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On-Demand Delivery Platforms and Restaurant Sales

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Abstract. 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 versus chain) and the type of customer channels (takeout versus 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 facilitates price competition and reduces 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.

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Keywords: multisided 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 (Morgan Stanley 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. 2022). 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 for restaurants. On one hand, on-demand delivery platforms provide restaurants with 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 budget for customer acquisition (McCann 2020, Li and Zhu 2021). 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 for 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 versus 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

Although several theoretical studies have looked into the effects of on-demand delivery platforms on restaurants (Chen et al. 2022, Feldman et al. 2023), empirical research on this topic has been scant, possibly because of a 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 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 versus chain) and the type of customer channels (takeout versus 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 facilitates price comparison for consumers, leading to increased price competition within the platform. Thus, these platforms reduce the opportunity for independent restaurants to differentiate themselves 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 premade physical products or digital contents (e.g., print books versus eBooks), whereas less is known about differentiated services such as food and dining. Our empirical findings reveal delivery platforms as a double-edged sword for restaurants: the positive effect as a new distribution channel to reach new customers and the negative effect of reduced restaurant differentiation and intensified competition. The relative strength of the positive and negative effects depends on restaurant characteristics and local market conditions. Independent restaurants can be at a disadvantage because of intensified competition 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 on online platforms and multichannel 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, demonstrating the heterogeneous effects of on-demand delivery platforms, offer important practical implications. 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 make informed decisions. Such contingent factors include restaurant characteristics (e.g., independent versus chain restaurants, the price level, restaurant quality/rating, and the restaurant size) and local market conditions such as platform penetration.

For instance, our findings suggest that high-priced restaurants may benefit from redesigning their menu, for example, by adding low-priced items in response to reduced differentiation and heightened price effects on platforms. Moreover, because 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 their 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 (Taylor 2018, Bai et al. 2019).

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 restaurant (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 multichannel interactions (complement or substitute), and to understand how on-demand delivery platforms widen the performance gap between fast-food chains and independent restaurants. We find distinct substitution/complementary patterns among channels during regular days and during the pandemic period. For instance, positive spillovers from delivery platforms to restaurant dine-ins are observed during regular days but are absent during the pandemic. These new findings shed light on the role of delivery platforms in equilibrium as the economy returns to regular operations.

2.1.2. Electronic Commerce and Electronic Markets.

This research is also related to electronic commerce and search costs in online markets and platforms. Although 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 facilitate price comparisons and intensify price competition, and thus consumers may favor low-priced fast-food chains over more expensive options.

2.1.3. Multichannel 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 multichannel 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 with and cannibalize a business's existing channels (Forman et al. 2009, Collison 2020), reducing the 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. 2023). Adding to these theoretical studies of the restaurant industry, our study provides empirical evidence of a complementary and substitution effect.

2.2. Theoretical Development: 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

with 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 multisided 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. 2023). However, these platforms may also hurt restaurants when they cannibalize restaurants' existing channels, as suggested by existing theoretical models (Chen et al. 2022, Feldman et al. 2023). 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, Reduced Frictions, and Restaurant Competition. On-demand delivery platforms can reduce geographic frictions (Feldman et al. 2023). 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 intensified intra-platform competition among nearby restaurants (Overby and Forman 2014, Ho et al. 2020).

Independent restaurants may be more negatively affected by competition because consumers ordering delivery do not have the chance to enjoy premium features such as dine-in experience/atmosphere and quality service, which are often the competitive advantages of independent restaurants (Sulek and Hensley 2004, Zervas et al. 2017). 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). Compared with independent restaurants, chain restaurants also gain operational advantages from the partnership with delivery platforms. Chains partner with these platforms for all stores across geographies, which helps to streamline the supply chain, users' experience, and marketing promotions, among others.

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 (Bai et al. 2020). 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](https://www.yellowpages.com), restaurant-platform partnerships 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 complement the transaction data because the foot traffic data allow us to identify takeout visits and dine-in visits, whereas the transaction data help 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 cover 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 in early 2020 disrupted restaurant operations. In Section 6.2.2, we also expand our analysis and

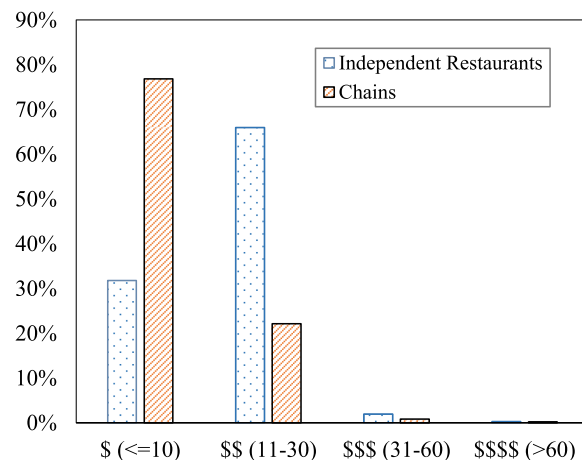
investigate the delivery platform effect during business disruption in the year 2020, which covers the COVID-19 pandemic.

3.1.1. Restaurants and the Adoption of Delivery Platforms. We first compiled a complete list of restaurants in each zip code using Yelp Application Programming Interface (API) and YellowPages' search portal. Restaurant-platform partnership data are collected from the three largest on-demand delivery platforms, that is, 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 2019).⁵

We obtained a complete list of restaurants on each of these platforms each week. Data on a restaurant's timing of joining the delivery platforms were collected weekly and cross-validated through multiple sources, including the platform restaurant pages and platform APIs. For each restaurant, we identified the week when the restaurant was first listed on any of the platform pages and the date the restaurant received its first customer order through the platform API. We used the earlier of these dates as the restaurant's adoption date of delivery platforms.

There are a total of 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 whether the restaurant is an independent restaurant or is affiliated with a chain. Per the definition by the National Restaurant Association and the Food and 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 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).

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



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 are provided by SafeGraph Inc., a data company that aggregates anonymized location data from numerous applications for approximately 35 million unique devices in the United States. Researchers from over 1,000 organizations have used the SafeGraph foot traffic data to understand visit patterns to points of interest.⁸ Studies using the data report that the data are generally representative of the U.S. population (Chen and Rohla 2018, Painter and Qiu 2021).

To preserve anonymity, the data are aggregated to the level of points of interest such as a restaurant on a weekly basis. SafeGraph further splits the total number of visits into four buckets based on the duration of stay: shorter than 20 minutes, between 21 and 60 minutes, between 61 and 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.

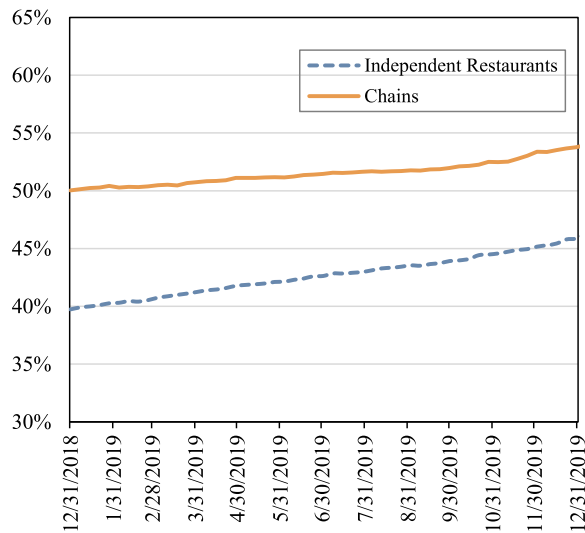
3.1.3. Transaction Data. The proprietary transaction data complement the foot traffic data by providing

Table 1. Restaurants and Platform Partnership

Restaurant type	Number of restaurants (% of total)	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

Notes. Price ranges are on the scale of 1 (\$) to 4 (\$\$\$\$), with four being the highest according to Yelp. Costs per person per meal are 1 (≤ 10), 2 ($11\text{--}30$), 3 ($31\text{--}60$), and 4 (>60).

Figure 2. (Color online) Fraction of Restaurants on Delivery Platforms



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 data set, we create a panel data set that consists of the weekly restaurant sales (number of transactions and total spend in U.S. dollars (USD)) through the delivery platforms and 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).⁹ Therefore, the transaction data include weekly restaurant sales through the delivery platforms (*PlatformSales*) and the own channels of independent/chain restaurants (*DirectSales*) in each zip code.

3.2. Variables and Measurement

The main variables and their summary statistics are presented in Tables 2 and 3, respectively. The outcome variables we are interested in are consumers’ visits to restaurants. As defined in Table 2, we investigate 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.¹⁰ Note that takeout visits could be either customers picking up orders themselves or 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.¹¹ 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, or 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 61–240 minutes as dine-in visits in Online Appendix A.3.¹² We do

Table 2. Definition of Variables

Variables	Definition	Sources
Dependent variables		
<i>TakeoutVisits</i>	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).	SafeGraph
<i>DineInVisits</i>	The number of visits staying between 21 and 60 minutes in a given week (a proxy for dine-in customers).	SafeGraph
Key independent variables		
<i>OnPlatform</i>	A dummy variable indicating whether a restaurant joined in an on-demand delivery platform in a given week.	DoorDash, Grubhub, Uber Eats
<i>Chain</i>	A dummy variable that indicates whether a restaurant is a chain restaurant (1 for a chain restaurant, 0 for an independent restaurant).	SafeGraph
<i>Price</i>	A categorical price-level indicating the approximate cost per person per meal for a restaurant. There are four levels: \$, less than \$10; \$\$, \$11–\$30; \$\$\$, \$31–\$60; \$\$\$\$, more than \$60.	Yelp
<i>PlatformPenetration</i>	The proportion of a focal restaurant’s nearby restaurants (within a 5-mile distance) that are on delivery platforms in a given week.	DoorDash, Grubhub, Uber Eats
<i>CommunityMobility</i>	The proportion of devices in a county leaving home for at least some time in a given day (average across days of a week).	SafeGraph

Table 3. Summary Statistics of Main Variables

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

not consider visits longer than 240 minutes, which usually correspond to a shift of staff working in a restaurant, instead of consumers' visits.

The main explanatory variable is the timing of 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.

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 community mobility because it helps rule out alternative explanations that our results are driven by time-varying region-specific characteristics.

To match restaurants on delivery platforms and those not yet 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, the price range, the age of the restaurant on Yelp, and the number of competitors near the focal restaurant. The list of variables, their definition, and statistics are included in Online 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:

$$\log(\text{WeeklyVisits}_{imt}) = \alpha + \beta \text{OnPlatform}_{it} + \phi \mathbf{X}_{mt} + \eta_i + v_t + \varepsilon_{imt}, \quad (1)$$

where i , m , and t index a restaurant, market, and week, respectively, $\mathbf{X}_{mt}$ is a vector of time-varying variables for the local market m the restaurant is in (e.g., county-level community mobility 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 Equation (1) 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 yet on the platforms ("control group") because of restaurants' self-selection. That is, a restaurant's decisions about whether to and when to partner with delivery platforms may be influenced by some factors which further affect a restaurant's takeout and dine-in demand. These factors may include characteristics and past performance of the restaurant, demographics of the locality, platform concentration and market competition in the focal market, etc. To address the self-selection bias issue, we use multiple matching methods to construct the treatment group and a comparable control group (Section 6.1.1). We also construct instrumental variables and estimate the model using two-stage least squares (Section 6.1.2). Furthermore, we conduct additional analyses leveraging a platform policy change to directly address potential restaurant self-selection: Grubhub expanded its restaurant listing by adding restaurants to the platform without notice (Section 6.1.3). We also validate the robustness of the findings with count models (Section 6.1.4) and alternative difference-in-differences (DiD) specifications (Section 6.1.5).

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. Because the dependent variables are log-transformed, the estimates can be interpreted as percentage changes.

4.1.1. Main Effect on Takeout Visits. The 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% (3.6% in Model 3) after a restaurant joins delivery platforms. This result suggests that takeout orders through delivery platforms do not completely substitute takeout orders from a restaurant's own channels. Instead, about 3.8% of takeout orders are incremental.

4.1.2. Spillovers to Dine-In Visits. Delivery platforms increase dine-in visits to restaurants on the platforms by 6.2% (Model 2). 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

Table 4. Parameter Estimates of Main Effects

DV: weekly visits	Before matching		After matching	
	Model 1 (takeout)	Model 2 (dine-in)	Model 3 (takeout)	Model 4 (dine-in)
<i>OnPlatform</i>	0.038*** (0.008)	0.062*** (0.010)	0.036*** (0.008)	0.044*** (0.011)
<i>CommunityMobility</i>	−0.008 (0.138)	0.687*** (0.150)	0.296 (0.259)	1.359*** (0.285)
Restaurant fixed effect	Yes	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes	Yes
No. of restaurants	14,036	14,036	2,964	2,964
Observations	603,244	603,244	126,810	126,810
Adjusted R^2	0.884	0.862	0.876	0.863

Notes. All continuous variables are log-transformed. Clustered standard errors (at the restaurant level) in parentheses. DV, dependent variable.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ (significance level).

result suggests that delivery platforms complement rather than substitute a restaurant's dine-in channel.

4.1.3. Fast-Food Chains vs. Independent Restaurants.

The positive effects of on-demand delivery platforms are substantially heterogeneous. The estimate of the interaction term (*OnPlatform* × *Chain*) in Model 1 in Table 5 shows that, compared with 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 9.4% 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 2 and Model 4). Both types of restaurants see about a 6% (Model 2) 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 for restaurants: the positive effect as a new distribution channel to reach new customers and the negative effect of intensified restaurant competition. The relative strength of the positive versus negative effect depends on restaurant characteristics. In the takeout channel, independent restaurants are at a disadvantage because of intensified price competition because delivery eliminates the opportunity to differentiate themselves 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

Table 5. Parameter Estimates of Moderation Effects

DV: weekly visits	Before matching		After matching	
	Model 1 (takeout)	Model 2 (dine-in)	Model 3 (takeout)	Model 4 (dine-in)
<i>OnPlatform</i>	0.024*** (0.009)	0.059*** (0.012)	0.023** (0.009)	0.041*** (0.012)
<i>OnPlatform</i> × <i>Chain</i>	0.070*** (0.020)	0.017 (0.021)	0.070*** (0.020)	0.014 (0.022)
<i>CommunityMobility</i>	−0.012 (0.138)	0.686*** (0.150)	0.283 (0.258)	1.357*** (0.285)
Restaurant fixed effect	Yes	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes	Yes
No. of restaurants	14,036	14,036	2,964	2,964
Observations	603,244	603,244	126,810	126,810
Adjusted R^2	0.884	0.862	0.876	0.863

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

thanks to the presence of offline service and dine-in experience as differentiators.

4.2.1. Price Effects. On-demand delivery platforms allow consumers to explore more options and facilitate price comparisons, which may reduce demand for high-priced restaurants. Because independent restaurants are on average 50% more expensive than fast-food chains (average price ranges, on a scale of one to four, 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.

4.2.1.1. Evidence of Price Effects from Yelp Customer Reviews. With aggregate foot traffic data at the restaurant level, it is challenging to directly demonstrate if consumers pay more attention to prices when they shop on delivery platforms, compared with when they dine in. Therefore, we supplement the foot traffic data with customer review data from Yelp. Specially, we track the sequence of an individual consumer's Yelp reviews. We classify restaurant reviews into delivery reviews (posted by customers who ordered platform delivery) and dine-in reviews (posted by dine-in consumers). Content analysis of these reviews shows that delivery reviews mention price more whereas dine-in reviews mention in-store service and experience more (Table B1 in Online Appendix B.1). These findings suggest that higher-priced independent restaurants can be at a disadvantage compared with lower-priced chain restaurants as independent restaurants are unable to use customer service and dine-in experience to differentiate from fast-food chains. More details on the analysis of Yelp customer review data are in Online Appendix B.1.

4.2.1.2. Price Effects on Takeout Visits. Empirical results in Table B2 in Online Appendix B.1 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 $OnPlatform \times Price$ are negative in Model 1, which includes all restaurants, as well as Model 2, which only includes independent restaurants). These findings are consistent with those of 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, which 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 ($\leq \$10$), as shown in Figure 1.

4.2.1.3. Price Effects on Chain vs. Independent Restaurants Across Cuisines. We conduct subsample analyses for each major cuisine type, which helps us control for the heterogeneity of foods offered by chain and independent restaurants, and allows us to focus on the price effects. We first compare the price level for restaurants in the top three cuisine types with the dominant number of restaurants (i.e., American, Mexican, and Italian). American and Italian restaurants are overall more expensive than Mexican restaurants (Table B4 in Online Appendix B.1).

- Within American or Italian cuisine, independent restaurants are more expensive than chain restaurants (statistically significant). However, within Mexican cuisine, independent restaurants have roughly the same prices as chain restaurants (i.e., the difference is not statistically significant) (Table B4 in Online Appendix B.1).

- Within American or Italian cuisine, chain restaurants benefit more from the partnership with delivery platforms (Table B5 in Online Appendix B.1). The differential effect is not statistically significant for Mexican restaurants. This within-cuisine analysis provides evidence that the stronger effects for chain restaurants than independent restaurants may be driven by price differences.

4.2.1.4. Role of Platform Penetration. The price effect can be stronger in a more competitive market. Competition on delivery platforms can be captured by the penetration of the platforms in the focal market (we use the lag of *PlatformPenetration* in this analysis, which alleviates the concerns that platform penetration could be endogenous). Table B3 in Online Appendix B.1 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).

4.2.2. Spillovers to Dine-In. Platform delivery may increase not only delivery orders but also dine-in visits to a restaurant. Such spillover effects occur when new consumers become aware of the restaurant via delivery platforms and subsequently choose to dine in.

4.2.2.1. Evidence of Spillover Effects from Yelp Customer Reviews. We analyze the sequence of an individual consumer's Yelp reviews. We find that consumers who were first attracted to a restaurant through delivery platforms may become dine-in customers in subsequent visits (Table B6 in Online Appendix B.2). This provides direct evidence of spillovers from delivery to dine-in. Content analysis of these reviews shows that delivery reviews mention price more whereas dine-in reviews mention in-store service and experience more (Table B1 in Online Appendix B.1).

4.2.2.2. Restaurant Reputation and Quality. Spillovers to dine-in can be stronger for restaurants that provide better customer service and dine-in experience. We use a restaurant's Yelp rating as a proxy of a restaurant's reputation and quality. Empirical results in Table B7 in Online Appendix B.2 show that restaurants with a higher Yelp rating see a larger increase in dine-in visits after being on delivery platforms.

4.3. Additional Evidence from Survey of Consumers

We conduct a survey study on users of delivery apps and further demonstrate how delivery platforms influence price competition, thereby altering the competitive advantages of independent restaurants versus chain restaurants. We recruit 205 participants from Prolific, one of the largest online survey research platforms. These participants reside in the United States and have used delivery apps before (Prolific allows filtering participants based on their location and self-reported activities). Prior research shows that participants on Prolific outperform other platforms (e.g., Amazon Mechanical Turk) by providing the highest-quality responses (Douglas et al. 2023). The survey questions collect information about the participants' demographics and how they choose a restaurant to dine in or order takeout/delivery from (Online Appendix E.1). The survey data provide detailed information about how delivery apps change consumer behavior (e.g., exploration of restaurant options and attention to different aspects of restaurant services) when the consumers are using the apps, compared with when they do not.

We summarize the survey results in Online Appendix E.2. The demographics of the participants are consistent with those in a larger-scale study of U.S. consumers of delivery apps in 2019 (Table E1 in the Online Appendix). The survey provides several insights into consumer behavior when using delivery apps. Compared with the dine-in scenario, consumers, when using delivery apps to order takeout/delivery, are more likely to choose chain restaurants over local independent restaurants (Table E2 in the Online Appendix). This result suggests that delivery apps steer overall consumer preferences toward chain restaurants.

Our survey also shows that when using delivery apps, consumers value restaurant price, service, ambiance, and location differently, compared with when they do not use such apps. Specifically, compared with the dine-in scenario, consumers who order food through delivery apps tend to pay more attention to price but pay less attention to restaurant service and ambiance (Table E3 and Figure E1 in the Online Appendix). This result explains why independent restaurants do not benefit from delivery apps as much as chain restaurants: independent restaurants are overall more expensive but provide better service and ambiance than chain

restaurants. Delivery apps reduce independent restaurants' competitive advantages as these apps allow consumers to easily compare restaurant prices and explore other options (Table E4 and Figures E1a and E1b in the Online Appendix) and reduce the relevance of using service/ambiance as differentiators (Table E4 and Figure E1d).

4.4. 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 versus dine-in), a restaurant's price level, and platform penetration. In the takeout channel, independent restaurants can be at a disadvantage because delivery eliminates their opportunity to differentiate with premium service and dine-in experience. Therefore, consumers ordering delivery may choose 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 consist of the weekly number of transactions 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

$$\begin{aligned} \text{NetTotalSales}_{it} &= \text{DirectSales}_{it} + (1 - \lambda_i) \text{PlatformSales}_{it} \\ &= \text{DineInSales}_{it} + \text{DirectTakeoutSales}_{it} \\ &\quad + (1 - \lambda_i) \text{PlatformSales}_{it} \\ &= \text{DineInSales}_{it} + \text{TotalTakeoutSales}_{it} \\ &\quad - \lambda_i \text{PlatformSales}_{it}, \end{aligned} \quad (2)$$

where *TotalTakeoutSales_{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 have 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:

$$\begin{aligned} PlatformSales_{zt} &= \sum_{\text{Restaurant } i \text{ in zip code } z} PlatformSales_{it}, \\ &= \sum_{\text{Restaurant } i \text{ in zip code } z} \gamma_{it} TotalTakeoutSales_{it} \end{aligned} \quad (3)$$

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 :

$$PlatformSales_{zt} = \sum_{\text{Restaurant } i \text{ in zip code } z} \gamma_{it} TotalTakeoutSales_{it} + \epsilon_{zt}, \quad (4)$$

$$\begin{aligned} DirectSales_{zt} &= \sum_{\text{Restaurant } i \text{ in zip code } z} [(1 - \gamma_{it}) TotalTakeoutSales_{it} \\ &\quad + DineInSales_{it}] + \epsilon_{zt} \end{aligned} \quad (5)$$

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 :

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

Because 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, and each can be run in a separate processor. Online Appendix C 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 on restaurants, we first investigate if sales through delivery platforms substitute sales through restaurants' own channels. As shown in Table 6, sales through delivery platforms substitute independent restaurants' own channels but complement chain restaurants' own channels (Model 2)—a 10% increase in platform sales

Table 6. Substitution Between Platform Sales and Direct Sales

	Restaurants' direct sales	
	Model 1	Model 2
<i>PlatformSales</i>	0.035*** (0.005)	−0.053*** (0.004)
<i>PlatformSales</i> × <i>Chain</i>		0.178*** (0.003)
<i>Chain</i>		−0.386*** (0.016)
<i>CommunityMobility</i>	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^2	0.840	0.904

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

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 whether 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.

5.3. Net Impact of On-Demand Delivery Platforms on Restaurants

We look into restaurant revenues from different channels to uncover the substitution effects and the net financial impact on restaurants, after subtracting the commission fee paid to the platforms. 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*), and (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 subtracting commission fees paid to the platforms.

Table 7 shows that for independent restaurants, partnership with delivery platforms reduces direct takeout sales by about 2.5% (Model 1) but has a neutral effect on total takeout sales after subtracting the commission fee paid to the platforms (Model 2). Thanks to the positive spillovers to dine-in, independent restaurants see an increase of 2.6% in net sales revenue from all

Table 7. The Impact of Delivery Platforms on Restaurant Revenue

DV: sales	Model 1 (DirectTakeoutSales)	Model 2 (NetTotalTakeoutSales)	Model 3 (NetTotalSales)
<i>OnPlatform</i>	−0.025** (0.010)	0.009 (0.009)	0.026** (0.010)
<i>OnPlatform</i> × <i>Chain</i>	0.080*** (0.020)	0.071*** (0.020)	0.044** (0.020)
<i>CommunityMobility</i>	0.280 (0.260)	0.282 (0.260)	0.777*** (0.254)
Restaurant fixed effect	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes
No. of restaurants	2,964	2,964	2,964
Observations	126,810	126,810	126,810
Adjusted R^2	0.877	0.877	0.905

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

channels combined (Model 3). For chain restaurants, the partnership with delivery platforms not only increases platform sales but also boosts direct takeout (Model 1) and dine-in in the restaurants, resulting in a 7% increase in net revenue, which is 4.4% larger compared with independent restaurants (Model 3).

6. Robustness Checks and Additional Analyses

We conduct robustness checks and additional analyses, enhance the robustness of the findings, and provide managerial implications for restaurant owners and platform design.

6.1. Robustness Checks

6.1.1. Other Matching Methods. Our main results above are based on the matched subsamples using a propensity score matching method. We evaluate the robustness of the findings with other matching methods, including forward matching, “donut” matching, and the matching frontier method. The findings with alternative matching methods remain qualitatively the same (Table A3 in Online Appendix A.1).

In forward matching, we use restaurants that joined platforms in the first half of 2019 as “treatments” to 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, that is, 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.¹³ 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).

In addition, we also conducted the matching frontier method proposed by King et al. (2017). This method helps us to calculate a set of matching solutions considering the tradeoff between bias (reduced from dropping some samples) and variance (increased from dropping some samples). Please find the detailed discussion of these matching methods in Online Appendix A.1.

6.1.2. 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 because of 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

$$b_{it} = \sum_{\tau=1}^{t-1} \sum_{j=1}^J \text{OnPlatform}_{j\tau} \times I_{ij}, \quad (6)$$

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; for example, 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).

Table 8. Estimation Results with Instrumental Variables

DV: weekly visits	Takeout		Dine-in	
	Model 1	Model 2	Model 3	Model 4
<i>OnPlatform</i>	0.039*** (0.004)	0.025*** (0.005)	0.065*** (0.005)	0.061*** (0.006)
<i>OnPlatform</i> × <i>Chain</i>		0.073*** (0.010)		0.020 (0.013)
<i>CommunityMobility</i>	−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
No. of restaurants	14,036	14,036	14,036	14,036
Observations	603,244	603,244	603,244	603,244
Adjusted R^2	0.082	0.083	0.066	0.066

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

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 Online Appendix A.2). We, therefore, choose the 10- to 25-mile range to be the donut area as it minimizes the concern of common unobservable factors. Table 8 shows that the empirical results remain qualitatively unchanged.

6.1.3. Restaurants Added to Platforms Without Notice.

To further address the concern of endogenous decisions to partner with delivery platforms, we conduct a robustness check by investigating a sample of restaurants that were added to delivery platforms without notice (Mayya and Li 2024). We compare the effect of being on the delivery platform on the 239 nonpartnered restaurants with that on partnered restaurants (i.e., restaurants with formal contracts with the delivery platform). Table 9 shows there is no significant difference in platform effects for partnered versus nonpartnered restaurants. This result suggests that self-selection bias might not be a major concern.

Table 9. Effects on Partnered vs. Nonpartnered Independent Restaurants

DV: weekly visits	Takeout	Dine-in
<i>OnPlatform</i>	0.034*** (0.010)	0.066*** (0.013)
<i>OnPlatformNon_Partnered</i>	0.067 (0.051)	−0.038 (0.069)
<i>CommunityMobility</i>	−0.121 (0.171)	0.593*** (0.186)
Restaurant fixed effect	Yes	Yes
Week fixed effect	Yes	Yes
Observations	451,928	451,928
Adjusted R^2	0.867	0.853

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

6.1.4. 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 those of the negative binomial model are in Table A6b in Online Appendix A.4.

6.1.5. Alternative Difference-in-Differences Specifications. We have conducted additional analyses with different DiD specifications. The results are consistent, reinforcing the validity of our main findings (Online Appendix A.5).

6.1.5.1. Bacon Decomposition Based on Goodman-Bacon (2021). Our setting is not exactly the same as a staggered difference-in-differences setup in prior studies, where a series of “events” (such as entering a city or policy changes) were at a platform level. Because the decisions to join a delivery platform in our study are at a restaurant level, the timing of joining a platform is quite dispersed across restaurants. Given the huge variations in adoption dates, we were unable to directly work on the Bacon decomposition suggested by Goodman-Bacon (2021) and other related papers, as there are too many “treatment events,” which renders the estimation impossible and the results difficult to interpret. We use the following steps to conduct the analysis:

1. Cluster Adoption Dates to Months. We cluster the adoption timing from a week to a month, which significantly reduces the number of “treatment events.” Using the consolidated monthly panel data, the results (Table A7 in Online Appendix A.5) are consistent with those from the base model.

2. Bacon Decomposition Analysis Using the Monthly Data. Recent methodology studies point out the potential

issue in selective treatment timing as the treatment effects might not be homogenous across groups (Callaway and Sant’Anna 2021, Goodman-Bacon 2021, Sun and Abraham 2021). In particular, the comparison between different timing groups can introduce bias if there are heterogeneous treatment effects. To test the validity of our main results, we use Bacon decomposition to identify the weight of the estimated treatment effect for each of the comparisons among different groups. As shown in Table A8 in Online Appendix A.5, a large portion (74.8%) of the estimated treatment effects is from the “Treated” versus “Untreated.” In contrast, the weight of the estimated treatment effect between “Earlier Treated” versus “Later Treated” is rather low (13.2%). Therefore, these results alleviate the concern that our estimate is biased.

6.1.5.2. Event-Study Approach. We adopt the event-study analysis to show the lack of pretrends by following the literature (Park et al. 2021, Cullen and Perez-Truglia 2023). Instead of using *OnPlatform*, we employed a vector of dummy variables to indicate the relative time to joining a delivery platform. Similar to the Bacon decomposition analysis above, we also aggregate our data to the monthly level. The specific event-study model is as follows:

$$\log(\text{TakeoutVisits}_{imt}) = \sum \text{Rel_Time_OnPlatform}_{it} + \phi X_{mt} + \eta_i + \nu_t + \epsilon_{imt}.$$

The parallel trend assumption is supported, and the empirical results remain consistent (Model 1 in Table A9 in Online Appendix A.5).

6.1.5.3. Staggered DiD Methods. As we noted for Bacon decomposition above, the two-way-fixed-effect specification (including the relative-time method above) may introduce bias. Although the problematic comparison (“Later Treated” versus “Earlier Treated”) does not seem to affect our conclusion (Table A8 in the Online Appendix), the staggered DiD methods may provide unbiased estimates by eliminating the problematic comparisons. Therefore, we also adopt the staggered DiD framework to validate our results using alternative model specifications proposed by Sun and Abraham (2021), Baker et al. (2022), and Imai et al. (2023). Again, the parallel trend assumption is supported and the empirical results remain consistent (Table A9 in the Online Appendix).

6.2. Additional Analyses

6.2.1. Moderating Effects of Restaurant Characteristics. Several relevant moderators may influence the magnitude of the effects of delivery platforms on independent restaurants. We summarize the results for all moderators below. More details can be found in Tables D2 and D3 in Online Appendix D.1.

- *Restaurant Age.* We use the date of the first review posted on Yelp as a proxy of the opening day, so that we can calculate the age of a restaurant at the beginning of our data period (*RestAge*). We observe a larger effect of delivery platforms on both takeout visits and dine-in visits for newer restaurants than for older restaurants. This result further shows the advertising effect of delivery platforms on independent restaurants.

- *Degree of Local Competition (the number of neighboring restaurants within a 5-mile distance).* Restaurants in a more competitive area see a stronger positive effect of delivery platforms on takeout visits, but not on dine-in visits. This result suggests that restaurants in a more competitive market can use the delivery channel to differentiate.

- *Multihoming.* We find no evidence of additional benefits from multihoming on delivery platforms on takeout visits, and find no evidence of a spillover effect on dine-in visits if a restaurant is on multiple platforms.

- *Restaurant Size (based on the square feet of area).* Large-sized restaurants benefit less from delivery platforms for takeout visits than small- and medium-sized restaurants. For dine-in visits, the effect of delivery platforms does not vary across different sizes of restaurants.

6.2.2. Pandemics and Business Disruption. This study focuses on the year 2019 because the coronavirus pandemic in 2020 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. In this subsection, 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 D4 in Online Appendix D.2) than on regular days in the main analyses. However, being on delivery platforms did not help boost dine-in visits during the pandemic because of 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.

6.2.3. Alternative Explanations

6.2.3.1. Operational Hours for Chain vs. Independent Restaurants. It is possible that independent restaurants may have shorter open hours than chain restaurants, which may explain why they do not enjoy benefits from delivery platforms as much as chain restaurants. To rule out this alternative explanation, we calculate the average daily open hours for the two

types of restaurants. Indeed, chain restaurants are on average open for about three hours longer than independent restaurants (Table D5 in Online Appendix D.3). We then investigate whether the differences in open hours explain the differential effects of partnering with delivery platforms. Empirical results (Table D6 in Online Appendix D.3) show that open hours do not explain the differential effects. This result suggests that although chain restaurants may remain open late at night or early in the morning, these restaurants may not receive/fulfill many delivery orders during these times. The reasons can be that there are not many customers who place delivery orders at these times or there are not many active delivery drivers around (customers might be discouraged by long delivery times).

6.2.3.2. Capacity and Staffing for Chain vs. Independent Restaurants. Chain restaurants may also have more capacity (e.g., have more staff and can cook fast) to realize the value of delivery platforms than independent restaurants. Although we have controlled for the relevant factors in our main analysis (e.g., the matching process), we conduct additional analyses to rule out the potential explanation that the differential impact of delivery platforms on chain versus independent restaurants is due to their difference in capacity (Online Appendix D.3). More specifically, we show that chain restaurants have a smaller space (Table D7 in the Online Appendix) and smaller staff count (Table D9) than independent restaurants. The empirical results (Tables D8 and D10 in the Online Appendix) further show that the capacity of a restaurant (the size of the store and the staff count) cannot fully explain the differential impacts of delivery platforms on chain versus independent 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 not benefit as much as chain restaurants. The empirical finding on the

heterogeneous effects adds to the ongoing debate on whether on-demand delivery platforms create value for restaurants (Hadfield 2020, Chen et al. 2022, Feldman et al. 2023). 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' takeout channel, but we do not find such a substitution effect for chains; we find a complementary effect.

This research also provides insights into multichannel interactions, that is, the substitution and complementary effects between on-demand delivery and restaurants' own channels. The literature has focused on premade physical products or digital contents (e.g., print books versus eBooks), whereas less is known about differentiated services such as food and dining (Forman et al. 2009, Xu et al. 2017, Chen et al. 2019). Our findings highlight delivery platforms as a double-edged sword for restaurants: the positive effect as a new distribution channel to reach new customers and the negative effect of intensified restaurant differentiation. Independent restaurants are more likely to be negatively affected by 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, which have implications for restaurants. Chain restaurants can better leverage on-demand delivery platforms to gain a competitive advantage over independent restaurants (chain restaurants see three times as much as what independent restaurants gain in revenue). The widened divide between chains and independent restaurants, caused by on-demand delivery platforms, may force more independent restaurants to struggle further or even close (Severson and Yaffe-Bellany 2020). To address this disparity, delivery platforms may come up with new features to promote independent restaurants. For instance, platforms can facilitate the search and discovery of independent restaurants by adding a "Local Restaurant" label and creating a filter to promote local restaurants.

Our findings suggest that high-priced independent restaurants may benefit from reengineering their menu, for example, by adding low-priced items targeting price-sensitive consumers ordering delivery on platforms. Moreover, because 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. 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 versus chain), price range, platform penetration in the local market, and other restaurant characteristics such as restaurant reputation and size.

7.3. Limitations and Future Research

This empirical study sheds light on the impact of on-demand delivery platforms on restaurants from a multichannel perspective. Further research may extend this research by leveraging new data sources and methodologies. For instance, consumer-level data may provide new insights into how consumers choose among different channels (takeout, delivery, or dine-in), which has implications for multichannel pricing (Cavallo 2017). Future research may also investigate restaurants' promotional effects across delivery and in-store channels when they join delivery platforms. Future research may also investigate on-demand delivery platforms from the platform design perspective, investigating how platform design and governance may enhance firm profit, consumer surplus, and social welfare. For instance, platform design may influence consumer search and transaction outcomes. It is interesting to investigate how different platform designs affect chain and local businesses. Lastly, this paper focuses on traditional restaurants that operate multiple channels, including dine-in and takeout/delivery. Future research may investigate the effects of delivery platforms on enabling "ghost kitchens" or "cloud kitchens," that is, restaurants without dine-in space.

Endnotes

¹ See <https://medium.com/@convershaken/mcdonalds-and-ubereats-have-a-happy-deal-81ed0b86825f>.

² See Hadfield (2020).

³ See <https://www.prnewswire.com/news-releases/restaurant-industry-in-free-fall-10-000-close-in-three-months-301187291.html>.

⁴ See <https://www.foodandwine.com/news/chains-independent-restaurant-divide>.

⁵ See <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).

⁸ See <https://www.safegraph.com/blog/safegraph-provides-cdc-fed-and-1000-organizations-with-data-to-fight-the-covid-19-crisis>.

⁹ The raw data have 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.

¹⁰ See <https://www.restaurantdive.com/news/chipotle-panera-starbucks-have-fastest-in-store-pickup-times-survey-find/566625/>.

¹¹ 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, and (2) meal delivery is rarely preordered 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.

¹² 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.

¹³ We thank a reviewer for suggesting this matching method.

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