month-size fixed effects. The analysis includes only restaurants observed in all months of 2020. We use the lag of food delivery platforms interacted with decile-type indicators as instruments for food-delivery-platform indicators.

costs, thereby increasing product variety and benefiting small-sized businesses. Firstly, regarding product variety, early literature characterized search costs as those related to information acquisition (Stigler, 1961; Diamond, 1971; Varian, 1980). Literature shows that operating both offline and online shopping channels helps increase consumer awareness, and provides consumers an option to save travel costs (Brynjolfsson et al., 2009; Forman et al., 2009; Avery et al., 2012; Pozzi, 2013; Wang and Goldfarb, 2017; Shriver and Bollinger, 2022). Online shopping may enable consumers to easily discover niche products, thereby increasing the variety of horizontally differentiated goods (Brynjolfsson et al., 2011; Yang, 2013; Zhang, 2018). This phenomenon is often referred to as the 'long tail' effect (Anderson, 2006).

Secondly, the effect of increased product variety on small-sized businesses may depend on industry characteristics. For instance, large multiproduct firms capable of offering niche products may particularly benefit from online platforms. Our study in the restaurant industry, where firms typically offer limited product variety, suggests that online shopping facilitates sales growth for small-sized businesses. This supports the model predictions of Bar-Isaac et al. (2012), where not only 'star' but also 'tail' firms can benefit from decreased search costs. Their model assumption that each firm produces a single product is particularly relevant in the restaurant industry, where menu variety is often limited due to capacity constraints.[12]

To summarize, our findings show that small firms—not just 'superstar' firms—can be the main beneficiaries of technological advancements in a horizontally differentiated industry. This contrasts with the cases in a vertically differentiated industry, where consumers can easily find 'superstar' products among vertically differentiated products (Rosen, 1981; Goldmanis et al., 2010; Koenig, 2023), potentially benefiting large firms (Goldmanis et al., 2010).

For Chinese restaurants, despite their cuisine being well suited for delivery (Section 2), they tend to have lower levels of food-delivery-platform adoption (Table 2). Employing food delivery platforms could help attract additional customers who frequently use these platforms to place orders.

Our study has implications for competition policy and industrial policy, as we find favorable impacts on producers—particularly small and medium-sized enterprises (SMEs). The impact of platforms on SMEs has been a subject of considerable policy debate, particularly given that most platforms match SMEs and consumers (Lee, 2021; Li and Wang, 2021). Our findings suggest that restaurants, especially smaller ones, can significantly benefit from platforms, even after accounting for platform fees. This evidence can be instrumental in shaping public policy on platform regulation, suggesting that careful consideration is needed when introducing potential regulations on platforms.

Regulating platforms to favor small-sized restaurants, such as promoting alternative platforms or regulating fees, may be based on an erroneous presumption that platforms harm SMEs incapable of paying platform fees, leading to unintended consequences. In South Korea, *Baemin*'s plan to revise its fee model from a flat to an ad-valorem structure failed due to intense opposition from

[12] On average, a restaurant occupies a space of $94.8m^2$, equivalent to 1020 square feet, and employs 2.93 workers (Lee et al., 2021).

the restaurant industry. Subsequently, local governments launched public food delivery platforms with lower fees. Despite these efforts, however, *Baemin* continues to hold a significant market share, and most public platforms have underperformed. This indicates that competitive fees alone are insufficient for the success of public platforms intended to help the restaurant industry (Lee, 2021). Imposing lower platform fees for small and independent restaurants could also have unintended effects, as platforms may be incentivized to promote large restaurants paying unregulated fees. Li and Wang (2021) demonstrate that the U.S. regulations that capped fees on independent restaurants actually harmed these businesses by reducing their orders and revenues.

6 Conclusions

We examined the heterogeneous influence of food delivery platforms on sales at the restaurant level. The use of food delivery platforms is estimated to increase restaurant-level total sales revenue by 1,931,556 KRW (approximately 1,545 USD). Without COVID-19 cases, the effect would be 1,665,237 KRW (approx. 1,332 USD). This effect is more pronounced in small restaurants, with a 97.6% increase in total sales revenue, approximately 11 times greater than the impact on the largest restaurants. We also show the impact is most substantial in Chinese restaurants. Our findings showed that small firms—not just 'superstar' firms—can be the main beneficiaries of technological advancements, depending on industry characteristics. Future studies could explore the underlying mechanism behind the sales increase and incorporate data that include restaurant activities before or after the COVID-19 pandemic to determine the extent to which our estimates are affected by the pandemic.

References

Ahuja, K., V. Chandra, V. Lord, and C. Peens (2021): "Ordering in: The rapid evolution of food delivery," *McKinsey & Company.*

Anderson, C. (2006): *The Long Tail: Why the Future of Business Is Selling Less of More*, New York: Hyperion.

Avery, J., T. J. Steenburgh, J. Deighton, and M. Caravella (2012): "Adding Bricks to Clicks: Predicting the Patterns of Cross-Channel Elasticities over Time," *Journal of Marketing*, 76.

Baemin (2020): *Introduction to Baemin and the structure of food delivery industry.*

——— (2021): *Baemin trends 2021.*

Bank of Korea (2020): *Survey on the Use of Payment Methods and Mobile Financial Services, 2019.*

——— (2022): *Survey on the Use of Payment Methods and Mobile Financial Services, 2021.*

Bar-Isaac, H., G. Caruana, and V. Cuñat (2012): "Search, Design, and Market Structure," *American Economic Review*, 102, 1140–1160.

Barogo (2022): *Shares of Payment Methods by Month and Region.*

Brynjolfsson, E., Y. J. Hu, and M. S. Rahman (2009): "Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition," *Management Science*, 55, 1755–1765.

Brynjolfsson, E., Y. J. Hu, and D. Simester (2011): "Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales," *Management Science*, 57, 1373–1386.

Callaway, B. and P. H. Sant'Anna (2021): "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, 225, 200–230.

Collison, J. (2020): "The Impact of Online Food Delivery Services on Restaurant Sales," *Working Paper.*

Diamond, P. A. (1971): "A model of price adjustment," *Journal of Economic Theory*, 3, 156–168.

Duch-Brown, N., L. Grzybowski, A. Romahn, and F. Verboven (2017): "The impact of online sales on consumers and firms. Evidence from consumer electronics," *International Journal of Industrial Organization*, 52, 30–62.

Financial Supervisory Service (2022): "Credit Card Usage, 2020," *Financial Statistics Information System.*

Forman, C., A. Ghose, and A. Goldfarb (2009): "Competition between local and electronic markets: how the benefit of buying online depends on where you live," *Management Science*, 55, 47–57.

Gentzkow, M. (2007): "Valuing New Goods in a Model with Complementarity: Online Newspapers," *American Economic Review*, 97, 713–744.

Goldmanis, M., A. Hortaçsu, C. Syverson, and Ö. Emre (2010): "E-Commerce and the Market Structure of Retail Industries," *The Economic Journal*, 120, 651–682.

Goolsbee, A. (2001): "Competition in the Computer Industry: Online Versus Retail," *The Journal of Industrial Economics*, 49, 487–499.

Koenig, F. (2023): "Technical Change and Superstar Effects: Evidence from the Rollout of Television," *American Economic Review: Insights*, 5, 207–223.

Lee, G. (2021): "A Study on the Change of Sales Concentration Linked to Platforms Providing On-demand Services," in *Policy Study*, Korea Development Institute, vol. 2021-17.

Lee, K.-i., S.-h. Kim, S.-y. Heo, S.-Y. Shin, and I.-h. Park (2020): *The Consumer Behavior Survey for Food 2020*, Korean Rural Economic Institute.

Lee, S. and H. Chun (2022): "Online Food Delivery Platform and Restaurant Sales: Evidence from a Local COVID-19 Outbreak," *Korean Journal of Economic Studies*, 70, 69–91.

Lee, Y.-s., Y. Hwang, and J. Choi (2021): *Restaurant Business Survey Report 2020*, Korean Rural Economic Institute.

Li, Z. and G. Wang (2020): "The Role of On-Demand Delivery Platforms in Restaurants," *Working Paper*.

——— (2021): "Regulating Powerful Platforms: Evidence from Commission Fee Caps in On-Demand Services," *Working Paper*.

Ministry of Health and Welfare (2021): *Province-level COVID-19 cases.*

Ministry of the Interior and Safety (2021): "COVID-19 relief grant program provided 10.7565 trillion won to 43.03 million people," *Press Release.*

Murray, M. P. (2006): "Avoiding Invalid Instruments and Coping with Weak Instruments," *Journal of Economic Perspectives*, 20, 111–132.

Pozzi, A. (2013): "The effect of Internet distribution on brick-and-mortar sales," *RAND Journal of Economics*, 44, 569–583.

Prince, J. T. (2007): "The beginning of online/retail competition and its origins: An application to personal computers," *International Journal of Industrial Organization*, 25, 139–156.

Raj, M., A. Sundararajan, and C. You (2023): "COVID-19 and Digital Resilience: Evidence from Uber Eats," *Working Paper.*

Relihan, L. E. (2022): "Is Online Retail Killing Coffee Shops? Estimating the Winners and Losers of Online Retail using Customer Transaction Microdata," *Working Paper.*

Rosen, S. (1981): "The Economics of Superstars," *The American Economic Review*, 71, 845–858.

Sedov, D. (2022): "Restaurant closures during the COVID-19 pandemic: A descriptive analysis," *Economics Letters*, 213, 110380.

Shriver, S. K. and B. Bollinger (2022): "Demand Expansion and Cannibalization Effects from Retail Store Entry: A Structural Analysis of Multichannel Demand," *Management Science*, 68, 8829–8856.

Statistics Korea (2020): *2020 Population and Housing Census.*

Stigler, G. J. (1961): "The Economics of Information," *Journal of Political Economy*, 69, 213–225.

Varian, H. R. (1980): "A Model of Sales," *American Economic Review*, 70, 651–659.

Wang, K. and A. Goldfarb (2017): "Can offline stores drive online sales?" *Journal of Marketing Research*, 54, 706–719.

Wise App Retailer (2021): *Retail Market Analysis, December 2020.*

Yang, H. (2013): "Targeted search and the long tail effect," *RAND Journal of Economics*, 44, 733–756.

Yang, Y.-K. (2005): "Jajangmyeon and Junggukjip: The Changing Position and Meaning of Chinese Food and Chinese Restaurants in Korean Society," *Korea Journal*, 45, 60–88.

Zhang, L. (2018): "Intellectual Property Strategy and the Long Tail: Evidence from the Recorded Music Industry," *Management Science*, 64, 24–42.

A Calculation of net sales

In a supplementary analysis, we also consider net sales as a dependent variable, which deducts the primary variable costs associated with using food delivery platforms, to assess the extent to which a restaurant benefits from using these platforms. We consider delivery costs to be the main variable costs associated with using food delivery platforms, because platform fees are mostly fixed. *Baemin,* which holds a dominant position, charged a fixed fee to the majority of the restaurants in 2020, the year covered by our data (see section 2). The estimated delivery costs are determined by multiplying the per-order delivery costs by the total number of platform orders.

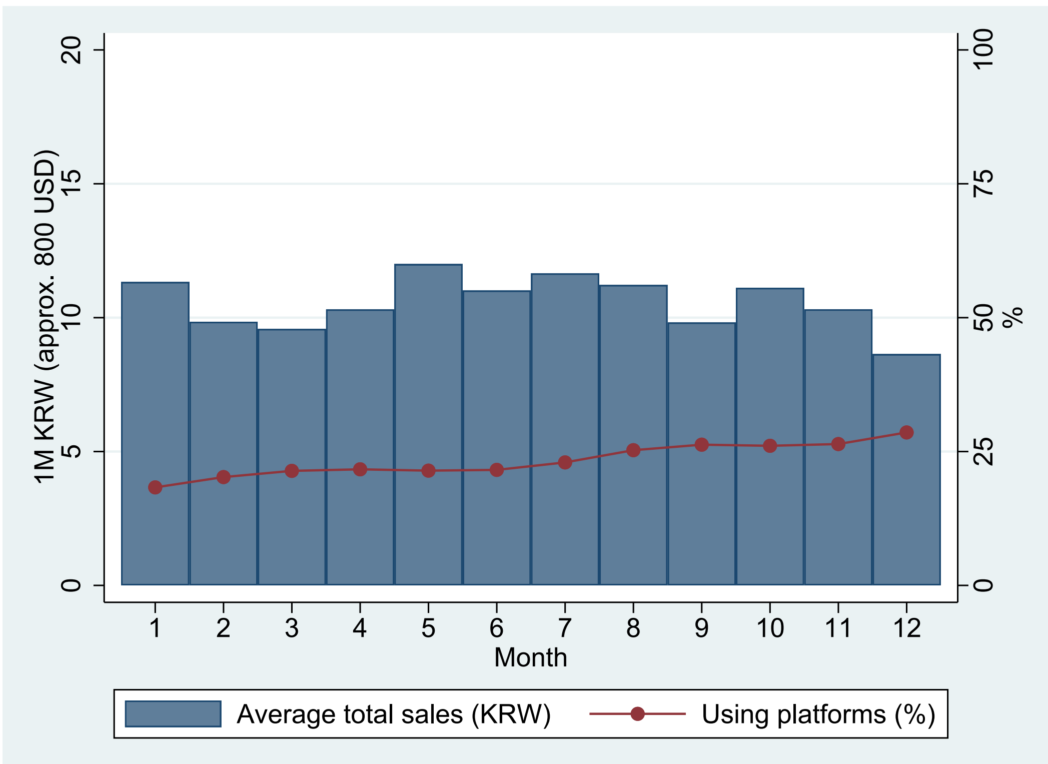
To determine the total number of platform orders, which includes both prepaid and collect-on-delivery (COD) orders, we combine two datasets: the credit card transaction data and delivery payment share data. The second dataset contains province-month-level delivery payment shares. We calculate the total number of online orders by separately computing platform pickup and delivery orders. The following equation is used to compute the net sales variable:

$$\begin{aligned}
\text{(Total platform orders)} =& \text{(Platform pickup orders)} + \text{(Platform delivery orders)} \\
=& \text{(\% of platform pickup orders)} \times \text{(Platform prepaid orders)} \\
&+ \text{(\% of platform delivery orders)} \times \frac{\text{(Platform prepaid orders)}}{\left(\frac{\text{(\% of prepaid orders)}}{\text{(\% of prepaid and card orders)}}\right)}.
\end{aligned}$$

The underlying assumptions are that all online pickup orders are prepaid (otherwise, the order will be made directly upon stopping by a restaurant), online delivery orders are either prepaid or paid for with credit cards, and the shares of prepaid pickup and delivery orders are equal to those of total pickup and delivery orders, respectively. The province-month-level prepaid-shares data were provided by *Barogo*, the largest independent delivery service provider as of December 2020 (Barogo, 2022). Eighty-two percent of total credit card orders in Seoul were prepaid as of December 2020. The percentages of platform pickup and delivery orders are from Baemin (2021). The percentage of *Baemin* pickup orders was 3.5% as of January 2020, reaching 12.6% during September 2020. To compute such percentages in other months, we use linear interpolation and extrapolation.

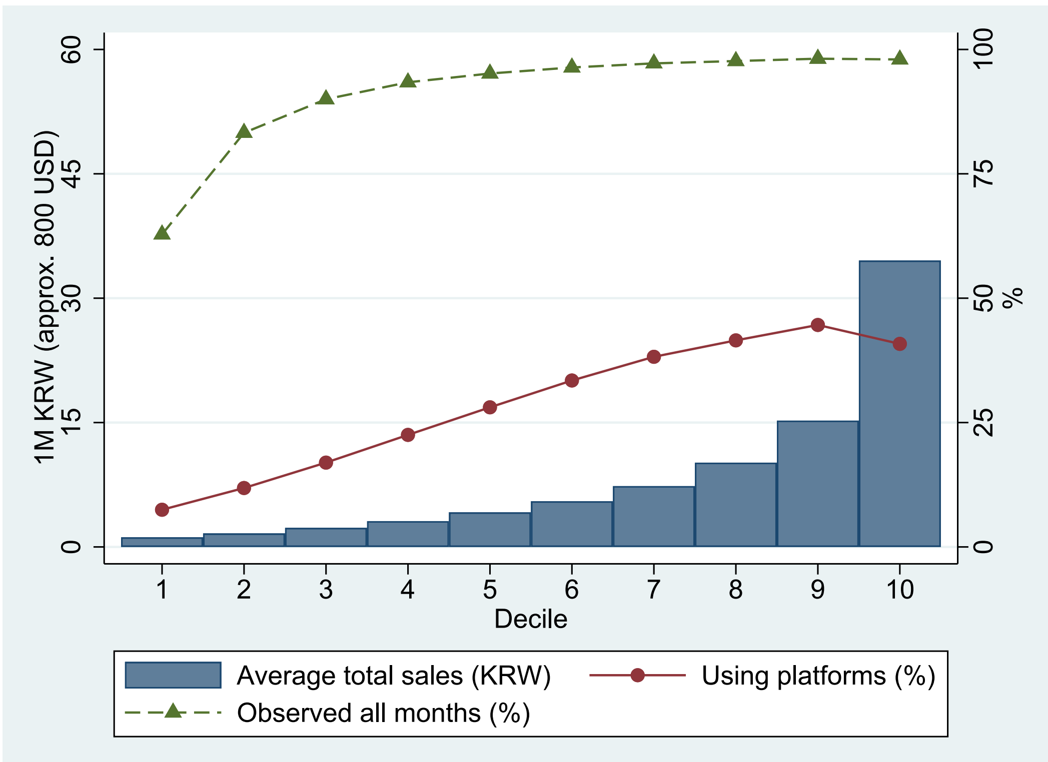
We assume a delivery cost of 4,000 KRW (approximately 3.2 USD) per order, which lies within the standard range of 2,000 to 4,000 KRW and is slightly higher than the average delivery costs of 3,556 KRW (as discussed in section 2). Note the results remain robust when we use a more conservative measure of per-order delivery costs, 5,000 KRW (approx. 4 USD), for our analysis (robustness-check results are available on request). Only 4.4% of the restaurants report that their delivery costs exceed 5,000 KRW (Lee et al., 2021).

Figure A.5: Summary statistics, by month



Notes: The unit of observation is a restaurant-month observed each month. Average total sales were measured in 1,000,000 KRW (approximately 800 USD). "Using platforms (%)" stands for the proportion of restaurant-months with positive online sales each month.

Figure A.6: Summary statistics, December 2020, by decile



Notes: The unit of observation is a restaurant-month observed in December 2020. "Decile" categorizes a restaurant's total sales in January 2020 into deciles. Average total sales were measured in 1,000,000 KRW (approximately 800 USD). "Using platforms (%)" stands for the proportion of restaurant-months with positive online sales. "Observed all months (%)" indicates the proportion of restaurant-months observed across all months in the sample period.

Table A.5: The effect of food delivery platforms on total sales: Robustness checks

Panel A: County-type-month-size fixed effects included

	(1)	(2)	(3)	(4)	(5)
Platforms_{t}	4,688.362***	1,176.612***	2,151.356***	2,087.977***	2,180.927***
	(40.395)	(17.229)	(39.610)	(40.846)	94.549
Restaurant FE		X	X	X	X
County-type-month FE					
County-type-month-size FE		X	X	X	X
IV regression?			X	X	X
Observed all months?				X	X
First stage					
$\text{Platforms}_{t\text{-}1}$			0.437***	0.459***	
			(0.001)	(0.001)	
					–13.333***
					(0.981)
Observations	7,626,223	6,695,668	5,978,170	5,042,796	5,042,195

Panel B: Top-decile restaurants not included

	(6)	(7)	(8)	(9)	(10)
Platforms_{t}	4,070.935***	1037.022***	1980.691***	1,960.329***	2,131.636***
	(20.786)	(12.421)	(29.601)	(30.443)	(113.657)
Restaurant FE		X	X	X	X
County-type-month FE		X	X	X	X
County-type-month-size FE					
IV regression?			X	X	X
Observed all months?				X	X
First stage					
$\text{Platforms}_{t\text{-}1}$			0.452***	0.450***	
			(0.002)	(0.002)	
$\text{Comp\_platforms}_{t\text{-}1}$					–5.792***
					(0.362)
Observations	5,977,756	5,977,756	4,436,564	4,436,564	4,435,978

Notes: The dependent variable is total sales, measured in 1,000 KRW (approximately 0.8 USD). The unit of observation is a restaurant-month. Top decile restaurants are determined from the restaurant sales distribution as of January 2020. "(t-1)" represents the lagged variable. "Type" represents the Korean Standard Industry Classification (KSIC) codes that indicate the main types of food served in the restaurant. "Size" categorizes a restaurant's total sales in January 2020 into deciles. "Observed all months?" indicates restaurants observed across all months in the sample period. Columns with the first-stage regression results indicate the first-stage regression results, where "Platforms" is the dependent variable of the regression and its lagged variable and the lagged proportion of competitors adopting platforms, $\text{Comp\_platforms}_{t\text{-}1}$, are used as instruments. Standard errors in parentheses are clustered at the restaurant level. Significance levels are *5%, **1%, and ***0.1%.

Table A.6: The effect of food delivery platforms on net sales

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Platforms}_{\text{t}}$	3,869.758***	963.846***	1,861.609***	1,448.104***	1695.022***	1448.592***
	(39.305)	(15.140)	(34.271)	(40.053)	(114.984)	(40.029)
Restaurant FE		X	X	X	X	X
County-type-month FE		X	X	X	X	X
IV regression?			X	X	X	X
Observed all months?				X	X	X
First stage						
$\text{Platforms}_{\text{t-1}}$			0.440***	0.461***		0.460***
			(0.001)	(0.001)		(0.001)
$\text{Comp\_platforms}_{\text{t-1}}$					–6.016***	–0.200***
					(0.351)	(0.053)
Observations	7,626,223	7,626,223	6,708,671	5,042,796	5,042,195	5,042,195

Notes: The dependent variable is net sales, measured in 1,000 KRW (approximately 0.8 USD). This variable refers to the total sales after deducting estimated delivery costs, which are the primary variable costs associated with using food delivery platforms; see Appendix Section A for derivation. The unit of observation is a restaurant-month. "(t-1)" represents the lagged variable. "Type" represents the Korean Standard Industry Classification (KSIC) codes that indicate the main types of food served in the restaurant. "Observed all months?" indicates restaurants observed across all months in the sample period. Columns with the first-stage regression results indicate the first-stage regression results, where "Platforms" is the dependent variable of the regression and its lagged variable and the lagged proportion of competitors adopting platforms, $\text{Comp\_platforms}_{\text{t-1}}$, are used as instruments. Standard errors in parentheses are clustered at the restaurant level. Significance levels are *5%, **1%, and ***0.1%.

Table A.7: The effect of food delivery platforms on total sales: Robustness checks

Panel A: The time-varying effect of food delivery platforms

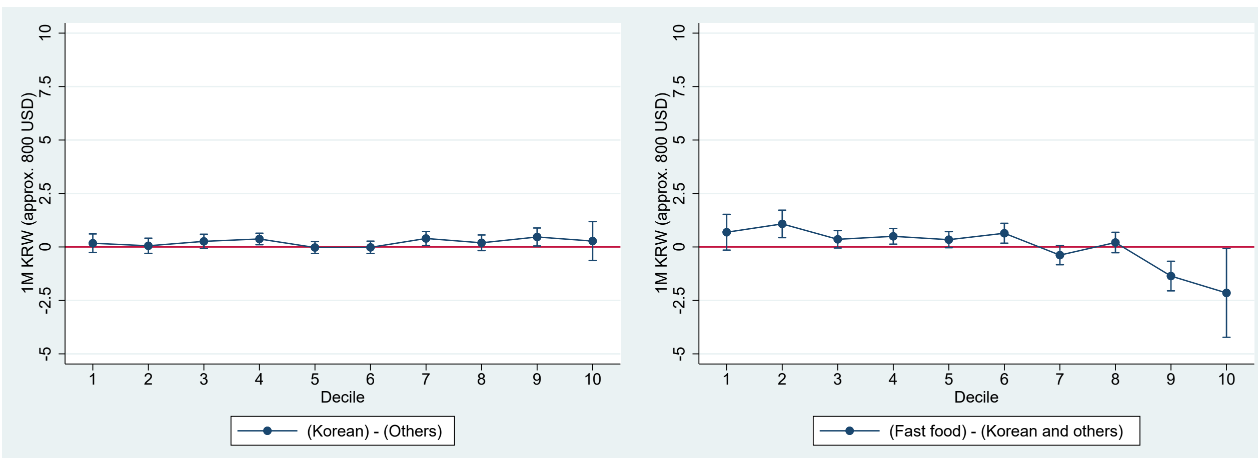
	(1)	(2)	(3)	(4)
Platforms_t	1,215.262***	2,135.609***	1,642.538***	1,591.855***
$\times 1\{t \leq \text{June 2020}\}$	(17.007)	(38.573)	(44.053)	(44.415)
Platforms_t	1,287.427***	2,533.493***	1,979.118***	1,687.344***
$\times 1\{\text{July 2020} \leq t\}$	(16.586)	(35.749)	(41.209)	(43.832)
Platforms_t				14.130***
$\times$COVID-19 cases				(0.869)
Restaurant FE	X	X	X	X
County-type-month FE	X	X	X	X
IV regression?		X	X	X
Observed all months?			X	X
Observations	7,626,223	6,708,671	5,042,796	5,042,796

Panel B: Longer lags as instruments

	(5)	(6)	(7)	(8)
Platforms_t	1,931.556***	2,198.158***	1,885.379***	1,990.965***
	(41.076)	(73.941)	(205.496)	(91.698)
Restaurant FE	X	X	X	X
County-type-month FE	X	X	X	X
IV regression?			X	X
Observed all months?	X	X	X	X
First stage				
Platforms_{t-1}	0.461***			
	(0.001)			
Platforms_{t-2}		0.258***		0.228***
		(0.001)		(0.002)
Platforms_{t-3}			0.096***	0.005***
			(0.001)	(0.001)
Observations	5,042,796	4,584,360	4,125,924	4,125,924

Notes: The dependent variable is total sales, measured in 1,000 KRW (approximately 0.8 USD). The unit of observation is a restaurant-month. "COVID-19 cases" are the number of COVID-19 cases per 100,000 people in the province in which the county is located. "(t-1)" represents the lagged variable. "Type" represents the Korean Standard Industry Classification (KSIC) codes that indicate the main types of food served in the restaurant. "Size" categorizes a restaurant's total sales in January 2020 into deciles. "Observed all months?" indicates restaurants observed across all months in the sample period. Instrumental-variable regression in Panel A uses the lag of food delivery platforms as an instrument for "Platforms." In Panel B, columns with the first-stage regression results indicate the first-stage regression results, where "Platforms" is the dependent variable of the regression and its lagged variable is used as an instrument. Standard errors in parentheses are clustered at the restaurant level. Significance levels are *5%, **1%, and ***0.1%.

Figure A.7: The effect of food delivery platforms on total sales, by decile and type



Notes: The left panel demonstrates the additional impact of food delivery platforms on Korean restaurants compared to other restaurants. The right panel shows the impact on fast food restaurants relative to Korean and other restaurants. Each point represents the corresponding decile on the X-axis; for instance, decile 1 refers to the effect on the restaurants in the 0%-10% quantile. The quantiles are determined from the restaurant sales distribution as of January 2020, and therefore, they do not vary across restaurant types. The Y-axis stands for the regression estimates for the additional effect of food delivery platforms on total sales, with a vertical line indicating the 95% confidence interval of each regression coefficient. The dependent variable is raw total sales, measured in 1,000 KRW (approximately 0.8 USD). The models estimate the additional impact on Korean and fast food restaurants, respectively, by decile. Both models include restaurant fixed effects and county-type-month-size fixed effects. The model in the left panel excludes fast food and Chinese restaurants, whereas the model in the right panel does not include Chinese restaurants. Only restaurants observed in all months of 2020 are included in the analysis. The lag of food delivery platforms interacted with decile-type indicators is used as instruments for food delivery platform indicators.