

Online Appendix

Appendix 1: Related Studies on Online Food Delivery and Subscriptions

Table A1 provides an overview of key studies examining the effects of OFD and subscription-based services across various industries.

Table A1 Related works on subscription and online food delivery

		This Study	Li and Wang (2025)	Babar et al. (2021)	Sun et al. (2024)	Reshef (2023)	Fang et al. (2025)	Godinho de Matos et al. (2018)	Iyengar et al. (2022)	Oh et al. (2016)	Pattabhiramaiah et al. (2022)	Gal-Or and Shi (2022)
Setting	Online food delivery	✓	✓	✓	✓	✓						
	Subscription	✓			✓		✓	✓	✓	✓	✓	✓
	Mobility Analysis	✓										
	Transportation Costs	✓										✓
	Variety-seeking	✓										✓
Level of Analysis	Individual	✓					✓		✓		✓	
	Platform/Item/Product	✓	✓		✓	✓		✓		✓		
	Geospatially Aggregated		✓	✓		✓						
Spillover Type	Online-to-online	✓										
	Online-to-offline	✓	✓			✓	✓				✓	
	Cascading spillovers*	✓										
Method	Empirical Model	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
	Theoretical/Qualitative				✓							

Notes: We define cascading spillovers as those that are indirect spillovers that occur after the initial spillover. For the present table, a cascading spillover is one that occurs after the online-to-offline one.

Appendix 2: Additional Details on Data

We obtain our dataset from a mobile portfolio app operating in South Korea. The dataset includes 226,337 individuals, accounting for approximately 0.5% of the entire national population. Considering the scale of the national population, this proportion reflects a substantial sample size for empirical research. In the dataset, 54,496 users (approximately 24%) have ordered food delivery services at least once in observation period. According to the Ministry of Agriculture, Food and Rural Affairs, 20% of the national population used food delivery services in 2020¹, suggesting that our sample is broadly representative in this regard. Regarding subscribed users, the focal platform reported 250,000 subscribers after the promotional period², or approximately 0.5% of the national population. Our dataset contains 1,085 subscribed

¹ https://kosis.kr/statHtml/statHtml.do?orgId=114&tblId=DT_114054_016&conn_path=I2

² https://www.chosun.com/site/data/html_dir/2019/09/19/2019091900904.html

users (0.47% of the total dataset), which is similar to the national rate. This comparison suggests that our dataset closely reflects the broader population in the context of our study.

Our manuscript also provides information on the frequency of offline restaurant visit. According to the descriptive statistics, the average daily frequency of dining out is 0.25 times, which translates to approximately 7.5 times per month when multiplied by 30. In contrast, Kim et al. (2019) defines eating-out behavior using the concept of a daily eating-out rate, which refers to the proportion of meals consumed outside the home out of all meals eaten in a day. Thus, this measure is closer to capturing the intensity of eating out in daily meals rather than the simple incidence or occurrence of eating out. Nevertheless, when eating out typically occurs zero or one time per day, the meal-based eating-out rate can be interpreted as being close to the probability of eating out on a given day. Kim et al. (2019) report that more than 70% of the samples have a daily eating-out rate between 1% and 50%, suggesting that a substantial share of individuals repeatedly engage in eating-out behavior within a certain probability, even if they do not eat out every day. Based on the distribution reported in that study, and weighting individuals in the 50–100% eating-out rate category by gender shares, the average daily eating-out rate is calculated to be approximately 0.32. This indicates that eating out constitutes relatively routine behavior among Korean adults. Meanwhile, statistics from the KNHANES define eating-out behavior as an incidence measure—whether individual eats out at least once on a given day—and report that this proportion is approximately 33.3% in 2019³. This figure is nearly identical to the average daily eating-out rate calculated from Kim et al. (2019), suggesting that although the two measures differ in definition, they provide consistent information regarding the frequency and everyday nature of eating out. When translated into a monthly scale, these probability-based measures imply that individuals eat out on approximately 8–9 days per month. This interpretation is further supported by survey-based evidence reported in prior studies. For example, using the frequency distribution of eating-out behavior in South Korea documented in Jang et al. (2024), and applying midpoint values to each category, the implied average eating-out frequency is approximately 1.9 times per week, corresponding to about 8 times per month. This estimate closely aligns with both the KNHANES incidence-based statistics and the average monthly eating-out frequency observed in our data, reinforcing the external validity of our measures. This estimate is also very close to the average monthly eating-out frequency of 8.5 times reported by the Korea Institute for Animal Products Quality Evaluation. While the average monthly eating-out frequency observed in our data (approximately 7.5 times) is somewhat lower, the magnitude and overall pattern are broadly consistent with external statistics and prior studies.

We clarify the sample construction process and the availability of location information across different stages of filtering. The full dataset initially consists of 226,337 users. We first restrict the sample to users who placed at least one food delivery order during the observation period, resulting in 54,496 active users (24.1% of the full user base). We then apply the matching procedure described in the paper, which yields a final analysis sample of 2,162 matched users. For analyses that rely on location information, we additionally report both user-level and transaction-level coverage within this matched sample. Among the 2,162 matched users, 1,556 users (approximately 72%) share location information. At the transaction level, location data are available for approximately 63% of all transactions generated by these matched users. The difference between these two figures reflects natural features of the data. In particular, users may not share

³ <https://knhanes.kdca.go.kr/knhanes/mntpcstat/ntriItkStat.do>

location information for every transaction, and users also differ in how frequently they place orders. As described in the previous paragraph, approximately 72% of matched users have shared location data. This does not mean that users who share their location have data for every transaction, but most of their payments are recorded with location information. A total of 63% of payment transactions contain location information, which is broadly consistent with the reported statistic that approximately 66% of users always keep location sharing enabled on their mobile phones⁴. While we cannot access the location of every individual due to privacy issues, the data collection process captures a significant proportion of users. Specifically, each payment transaction generates a real-time notification on the user's smartphone and, where location-sharing has been enabled at the device level, simultaneously logs the user's geographic coordinates. Considering that only about 12% of users kept their location sharing disabled⁵, the dataset captures location information for the vast majority of transactions.

Appendix 3: Propensity Score Matching

We show the propensity score estimation includes the following covariates in Figure A1. Gender is a binary variable, 1 for male and 0 for female. Age measures the individual's age in years. Dining out reflects the average frequency of eating out, while grocery shopping reflects the average frequency of grocery shopping (e.g. mart, convenience store etc.). Hospital visits represent the average number of visiting hospitals (e.g. pharmacy, dietary supplements, plastic surgery etc.).

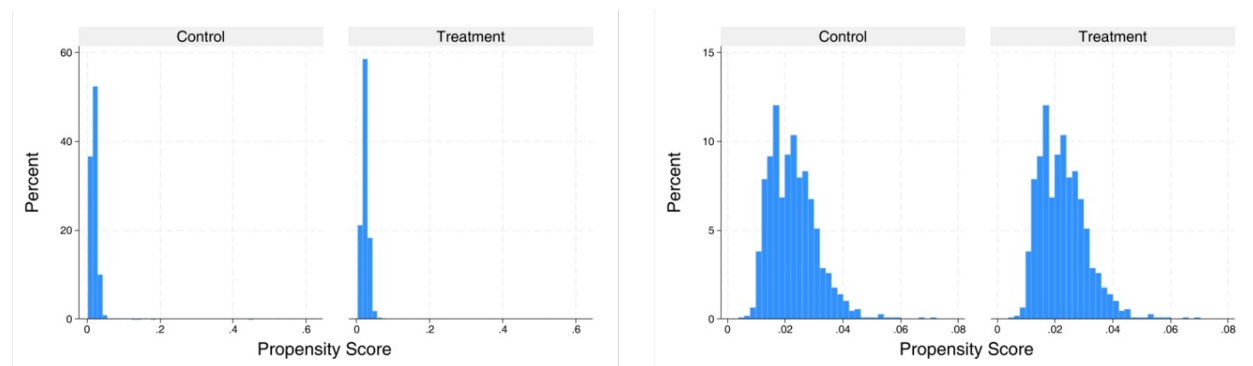


Figure A1 Propensity Score Distribution before/after Matching

Appendix 4: Estimates for Control Variables

This section reports the coefficient estimates for the control variables included in the primary models. For brevity, these estimates are not presented in the main tables but are provided here for completeness (please refer to A2, A3, A4).

Appendix 5: Baseline Differences Across Dine-out Categories

This section examines potential baseline differences across dine-out categories. To address this concern, we report tables based on category shares and conduct additional analyses using log-transformed dependent variables. In Table A5, statistics for dine-out transactions show that except for local food (34.5%), the distribution among other categories is relatively balanced. As shown in Table A6, the results remain consistent when the dependent variable is log-transformed.

⁴ <https://www.androidauthority.com/location-tracking-phone-poll-results-3110726/>

⁵ <https://www.androidauthority.com/location-tracking-phone-poll-results-3110726/>

Table A2 DID Results on the Focal and Competitor Platform

DV_{it}	Focal Platform			Competitor Platform		
	ln(Amount)	Frequency	ln(Amount per Order)	ln(Amount)	Frequency	ln(Amount per Order)
$Treatment_{it}$	0.706*** (0.028)	0.085*** (0.003)	-0.137*** (0.016)	-0.084*** (0.021)	-0.009*** (0.002)	-0.039** (0.019)
<i>Beauty</i>	0.014 (0.012)	0.001 (0.001)	-0.004 (0.012)	-0.011 (0.010)	-0.001 (0.001)	0.011 (0.014)
<i>Culture</i>	-0.001 (0.007)	-0.000 (0.001)	0.009 (0.008)	0.004 (0.006)	0.000 (0.001)	-0.004 (0.008)
<i>Transportation</i>	-0.004 (0.004)	-0.001 (0.000)	0.001 (0.005)	0.000 (0.004)	-0.000 (0.001)	0.003 (0.004)
<i>Cafe</i>	-0.042*** (0.005)	-0.005*** (0.001)	0.006 (0.006)	-0.021*** (0.005)	-0.003*** (0.001)	0.006 (0.006)
<i>Housing</i>	0.020*** (0.006)	0.002*** (0.001)	0.001 (0.007)	0.029*** (0.005)	0.003*** (0.001)	-0.002 (0.002)
<i>GroceryShopping</i>	-0.008** (0.004)	-0.001 (0.001)	0.007* (0.004)	0.003 (0.004)	0.000 (0.001)	0.009*** (0.003)
<i>HospitalVisits</i>	0.027*** (0.007)	0.003*** (0.001)	0.006 (0.009)	0.013*** (0.005)	0.001** (0.001)	-0.015*** (0.005)
User Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	856,152	856,152	28,145	856,152	856,152	24,796

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3 DID Results on Overall Food Delivery Consumption

DV_{it}	ln(Amount)	Frequency	ln(Amount per Order)
$Treatment_{it}$	0.615*** (0.033)	0.076*** (0.004)	-0.167*** (0.012)
<i>Beauty</i>	0.004 (0.015)	-0.000 (0.002)	0.005 (0.009)
<i>Culture</i>	0.003 (0.009)	-0.000 (0.001)	0.005 (0.005)
<i>Transportation</i>	-0.002 (0.006)	-0.001 (0.001)	0.005 (0.003)
<i>Cafe</i>	-0.061*** (0.008)	-0.008*** (0.001)	0.011** (0.005)
<i>Housing</i>	0.048*** (0.008)	0.005*** (0.001)	0.000 (0.003)
<i>GroceryShopping</i>	-0.003 (0.005)	-0.001 (0.001)	0.008*** (0.003)
<i>HospitalVisits</i>	0.040*** (0.008)	0.004*** (0.001)	-0.002 (0.006)
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	856,152	856,152	52,645

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4 Impact on Restaurant Visits

DV_{it}	All Dine-out
$Treatment_{it}$	0.035*** (0.006)
<i>Beauty</i>	0.089*** (0.005)
<i>Culture</i>	0.049*** (0.003)
<i>Transportation</i>	0.052*** (0.003)
<i>Cafe</i>	0.095*** (0.003)
<i>Housing</i>	0.011** (0.005)
<i>GroceryShopping</i>	0.059*** (0.002)
<i>HospitalVisits</i>	0.057*** (0.003)
User Fixed Effect	Yes
Time Fixed Effect	Yes
Number of Observations	856,152

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5 Proportion of Offline Restaurant Visit Categories

Dine-out Category	Percentage
Local food	34.5%
Fast food	12.1%
Family restaurant	0.8%
Fried chicken	6.7%
Chinese food	5.7%
Japanese food	6.6%
Cafeteria	4.2%
Western food (including Pizza)	6.1%
Asian cuisine (other than Chinese/Japanese)	1.2%
Buffet	2.3%
Snack food (Korean-style light meals)	13.1%
Barbecue	6.6%

Table A6 Impact on Top 3 vs. Non-Top 3 Restaurant Visits

DV_{it}	Dine-out Top 3	Dine-out Others
$Treatment_{it}$	0.002* (0.001)	0.020*** (0.003)
Controls	Yes	Yes
User Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
Number of Observations	856,152	856,152

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 6: Heterogeneous impact of subscription

In this analysis, we categorize the users into four attributes to examine the results according to the heterogeneity of the user. The four indicators considered were heavy user, single household, high age, and male. We organized data from a variety of data sources to construct these variables. Heavy users are defined as those with an average order frequency of at least one order per month during the 3 months before the service launched. This clarification was established to identify users with above-average values. Based on the pre-launch period, average order frequency was 3.8 during the prior 3 months. The single household is defined by comparing each user's average food delivery amount before the subscription was launched to the target country's national average per person, which is approximately \$12⁶, and organizing users into either single-person or multi-person categories based on this comparison. Analysis for the overall OFD consumption can be seen in Table A7 whereas offline dining heterogeneous analysis can be found in Table A8.

Table A7 Heterogeneity Analysis with Overall OFD Consumption

DV_{it}	$\ln(\text{Amount})$	Frequency	$\ln$ (Amount per order)
$Treatment_{it}$	0.535*** (0.066)	0.063*** (0.008)	-0.206*** (0.042)
$Treatment_{it} \times Heavy_i$	0.080 (0.057)	0.014** (0.007)	0.025 (0.042)
$Treatment_{it} \times Single\ Household_i$	0.001 (0.059)	0.001 (0.007)	0.102*** (0.021)
$Treatment_{it} \times High\ Age_i$	0.017 (0.060)	0.002 (0.007)	-0.008 (0.020)
$Treatment_{it} \times Male_i$	0.027 (0.060)	0.002 (0.007)	-0.041** (0.020)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	856,152	856,152	52,645

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 7: Cascading Spillovers of Altered Mobility Patterns on the Local Economy

As presented in Table A9, initial radius-based analysis provided preliminary evidence of mobility changes, with marginally significant increases in offline non-food economic activity within 2 miles ($p < 0.1$) and significantly decreases beyond 6 miles from subscribers' residences ($p < 0.1$).

Appendix 8: Before Matching Analysis

We use the entire dataset pre-matching to alleviate any potential biases that could arise during the matching procedure. We repeat the main analysis on the impact of subscription on the focal and competing platform and restaurant visits, using the full dataset including 54,496 food delivery users. As illustrated in Tables A10 and A11, all findings remain in alignment with the main results.

Table A8 Heterogeneity Analysis with Restaurant Visit

DV_{it}	Dine-out	Dine-out (Top3)	Dine-out (Others)
$Treatment_{it}$	0.053*** (0.013)	0.011*** (0.003)	0.042*** (0.012)
$Treatment_{it} \times Heavy_i$	-0.011 (0.011)	-0.006** (0.002)	-0.005 (0.009)
$Treatment_{it} \times Single\ Household_i$	0.008 (0.009)	0.001 (0.002)	0.007 (0.008)
$Treatment_{it} \times High\ Age_i$	-0.009 (0.009)	-0.004 (0.002)	-0.005 (0.008)
$Treatment_{it} \times Male_i$	-0.018** (0.009)	-0.006*** (0.002)	-0.013 (0.082)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	856,152	856,152	52,645

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9 Mobility Impact of Non-food Local Economy by Distance

DV_{it}	$\leq 2\text{-mile}$ radius	2-4 mile radius	4-6 mile radius	$\geq 6\text{-mile}$ radius
$Treatment_{it}$	0.062* (0.034)	-0.016 (0.015)	0.002 (0.013)	-0.058** (0.027)
Controls	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Number of Observations	320,821	320,821	320,821	320,821

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 9: Different Distance Unit

To further ensure the robustness of our distance-based results, as demonstrated in Table A12, we conduct the same analysis using a different distance unit, km. We define radius zones with a radius that increases in 2 km increments. This approach allows us to analyze dining behavior within smaller, more precise ranges. Our findings reveal a notable increase in dining activity within the 2 km radius closest to the user's residence following subscription adoption, confirming the localized impact of the service.

Appendix 10: Model Variation for Mobility Analysis

Table A13 presents an alternative specification examining the impact of food delivery subscriptions on individual mobility. Model 1 replicates the main results from Table 11 without including control variables, allowing for seeking unadjusted effect of subscription on individual mobility. Model 2, on the other hand, applies a log transformation to

⁶ <https://www.dbpia.co.kr/pdf/pdfView.do?nodeId=NODE10592112>

Table A10 DID Results before Matching

DV_{it}	Focal Platform			Competitor Platform		
	ln(Amount)	Frequency	ln (Amount per Order)	ln(Amount)	Frequency	ln (Amount per Order)
$Treatment_{it}$	0.690*** (0.027)	0.083*** (0.003)	-0.143*** (0.012)	-0.103*** (0.016)	-0.012*** (0.018)	-0.057*** (0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	21,580,416	21,580,416	132,305	21,580,416	21,580,416	545,289

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11 Impact on Restaurant Visits before Matching

DV_{it}	Dine-out	Dine-out (Top3 delivery categories)	Dine-out (Others)
$Treatment_{it}$	0.031** (0.013)	0.000 (0.001)	0.031** (0.012)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	21,580,416	21,580,416	21,580,416

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12 Impact of Restaurant Visits by Distance (km)

DV_{it}	$\leq 2\text{-km radius}$	2-4 km radius	4-6 km radius	$\geq 6\text{-km radius}$
$Treatment_{it}$	0.034** (0.013)	-0.012 (0.008)	0.001 (0.007)	-0.007 (0.011)
Controls	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Number of Observations	111,726	111,726	111,726	111,726

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the dependent variable, following the main analysis specification. The log transformation helps account for skewness in mobility data. This comparison helps assess the robustness of the findings across different model settings.

Appendix 11: Platform Level Analysis

To examine the broader impact of the subscription launch beyond individual-level effects, we analyzed platform-level sales before and after the launch. Table A14 presents the regression results, showing that the subscription introduction

Table A13 Impact of Food Delivery Subscription on Individual Mobility

DV_{it}	Model 1		Model 2	
	Local District [†]	Neighboring District ^{††}	ln(Local District [†])	ln(Neighboring District ^{††})
$Treatment_{it}$	0.070** (0.032)	-0.106*** (0.035)	0.031** (0.010)	-0.026*** (0.010)
Controls	No	No	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Number of Observations	320,821	320,821	320,821	320,821

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[†]Transaction distances revealed a median of 0.02 miles and a mean of 2.25 miles.

^{††}Transaction distances revealed a median of 4.86 miles and a mean of 19.81 miles.

led to a significant increase in both transaction frequency and total sales amount at the platform level. The estimated coefficients (0.922 and 0.919, both significant at $p < 0.01$) suggest that the subscription model had a substantial positive effect on overall platform performance. These findings reinforce the individual-level results, indicating that the subscription launch not only influenced user behavior but also contributed to platform-wide growth.

Table A14 Platform Level Regression Results

DV_{it}	Focal Platform	
	ln(Frequency)	ln(Amount)
$Treatment_i \times Post_t$	0.922*** (0.0604)	0.919*** (0.0594)
Number of Observations	792	792

Note: Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 12: Including Location-Time Fixed Effects

To further address potential location and time-specific confounding factors, we incorporate an additional set of fixed effects into the analysis. we introduce local district-month dummies based on users' residence and monthly period. Since fixed effects at the individual level already capture time-invariant factors of where users live, we construct monthly dummies to account for location-specific variations that change over time. We add these district-month dummies within the individual daily panel structure, then re-estimate the results are consistent with the main results, further supporting the robustness of the conclusions. All analysis can be seen in Tables [A15](#), [A16](#), [A17](#), and [A18](#).

Table A15 Impact on Restaurant Visits by Distance

DV_{it}	≤ 2-miles radius	2–4 mile radius	4–6 mile radius	≥ 6-mile radius
$Treatment_{it}$	0.029** (0.013)	-0.011 (0.007)	0.001 (0.006)	-0.007 (0.011)
Controls	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
District-month Fixed Effect	Yes	Yes	Yes	Yes
Number of Observations	111,726	111,726	111,726	111,726

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A16 Impact on Restaurant Visits by Food Category and Distance

DV_{it}	Top 3				Other			
	≤ 2-mile radius	2–4 mile radius	4–6 mile radius	≥ 6-mile radius	≤ 2-mile radius	2–4 mile radius	4–6 mile radius	≥ 6-mile radius
$Treatment_{it}$	0.010 (0.018)	0.002 (0.011)	0.005 (0.009)	-0.013 (0.015)	0.032** (0.013)	-0.013* (0.007)	0.001 (0.007)	-0.006 (0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	17,932	17,932	17,932	17,932	98,302	98,302	98,302	98,302

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A17 Impact on Restaurant Visits by Restaurant Type and Distance

DV_{it}	Franchise				Non-franchise			
	≤ 2 mile radius	2–4 mile radius	4–6 mile radius	≥ 6 miles radius	≤ 2 mile radius	2–4 mile radius	4–6 mile radius	≥ 6 miles radius
$Treatment_{it}$	0.0003 (0.014)	-0.004 (0.008)	0.010 (0.007)	-0.003 (0.012)	0.048*** (0.014)	-0.013* (0.007)	-0.004 (0.008)	-0.008 (0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	57,375	57,375	57,375	57,375	63,704	63,704	63,704	63,704

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A18 Cascading Spillovers of OFD Subscription Adoption and Local Consumerism

DV_{it}	Local District [†]	Neighboring District ^{††}
$Treatment_{it}$	0.081*** (0.031)	-0.087*** (0.032)
Controls	Yes	Yes
User Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
District-month Fixed Effect	Yes	Yes
Number of Observations	320,821	320,821

Note: Robust standard errors clustered by each user in parentheses and the DID sample is smaller because we analyze only days with observed locations.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 13: Alternative Matching Process

To ensure the robustness of our findings, we conduct a matching analysis using Coarsened Exact Matching (CEM) as an alternative to PSM, utilizing identical matching variables. CEM efficiently processes large datasets and continuous variables through a three-step process: temporarily categorizing variables into meaningful groups, conducting exact matching on these categorized data, and retaining the original values of matched observations [Blackwell et al. \(2009\)](#). This methodological variation enables a comprehensive examination of subscription impacts on consumer behavior in food delivery services. The results presented in Tables [A19](#) and [A20](#) align with the primary findings: subscribers demonstrate increased purchasing activity on the focal platform, enhanced substitution effects away from competing platforms, and complementary relationships with offline restaurant consumption.

Table A19 DID Results with CEM

DV_{it}	Focal Platform			Competitor Platform		
	In (Amount)	Frequency	In (Amount per Order)	In (Amount)	Frequency	In (Amount per Order)
$Treatment_{it}$	0.695*** (0.028)	0.084*** (0.003)	-0.142*** (0.017)	-0.115*** (0.020)	-0.013*** (0.002)	-0.036* (0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	853,776	853,776	27,664	853,776	853,776	24,667

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 14: Falsification Test

The falsification test employs a spurious outcome variable to verify that the analysis does not capture unintended correlations within the data. A spurious outcome variable represents a measure for which no relationship is expected between food delivery subscription and the outcome, thereby serving as a control to test the robustness of the findings.

Table A20 Impact on Restaurant Visits with CEM

DV_{it}	Dine-out	Dine-out (Top3 delivery categories)	Dine-out (Others)
$Treatment_{it}$	0.035*** (0.012)	0.001 (0.001)	0.034*** (0.012)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	853,776	853,776	853,776

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This methodological approach strengthens the evidence for a causal link between subscription adoption and delivery orders/restaurant visits. The selected spurious outcome variable exhibits variation across treatment and control groups while remaining independent of subscription influence. Estimation of a DID model with this outcome variable would yield an insignificant treatment effect if the observed relationships were not spurious. The DV incorporates all non-OFD online transactions, specifically those unrelated to individual mobility, including home shopping, online shopping, card points, and app store purchases. Table A21 demonstrates the absence of subscription effects on consumption patterns for these non-OFD online transactions.

Table A21 Falsification Test

DV_{it}	Online Category
$Treatment_{it}$	0.018 (0.013)
Controls	Yes
User Fixed Effect	Yes
Time Fixed Effect	Yes
Number of Observations	856,152

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 15: Look Ahead Matching

Within our empirical setting, subscriber's enrollment at different timings, which allows us to treat subscription timing as a plausibly less endogenous source of treatment. However, subscribers who signed up during the promotion period might have different features from subscribers who entered after promotion period. Even the promotion period was relatively short to divide into early and late adoption period for analysis. Thus, we restrict our look-ahead matching to regular subscribers (subscribers other than promotional subscribers) and split them into new treatment and control groups based on subscription timing. We implement a cutoff based on the start of the new calendar year (January 1, 2020), restricting the analysis to regular subscribers who enrolled after the promotional period. Subscribers who signed up before this date are considered as the new treatment group, and subscribers who signed up afterward are

considered as the new control group. Using the subscription enrollment data beyond our analysis period, we can correctly look ahead subscribers who signed up before Dec, 2020 and add them to the new control group. We focus on their transactions in the period when later adopters were still non-adopters, and we could control for confounding factors that may drive the treatment. Using this matching, we identify 139 users in the treatment and control groups respectively and find results consistent with our main findings (see Table A22).

Table A22 DID Results with Look-ahead Matching

	Focal Platform	Competitor Platform	Restaurant Visits
DV_{it}	Frequency	Frequency	Frequency
$Treatment_{it}$	0.089*** (0.012)	-0.034*** (0.008)	0.038** (0.018)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	101,748	101,748	101,748

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 16: Addressing Self-Selection in Treatment Definition

To address the ambiguity in defining the treatment group and mitigate concerns about potential self-selection bias, we conduct an additional analysis distinguishing between the intention-to-treat (ITT) effect and the treatment-on-the-treated (TOT) effect. In our research, users are classified as the treatment group from the date of subscription, regardless of order count, which means that subscribers who do not place orders are still included in the treatment group. We perform additional analyses to more clearly distinguish between intention-to-treat (ITT) and treatment-on-the-treated (TOT). Specifically, to more clearly separate active treatment exposure, we first exclude users who subscribed but did not place orders after subscribing (Table A23). As a complementary specification, we also exclude users in the top quartile (Q4) of order frequency after subscription to mitigate concerns about endogeneity due to heavy usage (Table A24). In both robustness tests, the results are consistent with the main results in terms of directionality, providing additional reliability to the interpretation.

Appendix 17: Specification without Control Variables

To assess whether our results depend on the inclusion of additional control variables, we re-estimate the main specification without the control variables used in the baseline model. This exercise allows us to examine whether the estimated effects are primarily driven by the identifying variation in the treatment rather than by the set of controls included in the regression. In Tables A25 and A26, the results remain qualitatively consistent to those reported in the main analysis. In particular, the estimated effects on the focal platform, the competing platform, and offline restaurant visits remain consistent in both magnitude and direction. This suggests that the main findings are not sensitive to the inclusion of control variables and are unlikely to be driven by model specification choices.

Table A23 Result When Removing Users Who Never Ordered Despite Subscribing (ITT)

	Focal Platform	Competitor Platform	Restaurant Visits
DV_{it}	Frequency	Frequency	Frequency
$Treatment_{it}$	0.093*** (0.004)	-0.001*** (0.003)	0.038*** (0.006)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	818,928	818,928	818,928

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A24 Result After Removing the Top Quartile of Order Frequency Users

	Focal Platform	Competitor Platform	Restaurant Visits
DV_{it}	Frequency	Frequency	Frequency
$Treatment_{it}$	0.040*** (0.002)	-0.008*** (0.002)	0.037*** (0.006)
Controls	Yes	Yes	Yes
User Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Number of Observations	750,816	750,816	750,816

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A25 DID Results on the Focal and Competitor Platform

	Focal Platform			Competitor Platform		
DV_{it}	ln (Amount)	Frequency	ln (Amount per Order)	ln (amount)	Frequency	ln (Amount per Order)
$Treatment_{it}$	0.704*** (0.028)	0.085*** (0.003)	-0.137*** (0.016)	-0.084*** (0.021)	-0.009*** (0.002)	-0.039** (0.019)
Controls	No	No	No	No	No	No
User Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	856,152	856,152	28,145	856,152	856,152	24,796

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A26 Impact on Restaurant Visits

DV_{it}	All Dine-out
$Treatment_{it}$	0.050*** (0.007)
Controls	No
User Fixed Effect	Yes
Time Fixed Effect	Yes
Number of Observations	856,152

Note: Robust standard errors clustered by each user in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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