The Role of On-Demand Delivery Platforms in Restaurants

Zhuoxin Li
Carroll School of Management, Boston College
Chestnut Hill, Massachusetts, USA 02467
zhuoxin.li@bc.edu

Gang Wang
Lerner College of Business and Economics, University of Delaware
Newark, Delaware, USA 19716
gangw@udel.edu

The authors thank Rob Fichman, Do Yoon Kim, Marios Kokkodis, Mingfeng Lin, Nan Liu, Sridhar Narasimhan, Marius Florin Niculescu, Eric Overby, Sam Ransbotham, Bill Ross, Mike Teodorescu, D.J. Wu, Lizhen Xu, Han Zhang, and seminar participants at Georgia Institute of Technology for their helpful comments.

The Role of On-Demand Delivery Platforms in Restaurants

Restaurants are increasingly relying on on-demand delivery platforms (e.g., DoorDash, Grubhub, and Uber Eats) to reach customers and fulfill takeout orders. Although on-demand delivery is a valuable option for consumers, whether restaurants benefit from or are being hurt by partnering with these platforms remains unclear. This paper investigates whether and to what extent the platform delivery channel substitutes restaurants' own takeout/dine-in channels and the net impact on restaurant revenue. Empirical analyses show that restaurants overall benefit from on-demand delivery platforms—these platforms increase restaurants' total takeout sales while creating positive spillovers to customer dine-in visits. However, the platform effects are substantially heterogeneous, depending on the type of restaurants (independent vs. chain) and the type of customer channels (takeout vs. dine-in). The overall positive effect on fast-food chains is four times as large as that on independent restaurants. For takeout, delivery platforms substitute independent restaurants' but complement chain restaurants' own takeout sales. For dine-in, delivery platforms increase both independent and chain restaurants' dine-in visits by a similar magnitude. Therefore, the value of delivery platforms to independent restaurants mostly comes from the increase in dine-in visits, whereas the value to chain restaurants primarily comes from the gain in takeout sales. Further, the platform delivery channel reduces geographic frictions and the opportunity for independent restaurants to differentiate with premium services and dine-in experience, which may explain why independent restaurants do not benefit as much from on-demand delivery platforms.

Keywords: *Multi-sided platforms; on-demand platforms; on-demand services; food delivery; restaurants*

1. Introduction

Food delivery via on-demand platforms such as DoorDash, Grubhub, and Uber Eats is projected to grow into a $60 billion business by 2025 (MorganStanley 2020). On-demand delivery platforms collect customer orders via their easy-to-use mobile apps, communicate the orders to restaurants, and have drivers pick up and deliver the food to customers (Chen et al. 2019). For consumers, these platforms offer convenient access to a variety of food options without having to physically visit the restaurants. For restaurants, whether on-demand delivery platforms benefit them, however, is an intriguing question with mixed responses from the industry. Some restaurants suggest that delivery orders are incremental. For instance, McDonald's reported that over 70% of orders were in addition to in-store and drive-thru orders.[1] However, anecdotal evidence also points out that on-demand delivery platforms may be "doing more harm than good".[2] To provide insights into the mixed observations from the industry, this empirical research investigates the impact of on-demand delivery platforms on restaurant demand and sales.

Delivery platforms can be a double-edged sword to restaurants. On one hand, on-demand delivery platforms provide restaurants flexible access to delivery capability on a pay-per-use basis. Such delivery capability can be too costly for restaurants to build in-house. Small independent restaurants may particularly benefit from such a flexible payment scheme because these restaurants are financially weaker (Severson and Yaffe-Bellany 2020). On-demand delivery platforms also offer another distribution channel, which may help restaurants reach new customers. Such a channel can be particularly valuable for independent restaurants with a limited

[1] https://medium.com/@convershaken/mcdonalds-and-ubereats-have-a-happy-deal-81ed0b86825f
[2] https://www.forbes.com/sites/forbesfinancecouncil/2020/05/04/why-food-delivery-companies-may-be-doing-more-harm-than-good-and-how-restaurants-can-fix-it/?sh=4c496dc1b3bb

budget for customer acquisition (Li and Zhu 2020; McCann 2020). On the other hand, however, the platform delivery channel may hurt restaurants when they cannibalize restaurants' existing takeout or dine-in channels—these platforms may simply attract customers who would otherwise choose to dine in or pick up orders by themselves.

The relationship between the platform delivery channel and restaurants' own takeout/dine-in channels is an important empirical question with implications to both theory and practice. A substitution effect would reduce restaurants' profit margin as for every order fulfilled by the platforms, restaurants pay a commission fee as high as 30% of the order amount (Hadfield 2020). Therefore, it is unclear whether and how delivery platforms benefit restaurants. The benefits are likely to be heterogeneous depending on, for example, restaurant characteristics (e.g., independent vs. chain restaurants) and local market conditions. The answers to these questions are important to restaurants, especially independent restaurants.[3] Accounting for two-thirds of restaurant outlets in the United States, independent restaurants play an important role in every local economy. However, recent studies suggest that chain restaurants are thriving as independent restaurants suffer, and the coronavirus pandemic is widening such a divide.[4]

While several theoretical studies have looked into the effects of on-demand delivery platforms on restaurants (Chen et al. 2019; Feldman et al. 2019), empirical research on this topic has been scant, possibly due to lack of demand and sales data across multiple channels (e.g., both platform orders and sales through restaurants' own channels). Raj et al. (2020) collect data from Uber Eats to analyze how restaurants benefit from delivery platforms during the COVID-19 pandemic, but their focus is only on platform orders and has not investigated the substitution or

[3] https://www.prnewswire.com/news-releases/restaurant-industry-in-free-fall-10-000-close-in-three-months-301187291.html
[4] https://www.foodandwine.com/news/chains-independent-restaurant-divide

complementary effects on restaurants' own takeout or dine-in channels. In this research, we capture restaurant demand across channels by pooling data from multiple sources, including foot traffic and bank card transaction data, which allow us to gain a holistic view of the impact of delivery platforms on restaurants across channels.

Our empirical analyses show that restaurants overall benefit from on-demand delivery platforms—these platforms increase restaurants' total takeout sales while creating positive spillovers to customer dine-in visits. However, the platform effects are substantially heterogeneous, depending on the type of restaurants (independent vs. chain) and the type of customer channels (takeout vs. dine-in). The overall positive effect on fast-food chains is four times as large as that on independent restaurants. For takeout, delivery platforms substitute independent restaurants' but complement chain restaurants' own takeout sales. For dine-in, delivery platforms increase both independent and chain restaurants' dine-in visits by a similar magnitude. Therefore, the value of delivery platforms to independent restaurants mostly comes from the increase in dine-in visits, whereas the value to chain restaurants primarily comes from the gain in takeout sales. We provide evidence that the platform delivery channel reduces geographic frictions (Brynjolfsson and Smith 2000; Granados et al. 2012) and eliminates the opportunity for independent restaurants to differentiate with premium services and dine-in experience (Sulek and Hensley 2004), which may explain why independent restaurants (particularly higher-priced ones) do not benefit much from on-demand delivery platforms.

This research contributes to the literature on digital platforms and electronic commerce as a new distribution channel. The literature has focused on pre-made physical products or digital contents (e.g., print books vs. eBooks), whereas less is known about differentiated services such as food and dining. Our empirical findings highlight delivery platforms as a double-edged sword to restaurants: the positive effect as a new distribution channel to reach new customers and the negative effect of reduced geographic frictions and restaurant differentiation. The relative strength of the positive and negative effects depends on restaurant characteristics and local market conditions. Independent restaurants fall victim to reduced geographic frictions because delivery eliminates their opportunity to differentiate with premium services and dine-in experience in the takeout channel. In the dine-in channel, these premium services and dine-in experience are present, and restaurants benefit from the positive spillovers from the delivery platforms to dine-in visits. These unique features of the restaurant industry have not been documented in the literature of online platforms and multi-channel interactions. Our study provides novel insights into how online platforms may create differential effects on service providers in traditionally differentiated service sectors.

Our empirical findings highlight the heterogeneous effects of on-demand delivery platforms, and have practical implications for restaurants. For restaurants that are considering whether to offer delivery through on-demand delivery platforms, this paper highlights several important factors and quantifies the effects to help restaurants to make informed decisions. Such contingent factors include restaurant characteristics (e.g., independent vs. chain restaurants, cuisine types, price level, restaurant quality/rating, and whether a restaurant has its own delivery capability) and local market conditions such as platform penetration. For instance, our findings suggest that high-priced restaurants may benefit from re-designing their menu, for example, by adding low-priced items in response to reduced differentiation and heightened price effects on platforms. Moreover, since the value of delivery platforms to independent restaurants comes from the positive spillovers to dine-in visits, independent restaurants may feature their premium services and dine-in experiences on their platform pages to enhance the spillover effects.

2. Literature and Theoretical Development

2.1 Related Literature

2.1.1 On-Demand Platforms

On-demand platforms create economic value and social welfare for participants by facilitating interactions and transactions among them. They reduce search frictions and transaction costs, thanks to network effects as well as the implemented digital technologies that help efficiently match supply and demand (Katz and Shapiro 1985; Zhu and Iansiti 2012). By working with on-demand service providers, businesses can avoid the fixed cost of building their in-house capabilities, at the expense of paying a variable fee for the capacity used (Chen and Wu 2013). Besides its variable cost structure, on-demand platforms offer the benefits of scalability – the ability to quickly and easily increase or decrease the utilization of delivery capacity provided by on-demand platforms (Chen and Wu 2013; Gurvich et al. 2018), which is particularly valuable for businesses during periods of demand uncertainty and fluctuation (Bai et al. 2019; Taylor 2018).

Empirical studies on on-demand delivery platforms are scant. A recent study by Raj et al. (2020) investigates online orders for independent restaurants on Uber Eats, and their focus is on one particular platform (i.e., Uber Eats) and one type of restaurants (i.e., independent restaurants) during the COVID-19 pandemic. Our research considers all three major delivery platforms, both national chains and independent restaurants, and overall demand/revenue across multiple channels (both the platforms and restaurants' own channels) on regular days rather than a pandemic period. Different from Raj et al. (2020), we aim to capture the multi-channel interactions (complement or substitute), and to understand how on-demand delivery platforms widen the performance gap between fast-food chains and independent restaurants.

2.1.2 Electronic Commerce and Electronic Markets

This research is also related to electronic commerce and search costs in online markets and platforms. While no empirical studies have investigated on-demand delivery platforms, the literature has looked into a variety of other e-commerce settings with mixed findings. Some studies find that the average prices are lower online, suggesting more price competition online than offline (Brynjolfsson and Smith 2000), whereas other studies find that consumers are less price-sensitive online than offline (Chu et al. 2008). Consumer demand in online channels is more price elastic because the internet has granted consumers increased access to information to make purchase decisions (Granados et al. 2012; Overby and Forman 2014). Price effects can also be stronger if products or services are less differentiated (Clemons et al. 2002). Our research provides some suggestive evidence that consumers on on-demand delivery platforms reduce geographic frictions and search costs, and thus consumers may favor low-priced fast-food chains over more expensive options.

2.1.3 Multi-Channel Interactions

This research also relates to the broader literature on opportunities and risks of leveraging digital platforms as a new distribution channel (Ceccagnoli et al. 2014; Chan and Ghose 2014; Xu et al. 2017). The literature suggests that multi-channel interactions are context-specific, and the findings (substitution effects, complementary effects, or no effects) depend on the specific setting being studied. Online platforms and digital distribution channels lower the costs of entry for small businesses (Einav et al. 2016; Li et al. 2018), and may also complement existing channels (Etzion and Pang 2014; Xu et al. 2014, 2017). However, these new channels can compete and cannibalize a business's existing channels (Forman et al. 2009), reducing business' profit margin or driving business closures (Li 2016). Some other studies also find no evidence of substitution or complementary effect (e.g., Chen et al. 2019). Several theoretical studies using analytical modeling have provided insights into the demand effect of on-demand delivery platforms. For instance, on-demand delivery platforms can interfere with restaurants' existing channels, calling for the optimal design of revenue sharing mechanisms between restaurants and the platforms (Feldman et al. 2019). Adding to these theoretical studies of the restaurant industry, our study provides empirical evidence of a complementary and substitution effect.

2.2 The Roles of On-Demand Delivery Platforms

On-demand delivery platforms provide several affordances, which influence business operations and shape the competitive dynamics in the restaurant industry. On-demand delivery platforms provide restaurants flexible access to delivery capabilities, which is essential for restaurants without in-house delivery capabilities. Moreover, these platforms serve as a new distribution channel for restaurants, which may complement or substitute restaurants' own channels. However, these platforms also reduce geographic frictions and thus intensify restaurant competition because restaurants become less horizontally differentiated.

2.2.1 On-Demand Delivery Platforms and Flexible Access to Delivery Capabilities

By joining on-demand delivery platforms, restaurants can avoid the fixed cost of building their in-house delivery capabilities (e.g., hiring in-house delivery drivers), at the expense of paying a variable commission fee for each order delivered by the platforms. Also, on-demand platforms offer the benefits of scalability—the ability to quickly and easily scale up/down the utilization of delivery capacity provided by on-demand platforms (Chen and Wu 2013; Gurvich et al. 2018). Leveraging the seemingly low-cost on-demand platforms is not without risks to adopting restaurants. Flexible and swift access to delivery capabilities reduces the barriers of entry for restaurants to offer delivery services, which may intensify restaurant competition (Chen and Wu 2013).

2.2.2 On-Demand Delivery Platforms as a Distribution Channel

Functioning as multi-sided markets, on-demand platforms provide digital distribution channels that lower the costs for restaurants to reach customers (Einav et al. 2016; Li et al. 2018). Several theoretical studies using analytical modeling have provided insights into the demand effect of on-demand delivery platforms. For instance, on-demand delivery platforms as a new distribution channel can expand restaurants' customer base (Feldman et al. 2019). However, these platforms may also hurt restaurants when they cannibalize restaurants' existing channels, as suggested by existing theoretical models (Chen et al. 2019; Feldman et al. 2019). That is, these platforms may simply attract customers who would otherwise choose to dine in or pick up orders by themselves.

2.2.3 On-Demand Delivery Platforms, Geographic Frictions, and Restaurant Competition

On-demand delivery platforms can reduce geographic frictions (Feldman et al. 2019). Consumers on the platforms have access to a variety of food options without having to physically visit the restaurants themselves. Reduced geographic frictions suggest that geographic locations and transportation costs may no longer play a major role in horizontal differentiation (Sankaranarayanan and Sundararajan 2010). Therefore, on-demand delivery platforms have reduced restaurant differentiation and intensify intra-platform competition among nearby restaurants (Ho et al. 2020; Overby and Forman 2014). Independent restaurants may be more negatively affected by competition because consumers ordering delivery do not have the chance to enjoy the dine-in experience/atmosphere and quality service, which are often the competitive advantages of independent restaurants (Sulek and Hensley 2004). In other words, on-demand delivery platforms not only reduce search costs but also eliminate premium offline service and customer experience as differentiators. Therefore, consumers care more about prices because restaurants with delivery are considered less differentiated by consumers (Clemons et al. 2002).

3. Data and Methods

3.1 Empirical Context and Data Sources

This research empirically examines how on-demand delivery platforms affect consumer demand and restaurant revenue in the Chicago metropolitan area. We focus on the Chicago area for two reasons. First, there are sufficient adoptions of on-demand delivery platforms by restaurants in the Chicago area, partially because Grubhub, the pioneer of on-demand food delivery, was founded in Chicago in 2004. Second, the Chicago area includes the city of Chicago and a number of well-populated suburbs, covering 17 counties across the states of Illinois, Indiana, and Wisconsin. Such diversity provides rich geographical variations for empirical analyses.

We compose a comprehensive panel data set from multiple sources, including restaurant profiles and characteristics from Yelp and YellowPages.com, restaurant-platform partnership from on-demand delivery platforms, foot traffic data from a mobile-device location tracking company, and bank card transaction data from a financial data provider. The foot traffic data complements the transaction data because the foot traffic data allows us to identify takeout visits and dine-in visits, whereas the transaction data helps us separate indirect sales through delivery platforms from direct sales through restaurants' own channels. The combination of foot traffic and transaction data allows us to investigate the substitution/complementary effects among the platform delivery channel, restaurants' own takeout channel, and restaurants' dine-in channel.

Our data covers a period from January 1, 2019 to June 30, 2020. This research focuses on the year 2019 (January 1 to December 31) because the COVID-19 pandemic starting from early

2020 disrupted restaurant operations. As a robustness check, we also investigate the year 2020 that covers the COVID-19 pandemic.

3.1.1 Restaurants and the Adoption of Delivery Platforms

We first compiled a complete list of restaurants in each zip code using Yelp API and YellowPages' search portal. Restaurant-platform partnership data are collected from the three largest on-demand delivery platforms, i.e., DoorDash, Grubhub, and Uber Eats, which together account for about 95% of the market share in food delivery in the Chicago area (Holland and Reed 2020)[5]. We obtained a complete list of restaurants on each of these platforms each week.

There are in total 19,117 restaurants located in the Chicago area, and about 48% of them are on at least one of the three delivery platforms by the end of 2019 (Table 1). We classify these restaurants into two categories based on if the restaurant is an independent restaurant or is affiliated with a chain. Per the definition by National Restaurant Association and Federal Drug Administration, a restaurant chain is a national or regional brand with 20 or more locations in the United States.[6] Independent restaurants are primarily full-service restaurants (about 93%), whereas the chain restaurants are dominantly limited-service fast-food restaurants (e.g., McDonald's and KFC).[7] We remove the small sample of independent restaurants that are limited-service restaurants and chain restaurants that are full-service restaurants. As we can see in Table 1, among all the restaurants, two-thirds are independent restaurants; independent

---

[5] https://foodondemandnews.com/04302020/report-shows-restaurant-delivery-surging-24-percent/

[6] See https://www.thedailymeal.com/eat/regional-chain-restaurants-we-wish-were-national and https://www.nytimes.com/2010/03/24/business/24menu.html

[7] Full-service restaurants (NAICS Code: 722511) typically provide food services to customers who order and are served while seated and pay after eating, whereas limited-service restaurants (NAICS Code: 722513) provide food services where customers generally order or select items and pay before eating (e.g., fast-food and pizza shops).

restaurants are substantially higher priced than chain restaurants (see also Figure 1); roughly half of the restaurants have joined one of the delivery platforms (Figure 2).

Table 1. Restaurants and Platform Partnership

Restaurant Type	Number of Restaurants	Percent on Platforms (December 2019)	Price Range
Independent	12,927 (68%)	46%	1.71
Chains	6,190 (32%)	54%	1.14
All	19,117	48%	1.53

Note: Price ranges are on the scale of 1 ($) to 4 ($$$$), with 4 being the highest according to Yelp. Costs per person per meal are: 1 (<=$10), 2 ($11~30), 3 ($31~60), and 4 (>$60).

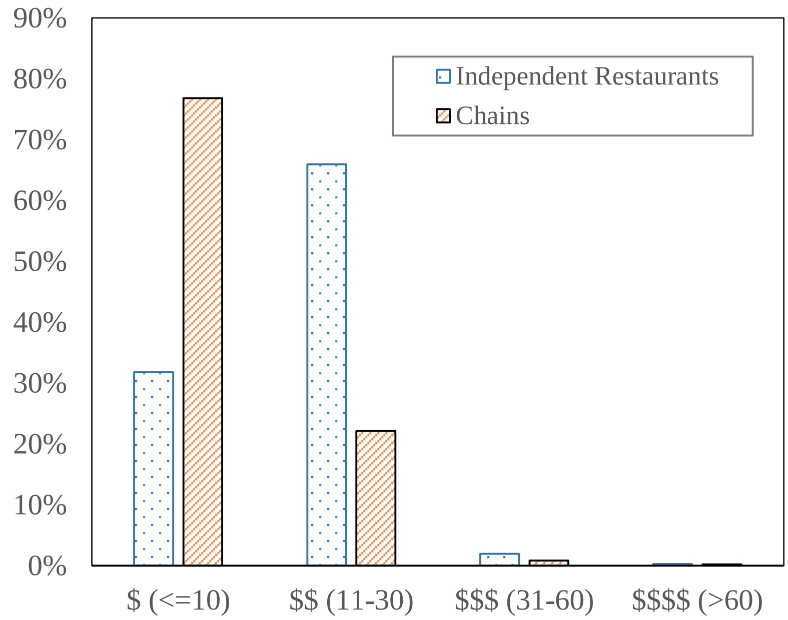

Figure 1. Distribution of Price (per Person/Meal)

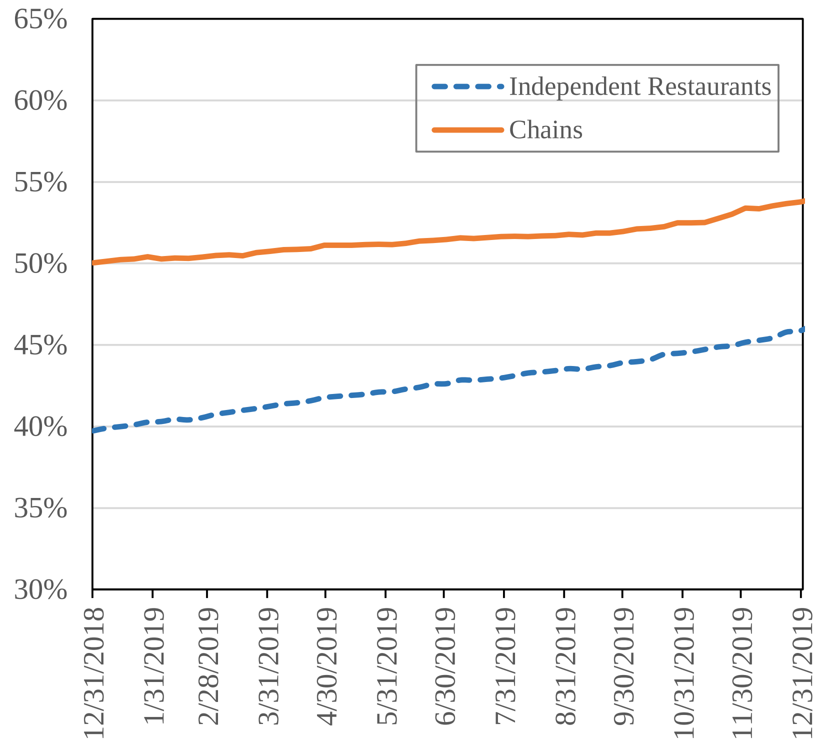

Figure 2. Fraction of Restaurants on Delivery Platforms

3.1.2 Restaurant Foot Traffic Data

We combine foot traffic data with restaurant-platform partnership data to study how joining on-demand delivery platforms impacts restaurant demand, measured by customer visits to restaurants. The foot traffic data is provided by a data company that aggregates anonymized location data from numerous applications for approximately 35 million unique devices in the United States. Researchers from over 1000 organizations have used the foot traffic data to understand visit patterns to point of interests. Studies using the data report that the data are generally representative of the US population (Chen and Rohla 2018; Painter and Qiu 2020).

To preserve anonymity, the data is aggregated to the level of point-of-interests such as a restaurant on a weekly basis. The total number of visits were further split into four buckets based on the duration of stay: shorter than 20 minutes, between 21 and 60 minutes, between 61 to 240 minutes, and longer than 240 minutes. The unique value of this foot traffic data is that it allows us to identify takeout visits and dine-in visits based on a customer's duration of stay in a restaurant. Such information is not available from transaction data.

3.1.3 Transaction Data

The proprietary transaction data complements the foot traffic data by providing additional information about indirect sales generated through delivery platforms and direct sales from restaurants' own takeout/dine-in channels. We obtained anonymized, aggregate debit/credit card transaction data from a large financial data provider. The data provider has partnered with over 1,000 financial institutions to create a panel data set of customer spending aggregated at the level of zip code and merchants. With this dataset, we create a panel data set that consists of the weekly restaurant sales (number of transitions and total spend in USD) through the delivery platforms and through restaurants' own channels in each zip code. Sales through restaurants' own channels are aggregated by the types of restaurants using the merchant category codes (5812 for independent restaurants and 5814 for fast-food chains).[8] Therefore, the transaction data includes weekly restaurant sales through the delivery platforms (*PlatformSales*) and the own channels of independent/chain restaurants (*DirectSales*) in each zip code.

[8] The raw data has the merchant name, but it is hard to match the merchant name to a restaurant because the merchant name of a restaurant registered with a bank (i.e., the one in a credit card statement) can be quite different from the actual restaurant name.

3.2 Variables and Measurement

The main variables and their summary statistics are presented in Table 2 and Table 3, respectively. The outcome variables we are interested in are consumers' visits to restaurants. As defined in Table 2, we look into two types of visits based on their duration:

- **Takeout Visits** (visits staying for less than 20 minutes). Upon arriving at a restaurant, customers typically wait less than 20 minutes before their orders are ready for takeout. Industry reports show that the average wait time for takeout orders in restaurants is about 2.5 minutes, with 58% of all orders ready in less than 2 minutes and 78% ready in less than 4 minutes.[9] Note that takeout visits could be either customers picking up orders themselves or by delivery drivers fulfilling platform orders, the number here should be interpreted as the total orders (platform orders plus takeout orders through a restaurant's own channel) for restaurants that are using on-demand delivery platforms.[10] In Section 5, we combine foot traffic data with bank card transaction data to separate platform orders from the total takeout orders.
- **Dine-in Visits** (visits staying for 21~60 minutes). Customers typically stay for about half an hour if dining in individually, to one hour if with a small/medium group. The duration of visits could be longer for a party, but the fraction of such visits is small. As a robustness check, we also consider visits that stay for 61 to 240 minutes as dine-in visits

[9] https://www.restaurantdive.com/news/chipotle-panera-starbucks-have-fastest-in-store-pickup-times-survey-find/566625/

[10] A driver might pick up more than one order from a restaurant in one visit, but this is rare in meal delivery for two reasons: 1) the number of restaurants is large but the number of customers ordering meal delivery is still relatively small; 2) meal delivery is rarely pre-ordered to be delivered in a given time window. Instead, customers place orders when they are hungry and want their meals delivered right away. The sparseness of orders and the urgency constraint make it difficult to pool orders from geographically dispersed customers in one delivery.

in Appendix A.3.[11] We do not consider visits longer than 240 minutes, which usually corresponds to a shift of staffing working in a restaurant, instead of consumers' visits.

The main explanatory variables are the timing when a restaurant joined an on-demand delivery platform. As defined in Table 2, we code a binary variable ($OnPlatform$) to capture whether a restaurant joined any of the on-demand delivery platforms in a given week.

Table 2. Definition of Variables

Variables	**Definition**
Dependent Variables	
$TakeoutVisits$	The number of visits staying between 0 and 20 minutes in a given week (a proxy for takeout visits, including both platform orders and takeout by customers themselves).
$DineInVisits$	The number of visits staying between 21 and 60 minutes in a given week (a proxy for dine-in customers).
Key Independent Variables	
$OnPlatform$	A dummy variable indicating whether a restaurant joined in an on-demand delivery platform in a given week.
$Chain$	A dummy variable that indicates whether a restaurant is a chain restaurant (1 for a chain restaurant, 0 for an independent restaurant).
$Price$	A categorical price-level indicating the approximate cost per person per meal for a restaurant. There are four levels: $\$$ ~ less than $10; $\$\$$ ~ $11 to $30; $\$\$\$$ ~ $31 to $60; $\$\$\$\$$ ~ more than $60)
$PlatformPenetration$	The proportion of a focal restaurant's nearby restaurants (within a 5-mile distance) that are on delivery platforms in a given week.
$CommunityMobility$	The proportion of devices in a county leaving home for at least some time in a given day (average across days of a week).

[11] In the main analyses, we do not include the 61~240 bucket as visits in this bucket are possibly mixed with both customer visits and staff working in the restaurant.

Other variables include the proportion of a focal restaurant's nearby restaurants that are on delivery platforms ($PlatformPenetration$) in a given week, which measures the adoption rate of delivery platforms, and community mobility ($CommunityMobility$) which is measured by the weekly average of the proportion of residents (i.e., mobile devices being tracked) in the county not completely staying at home on a given day. We control for platform penetration and community mobility because they influence visits to restaurants in a particular region, ruling out alternative explanations that our results are driven by time-varying region-specific characteristics.

Table 3. Summary Statistics of Main Variables

	Mean	SD	Min	Median	Max
$TakeoutVisits$	26.430	26.446	0	19	175
$DineInVisits$	17.465	19.553	0	11	127
$OnPlatform$	0.247	0.431	0	0	1
$Chain$	0.243	0.429	0	0	1
$Price$	1.600	0.541	1	2	4
$PlatformPenetration$	0.458	0.064	0	0.467	0.645
$CommunityMobility$	0.681	0.037	0.524	0.686	0.793

To match restaurants on delivery platforms and those not on delivery platforms, we also construct a set of variables of restaurant characteristics using data from Yelp. These variables include the number of ratings for a restaurant, the average star rating, price range, the age of the restaurant on Yelp, the type of the restaurant and cuisine, and the number of competitors near the focal restaurant. The list of variables, their definition, and statistics are included in Appendix A.1.

3.3 Empirical Model

The outcome variable of interest is $WeeklyVisits$, which is the dependent variable defined in Table 2. We specify the empirical model as follows:

$$\log(WeeklyVisits_{imt}) = \alpha + \beta\, OnPlatform_{it} + \boldsymbol{\phi X}_{mt} + \eta_i + v_t + \varepsilon_{imt} \tag{1}$$

where i, m, and t index a restaurant, market and week, respectively, $\boldsymbol{X}_{mt}$ is a vector of time-varying variables for the local market m the restaurant is in (e.g., county-level community mobility and the platform penetration in the local market defined in Table 2), and η_i and v_t represent the fixed effect for restaurant i and week t. The coefficient β captures the effect of on-demand delivery platforms on a restaurant's takeout or dine-in sales (depending on the left-hand side variable included in the equation above).

The model has included a set of fixed effects plus time-varying variables to control for observed and unobserved restaurant heterogeneity and geo-temporal characteristics. However, restaurants on on-demand delivery platforms ("treatment group") could be different from those not on the platforms ("control group"). As robustness checks, we use multiple matching methods to construct the treatment group and a comparable control group (Section 6.1). We also construct instrumental variables and estimate the model using two-stage least squares (Section 6.2).

4. Empirical Results

4.1 Parameter Estimates using Foot Traffic Data

We estimate the impact of joining on-demand delivery platforms on restaurant demand, measured by takeout visits and dine-in visits. Empirical results in Table 4 show the parameter estimates of the model. Since the dependent variables are log-transformed, the estimates can be interpreted as percentage changes.

Main Effect on Takeout Visits Estimate of Model 1 in Table 4 shows a positive effect of joining delivery platforms on total takeout demand: on average total takeout visits increase by 3.8% after a restaurant joins delivery platforms. This result suggests that takeout orders through delivery platforms are not completely substituting takeout orders from a restaurant's own channels. Instead, about 3.8% of takeout orders are incremental.

Spillovers to Dine-In Visits Delivery platforms increase dine-in visits to restaurants on the platforms by 6.3% (Model 3). The positive spillover effect may be due to the advertising effect—being on these platforms may increase customers' awareness of the restaurants, and some of the customers may choose to dine in. This result suggests that delivery platforms complement rather than substitute a restaurant's dine-in channel.

Table 4. Parameter Estimates of Substitution and Spillover Effects

DV: Weekly Visits	Takeout		Dine-In	
	Model 1	Model 2	Model 3	Model 4
$OnPlatform$	0.038*** (0.004)	0.024*** (0.005)	0.063*** (0.005)	0.059*** (0.006)
$Onlatform \times Chain$		0.069*** (0.010)		0.017 (0.012)
$PlatformPenetration$	0.235*** (0.058)	0.232*** (0.058)	-0.023 (0.069)	-0.024 (0.069)
$CommunityMobility$	0.001 (0.071)	-0.002 (0.071)	0.686*** (0.084)	0.685*** (0.084)
Restaurant Fixed Effect	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes
Observations	603,244	603,244	603,244	603,244
Adjusted R-squared	0.884	0.884	0.862	0.862

Notes: All continuous variables are log-transferred.
Standard errors in parentheses. Significance level: p<0.01 (***), p<0.05 (**), and p<0.1 (*).

Fast-Food Chains vs. Independent Restaurants The positive effects of on-demand delivery platforms are substantially heterogeneous. The estimate of the interaction term

($OnPlatform \times Chain$) in Model 2 in Table 4 shows that, compared to the baseline of independent restaurants, chain restaurants benefit more from being on delivery platforms. Specifically, the increase in takeout visits is only 2.4% for independent restaurants but is as high as 9.3% for chain restaurants (i.e., three times higher than independent restaurants). Interestingly, for dine-in visits, the positive effects are not significantly different across independent restaurants and chain restaurants (Model 4): both types of restaurants see about a 6% increase in dine-in visits. This result suggests that on-demand delivery platforms benefit independent restaurants primarily through their positive spillover effects on dine-in visits, whereas these platforms benefit chain restaurants primarily through incremental takeout orders as well as dine-in visits.

4.2 Possible Mechanisms

The empirical results in Section 4.1 reveal some interesting patterns. Although on-demand delivery platforms overall increase takeout orders for restaurants on the platforms, the effects are much stronger for chain restaurants than independent restaurants. However, such a performance gap disappears for dine-in visits.

This section explores plausible explanations for these findings. We explore two competing forces that determine the value of on-demand delivery platforms to restaurants: the positive effect as a new distribution channel to reach new customers and the negative effect of reduced geographic frictions and intensified restaurant competition. The relative strength of the positive and negative effects depends on restaurant characteristics. In the takeout channel, independent restaurants fall victim to reduced geographic frictions because delivery eliminates the opportunity for them to differentiate with service and dine-in experience (Sulek and Hensley 2004). Therefore, online platforms facilitate price comparisons and consumers ordering delivery are more likely to choose the low-priced options. In the dine-in channel, despite higher prices, independent restaurants gain customer demand thanks to the presence of offline service and dine-in experience as differentiators.

4.2.1 Search Costs, Price Comparisons, and Restaurant Competition

On-demand delivery platforms reduce geographic frictions and facilitate price comparisons, which may reduce demand for high-priced restaurants. Since independent restaurants are on average 50% more expensive than fast-food chains (average price ranges, on the scale of 1 to 4, are 1.71 and 1.14 for independent restaurants and fast-food chains, respectively), independent restaurants can be at a disadvantage on on-demand delivery platforms when consumers compare them to the significantly lower-priced fast-food chains.

Takeout Visits Empirical results in Table 5 support this conjecture: the negative price effect on takeout visits is salient for restaurants that are on on-demand delivery platforms. Higher-priced restaurants are associated with a smaller increase in takeout visits (the estimates of $OnPlatform \times Price$ is negative in Model 1 that includes all restaurants as well as Model 2 that only includes independent restaurants). These findings are consistent with prior studies that the internet channel reduces geographic frictions and facilitates price comparisons (Brynjolfsson and Smith 2000; Granados et al. 2012). The estimate for Model 3 that only includes chain restaurants is statistically insignificant, possibly because there is not much variation in prices for chain restaurants—about 80% of chain restaurants have the same price level (<=$10) as shown in Figure 1.

Dine-In Visits Interestingly, although higher-priced restaurants' takeout channel benefits less from being on delivery platforms, these restaurants' dine-in channel can actually benefit more from being on the platforms (Table 6). The estimate of Model 4 in Table 6 shows that higher-priced restaurants' dine-in visits benefit more from being on delivery platforms.

Platform Penetration Table 6 shows that as the penetration of these platforms in a focal restaurant's neighborhood increases, the negative moderating effect of price increases (the estimate of $OnPlatform \times Price \times PlatformPenetration$ in Model 3 is negative for takeout visits). Dine-in visits, however, are not negatively affected by intra-platform competition (Model 6). Instead, the advertising and awareness effect can help attract new customers.

Table 5. Price Effects in the Takeout Channel

DV: Takeout Visits	Model 1 All Restaurants	Model 2 Independents	Model 3 Chains
$OnPlatform$	0.109*** (0.015)	0.091*** (0.019)	0.082*** (0.024)
$OnPlatform \times Price$	-0.042*** (0.008)	-0.031*** (0.008)	-0.021 (0.016)
$PlatformPenetration$	0.235*** (0.058)	0.354*** (0.071)	-0.020 (0.096)
$CommunityMobility$	0.000 (0.071)	-0.117 (0.086)	0.264** (0.119)
Restaurant Fixed Effect	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes
Observations	603,244	456,788	146,456
Adjusted R-squared	0.884	0.867	0.900

Table 6. Moderating Role of Price and Intra-Platform Competition

DV: Weekly Visits	Takeout			Dine-In		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$OnPlatform$	0.109*** (0.015)	0.107*** (0.028)	0.091 (0.088)	0.002 (0.017)	0.143*** (0.034)	0.446*** (0.104)
$Onlatform \times Price$	-0.042*** (0.008)		0.117** (0.051)	0.036*** (0.010)		-0.182*** (0.060)
$Onlatform \times PlatformPenetration$		-0.177** (0.072)	0.505** (0.222)		-0.206** (0.086)	-1.143*** (0.263)
$Onlatform \times Price \times PlatformPenetration$			-0.404*** (0.128)			0.560*** (0.152)
$PlatformPenetration$	0.235*** (0.058)	0.264*** (0.059)	0.261*** (0.059)	-0.023 (0.069)	0.010 (0.070)	0.013 (0.070)
$CommunityMobility$	0.000 (0.071)	-0.005 (0.071)	-0.006 (0.071)	0.687*** (0.084)	0.679*** (0.084)	0.681*** (0.084)
Restaurant Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	603,244	603,244	603,244	603,244	603,244	603,244
Adjusted R-squared	0.884	0.884	0.884	0.862	0.862	0.862

4.2.2 Discussion

The empirical findings above suggest that joining on-demand delivery platforms can be a double-edged sword. The effects are also substantially heterogeneous, depending on the type of customer channels (takeout vs. dine-in), a restaurant's price level, and platform penetration. In the takeout channel, independent restaurants fall victim to reduced geographic frictions because delivery eliminates their opportunity to differentiate with premium service and dine-in experience. Therefore, consumers ordering delivery may choose the low-priced fast-food chains over independent restaurants. For the dine-in channel, independent restaurants gain customer demand despite higher prices thanks to the presence of premium service and dine-in experience as differentiators. To further investigate whether restaurants' net revenue (subtracting the commission fee) still benefits from joining on-demand delivery platforms, in the next section, we combine the foot traffic data with transaction data and conduct additional analyses.

5. Revenue Analysis Combining Transaction Data

The transaction panel data consists of the weekly number of transitions and total sales ($) for the delivery platforms ($PlatformSales$) and independent/chain restaurants ($DirectSales$) in each zip code.

5.1 Calculating Platform Sales and Sales through Restaurants' Own Channels

To measure the net effects of partnering with delivery platforms, we separate platform sales from direct sales through a restaurant's own takeout/dine-in channels. We then subtract the commission fees from platform sales. Denote a restaurant's commission rate by λ_i , the total net (after-fee) total sales for restaurant i and at week t is

$$\begin{aligned} NetTotalSales_{it} &= DirectSales_{it} + (1-\lambda_i)\ PlatformSales_{it} \\ &= DineInSales_{it} + DirectTakeoutSales_{it} + (1-\lambda_i)\ PlatformSales_{it} \\ &= DineInSales_{it} + TotalTakeoutSales_{it} - \lambda_i\ PlatformSales_{it}, \end{aligned} \tag{2}$$

where $TotalTaketoutSales_{it}$ can be computed from the number of takeout visits (sales through delivery platforms plus sales through a restaurant's own takeout channel) using the foot traffic data, whereas $DineInSales_{it}$ can be computed from the number of dine-in visits to the restaurant. The number $PlatformSales_{it}$ (takeout sales through delivery platforms) is not immediately available but can be estimated from the combination of foot traffic data and transaction data. Specifically, the transaction data has information on total sales through delivery platforms ($PlatformSales_{zt}$) in zip code z, which is the total platform sales for all restaurants in that zip code:

$$PlatformSales_{zt} = \sum_{Restaurant\ i\ in\ zip\ code\ z} PlatformSales_{it},$$
$$= \sum_{Restaurant\ i\ in\ zip\ code\ z} \gamma_{it}\ TotalTakeoutSales_{it} \tag{3}$$

where γ_{it} is the fraction of takeout sales through delivery platforms ($\gamma_{it} = 0$ if restaurant i is not on delivery platforms). Treating γ_{it} as unknown parameters, we infer these parameters from the combination of foot traffic data and transaction data by estimating the following system of equations for each zip code z:

$$PlatforSales_{zt} = \sum_{\substack{Restaurant\ i \\ in\ zip\ code\ z}} \gamma_{it}\ TotalTakeoutSales_{it} + \epsilon_{zt}, \tag{4}$$

$$DirectSales_{zt} = \sum_{\substack{Restaurant\ i \\ in\ zip\ code\ z}} [(1 - \gamma_{it})\ TotalTakeoutSales_{it} + DineInSales_{it}] + \varepsilon_{zt} \tag{5}$$

Denote by Y_z the left-hand side of the system of equations above and $F(X_z|C_z, \gamma)$ the right-hand side (excluding the error terms). The estimation procedure searches for a set of parameters $\{\gamma\}$ that minimize the squared errors for each zip code z:

$$\arg\max_{\{\gamma\}} -\|Y_z - F(X_z|C_z, \gamma)\|$$

Since each zip code has its own set of parameters and the objective function can be decoupled, we can speed up the estimation process with parallel computing by splitting estimation into smaller jobs, each can be run in a separate processor. Appendix B provides more discussion on the estimation procedure.

5.2 Indirect Sales through Platforms and Direct Sales through Own Channels

Before analyzing the net impact of delivery platforms to restaurants, we first investigate if sales through delivery platforms substitute sales through restaurants' own channels. As shown in

Table 7, sales through delivery platforms substitute independent restaurants' but complement chain restaurants' own channels (Model 2)—a 10% increase in platform sales reduces independent restaurants' own channel sales by about 0.5%, but increases chain restaurants' own channel sales by about 1.3%. These results suggest that the net impact of delivery platforms on chain restaurants should be positive. However, the net impact on independent restaurants can be either positive or negative, depending on if the increase in platform sales (after subtracting commission fees from the total sales) can compensate for the loss of sales through restaurants' own channels. We conduct additional analyses to answer this question.

Table 7. Substitution between Platform Sales and Direct Sales

	Restaurants' Direct Sales	
	Model 1	Model 2
$PlatformSales$	0.035*** (0.005)	-0.053*** (0.004)
$PlatformSales \times Chain$		0.178*** (0.003)
$Chain$		-0.386*** (0.016)
$PlatformPenetration$	0.235*** (0.058)	0.232*** (0.058)
$CommunityMobility$	0.001 (0.071)	-0.002 (0.071)
ZIP Code Fixed Effect	Yes	Yes
Week Fixed Effect	Yes	Yes
Observations	24,059	24,059
Adjusted R-squared	0.840	0.904

5.3 Net Impact of On-Demand Delivery Platforms on Restaurants

With estimated platform sales, we can: 1) subtract them from total takeout sales to get the takeout sales through a restaurant's own takeout channel (*DirectTakeoutSales*); 2) calculate the net total takeout sales by subtracting the commission fee from total takeout sales (*NetTotalTakeoutSales*); 3) add *DineInSales* to *NetTotalTakeoutSales* to get the net total sales for the restaurant (*NetTotalSales*). With these new outcome variables, we can estimate how sales through the platform channel substitute a restaurant's own takeout sales, the net impact on total takeout sales, and the net impact on total sales after the subtracting commission fees paid to the platforms.

Table 8. The Impact of Delivery Platforms on Restaurant Revenue

DV: Sales	Model 1 DirectTakeoutSales	Model 2 NetTotalTakeoutSales	Model 3 NetTotalSales
$OnPlatform$	-0.023*** (0.005)	0.010** (0.005)	0.034*** (0.004)
$OnPlatform \times Chain$	0.082*** (0.010)	0.073*** (0.010)	0.047*** (0.010)
$PlatformPenetration$	0.236*** (0.058)	0.233*** (0.058)	0.094* (0.054)
$CommunityMobility$	-0.005 (0.071)	-0.003 (0.071)	0.302*** (0.066)
Restaurant Fixed Effect	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes
Observations	603,203	603,203	603,203
Adjusted R-squared	0.884	0.884	0.907

6. Robustness Checks and Additional Analyses

6.1 Matching

We use the standard propensity score matching method as well as its two variations to construct two similar groups of restaurants: one group of restaurants on on-demand delivery platforms and the other group of restaurants not on these platforms. Table A1 in Appendix A summarizes the set of variables used for matching, including restaurant characteristics such as price range, restaurant age, the number of ratings, and the average rating on Yelp, and foot traffic patterns at the beginning of our data period, etc. Table A2 provides evidence that the one-to-one matching creates two comparable groups of restaurants that are similar in characteristics and customer visit patterns. The empirical results with matching remain unchanged (Table 9).

Table 9. Estimation Results with Matching

DV: Weekly Visits	Takeout		Dine-In	
	Model 1	Model 2	Model 3	Model 4
$OnPlatform$	0.036*** (0.004)	0.022*** (0.005)	0.045*** (0.005)	0.042*** (0.006)
$Onlatform \times Chain$		0.066*** (0.010)		0.016 (0.012)
$PlatformPenetration$	0.381*** (0.118)	0.366*** (0.118)	0.109 (0.140)	0.106 (0.140)
$CommunityMobility$	0.424*** (0.144)	0.411*** (0.144)	1.043*** (0.172)	1.040*** (0.172)
Restaurant Fixed Effect	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes
Observations	129,109	129,109	129,109	129,109
Adjusted R-squared	0.875	0.875	0.864	0.864

Other Matching Methods We also check the robustness of the findings with other matching methods, including forward matching and "donut" matching. In forward matching, we use restaurants that joined platforms in the first half of 2019 as "treatments" match restaurants that joined in the second half of 2019 as "controls", see for example, Bapna et al. (2018) and Li (2016). The assumption is that the "treatment" group joined the platforms just several months before the "control" group, so they should be similar even with unobserved characteristics.

In "donut" matching, we restrict matching to restaurants that are geographically closer, i.e., matching a "treated" restaurant with a "controlled" restaurant that is located within a certain distance. The reason is that there could be unobserved differences for restaurants located far away from each other. We also exclude restaurants that are too close to a focal restaurant from matching as they may compete in the same local market (Hausman 1996; Nevo 2001). The findings with alternative matching methods remain qualitatively the same (Table A3 in Appendix A). Please find the detailed discussion of these matching methods in Appendix A.1.

6.2 Instrumental Variables

Restaurants' decisions to join on-demand delivery platforms can be driven by unobserved factors that are correlated with the error term in Equation (1), and thus may bias the parameter estimates. We use the number of other restaurants in nearby markets that have joined the platforms as an instrument. Other restaurants' adoption of these platforms may influence a focal restaurant's decisions due to peer effects and word of mouth (Bollinger and Gillingham 2012; Narayanan and Nair 2013). Therefore, this variable is likely to correlate with a focal restaurant's platform adoption. The number of other restaurants in restaurant i's nearby markets that have joined the platforms is

$$b_{it} = \sum_{\tau=1}^{t-1} \sum_{j=1}^{J} OnPlatform_{j\tau} \times I_{ij}$$

where $I_{ij} = 1$ indicates that restaurant j is in restaurant i's nearby markets.

One potential issue with the instrumental variable is that common shocks in a local market may drive adoptions across restaurants in the market. To address this issue, we modify the variable by excluding restaurants in a restaurant's local market defined by a smaller radius $\underline{D}$. Therefore, we only consider restaurants in the "donut" area defined by $\underline{D} \leq D_{ij} \leq \overline{D}$. The assumption is that restaurant competition is mostly local but peer effects travel far, e.g., restaurant owners are exposed to other restaurants in a broader radius. Such an instrument would not be correlated with the error term in Equation (1) after controlling for common factors (Hausman 1996; Nevo 2001).

To empirically test the validity of the instrument, we vary the values of $\underline{D}$ and $\overline{D}$ and check if the instrument is correlated with a focal restaurant's platform adoption. The correlation remains significant from 5~10 miles to 10~20 miles, but becomes insignificant when the radius goes outside 30 miles (Table A4 in Appendix A.2). We therefore choose the 10~25 range to be the donut area as it minimizes the concern of common unobservable factors. Table 10 shows that the empirical results remain qualitatively unchanged.

Table 10. Estimation Results with Instrumental Variables

DV: Weekly Visits	Takeout		Dine-In	
	Model 1	Model 2	Model 3	Model 4
$OnPlatform$	0.039*** (0.004)	0.025*** (0.005)	0.065*** (0.005)	0.061*** (0.006)
$OnPlatform \times Chain$		0.073*** (0.010)		0.020 (0.013)
$PlatformPenetration$	0.235*** (0.058)	0.232*** (0.058)	-0.023 (0.069)	-0.024 (0.069)
$CommunityMobility$	-0.025 (0.071)	-0.029 (0.071)	0.692*** (0.084)	0.691*** (0.084)
Restaurant Fixed Effect	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes
Observations	603,244	603,244	603,244	603,244
Adjusted R-squared	0.082	0.083	0.066	0.066

6.3 Count Models

Our main analyses use linear regression models as the parameter estimates of the explanatory variables can be directly interpreted as the percentage changes to the outcome variables. We conduct additional analyses with count models, including Poisson regression and Negative Binomial models, to analyze takeout and dine-in visits to a restaurant. The results are robust to these alternative model specifications. Parameter estimates of the Poisson model are in Table A6a) and the Negative Binomial model in Table A6b) in Appendix A.4.

6.4 Moderating Variables and Heterogeneous Effects

Several relevant moderators may influence the effects of delivery platforms. We summarize the main results below. More details can be found in Tables A7 and A8 in Appendix A.5.

- *Own-Delivery Capability*. Restaurants without own delivery capacity gain more from on-demand delivery platforms in boosting takeout orders, but restaurants with own delivery capability can still benefit from the positive spillovers to dine-in visits. These results point out a trade-off for restaurants when they decide whether to add on-demand delivery platforms to their existing delivery capability.
- *Multi-Homing*. We find no evidence of additional benefits from multi-homing on delivery platforms on takeout visits, but find some evidence of a larger positive spillover effect on dine-in visits if a restaurant is on multiple platforms.
- *Restaurant Word-of-Mouth (Yelp Rating)*. Higher-rated restaurants benefit more from delivery platforms for both takeout and dine-in visits.
- *Cuisine Type*. The top six cuisines are American, Sandwiches, Mexican, Italian, Chinese, and Chicken Wing. Empirical results show that restaurants providing Chicken Wing see a larger increase in takeout demand whereas Chinese restaurants see a larger increase in dine-in visits.

6.5 Pandemics and Business Disruption

This study focuses on the year 2019 because the coronavirus pandemic in 2020 has disrupted restaurant operations and possibly altered consumer behaviors. The findings from the previous analysis of regular-day operations may or may not extend to the period of pandemics. As a robustness check, we conduct additional analyses to estimate the effects of on-demand delivery platforms on restaurants during the COVID-19 pandemic and national lockdown, starting March 1, 2020.

We focus on takeout visits as the dine-in option was not operating as normal during the pandemic. The findings on the positive effects from joining on-demand delivery platforms remain qualitatively consistent, but the magnitudes of the effects are stronger during the pandemic (Table A9 in Appendix A.6) than on regular days in the main analyses. However, being on delivery platforms does not help boost dine-in visits during the pandemic due to the shelter-in-place orders, which is different from the findings from regular days, where we observe positive spillovers from the platform channel to dine-in visits to restaurants.

7. Discussion and Conclusions

This research provides empirical evidence on how on-demand delivery platforms influence restaurant demand and revenue. Our empirical findings highlight the platforms' heterogeneous effects on fast-food chains and independent restaurants, which have important implications for restaurants and policymakers.

7.1 Theoretical Implications

On-demand platforms provide flexible delivery services on a pay-per-use basis, and can quickly scale up if restaurants need more delivery capacity. Prior studies find that on-demand delivery platforms can increase restaurant demand and revenue, and small independent restaurants may particularly benefit from such a flexible payment scheme because they are financially more vulnerable (Raj et al. 2020). However, our research suggests that independent restaurants do no benefit as much as chain restaurants do. The empirical finding on the heterogeneous effects adds to the ongoing debate on whether on-demand delivery platforms create value for restaurants (Chen et al. 2019; Feldman et al. 2019; Hadfield 2020). Our research suggests that the value of these platforms depends on the type of restaurants and the specific customer channel (takeout or dine-in). Our findings suggest that on-demand delivery platforms do not substitute for restaurants' dine-in channel. Instead, these platforms increase dine-in visits to restaurants. However, on-demand delivery platforms can substitute independent restaurants' own takeout channel, but we find a complementary effect for chain restaurants. Our findings suggest that on-demand delivery platforms do not substitute for restaurants' dine-in channel. Instead, these platforms increase dine-in visits to restaurants. However, on-demand delivery platforms can substitute independent restaurants' takeout channel, but we do not find such a substitution effect for chains.

This research also provides insights into multi-channel interactions, i.e., the substitution and complementary effects between on-demand delivery and restaurants' own channels. The literature has focused on pre-made physical products or digital contents (e.g., print books vs. eBooks), whereas less is known about differentiated services such as food and dining (Chen et al. 2019; Forman et al. 2009; Xu et al. 2017). Our findings highlight delivery platforms as a double-edged sword to restaurants: the positive effect as a new distribution channel to reach new customers and the negative effect of reduced geographic frictions and restaurant differentiation. Independent restaurants fall victims to reduced geographic frictions because delivery eliminates their opportunity to differentiate with premium services and dine-in experience in the takeout channel. In the dine-in channel, these premium services and dine-in experience are present, and restaurants benefit from the positive spillovers from the delivery platforms to dine-in visits. Our study provides novel insights into how online platforms may create differential effects on service providers in traditionally differentiated service sectors.

7.2 Practical Implications

Our empirical findings highlight the heterogeneous effects of on-demand delivery platforms, and have implications for restaurants. For restaurants that are considering whether to offer delivery through on-demand delivery platforms, our findings highlight several factors and quantify their effects for restaurants to make informed decisions: the type of restaurants (independent vs. chain), price range, platform penetration in the local market, and other restaurants characteristics such as whether the restaurant has its own delivery capability and customer rating. Chain restaurants can better leverage on-demand delivery platforms to gain a competitive advantage over independent restaurants. The widened divide between chains and independent restaurants, caused by on-demand delivery platforms, may force more independent restaurants to struggle further or even closing (Severson and Yaffe-Bellany 2020). Our findings suggest that high-priced independent restaurants may benefit from re-engineering their menu, for example, by adding low-priced items targeting price-sensitive consumers ordering delivery on platforms. Moreover, since the value of delivery platforms to independent restaurants comes from the positive spillovers to dine-in visits, independent restaurants may feature their premium services and dine-in experiences on their platform pages to enhance the spillover effects.

References

Bai, J., So, K. C., Tang, C. S., Chen, X., and Wang, H. 2019. "Coordinating Supply and Demand on an On-Demand Service Platform with Impatient Customers," *Manufacturing & Service Operations Management* (21:3), pp. 556–570.

Bapna, R., Ramaprasad, J., and Umyarov, A. 2018. "Monetizing Freemium Communities: Does Paying for Premium Increase Social Engagement?," *MIS Quarterly* (42:3), pp. 719–736.

Bollinger, B., and Gillingham, K. 2012. "Peer Effects in the Diffusion of Solar Photovoltaic Panels," *Marketing Science* (31:6), pp. 900–912.

Brynjolfsson, E., and Smith, M. D. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science* (46:4), pp. 563–585.

Ceccagnoli, M., Forman, C., Huang, P., and Wu, D. J. 2014. "Digital Platforms: When Is Participation Valuable?," *Communications of the ACM* (57:2), pp. 38–39.

Chan, J., and Ghose, A. 2014. "Internet's Dirty Secret: Assessing the Impact of Online Intermediaries on HIV Transmission," *MIS Quarterly* (38:4), pp. 955–976.

Chen, H., Hu, Y. J., and Smith, M. D. 2019. "The Impact of E-Book Distribution on Print Sales: Analysis of a Natural Experiment," *Management Science* (65:1), pp. 19–31.

Chen, M., Hu, M., and Wang, J. 2019. "Food Delivery Service and Restaurant: Friend or Foe?," *Available at SSRN 3469971*.

Chen, M. K., and Rohla, R. 2018. "The Effect of Partisanship and Political Advertising on Close Family Ties," *Science* (360:6392), pp. 1020–1024.

Chen, P., and Wu, S. 2013. "The Impact and Implications of On-Demand Services on Market Structure," *Information Systems Research* (24:3), pp. 750–767.

Chu, J., Chintagunta, P., and Cebollada, J. 2008. "A Comparison of Within-Household Price Sensitivity across Online and Offline Channels," *Marketing Science* (27:2), pp. 283–299.

Clemons, E. K., Hann, I.-H., and Hitt, L. M. 2002. "Price Dispersion and Differentiation in Online Travel: An Empirical Investigation," *Management Science* (48:4), pp. 534–549.

Einav, L., Farronato, C., and Levin, J. 2016. "Peer-to-Peer Markets," *Annual Review of Economics* (8), pp. 615–635.

Etzion, H., and Pang, M.-S. 2014. "Complementary Online Services in Competitive Markets: Maintaining Profitability in the Presence of Network Effects," *MIS Quarterly* (38:1), pp. 231–248.

Feldman, P., Frazelle, A. E., and Swinney, R. 2019. "Can Delivery Platforms Benefit Restaurants?," *Available at SSRN 3258739*.

Forman, C., Ghose, A., and Goldfarb, A. 2009. "Competition between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live," *Management Science* (55:1), pp. 47–57.

Granados, N., Gupta, A., and Kauffman, R. J. 2012. “Online and Offline Demand and Price Elasticities: Evidence from the Air Travel Industry,” *Information Systems Research* (23:1), pp. 164–181.

Gurvich, I., Lariviere, M., and Moreno-Garcia, A. 2018. *Operations in the On-Demand Economy: Staffing Services with Self-Scheduling Capacity. M. Hu, Ed., Sharing Economy: Making Supply Meet Demand*, Springer Series in Supply Chain Management.

Hadfield, P. 2020. “Why Food Delivery Companies May Be Doing More Harm Than Good, And How Restaurants Can Fix It,” *Forbes*. (https://www.forbes.com/sites/forbesfinancecouncil/2020/05/04/why-food-delivery-companies-may-be-doing-more-harm-than-good-and-how-restaurants-can-fix-it).

Hausman, J. A. 1996. “Valuation of New Goods under Perfect and Imperfect Competition,” in *The Economics of New Goods*, University of Chicago Press, pp. 207–248.

Ho, Y.-J., Dewan, S., and Ho, Y.-C. 2020. “Distance and Local Competition in Mobile Geofencing,” *Information Systems Research*.

Holland, F., and Reed, J. R. 2020. “DoorDash Continues to Lead in the Food Delivery Wars,” *CNBC*. (https://www.cnbc.com/2019/11/21/doordash-continues-to-lead-in-the-food-delivery-wars.html).

Katz, M., and Shapiro, C. 1985. “Network Externalities, Competition, and Compatibility,” *The American Economic Review* (39:10), pp. 424–440.

Li, H., Shen, Q., and Bart, Y. 2018. “Local Market Characteristics and Online-to-Offline Commerce: An Empirical Analysis of Groupon,” *Management Science* (64:4), pp. 1860–1878.

Li, H., and Zhu, F. 2020. “Information Transparency, Multi-Homing, and Platform Competition: A Natural Experiment in the Daily Deals Market,” *Forthcoming at Management Science*.

Li, X. 2016. “Could Deal Promotion Improve Merchants’ Online Reputations? The Moderating Role of Prior Reviews,” *Journal of Management Information Systems* (33:1), pp. 171–201.

McCann, K. 2020. *CaTouchBistro*. (https://www.touchbistro.com/blog/pros-and-cons-of-offering-food-delivery-service/).

MorganStanley. 2020. *Can Food Delivery Apps Deliver Profits for Investors?* (https://www.morganstanley.com/ideas/food-delivery-app-profits).

Narayanan, S., and Nair, H. S. 2013. “Estimating Causal Installed-Base Effects: A Bias-Correction Approach,” *Journal of Marketing Research* (50:1), pp. 70–94.

Nevo, A. 2001. “Measuring Market Power in the Ready-to-Eat Cereal Industry,” *Econometrica* (69:2), pp. 307–342.

Overby, E., and Forman, C. 2014. “The Effect of Electronic Commerce on Geographic Purchasing Patterns and Price Dispersion,” *Management Science* (61:2), pp. 431–453.

Painter, M., and Qiu, T. 2020. “Political Beliefs Affect Compliance with Covid-19 Social Distancing Orders,” *Available at SSRN 3569098*.

Raj, M., Sundararajan, A., and You, C. 2020. "COVID-19 and Digital Resilience: Evidence from Uber Eats," *Available at SSRN 3625638*.

Sankaranarayanan, R., and Sundararajan, A. 2010. "Electronic Markets, Search Costs, and Firm Boundaries," *Information Systems Research* (21:1), pp. 154–169.

Severson, K., and Yaffe-Bellany, D. 2020. "Can Food Delivery Apps Deliver Profits for Investors?," *New York Times*. (https://www.nytimes.com/2020/03/20/dining/local-restaurants-coronavirus.html).

Sulek, J. M., and Hensley, R. L. 2004. "The Relative Importance of Food, Atmosphere, and Fairness of Wait: The Case of a Full-Service Restaurant," *Cornell Hotel and Restaurant Administration Quarterly* (45:3), pp. 235–247.

Taylor, T. A. 2018. "On-Demand Service Platforms," *Manufacturing & Service Operations Management* (20:4), pp. 704–720.

Xu, J., Forman, C., Kim, J. B., and Van Ittersum, K. 2014. "News Media Channels: Complements or Substitutes? Evidence from Mobile Phone Usage," *Journal of Marketing* (78:4), pp. 97–112.

Xu, K., Chan, J., Ghose, A., and Han, S. P. 2017. "Battle of the Channels: The Impact of Tablets on Digital Commerce," *Management Science* (63:5), pp. 1469–1492.

Zhu, F., and Iansiti, M. 2012. "Entry into Platform-Based Markets," *Strategic Management Journal* (33:1), pp. 88–106.

Appendices available upon request