Food in the Time of COVID: Estimating the Effects of Delivery Platforms on Small-Business Restaurants in California

Abstract

Small businesses and the restaurant industry have been among the most severely impacted by the global pandemic and government-mandated restrictions. In this paper, we explore the impact of online food delivery platforms (e.g., via DoorDash, UberEats, Grubhub, Postmates) in mitigating revenue loss for small-business restaurants during the ongoing pandemic. We use Cost Of Goods Sold (COGS) data from a food supplier who provides food and beverage products to hundreds of small-business restaurants across urban and rural California, in combination with our survey/web-crawling data, and U.S. Census data. Using a quasi-experimental design, we show that food delivery via online platforms has an overall positive effect on restaurants' revenue (an increase of 31.1% or higher in COGS). However, restaurants contracted with platforms may be hurt by a high commission rate (e.g., 30%). Legislating a reasonable ceiling on the commission rate (e.g., 15%) may alleviate this imbalance. Surprisingly, we find that restaurants, whose menus were listed on the platforms without permission, are likely to have received a net benefit in terms of increased net revenue, despite the reported service-related issues. This finding calls into question whether recent laws requiring platforms to remove menus from restaurants that have not explicitly engaged the platform's services will achieve their intended goal of helping these restaurants. We also identified a positive effect of food delivery via platforms among restaurants in areas with low population densities and a substantial benefit for restaurants with existing self-delivery capabilities in terms of significantly increased COGS.

Keywords: Food Delivery, Online Platforms, Small-Business Restaurants, Econometric, Machine Learning

1. Introduction

The global COVID-19 pandemic has caused innumerable societal challenges. In 2020, many state governments in the U.S. implemented "stay-at-home" mandates to flatten the curve of infections, resulting in an unintended but foretold economic impact.

Small businesses, which accounted for 44% of the U.S. economy in 2019 (Rowinski 2022) and the restaurant industry have been among the most severely affected by such policies (Dua et al. 2020). In particular, the well-intended limits on indoor dining restricted restaurant sales to drive-through, take-out, or delivery. In the state of California, many counties implemented such policies in March 2020 (Snyder and Harris 2020). Restrictions were relaxed in May 2020, however, California continued to limit indoor dining at restaurants (State of California 2020). In March 2022, the U.S. further relaxed restrictions and attempted to restore some semblance of normalcy, but Mueller (2022) has cautioned that "Another COVID Surge May Be Coming", citing epidemiologists and infectious disease experts. Indeed, Haas et al. (2020) suggest that indoor dining in restaurants might not return to the pre-pandemic level for years, creating ongoing uncertainty in restaurants that rely heavily on indoor dining.

The impact of pandemic-related restrictions has fallen disproportionately on small-business restaurants (Long 2022). Most chain restaurants already had the infrastructure to accommodate drive-through customers and the technology required to fulfill orders via their website or app for take-out and delivery (Hsu 2020). In contrast, most small-business restaurants do not have such infrastructure or technology, limiting their ability to adapt to the pandemic. This led many small-business restaurants to go out of business (Thompson 2021).

The National Restaurant Association (2022) forecasts the food service industry will reach $898 billion in sales in 2022: 60% of consumers used food delivery via online platforms, and 70% of Gen Z adults (age 21+) and 62% of millennials prefer restaurants offering food delivery. Online platforms have democratized food delivery to some extent, providing an avenue via which small-business restaurants can access some of this market without heavy up-front investment. However, it is important to note that restaurants that contract with platforms to have their menus listed for delivery typically pay a commission of 15 to 30%, and thus they retain only 70 to 85% of the revenue from food sold via platforms (Feldman et al. 2022).

There have been reports of some food delivery apps listing restaurants' menus without their knowledge or consent (Garun 2020). Some of these restaurants have expressed concerns over inaccurate or out-of-date menus and service-related issues that may damage their reputations. In response, in California a new law came into effect on January 1, 2021, requiring that the food delivery apps remove the menus of any restaurant that had not contracted to be listed (Batey 2021), and similar laws have been put into effect in other places, e.g., in Texas starting 2022 (Canham-Clyne 2022) purporting to protect restaurants. However, an unintended consequence of these laws is that they effectively force these restaurants to sign a formal contract and pay the commissions or implement self-delivery services to retain the revenue stream from food delivery. This raises the question: Do these well-intended laws actually help small business restaurants?

Our overarching research question in this study was: What is the impact of food delivery via online platforms on small-business restaurants' revenue during the pandemic, and can the online food delivery services improve operations and help businesses to adapt to a changing environment (speculated in Dua et al. 2020 and Haas et al. 2020)? More specifically, we sought to understand (1) Whether food delivery via online platforms (e.g., DoorDash, UberEats, Grubhub, Postmates) can impact the overall revenue of small-business restaurants in California; (2) Are the effects deferentially distributed if the restaurants are stratified by whether they have a formal contract with the platforms or not?; (3) How much can restaurants with existing self-delivery capability benefit from additional food delivery via online platforms?; and finally, given that prior empirical research on food delivery has focused on major cities with high population densities (Chicago metropolitan area in Li et al. 2019; five major cities in Raj et al. 2021), we also ask: (4) How does food delivery via online platforms impact restaurants in areas with low population densities?

1.1 Main Findings and Contributions

Using a quasi-experimental design, we show that food delivery via online platforms is likely to have led to an overall increase of 25.0% to 30.1% in weekly Cost Of Goods Sold (COGS; depending on the estimation models used) among the small-business restaurants in California in our study period (February to May 2020).

While we expect restaurants that had contracted with the food delivery platforms obtained a slightly larger increase of 31.1% to 33.2% in COGS, they may have been negatively impacted by the platform's high commission rate of 30% (net revenue decreased from 33.3% of COGS to −25.2% to −22.4% of COGS) but may have benefited from the low commission rate of 15% (net revenue increased from 33.3% of COGS to 40.4% to 44.2% of COGS). We estimate the break-even commission rate in our setting to be 16.3% to 17.4%. Our finding provides empirical evidence that legislation such as the permanent 15% cap on commission rate imposed by the Minneapolis City Council (Mahamud 2021) might be a meaningful compromise that would ultimately benefit restaurants and online platforms.

In contrast, our research shows that the restaurants whose menus were listed on the platforms without permission, despite the reported service-related issues, are likely to have gained a 21.2% to 35.0% increase in COGS due to food delivery. Given that these restaurants do not pay any commission to the platforms, this translates to a 49.5% to 81.7% increase in net revenue. The finding calls into question whether the laws requiring platforms to remove such restaurants from their platforms actually achieve their intended goal of helping small-business restaurants that are struggling to stay in business.

Surprisingly, we find that food delivery via online platforms may have increased the COGS at restaurants with existing self-delivery capability by 121.7% to 152.7%. The large effect sizes may be in part attributable to customers' pandemic-related behavioral adaptations and these restaurants' lower dependence on dine-in customers. Finally, we discover that the treatment effect of food delivery via online platforms for restaurants in areas with lower population densities is a 34.9% to 40.1% increase in COGS.

1.2 Related Literature

Our research makes contributions to three main streams of literature in operations management (OM): (i) food delivery platforms, (ii) omnichannel retailing, and (iii) restaurant revenue management.

There is limited literature on food delivery platforms, but it is a rapidly growing area of research (see Mao et al. 2022 for discussions and research opportunities). For example, Liu et al. (2021) developed order assignment policies of platforms, and Feldman et al. (2022), Chen et al. (2022) studied revenue sharing between restaurants and food delivery platforms. There are few empirical works related to our study. Mao et al. (2019) found empirical evidence that early delivery is positively correlated with customer retention. Li et al. (2019) showed that both small and chain restaurants in the Chicago metropolitan area benefited from food delivery platforms using food traffic and bank-card transaction data. Raj et al. (2021) studied small-business restaurants only on UberEats and found a positive effect of food delivery for restaurants in five major U.S. cities. Our paper takes a different estimation approach using COGS data, survey/web-crawling data, and U.S. Census data to study small-business restaurants in both urban and rural areas across the state of California. To the best of our knowledge, our paper is the first empirical work to show that food delivery leads to an increase in small-business restaurants' revenue (proxied by COGS), but the effect of food delivery on the restaurants' net revenue may vary sharply depending on whether or not the restaurants had contracted with the platforms, and by the platform's commission rates. Our paper sheds light on the effect of platforms listing restaurant menus without permission and explores the impact of online food delivery on small-business restaurants with existing self-delivery capabilities and in areas with low population densities.

Our work also contributes to omnichannel retailing, the strategy by which multiple channels (both online and offline) are utilized to engage with customers (see Gao and Su 2017). Much of the literature in this field considers the coordination of online and offline retailing. For example, Bell et al. (2018) found a positive effect of offline showrooms in the context of an online eyeglasses firm using a quasi-experimental design. Our study concerns a different setting — small-business restaurants with existing dine-in capabilities (offline) — and considers the impact of food delivery (online) when the offline channel is available and when it is absent (after indoor dining restrictions). We adopt a similar empirical approach, but also employ estimation strategies using difference-in-difference-in-differences (DDD) framework (Gruber 1994) and machine learning.

OM research on restaurant revenue management often focused on operational issues (e.g., impact of workload in Tan and Netessine 2014, just-in-time scheduling in Kamalahmadi et al. 2021). Tan and Netessine (2020) studied the impact of tabletop technology on sales in chain restaurants using a quasi-experimental research design and found that tabletop technology may improve average sales per check (pre-pandemic). We consider small independent restaurants and study the impact of online channels (rather than the offline channels in the restaurants) as another way to improve the restaurants' revenue during the ongoing pandemic.

The remainder of the paper is organized as follows. We first discuss our unique empirical setting, data, and measures in §2. Then, we discuss our estimation strategy in §3 and present the results in §4. We conclude with a discussion in §5 and provide sample data and all the numerical results in the online appendix.

2. Empirical Setting, Data, and Measures

To address our research questions, we need to identify an ideal empirical setting. Large food distributors such as US Foods and Sysco do not primarily focus on small-business restaurants. Also, small-business restaurants, especially those owned by immigrants, often prefer to work with small and mid-sized food distributors because of lower language and technology barriers, and a higher variety of imported food products. However, small and mid-sized food distributors often do not systematically maintain a clean record of detailed transactions.

2.1 Empirical Setting

For this study, we acquired access to unique and detailed panel data from a mid-sized food distributor in California (referred to as Company B hereafter due to confidentiality), which employs a state-of-the-art ERP system to track the details of food and beverage product purchases (e.g., 50-lb rice) for each restaurant, who in turn uses them to prepare food for consumers. Company B is an exclusive provider of these products, by contract, to hundreds of small-business restaurants (with less than 50 employees), mostly in California.

Thus, we can identify the entire COGS for each restaurant using the data in Company B's ERP system.

We use COGS as a proxy for restaurants' revenue for three reasons. First, Dua et al. (2020) showed that COGS represents 30% of sales revenue among small-business restaurants with less than 50 employees. Second, collecting the revenue data from independent small-business restaurants on a large scale for a long period is not feasible as many of them do not use an ERP system (or similar) to keep track of revenue systematically. Third, based on our conversations with some of the restaurants and the management of Company B, all of these small-business restaurants accept cash which could be a substantial portion of their revenue. Thus, in our setting credit card transaction data may not provide an accurate estimate of their actual revenue.

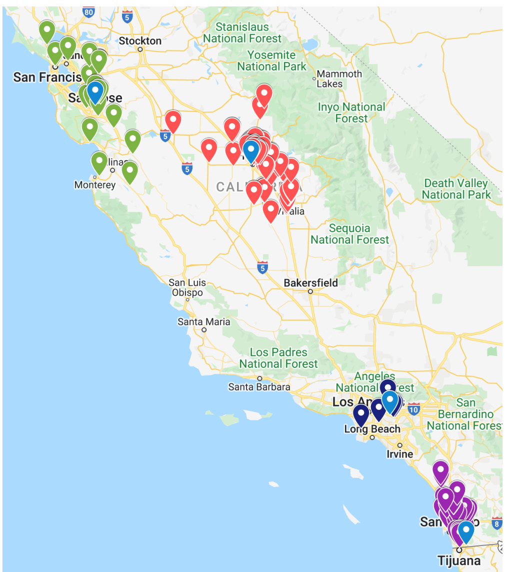

Figure 1: Locations of restaurant/warehouse

We focused on 219 small-business restaurants for which Company B was the exclusive provider (locations shown in Figure 1[1] on the left; see color online). Company B has four warehouses (distribution centers) marked as blue pins (San Jose, Fresno, Los Angeles, and San Diego) which serve restaurants in their respective regions. Restaurants submit orders to their corresponding warehouse via phone two to three times per week. Orders are delivered by Company B's drivers on the day requested by the restaurants (usually the next day, but sometimes on the same day if needed). Each order/SKU is saved and tracked in Company B's ERP system.

Suppose a restaurant offers N items on the menu. Denote the price and demand of each as $p_i, D(p_i)$ for $i \in \{1, ..., N\}$. The revenue of the restaurant can be computed as $R_0 = \sum_{i=1}^{N} p_i D(p_i)$. For simplicity, normalize the total demand to 1, that is, $\sum_{i=1}^{N} D(p_i) = 1$. Then, R_0 is equivalent to the weighted average of prices. Denote the average treatment effect of food delivery via online platforms as δ and the platform's commission rate as ζ. Then, the counterfactual revenue of the restaurant with food delivery via online platforms can be derived as $R_1 = (1+\delta)(1-\zeta)\sum_{i=1}^{N} p_i D(p_i) = (1+\delta)(1-\zeta)R_0$. Dua et al. (2020) also shows that operating costs (including labor and rent) account for 60% of restaurant revenue and 10% is net revenue. So, the COGS equals $30\%R_0$, operating costs are $60\%R_0 = 2COGS$, and the net revenue is $10\%R_0 = \frac{1}{3}COGS$. Increased demand may increase the labor cost slightly, but for small-business restaurants from February 2020 and May 2020, it may be reasonable to assume the operating costs remain the same with food delivery via online platforms. With these simplifying assumptions[2], the net revenue changes to $R_1 - 60\%R_0 - (1+\delta)COGS = (1+\delta)(1-\zeta)R_0 - 2COGS - (1+\delta)COGS = (1+\delta)(1-\zeta)\frac{10}{3}COGS - (3+\delta)COGS = \frac{1}{3}COGS + \frac{7\delta-10\zeta-10\zeta\delta}{3}COGS$. Note $\frac{7\delta-10\zeta-10\zeta\delta}{3}COGS$ is the change in net revenue, which ranges from $\frac{5.5\delta-1.5}{3}COGS$ and $\frac{4\delta-3}{3}COGS$ because the commission rate ζ ranges from 15% to 30% (Feldman et al. 2022) and becomes $\frac{7\delta}{3}COGS$ when $\zeta = 0$. We aim to first estimate the treatment effect, δ, and then investigate how it changes for subsequent research questions (see §3).

2.2 Data Description

We use three sources of data: (i) the proprietary data from Company B's ERP system, (ii) our survey/web-crawling data, and (iii) the U.S. Census data.

This proprietary data set contains all raw transaction data of Company B from February 1, 2020, to May 23, 2020, encompassing the period before the 1st stay-at-home order and during different stages of this order[3]. This raw data set contains the warehouse location, order information (ID, date), restaurant information (ID, name, street address, city, state, and ZIP5), item information (SKU, description, category), quantity, and unit price. We provide an example of two orders submitted to the Fresno and San Diego warehouses, respectively, in Table A1 in the online appendix. As expected, the price paid for an SKU can vary by the distribution center and can also fluctuate weekly. In our data, we find that the prices sometimes also vary by the restaurants due to contractual differences (the average coefficient of variation was 0.012; 99% of SKU's had a coefficient of variation below 0.15). To control for the price variation in SKU due to the contract, we take the median of the SKU prices paid by restaurants within each distribution center by each week and use the median value for an SKU when calculating the COGS.

To supplement the proprietary COGS data, we collected additional important features of the small-business restaurants by a combination of survey and web-crawling from in June 2020: (a) food delivery via online platforms or using their own infrastructure, and whether the restaurants' menus were listed on the platforms without permission[4], (b) food type (e.g., Chinese food), (c) hours of operation (opening, closing, break), (d) online presence (Facebook, Yelp, or own website), (e) government's health inspection ratings, (f) proximity to universities (see the full list in Table B1; discussed further in §2.3.3). Lastly, we obtained the U.S. census data on consumers' socioeconomic and demographic information in the ZIP5 of each restaurant from SimplyAnalytics (see the full list in Table B2; discussed further in §2.3.3).

2.3 Measures

2.3.1 Dependent Variable

The primary dependent variable in our study is the weekly COGS of a restaurant denoted by $COGS_{i,t}$ where the subscripts i, t represent the restaurant ID and week number, respectively. This is a sum of all the food products regardless of whether they are perishable or non-perishable, that is, $COGS_{i,t} := COGS\_P_{i,t} + COGS\_NP_{i,t}$. The perishable category includes fresh produce, eggs, dairy, and tofu, among others. The non-perishable category includes frozen vegetables, coffee, tea, meat, poultry, and seafood (which can be frozen for later usage). We find that $COGS_{i,t} = 0$ for some pairs of i, t. It is probable that some restaurants were closed for certain weeks. Note that we are interested in the treatment effect of food delivery via online platforms when restaurants are open. So, we do not include $COGS_{i,t} = 0$ in our primary measure, thus treating it as a missing value, to avoid bias in our result. We aggregated COGS weekly as our primary measure from Sunday to Saturday because the delivered goods are generally used for the next day or later and we want to capture restaurants' weekly sales from Monday until Sunday.

Based on conversations between the inventory managers and restaurant owners, however, some restaurants were open when $COGS_{i,t}$ is zero: early in the pandemic consumer demand was unpredictable and thus restaurant owners used excess non-perishable inventory from the previous week. To account for such scenarios, we develop an alternative measure $COGS\_ALT_{i,t} \coloneqq COGS\_P_{i,t} + \eta COGS\_NP_{i,t} + (1-\eta) COGS\_NP_{i,t-1}$, where $1-\eta$ denotes the fraction of non-perishable food products that were carried over from the previous week. In our main analysis, we use $\eta = \frac{1}{2}$.

2.3.2 Treatment Variable

Our primary treatment variable is $DELIVERY_{i,t}$ which equals 1 if restaurant i had food delivery via online platforms in week t and equals 0 otherwise. Similarly, we define $DELIVERY\_WP_{i,t}$ ($DELIVERY\_WOP_{i,t}$) which equals 1 if online platforms listed restaurant i's menus with (without) permission for food delivery in week t and equals 0 otherwise. We use $DELIVERY_i \coloneqq \max_{t\in\{6...21\}} DELIVERY_{i,t}$ to denote whether restaurant i had food delivery via online platforms at some point of time during weeks 6 to 21 in the year 2020. Our data shows $DELIVERY_i = 0$ for 119 restaurants, and $DELIVERY_i = 1$ for 100 restaurants out of which 36 had a formal contract with one or more food delivery platforms ($DELIVERY\_WP_i = 1$) and 64 had their menus listed on the platforms without their permission ($DELIVERY\_WOP_i = 1$).

2.3.3 Control Variables and Potential Endogeneity Issues

Primary Control Variables

We use the week index, $t \in \{6...21\}$, to control for seasonality. As the products are delivered to the restaurants from one of four distribution centers, we use the warehouse fixed effect to control for this variation. Further, we control for food type (determined by the restaurant's names or menus) and hours of operation (derived from online sources, such as Yelp or their website) because they may be associated with the treatment and outcome variables. See Table B1 for more details.

In addition, we control for consumer socio-economic and demographic variables (see Chen et al. 2022 who model tech savvy vs. traditional customers). The primary control variables we consider are common U.S. Census variables used in empirical research (Cui et al. 2021), including the median household income, average household size, median age, as well as population density, and percentage of college (or higher) education. We also consider alternative model specifications using ZIP3 fixed effect in place of these variables to control for unobservables at the ZIP3 level. We are not able to control at the ZIP5 level due to the limited number of observations. See Table B2 for more details.

Alternative Control Variables

To check the robustness of our results and to address potential endogeneity issues, we also consider the following alternative restaurant-level and consumer socio-economic and demographic variables.

- *Hours of Operations*: During the data collection, we noticed that some restaurants closed for up to 3 hours between lunch and dinner, so we subtracted such breaks from hours of operation to derive an alternative measure for hours of operation.

- *Health Inspection Rating*: In the state of California, the health rating is governed by the county. In our study, 61% of restaurants had a letter (e.g., A or B) or numerical health inspection rating (e.g., 91 or 82). We converted the numerical rating to letter rating as follows: $[90, 100] = A, [80, 90) = B, < 80 =$ Below B. Some restaurants had qualitative health inspection reports (mainly in Fresno county) but had no letter or numerical health rating; we define their health rating as "No quantitative ranking".

- *Proximity to Universities*: We noticed that 79% of the restaurants in our study were within 1.5 miles of universities (or colleges) according to Google's database. Due to the switch to online learning, the consumer population near universities may have changed during our study period which could impact our outcome variable but would not be captured in the U.S. Census data. Thus, we consider three binary control variables to denote whether a restaurant is within 1, 1.25, and 1.5 miles of universities.

- Similar to Bell et al. (2018), we consider a long list of consumer socio-economic and demographic variables at the restaurant ZIP5 location. We consider these additional variables to capture the market size, gender effect, age effect, consumer's purchasing power, and consumer expenditure on restaurant foods (see the full list in Table B2).

Potential Endogeneity Issues

The decision to adopt food delivery via online platforms may be endogenous and could be impacted by the following factors. Lower sales compared to historical data may cause the restaurant to use online platforms to deliver foods to increase sales. We capture this factor by *Lagged COGS* defined as $COGS\_LAG^n_{i,t} := \sum_{j=1}^{n} \frac{COGS_{i,t-j}}{n}$ for $n = 1, 2, 3, 4$ to represent historical sales for up to 4 weeks prior to the current week. For example, if a restaurant manager observes poor sales for two consecutive weeks, he or she may decide to adopt online platforms for food delivery to increase sales. This means $COGS\_LAG^2_{i,t} = \frac{COGS_{i,t-1}+COGS_{i,t-2}}{2}$ impacts the treatment variable $DELIVERY_{i,t}$.

It is possible that restaurant managers who are more tech-savvy may be more likely to implement food delivery via online platforms. This is an omitted variable in our study and we use *Online Presence* as a proxy to capture this factor. We use two binary variables to identify whether a restaurant is listed on Yelp or Facebook. Granted, some of these are not directly created by the restaurant management. So, we also use a third variable to identify whether a restaurant has its own website.

The restaurant management may take into account the likelihood of customers being tech savvy and proficient in English enough to use online platforms for food delivery (there are many minority and immigrant communities in California). So, we use *Percentage of Education Attainment* (less than high school, high school, some college, associate's degree, bachelor's degree, post-graduate degree) and *Percentage of Language Spoken at Home* (only English, Spanish, Chinese including Mandarin and Cantonese, Vietnamese, and other Asian and Pacific Island languages) to minimize the unobserved characteristics of consumers and restaurant management which may impact the treatment and outcome variables.

2.3.4 Summary Statistics

We provide summary statistics in Table B1 and B2 in the online appendix.

3. Estimation Strategy

In this section, we first discuss our econometric approach to estimating the effects of food delivery via online platforms on small-business restaurants in different dimensions (e.g., overall impact during the study period, and the impact of listing restaurant menus without contract). To do this, we adopt the framework of difference-in-differences (DID) and difference-in-difference-in-differences (DDD) in conjunction with propensity score matching (Rosenbaum and Rubin 1983) and a three-step variable selection (Belloni et al. 2014) using machine learning methods. We present our results in §4 and discuss our findings in §5.

The DID model is one of the most widely used casusal inference methods utilized by researchers in empirical operations management (see an excellent review of methods in Terwiesch et al. 2020). We apply DID to estimate the average treatment effect on the treated group. As we use panel data in our study, we want to identify this average treatment effect by estimating the change in a unit of analysis before and after exposure to the treatment, in comparison to a control group that was not exposed to the treatment in the same period (Angrist and Pischke 2009). In our study, the unit of analysis is a restaurant and each period of observation is one week. The treated units are restaurants with food delivery via online platforms and the control group includes restaurants without food delivery via online platforms for a given period. Note that in our main analyses we include restaurants whose menus were listed on food delivery via online platforms without permission. We separate these cases and conduct further analyses in §4.3. We follow an approach similar to ones in Bell et al. (2018), Tan and Netessine (2020) in the next section.

3.1 Difference-In-Difference

We aggregate the COGS data weekly and then transform COGS into their natural logarithms following Tan and Netessine (2014) and use it as the dependent variable in the following DID model for panel data.

$$log(COGS_{i,t}) = \alpha + \gamma_t + \boldsymbol{\beta}^T \boldsymbol{z}_{i,t} + \delta DELIVERY_{i,t} + \epsilon_{i,t} \ , \tag{1}$$

where i is the restaurant ID, t is the week number as discussed previously, α represents a constant term, γ_t are weekly fixed effects, $\boldsymbol{z}_{i,t}$ is a column vector of control variables explained in §2.3.3, $\boldsymbol{\beta}$ is the corresponding column vector of coefficients, $\epsilon_{i,t}$ is the random error term, and $DELIVERY_{i,t}$ is a binary treatment variable that varies at the group and time levels (see STATA command *xtdidregress*).

Note that (i) our DID specification allows for various treatment timings because our data show that different restaurants may have had food delivery via online platforms during different weeks; (ii) we have one observation (the total COGS) for each restaurant in each week, thus the constant value for α; and (iii) we use the cluster-robust standard errors clustered at each restaurant level. Our objective is to estimate the treatment effect δ. If δ is found to be significant and positive, then we find support that food delivery via online platforms significantly increases the log(COGS). Note that the correct interpretation of the treatment effect of food delivery via online platforms on COGS is $e^{\delta} - 1$, because we model log(COGS) in (1).

3.2 Propensity Score Matching

As we discussed in §2.3.3, potential biases may occur when control variables impact whether a restaurant has food delivery via online platforms, that is, whether the restaurant receives a treatment. In other words, the aforementioned $\boldsymbol{z}_{i,t}$ may be correlated to the treatment variable $DELIVERY_{i,t}$. We used the Logit model to check this possibility and indeed found that quite a few control variables are significantly correlated to the treatment variable. We provide one model specification in Table C1 in the online appendix. We use two different methods to address this issue. We start with Propensity Score Matching in this section and discuss machine learning-based methods in the next two sections.

Propensity Score Matching was first introduced by Rosenbaum and Rubin (1983) and is among the most widely used empirical methods to reduce endogeneity issues (see Terwiesch et al. 2020). The propensity score is defined as the selection probability conditional on the confounding variables. Rosenbaum and Rubin (1983) showed that conditioning on the propensity score is sufficient to establish independence between treatment variables and potential outcomes. Matching on the propensity score also has a substantial advantage over matching on the covariates which suffer from the curse of dimensionality. We show that in our setting Propensity Score Matching improves the balancing between the control group and treated group in balance plots in Figure C1 for different model specifications.

In our main analyses, we employ the Logit model with different model specifications including different subsets of control variables. We also tried the same model specifications with the Probit model but did not notice a significant difference between the choice of Logit vs. Probit models. While we explored different model specifications with reasonable subsets of the control variables, it is not entirely clear which one should be considered the best given the large number of control variables. This led us to consider another approach: a three-step variable selection (Belloni et al. 2014) using machine learning methods discussed next.

3.3 Difference-In-Differences with Machine Learning

Belloni et al. (2014) propose robust methods to infer the effects of a treatment variable on an outcome variable given a large number of covariates with possibly non-Gaussian and heteroscedastic errors. Their procedure involves two different variable selection steps and one final step estimation step as follows.

In step 1, we select a set of control variables that are important in predicting the treatment variable $DELIVERY_{i,t}$. This step helps ensure that the post-model-selection inference is valid by finding control variables strongly correlated to the treatment variable and therefore possibly important confounding variables. In step 2, we also select a set of control variables, but only those useful for predicting the outcome variable $log(COGS_{i,t})$. This step helps ensure that we have incorporated useful elements in the model of interest to, ideally, help reduce the residual variance ideally and provide an additional option for finding useful confounding factors. In step 3, we take the union of both sets of variables from step 1 and step 2 and use them to estimate the treatment effect of interest, δ, by the linear regression of the outcome variable $log(COGS_{i,t})$ on the treatment variable $DELIVERY_{i,t}$.

In our study, we use the Adaptive LASSO (Zhou 2006) and Random Forest (Breiman 2001) to select variables. To begin with, we used Random Forest to visually inspect the variance importance of the control variables (see §8.2 in James et al. 2017 for more details) for both step 1 and step 2 discussed above. We find that the lagged COGS that we discussed in §2.3.3 have the highest variable importance values. We considered $COGS\_LAG^1_{i,t}$, $COGS\_LAG^2_{i,t}$, $COGS\_LAG^3_{i,t}$, $COGS\_LAG^4_{i,t}$ as well as the natural logarithms of these variables $log(COGS\_LAG^1_{i,t})$, $log(COGS\_LAG^2_{i,t})$, $log(COGS\_LAG^3_{i,t})$, $log(COGS\_LAG^4_{i,t})$. As expected, we also find a strong correlation between these variables. To avoid unnecessary overfitting in our estimation model, we used the Adaptive LASSO with 10-fold cross valuation (CV) in STATA 17 for variable selection which yielded $COGS\_LAG^2_{i,t}$. Next, we include $COGS\_LAG^2_{i,t}$ as the only lagged COGS and include all the remaining control variables, and apply the Adaptive LASSO with 10-fold CV for step 1 and step 2. The selected variables are shown in §D in the online appendix. Then, in step 3, we choose the variables selected in step 1 or step 2, and use them as control variables to run DID models denoted as DID-ML hereafter.

3.4 Difference-in-Difference-in-Differences (DDD) with Machine Learning

We use the aforementioned estimation strategies to estimate the overall impact of food delivery via online platforms on the weekly COGS. However, to understand the treatment effect within another group, we need to adopt the triple regression framework known as difference-in-difference-in-differences (DDD, e.g., see Gruber 1994, Chan et al. 2022). DDD essentially adds another level of the control group to the DID framework to control for unobservable interactions between group and time that might not have been captured by DID. In our study, we want to understand (i) the treatment effect on restaurants in areas with low population densities, and (ii) the treatment effect on restaurants with existing self-delivery capability. To do this, we use the following model specification,

$$log(COGS_{i,t,g}) = \alpha + \gamma_t + \gamma_t\gamma_i + \gamma_t\gamma_g + \boldsymbol{\beta}^T \boldsymbol{z}_{i,t} + \delta^{'} DELIVERY_{i,t} + \epsilon_{i,t,g} \ , \tag{2}$$

in which g is the group-level index we are interested in, and γ_g are group fixed effects. The parameter we are interested in estimating in this triple-difference regression model is $\delta^{'}$. Then, we further apply the aforementioned machine learning method to select variables in three steps to obtain a spare model and refer to it as DDD-ML model hereafter.

4. Results

In this section, we first discuss the estimation results for the overall impact of food delivery during our study period in §4.1. Then, we show the results broken down into two time periods: before the no-dine-in policy and after the no-dine-in policy §4.2. We also separate our treatment variable ($DELIVERY_{i,t}$) into two cases: listing restaurant menus with permission through a formal contract ($DELIVERY\_WP_{i,t}$) vs. listing restaurant menus without permission ($DELIVERY\_WOP_{i,t}$) discussed in §2.3.2, and study each treatment effect individually in §4.3. Finally, we investigate the impact of food delivery via online platforms in areas with low population densities in §4.4 and the scope of impact on restaurants that have existing self-delivery capabilities in §4.5 using the DDD-ML models.

4.1 Overall Impact of Food Delivery via Online Platforms

To begin our analysis, we first explored different model specifications for the DID model using our primary measure of outcome shown as Model 1a and Model 1b in Table E1. We tested the parallel trend assumptions in our data and did not find a violation of the assumptions. In both models, we use the same control for time fixed effect, distribution center fixed effect, food type fixed effect, and hours of operation (which was shown to have high variable importance in the analysis using Random Forest; see Table C1). The difference is that in Model 1a we control for common consumer socio-economic and demographic characteristics at the restaurant's ZIP5 level (see Cui et al. 2021 for an example) and in Model 1b we control for ZIP3 level fixed effect (we are not able to control at ZIP5-level due to the data size). The estimated treatment effects are significant in both models and vary by very little. For example, $\delta = 0.223$ in Model 1 which shows that the food delivery via online platforms leads to a overall increase of $e^{\delta} - 1 = 25.0\%$ in the COGS during our study period.

Model 2a and Model 2b, are identical to Model 1a and Model 1b, respectively, except that we use our alternative measure of the outcome variable, $COGS_{ALT}$, discussed in §2.3.1. Here, $\delta = 0.377$ suggests that if we assume that restaurants continue to use 50% of non-perishable goods (e.g., frozen vegetables) in the following week, the estimated overall increase is much larger at $e^{\delta} - 1 = 45.8\%$. The reason for the increase in the number of observations is that there are fewer missing data in $COGS_{ALT}$ compared to $COGS$.

We also use Propensity-Score-Matching (PSM) as our estimation strategy from §3.2 and show the corresponding results for our primary measure of the outcome variable in Table E2 and the results for our secondary measure of the outcome variable in Table E3. We checked for balancing in the control and treated observations using density plot and box plot (see Figure C1) and the result shows that PSM generates good balanced matched groups. In these PSM model specifications, we gradually consider more control variables to reduce potential endogenieity issues with our treatment variable as discussed in §2.3.3. Not surprisingly, the treatment effect is smallest in Model 3d (4d) with $\delta = 0.260$ (0.352) which translates to an overall increase of COGS ($COGS_{ALT}$) of 29.7% (42.2%).

As another defense against endogeneity, we employ the DID-ML model discussed in §3.3. Using the control variables selected following the method in Belloni et al. (2014), we find that food delivery via online platforms leads to an overall increase of COGS ($COGS_{ALT}$) of 30.1% (53.4%) as shown in Model 5 (6). We use only one of the three measures for proximity to universities (within 1 mile of universities) here, but consider all three measures in DD-ML and DDD-ML models.

The reason that PSM and DID-ML show higher treatment effects of 29.7% to 30.1% when compared to the treatment effect in the DID model which was 25.0% in our setting is likely due to the endogeneity of the treatment variable. More specifically, it is plausible that restaurants which experienced more challenges in sales during the pandemic are, on average, more likely to adopt food delivery via online platforms. This direction is opposite to that in Bell et al. (2018) who find a smaller treatment effect when using PSM because in their focal retailer is more likely to open offline showrooms where there is a higher likelihood of sales.

4.2 Impact of Food Delivery via Online Platforms: Before and After No-Dine-In Policy

Our next research question was to explore how the treatment effects compare across two time periods: before the no-dine-in policy (weeks 6 to 11 in the year 2020) and after the no-dine-in policy (weeks 13 to 21). Our data shows that 59 restaurants had food delivery via online platforms (prior to our study period); only 2 adopted food delivery via online platforms in week 11, 2 in week 12, and 39 during weeks 13 to 21; and 117 never had food delivery via online platforms. We drop the data in week 12, because the no-dine-in policy was implemented during week 12 (dates vary by county), and create two data sets: one containing data from weeks 6 to 11 and the other with data from weeks 13 to 21.

During weeks 6 to 11, we found that the treatment effects were between 0.178 (DID-ML) and 0.227 (PSM) which suggests that food delivery via online platforms leads to an increase in COGS by 19.5% to 25.5% as shown in Table E5. However, likely due to the short time period and treatment timing, we do not find significant results in the basic DID specifications using Model 1a and Model 2. When we use the time index as a continuous variable (instead of using the time fixed effect), we found a positive effect, but the corresponding p-value was still higher than 0.10. We want to note that $COGS_{ALT}$ was found to have an increase of 31.8% (PSM) to 32.3% (DID-ML).

The results for weeks 13 to 21 are provided in Table E6. We find the treatment effect of food delivery via online platforms is robust: 0.511 (DID), 0.522 (PSM), and 0.520 (DID-ML) which is equivalent to an increase in COGS between 66.7%, 68.5%, and 68.2% respectively. We also find that food delivery via online platforms lead to a significant increase in $COGS_{ALT}$ by 150.9% (DID), 110.4% (PSM), and 145.2% (DID). Recall this was the beginning of the pandemic in the U.S. when restaurants closed doors to dine-in customers.

4.3 Impact of Listing Restaurant Menus With Contract and Without Contract

In this subsection, we investigate the treatment effects of two groups of restaurants: (a) one that signed formal contracts with online platforms (thus paying 15% to 30% fees; $DELIVERY\_WP_{i,t} = 1$), and (b) the other whose menus were listed on the platforms without permission ($DELIVERY\_WOP_{i,t} = 1$). The results are provided in Table E7.

All model specifications show that the former group had a higher treatment effect than the restaurants in the latter group. Restaurants that signed formal contracts with online platforms experienced an increase in COGS of 33.2% (DID), 32.8% (PSM), and 31.1% (DID-ML), whereas restaurants whose menus were listed without permission had an increase in COGS of 22.0% (DID), 21.2% (PSM), and 35.0% (DID-ML). Though restaurants' concerns that they may be hurt by online platforms listing their menus without permission were valid (as discussed in §1), our results suggest that there is a significant positive benefit.

In the next two subsections, we present the results on the impact of food delivery via online platforms in two additional dimensions: restaurants in areas with low population densities in §4.4, and restaurants with existing self-delivery capabilities in §4.5. The first question is of importance to both restaurants and online platforms because consumers in areas with low population densities and high population densities may exhibit different spending patterns on food delivery. The second question sheds light on how much additional benefit restaurants, which can deliver foods to customers via their own drivers, may expect by using online platforms. Both of these questions require an additional layer of difference, thus the DDD framework.

4.4 Impact of Food Delivery via Online Platforms in Restaurants in Low-Population-Density Areas

In our study, we define restaurants in high population density areas as ones serviced by the focal firm's San Diego distribution center (35% of restaurants; average population density of 6,407 people per square mile) and the restaurants in low population density areas as ones serviced by the Fresno distribution center (47% of restaurants; average population density of 2,675 people per square mile). We do not consider the Los Angeles distribution center because of the smaller sample size (5%) and exclude the San Jose distribution center (13%) because the restaurants it serves included both high and low population densities as shown in Figure 1. Our analyses show that the treatment effect for restaurants in low-population-density areas is 36.8% (DDD), 40.1% (PSM), and 34.9% (DDD-ML) (see details on Table E8). To the best of our knowledge, this is the first study shedding light on restaurants in low-population-density areas given that prior research has focused on big cities or metro areas. We also conducted a separate analysis for restaurants in high-population-density areas and found the average treatment effect to be smaller in most models (though there was no statistically significant difference). This appears to be in line with the finding in Banerjee et al. (2021) using consumers' cell phone geolocation data to show that restaurant visits declined almost twice as much in urban counties in 2020 compared to rural counties.

4.5 Impact of Food Delivery via Online Platforms on Restaurants with Self Delivery

Our last analysis was to address the question: Does food delivery via online platforms help increase the COGS of restaurants that already have self-delivery capabilities via their own drivers? If so, what is the effect size? We use the same DDD framework to answer this question.

The results in Table E9 show that the effect is not only significant but substantial. The treatment effect is an increase in COGS by 137.5% (DDD), 152.7% (PSM), and 121.7% (DDD-ML). This suggests that even restaurants that have their own drivers delivering food to customers may receive substantial benefit from food delivery via online platforms, due to the increased number of new customers it can reach, but may also be in part attributable to customers' COVID-related behavioral adaptations and these restaurants' lower dependence on dine-in customers.

4.6 Model Valuations and Robustness

In this section, we report upon robustness checks performed to validate our findings (all conducted in STATA 17 unless otherwise noted; results available upon request). First, we considered two alternative measures of the outcome variable. We used $\eta = \frac{3}{4}$ for $COGS_{ALT}$ (thus $\frac{1}{4}COGS\_NP_{i,t-1}$ carried over to the next week) and found a stronger effect, similar to when we used $\eta = \frac{1}{2}$. We considered $log(1 + COGS)$, instead of $log(COGS)$, which is common in an online retail setting. When $COGS = 0$, $log(COGS)$ becomes a missing value in our primary measure, but $log(1 + COGS)$ equals 0 which does not create the same issue. This allows us to use all 219 restaurants' COGS for weeks 6 to 22 and we obtained much stronger results than the corresponding results in Models 1a-1b, 3a-3b, 5, and 6 using our primary and secondary measures. However, this measure assumes that the restaurants were open even when $log(COGS) = 0$ which is not very realistic in our study period. We also tried aggregating COGS weekly from Friday to Thursday to capture restaurants' weekly sales from Saturday to Friday, and including beverage products in the total COGS, and neither yielded a meaningful difference in the estimates. Second, we considered alternative estimation strategies. We tried alternative machine learning methods (e.g., using BIC, LASSO, Gradient Boosting) and found no significant difference in our estimates. We employed the Inverse-Probability Weighting model using the Logit or Probit link function and found slightly stronger results. We also explored a few specifications of linear regression with the endogenous treatment model and found much stronger results compared to Models 3d and 4d; we observed larger effect sizes when using a new method in Callaway and Sant'Anna (2021) to address variation in treatment timing in DID (conducted in R package *did 2.1.2*). Third, we dropped the LA distribution center and data from week 12 and found the results to remain robust.

5. Discussion and Conclusion

In this paper, we investigated the effect of food delivery via online platforms on small-business restaurants' revenue in urban and rural areas across in California from February to May 2020. We are among the first to provide empirical evidence that food delivery via online platforms helps restaurants increase their COGS

– a proxy for revenue – while controlling for numerous factors and addressing potential endogeneity issues.

Using multiple econometric methods in conjunction with machine learning methods, our study shows that restaurants who contracted with food delivery platforms to pay the higher commission (e.g, 30%) may have been negatively impacted, while a lower commission (e.g., 15%) facilitated a net benefit. Our finding provides support for popular viewpoints (e.g., see Hadfield 2020) that high commission rates leave very little net revenue for restaurants, while also providing empirical evidence for legislation capping the commission at 15% (as was passed in Minneapolis; Mahamud 2021) could benefit small-business restaurants. This is particularly important as the market for restaurants relying on food delivery keeps increasing (see "ghost kitchen" in Canada 2022).

Surprisingly, our analysis also showed that restaurants whose menus were posted without permission reaped the most benefit. It has been widely reported that some of these restaurants have experienced service-related issues including the fall-out from platforms listing inaccurate or out-of-date menus (e.g., see Guarente 2020). In a bid to address this problem, California (Batey 2021) and Texas (Canham-Clyne 2022) responded to this issue by passing laws to require food delivery apps to remove tens of thousands of such restaurants to protect the restaurants. However, our research calls into question whether these laws will achieve their intended goal, and more importantly the harm that may be caused if other jurisdictions adopt similar laws. A more effective approach may be to require platforms to disclose to the consumers whether restaurants are formally contracted with the platforms and that any inaccuracies are the fault of the platform, not the restaurant, more transparently allocating responsibility. We also found that food delivery via online platforms increased the COGS of restaurants with existing self-delivery capability by 121.7% to 152.7%. This is likely because the online platform may increase visibility both in terms of engaging existing consumers and recruiting new customers. Finally, we discover that the effects of food delivery via online platforms for restaurants in areas with low population densities are also quite substantial (no statistically significant difference compared to restaurants in areas with high population densities).

Moving forward, research in this area could be targeted to determining the impact of platform's commission rates; determining how delivery time disclosure impacts a customer's subsequent purchase; how these findings apply to businesses not experiencing the extenuating circumstances of severe stay-at-home orders.

Notes

[1] In our study, we do not include some chain restaurants, food courts in malls, buffets, and food trucks.

[2] Current inflation started in 2021 (see `https://www.usinflationcalculator.com/inflation/current-inflation-rates/`), thus price inflation is not an issue in our study period. We provide a net revenue calculation here for the purpose of illustration. The net revenue is an estimated average and it may vary by each restaurant's operating costs (e.g., the rent).

[3] California prohibited indoor dining from mid-March, and allowed dine-in service from May 12, conditional on that restaurants could implement demanding operational changes. Based on surveys with all the restaurants, we found that none of them resumed dine-in service until mid-June 2020; none had the drive-through capability; all accommodated take-out orders.

[4] We used the name and address each restaurant to search whether each restaurant was listed on food delivery platforms

(including DoorDash, UberEats, Grubhub, Postmates, Seamless, and Yelp - defined as "DELIVERY_5: Other" in Table B1). We hired five graduate students to call each restaurant to find out if each restaurant had formally contracted with platforms (in this case, the restaurants were provided tablets from the platforms to keep track of orders). Restaurants, not contracted with the platforms, were aware of platforms sending workers to order food for take-out/delivery and that their menus were listed online without permission. We also asked the first week when the food delivery through the platforms started. We also searched whether the restaurant had its own official website and whether the restaurant delivered food on their own.

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Online Appendix to "Food in the Time of COVID: Estimating the Effects of Delivery Platforms on Small-Business Restaurants in California"

A. Sample of COGS data

Order No.	Order Date	SKU	SKU Description	Category	Qty	UnitPrice	Warehouse	Restaurant ID	Restauran Type	Street Address	ZIPcode
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Poultry	6	$54.65	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Produce	4	$11.5	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Produce	2	$14.95	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Produce	1	$13.45	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Produce	5	$1.59	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Produce	1	$14.95	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Supply	5	$16.95	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
FNxxxxxx	3/2/2020	xxxx	xxxxxxxxxxxx	Supply	1	$25.4	Fresno	xxxx	Chinese Food	xxxxxxxxxxxx	93277
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Poultry	1	$65.6	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Poultry	2	$44.8	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Produce	1	$62.95	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Grocery Frozen	1	$37.95	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Grocery Dry	1	$28.5	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Grocery Dry	1	$24.95	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Produce	1	$13.5	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915
SDxxxxxx	4/16/2020	xxxx	xxxxxxxxxxxx	Supply	1	$26.95	San Diego	xxxxx	Japanse Food	xxxxxxxxxxxx	91915

Table A1: A sample of restaurant's COGS data.

Note: supply (e.g., cleaning) products are not included in the weekly COGS in our study.

B. Summary Statistics

Table B1: Summary Statistics of Restaurant-Level Panel Data

Variable Name	Variable Description	Mean	Std Dev	Min	Max
	Cost of Goods Sold (COGS)				
COGS	Perishable + Non-perishable (current week)	$1,046.21	$2,400.31	$0.00	$45,333.89
COGS_P	Perishable (current week)	$207.60	$375.26	$0.00	$5,599.75
COGS_NP	Non-perishable (current week)	$838.62	$2,075.72	$0.00	$39,734.14
COGS_ALT	Perishable (current week) + Non-perishable (current and next week average)	$1,035.02	$2,356.51	$0	$43,102.03
COGS_LAG	Perishable + Non-perishable (last week)	$1,052.96	$2,444.96	$0	$45,333.89
	Food Delivery				
DELIVERY	Delivery (via any of platforms below†)	0.33	0.47	0	1
DELIVERY_1	Postmates	0.22	0.42	0	1
DELIVERY_2	Doordash	0.2	0.4	0	1
DELIVERY_3	Grubhub	0.18	0.38	0	1
DELIVERY_4	Ubereats	0.07	0.26	0	1
DELIVERY_5	Other	0.14	0.35	0	1
DELIVERY_WOP	Without contract, i.e., restaurant's menu is listed without consent	0.21	0.41	0	1
DELIVERY_WP	With contract, i.e., restaurant has a formal delivery contract with a platform	0.11	0.32	0	1
DELIVERY_SELF	Delivery by restaurant	0.05	0.22	0	1
	Distribution Center				
DC_1	City of Industry	0.05	0.22	0	1
DC_2	Fresno	0.47	0.5	0	1
DC_3	San Diego	0.35	0.48	0	1
DC_4	San Jose	0.13	0.34	0	1
	Food Type				
FOOD_1	Chinese	0.76	0.43	0	1
FOOD_2	Vietnamese	0.12	0.33	0	1
FOOD_3	Japanese	0.08	0.27	0	1
FOOD_4	Other Asian, Hispanic, and American Food	0.03	0.18	0	1
	Hours of Operation				
HOURS	Daily hours	10.05	1.06	5	15
HOURS_BREAK	Daily hours excluding break	9.89	1.21	5	15
HOURS_ALT	Break hours	0.16	0.57	0	3
	Online Presence				
ONLINE_1	On Facebook	0.83	0.37	0	1
ONLINE_2	On Yelp	0.97	0.18	0	1
ONLINE_3	Own website	0.57	0.5	0	1
	Health Inspection Rating				
HEALTH_A	A or equivalent	0.48	0.5	0	1
HEALTH_B	B or equivalent	0.1	0.29	0	1
HEALTH_BELOW_B	Below B or equivalent	0.04	0.19	0	1
HEALTH_M	No quantitative ranking	0.39	0.49	0	1
	Proximity to universities				
UNIV_1	Within 1 mile	0.19	0.39	0	1
UNIV_1.25	Within 1.25 mile	0.2	0.4	0	1
UNIV_1.5	Within 1.5 mile	0.79	0.41	0	1

† Note that a restaurant may be listed in multiple food delivery platforms.

Table B2: Summary Statistics of Consumer Socio-Economic and Demographic Characteristics at Restaurant ZIP5

Variable Name	Variable Description	Mean	Std Dev	Min	Max
HOUSEHOLD_SIZE	Average Household Size	2.98	0.55	1.49	4.51
POPULATION_DENSITY	Population Density (unit: people per square mile)	4,479	3,831	97	31,930
POPULATION	Population (unit: 1,000 people)	49,814	21,450	2,379	87,914
FEMALE	Female Population (unit: 1,000 people)	25,024	10,652	1,110	43,103
	Female Population (unit: 1,000 people) by Age Groups				
FEMALE_1	Under 25 Years	8,404	4,030	52	17,737
FEMALE_2	25 to 44 Years	7,131	3,203	183	14,053
FEMALE_3	45 to 65 Years	5,776	2,665	364	11,013
FEMALE_4	65 Years and Above	3,713	1,624	160	6,480
FEMALE_PERCENTAGE	Percentage of Female Population	0.5	0.03	0.29	0.57
INCOME_PER_CAPITA	Per Capita Income (unit: $1,000)	$32,132.25	$16,369.57	$9,880.48	$133,902.80
INCOME_HOUSEHOLD	Median Household Income (unit: $1,000)	$66,975.83	$27,028.37	$20,826.74	$161,390.10
	Median Household Income (unit: $1,000) by Age Groups				
INCOME_HOUSEHOLD_1	Under 25 Years	$43,606.50	$21,622.56	$11,137.85	$155,508.50
INCOME_HOUSEHOLD_2	25 to 44 Years	$74,220.61	$32,970.13	$26,140.02	$186,587.50
INCOME_HOUSEHOLD_3	45 to 65 Years	$82,800.74	$32,940.77	$16,654.65	$209,907.00
INCOME_HOUSEHOLD_4	65 Years and Above	$51,656.84	$19,755.84	$10,207.72	$158,352.20
	Household Expenditures				
EXPEND	Total	$70,794.90	$14,655.35	$26,494.89	$133,444.60
EXPEND_FOOD	Food	$10,411.94	$1,949.19	$4,046.27	$19,642.73
EXPEND_FOOD_HOME	Food at Home	$5,835.28	$1,003.23	$2,346.38	$10,504.71
EXPEND_FOOD_N_HOME	Food away from Home	$4,576.67	$948.04	$1,699.89	$9,138.02
EXPEND_FOOD_N_HOME_1	Breakfast and brunch	$393.68	$70.09	$167.56	$767.81
EXPEND_FOOD_N_HOME_2	Lunch	$1,238.58	$237.44	$475.23	$2,364.21
EXPEND_FOOD_N_HOME_3	Dinner	$1,948.49	$431.87	$691.04	$4,011.75
EXPEND_FOOD_N_HOME_4	Other	$995.92	$211.53	$366.05	$1,994.26
AGE	Median Age	34.59	5.38	25.7	65.81
	Percentage of Age by Groups				
AGE_1	Under 25 Years	0.34	0.07	0.1	0.46
AGE_2	25 to 44 Years	0.29	0.05	0.12	0.49
AGE_3	45 to 65 Years	0.23	0.03	0.15	0.32
AGE_4	65 Years and Above	0.13	0.05	0.06	0.5
	Education Attainment				
EDU_1	Less than High School	0.18	0.12	0.01	0.62
EDU_2	High School	0.21	0.06	0.03	0.33
EDU_3	Some College	0.23	0.05	0.07	0.33
EDU_4	Associate's Degree	0.09	0.02	0.02	0.14
EDU_5	Bachelor's Degree	0.19	0.1	0.02	0.42
EDU_6	Post Graduate Degree	0.11	0.11	0	1
EDU_COLLEGE	Bachelor's Degree or Higher	0.29	0.18	0.02	0.79
	Percentage of Language Spoken at Home				
LANGUAGE_1	Speak Only English	0.53	0.18	0.08	0.94
LANGUAGE_2	Spanish	0.31	0.2	0.01	0.9
LANGUAGE_3	Chinese (including Mandarin, Cantonese)	0.03	0.07	0	0.43
LANGUAGE_4	Vietnamese	0.01	0.03	0	0.17
LANGUAGE_5	Other Asian and Pacific Island languages	0.06	0.05	0	0.21

C. Supportive analyses for PSM

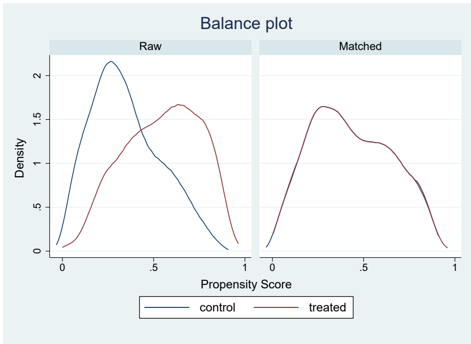
Table C1: Result of Logistic Regression Model in which Dependent Variable is Food Delivery

Variable Name	Coefficient	Std. err.	p-value	Variable Name	Coefficient	Std. err.	p-value
COGS_LAG	0.001	0.000	0.000	INCOME_HOUSEHOLD	0.000	0.000	0.055
DC_1	1.621	0.507	0.001	INCOME_HOUSEHOLD_1	0.000	0.000	0.153
DC_2	1.972	0.447	0.000	INCOME_HOUSEHOLD_2	0.000	0.000	0.266
DC_3	3.809	0.482	0.000	INCOME_HOUSEHOLD_3	0.000	0.000	0.017
FOOD_1	0.040	0.267	0.881	INCOME_HOUSEHOLD_4	0.000	0.000	0.229
FOOD_2	−0.400	0.321	0.213	EXPEND	0.007	0.004	0.061
FOOD_3	−0.291	0.297	0.328	EXPEND_FOOD	−0.006	0.004	0.094
HOURS	0.755	0.120	0.000	EXPEND_FOOD_N_HOME	−0.049	0.009	0.000
HOURS_ALT	−0.323	0.101	0.001	EXPEND_FOOD_N_HOME_1	0.006	0.007	0.394
ONLINE_1	0.017	0.165	0.920	EXPEND_FOOD_N_HOME_2	−0.016	0.005	0.000
ONLINE_2	1.181	0.483	0.015	EXPEND_FOOD_N_HOME_4	−0.438	0.082	0.000
ONLINE_3	0.829	0.125	0.000	AGE	582.864	159.846	0.000
HEALTH_A	1.353	0.230	0.000	AGE_1	591.085	159.538	0.000
HEALTH_B	1.366	0.276	0.000	AGE_2	597.081	158.470	0.000
UNIV_1	16.823	838.555	0.984	AGE_3	640.285	163.465	0.000
UNIV_1.25	−16.401	838.555	0.984	AGE_4	51.015	7.814	0.000
UNIV_1.5	0.752	0.497	0.130	EDU_1	30.602	7.723	0.000
HOUSEHOLD_SIZE	−1.228	0.586	0.036	EDU_2	22.849	7.451	0.002
POPULATION_DENSITY	0.000	0.000	0.312	EDU_3	47.682	9.475	0.000
POPULATION	0.000	0.000	0.253	EDU_4	−20.938	4.882	0.000
FEMALE	−0.001	0.000	0.000	EDU_6	33.601	7.058	0.000
FEMALE_1	0.001	0.000	0.000	EDU_COLLEGE	1.872	2.662	0.482
FEMALE_2	0.001	0.000	0.071	LANGUAGE_1	−9.316	2.127	0.000
FEMALE_3	0.002	0.000	0.000	LANGUAGE_2	3.804	2.913	0.192
FEMALE_PERCENTAGE	14.965	6.468	0.021	LANGUAGE_3	−26.955	6.106	0.000
INCOME_PER_CAPITA	0.000	0.000	0.011	LANGUAGE_4	−4.004	3.450	0.246

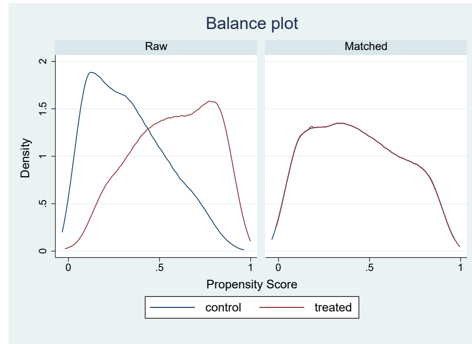
Note: Logit coefficients are shown. Some variables are dropped due to multicolinearity. No. of obs = 3,045. Pseudo $R^2 = 0.302$.

Figure C1: Balancing in Control vs. Treated Observations in Raw and Matched Data: Model 3a-3d, 4a-4d

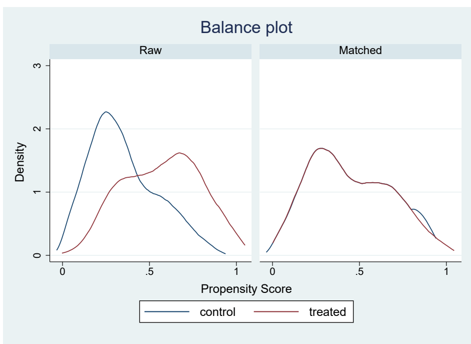
(a) Density comparison (Model 3a)



(b) Density comparison (Model 3b)

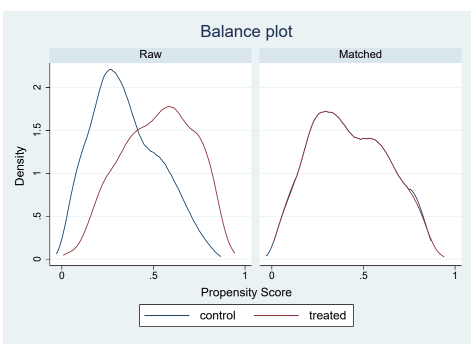


(c) Density comparison (Model 3c)

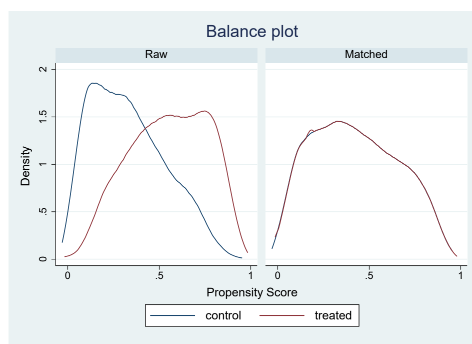


(d) Density comparison (Model 3d)

(e) Density comparison (Model 4a)



(f) Density comparison (Model 4b)



(g) Density comparison (Model 4c)

(h) Density comparison (Model 4d)

D. Variable Selection Result

Variable Name	Selected in Step 1	Selected in Step 2	Selected in Step 1 or 2
COGS_LAG	Yes	Yes	Yes
DC_1	Yes	Yes	Yes
DC_2	No	No	No
DC_3	Yes	Yes	Yes
DC_4	Yes	Yes	Yes
FOOD_1	Yes	Yes	Yes
FOOD_2	No	No	No
FOOD_3	No	No	No
FOOD_4	No	No	No
HOURS	No	No	No
HOURS_BREAK	No	No	No
HOURS_ALT	Yes	Yes	Yes
ONLINE_1	No	No	No
ONLINE_2	No	No	No
ONLINE_3	Yes	Yes	Yes
HEALTH_A	Yes	Yes	Yes
HEALTH_B	Yes	Yes	Yes
HEALTH_BELOW_B	Yes	Yes	Yes
HEALTH_M	No	No	No
UNIV_1	Yes	Yes	Yes
UNIV_1.25	Yes	Yes	Yes
UNIV_1.5	Yes	Yes	Yes
HOUSEHOLD_SIZE	Yes	Yes	Yes
POPULATION_DENSITY	No	No	No
POPULATION	No	Yes	Yes
FEMALE	No	No	No
FEMALE_1	No	No	No
FEMALE_2	Yes	No	Yes
FEMALE_3	Yes	Yes	Yes
FEMALE_4	Yes	Yes	Yes
FEMALE_PERCENTAGE	No	No	No
INCOME_PER_CAPITA	Yes	Yes	Yes
INCOME_HOUSEHOLD	No	Yes	Yes
INCOME_HOUSEHOLD_1	Yes	Yes	Yes
INCOME_HOUSEHOLD_2	No	Yes	Yes
INCOME_HOUSEHOLD_3	No	No	No
INCOME_HOUSEHOLD_4	No	Yes	Yes
EXPEND	Yes	Yes	Yes
EXPEND_FOOD	Yes	Yes	Yes
EXPEND_FOOD_HOME	No	No	No
EXPEND_FOOD_N_HOME	Yes	Yes	Yes
EXPEND_FOOD_N_HOME_1	Yes	Yes	Yes
EXPEND_FOOD_N_HOME_2	No	No	No
EXPEND_FOOD_N_HOME_3	Yes	Yes	Yes
EXPEND_FOOD_N_HOME_4	No	No	No
AGE	Yes	Yes	Yes
AGE_1	No	No	No
AGE_2	Yes	Yes	Yes
AGE_3	No	Yes	Yes
AGE_4	Yes	Yes	Yes
EDU_1	Yes	Yes	Yes
EDU_2	No	No	No
EDU_3	Yes	Yes	Yes
EDU_4	Yes	Yes	Yes
EDU_5	Yes	Yes	Yes
EDU_6	No	No	No
EDU_COLLEGE	No	No	No
LANGUAGE_1	No	No	No
LANGUAGE_2	Yes	Yes	Yes
LANGUAGE_3	No	Yes	Yes
LANGUAGE_4	Yes	Yes	Yes
LANGUAGE_5	Yes	Yes	Yes

E. Results

Table E1: Effect of Food Delivery via Online Platforms on Weekly COGS and Alternative Measure using Difference-In-Difference

	Model 1a	Model 1b	Model 2a	Model 2b
Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
food delivery via online platforms	0.223**	0.224**	0.377***	0.377***
	(.079)	(0.079)	(.099)	(.099)
Controls				
Week, Distribution Center, Food Type, Hours of Operation	Included	Included	Included	Included
Household Income, Size, Age, Population Density, Education	Included	Not Included	Included	Not Included
ZIP3 (fixed effect)	Not Included	Included	Not Included	Included
R^2	0.117	0.117	0.213	0.213
Observations	2,455	2,455	2,578	2,578

Note. Robust standard errors in parentheses. $^{***}p$-value ≤ 0.001; $^{**}p$-value ≤ 0.01; $^{*}p$-value ≤ 0.05; $^{\dagger}p$-value ≤ 0.10.

Table E2: Effect of Food Delivery via Online Platforms on Weekly COGS using Propensity-Score-Matching (PSM)

	Model 3a	Model 3b	Model 3c	Model 3d
Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS)$	$log(COGS)$
food delivery via online platforms	0.483***	0.469***	0.267***	0.260***
	(0.060)	(0.053)	(0.044)	(.057)
Controls				
Week, Distribution Center, Food Type, Hours of Operation	Included	Included	Included	Included
Online Presence, Health Inspection Rating, Within 1 mile of universities	Not Included	Included	Not Included	Included
Household Income, Size, Age, Population Density, Education	Included	Included	Included	Included
Household Expenditure Food away from Home	Not Included	Included	Not Included	Included
COGS from Previous Week	Not Included	Not Included	Included	Included
R^2	0.230	0.266	0.523	0.539
Observations	2,455	2,448	2,239	2,233

Note. Robust standard errors in parentheses. $^{***}p$-value ≤ 0.001; $^{**}p$-value ≤ 0.01; $^{*}p$-value ≤ 0.05; $^{\dagger}p$-value ≤ 0.10.

Table E3: Effect of Food Delivery via Online Platforms on Weekly Alternative Measure of COGS using PSM

	Model 4a	Model 4b	Model 4c	Model 4d
Dependent Variables	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
food delivery via online platforms	0.591***	0.521***	0.394***	0.352***
	(0.063)	(.055)	(0.047)	(0.047)
Controls				
Week, Distribution Center, Food Type, Hours of Operation	Included	Included	Included	Included
Online Presence, Health Inspection Rating, Within 1 mile of universities	Not Included	Included	Not Included	Included
Household Income, Size, Age, Population Density, Education	Included	Included	Included	Included
Household Expenditure Food away from Home	Not Included	Included	Not Included	Included
COGS from Previous Week	Not Included	Not Included	Included	Included
R^2	0.281	0.357	0.456	0.589
Observations	2,578	2,571	2,362	2,356

Note. Robust standard errors in parentheses. $^{***}p$-value ≤ 0.001; $^{**}p$-value ≤ 0.01; $^{*}p$-value ≤ 0.05; $^{\dagger}p$-value ≤ 0.10.

Table E4: Effect of Food Delivery via Online Platforms on Weekly COGS using DID and ML

	Model 5	Model 6
Dependent Variables	$log(COGS)$	$log(COGS_{ALT})$
food delivery via online platforms	0.263***	0.428***
	(0.071)	(0.090)
Controls: Variables Selected in Step 1 and Step 2	Included	Included
R^2	0.687	0.637
Observations	2,157	2,276

Note. Robust standard errors in parentheses. $^{***}p$-value ≤ 0.001; $^{**}p$-value ≤ 0.01; $^{*}p$-value ≤ 0.05; $^{\dagger}p$-value ≤ 0.10.

Table E5: Effect of Food Delivery via Online Platforms on Weekly COGS: Before Indoor Dining Closure

Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS)$	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
Week 6 to Week 11	−0.023	0.227**	0.178***	−0.109	0.276***	0.280***
	(0.053)	(0.083)	(0.038)	(0.279)	(0.057)	(0.027)
R^2	0.006	0.576	0.023	0.132	0.647	0.190
Observations	1,295	1,074	999	1,296	1,075	1,025
Same Controls As	Model 1a	Model 3d	Model 5	Model 2a	Model 4d	Model 6
Estimation Model	DID	PSM	DID-ML	DID	PSM	DID-ML

Note. Robust standard errors in parentheses. $^{***}p$-value ≤ 0.001; $^{**}p$-value ≤ 0.01; $^{*}p$-value ≤ 0.05; $^{\dagger}p$-value ≤ 0.10.

Table E6: Effect of Food Delivery on Weekly COGS: After Indoor Dining Closure

Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS)$	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
Week 13 to Week 21	0.511*	0.522***	0.520*	0.920***	0.744***	0.897***
	(0.253)	(0.079)	(0.245)	(0.142)	(0.091)	(0.139)
R^2	0.111	0.631	0.753	0.218	0.682	0.794
Observations	1,007	1,007	986	1,123	1,123	1,098
Same Controls As	Model 1a	Model 3d	Model 5	Model 2a	Model 4d	Model 6
Estimation Model	DID	PSM	DID-ML	DID	PSM	DID-ML

Note. Robust standard errors in parentheses. $^{***}p$-value ≤ 0.001; $^{**}p$-value ≤ 0.01; $^{*}p$-value ≤ 0.05; $^{\dagger}p$-value ≤ 0.10.

Table E7: Effect of Food Delivery on Weekly COGS: Food Delivery With Contract and Without Contract

Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS)$	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
Food Delivery With Contract	0.287*	0.284***	0.271*	0.532***	0.395***	0.518***
	(0.131)	(0.050)	(0.123)	(0.144)	(0.054)	(0.138)
R^2	0.133	0.627	0.795	0.250	0.573	0.576
Observations	1,567	1,409	1,341	1,651	1,493	1,422
Food Delivery Without Contract	0.199*	0.192*	0.300***	0.296*	0.357†	0.388***
	(0.093)	(0.084)	(0.079)	(0.123)	(0.220)	(0.107)
R^2	0.136	0.574	0.635	0.226	0.554	0.620
Observations	1,984	1,798	1,735	2,083	1,897	1,831
Same Controls As	Model 1a	Model 3d	Model 5	Model 2a	Model 4d	Model 6
Estimation Model	DID	PSM	DID-ML	DID	PSM	DID-ML

Note. Robust standard errors in parentheses. ***p-value ≤ 0.001; **p-value ≤ 0.01; *p-value ≤ 0.05; †p-value ≤ 0.10.

Table E8: Effect of Food Delivery on Weekly COGS on Restaurants in Low-Population-Density Areas

Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS)$	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
Food Delivery						
Fresno DC	0.313**	0.337***	0.299**	0.513***	0.355***	0.500**
	(0.102)	(0.035)	(0.094)	(0.105)	(0.039)	(0.100)
R^2	0.117	0.728	0.163	0.213	0.655	0.247
Observations	2,455	2,233	2,157	2,578	2,356	2,276
Same Controls As	Model 1a	Model 3d	Model 5	Model 2a	Model 4d	Model 6
Estimation Model	DDD	PSM	DDD-ML	DDD	PSM	DDD-ML

Note. Robust standard errors in parentheses. ATET estimate adjusted for covariates, panel effects, time effects, and panel- and time-effects interactions. ***p-value ≤ 0.001; **p-value ≤ 0.01; *p-value ≤ 0.05; †p-value ≤ 0.10.

Table E9: Effect of Food Delivery on Weekly COGS on Restaurants with Existing Self Delivery Capability

Dependent Variables	$log(COGS)$	$log(COGS)$	$log(COGS)$	$log(COGS_{ALT})$	$log(COGS_{ALT})$	$log(COGS_{ALT})$
Food Delivery						
Self Delivery vs. No Self Delivery	0.865***	0.927***	0.796***	1.073**	1.071***	1.001***
	(0.118)	(.023)	(0.080)	(0.087)	(0.024)	(0.055)
R^2	0.117	0.990	0.162	0.207	0.982	0.239
Observations	2,455	2,132	2,157	2,578	2,356	2,276
Same Controls As	Model 1a	Model 3d	Model 5	Model 2a	Model 4d	Model 6
Estimation Model	DDD	PSM	DDD-ML	DDD	PSM	DDD-ML

Note. Robust standard errors in parentheses. ATET estimate adjusted for covariates, panel effects, time effects, and panel- and time-effects interactions. ***p-value ≤ 0.001; **p-value ≤ 0.01; *p-value ≤ 0.05; †p-value ≤ 0.10.