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Regulating Powerful Platforms: Evidence from Commission Fee Caps

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Abstract. Platform giants typically possess strong power over other participants on the platforms. Such power asymmetry gives platform owners the edge on setting platform fees to capture the surplus created on their platforms. Although there is a heated debate on regulating these powerful platforms, the lack of empirical studies hinders the progress toward evidence-based policymaking. This research empirically investigates this regulatory issue in the context of on-demand delivery. Delivery platforms (e.g., DoorDash) charge restaurants a commission fee, which can be as high as 30% per order. To support small businesses, recent regulatory scrutiny has started to cap the commission fees for independent restaurants. This research empirically evaluates the effectiveness of platform fee regulation, by investigating recent regulations across 14 cities and states in the United States. Our analyses show that independent restaurants in regulated cities (i.e., those paying reduced commission fees) experience a decline in orders and revenue, whereas chain restaurants (i.e., those paying the original fees) see an increase in orders and revenue. This intriguing finding suggests that chain restaurants, not independent restaurants, benefit from the regulations that were intended to support independent restaurants. We find that platforms' discriminative responses to the regulation may explain the negative effects on independent restaurants. That is, after cities enact commission fee caps, delivery platforms become less likely to recommend independent restaurants to consumers, and instead turn to promoting chain restaurants. Moreover, delivery platforms increase their delivery fees for consumers in regulated cities, suggesting that these platforms attempt to cover the loss of commission revenue by charging customers more.

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1. Introduction

Digital platforms have profoundly reshaped many industries. They have opened new distribution channels, transformed how businesses reach their customers, and affected people as consumers and citizens. Although digital platforms have created enormous economic and societal value, the dominance of these platforms also creates substantial risks to the economy and society. One major concern is that digital platforms have been increasingly gaining power over other participants on the platforms (e.g., Apple versus app/game developers on its iOS platform, Amazon versus third-party sellers in its e-commerce marketplace, and DoorDash versus independent restaurants on its on-demand delivery platform). Such power asymmetry gives platform owners the edge on setting platform fees to extract most of the surplus created on their platforms (Jacobides 2021). For instance, delivery platforms (e.g., DoorDash, Grubhub, and Uber Eats) charge restaurants a commission fee as high as 30% of the restaurant sales from orders placed through the platforms. Although there is a heated debate on whether and how to regulate these powerful platforms, the lack of empirical studies hinders progress toward policymaking. This research empirically investigates the regulation of platform fees in the context of on-demand delivery platforms.

On-demand delivery enabled by platforms such as DoorDash, Grubhub, and Uber Eats is projected to grow into a $60 billion business by 2025 (MorganStanley 2020). These 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). On-demand delivery platforms can potentially benefit restaurants in two ways. First, these platforms provide restaurants with flexible access to delivery capacity via the revenue-sharing model with no upfront costs (Chen and Wu 2013, Feldman et al. 2023). Second, these platforms also offer another distribution channel, which may bring in new customers. However, these platforms can also reduce restaurants' profit margins, as for every order fulfilled by the platforms, restaurants pay a 30% commission fee (Hadfield 2020). The added costs can be particularly salient for independent restaurants that are financially vulnerable. Small independent restaurants often lack the bargaining power to negotiate a reduced commission rate with delivery platforms. Therefore, the high fee can eliminate independent restaurants' profit margins and force them to close.

High platform fees have increasingly sparked concerns from not only restaurant owners but also policymakers.[1] To support local restaurants, on April 13, 2020, San Francisco became the first city to order delivery platforms to cap their commission fees at 15%, which is about half of the original rate.[2] The regulation covers independent restaurants but not chain restaurants. Similar measures are imposed by other cities such as Los Angeles, Seattle, Washington, DC, and New York City (see Table 1 for a list of cities that have enacted such regulations). Although a commission cap at first glance appears beneficial to independent restaurants as they keep a larger cut of their revenue, it is unclear if such regulations may create second-order effects that end up hurting independent restaurants. For instance, the commission cap reduces delivery platforms' revenue and may trigger negative responses from on-demand delivery platforms, such as adding additional fees to customer orders[3] or reducing efforts to serve independent restaurants.[4]

This research empirically investigates how imposing a commission cap affects restaurants' customer demand and restaurant revenue, which are of primary interest to restaurant owners and policymakers. The literature on platform regulation focuses on primarily software-based platforms (e.g., Microsoft, Google, and Facebook) that incur zero or negligible marginal cost for serving one additional customer, but delivery businesses enjoy lower economies of scale because of the last-mile problem (Ho et al. 2017)—delivery to an individual consumer incurs considerable marginal costs (e.g., labor and fuel) for each order. It is unclear how imposing a commission cap may change the dynamics of delivery platforms and the corresponding welfare implications in the new equilibrium.

Using a staggered difference-in-differences (DiD) analysis of cities that impose commission caps at different times, we find that independent restaurants on delivery platforms in regulated cities (i.e., those restaurants paying reduced commission fees) experience a decline in orders and profit, compared with similar restaurants in unregulated cities on the platforms. In contrast, chain restaurants in regulated cities (i.e., those restaurants paying the original fees) see an increase in orders and profit. We find that the shift in platforms' promotion strategies may explain why independent restaurants are negatively affected by the regulation. After cities cap platforms' commission fees, delivery platforms become less likely to recommend to consumers independent restaurants with reduced commission fees. Instead, these platforms become more likely to recommend restaurants from unregulated cities near regulated cities, and become more likely to recommend chain restaurants rather than independent restaurants. Further, we find that delivery platforms increase their delivery fees for consumers in regulated cities, suggesting that these platforms attempt to cover the loss of commission revenue by charging customers more. These findings provide novel insights into the complex platform dynamics when governments impose commission fee regulation.

This study contributes to the literature in several ways. As digital platforms become increasingly dominant, these powerful platforms are subject to regulatory scrutiny that aims to protect small businesses (Sokol and Van Alstyne 2021). Our empirical study adds to the emerging literature and regulatory practices by highlighting the unintended consequences of regulating powerful platforms. We show that under regulation, powerful delivery platforms can transfer the loss to other participants on the platforms, which leads to increased inequality between small and established businesses. The literature has mainly used theoretical models to study the regulation of powerful platforms (Gomes and Mantovani 2022, Feldman et al. 2023). Our empirical findings provide insights into the strategic behavior of these platforms when regulation alters the existing pricing scheme. That is, the regulation imposing a fee cap may trigger negative responses from the platforms, creating second-order effects that end up hurting small businesses and consumers.

Our empirical findings highlight the complexity and challenges of regulating on-demand delivery platforms and have important practical implications for policymakers. Although more and more governmental regulatory policies have been proposed to protect the interests of small businesses with little bargaining power over platform owners, such regulation should proceed with caution. Our findings on delivery platforms' shift of efforts to promote other restaurants should sound alarm bells about the unintended consequence of imposing a commission cap. Policymakers should consider these second-order effects when developing regulatory policies. For instance, auditing on-demand delivery platforms' discriminatory promotion behavior may reduce the instances where independent restaurants are being excluded by the platforms.

2. Related Literature

2.1. Platform Market Power

Digital platforms create economic value and social welfare for participants by facilitating interactions and transactions among them (Katz and Shapiro 1985, Zhu and Iansiti 2012, Qiu et al. 2015, Parker et al. 2016). Thanks to direct and indirect network effects, digital platforms grow in a virtuous cycle and can quickly dominate the industry (Zhu and Iansiti 2012).

As these platforms become essential and indispensable, they may take advantage of their market power to extract excessive surplus created on the platform, putting some platform participants (i.e., third-party producers) in an unfavorable position (Wen and Zhu 2019). For instance, platform owners can unilaterally set high commission fees to extract surplus from each transaction, leaving third-party producers with little margin (Evans 2012). Small businesses can be particularly vulnerable to platform owners' exploitation as they lack bargaining power. He et al. (2020) show that the entry of an e-commerce platform into its own marketplace can reduce the demand for third-party stores, because the platform has reputation and information advantages over direct competition with third-party stores. The increasing dominance of these powerful platforms may also dramatically alter the power structure of value creation and appropriation, enhancing big establishments but harming small players (Mitchell 2016). These damaging side effects of digital platforms have become a pressing issue in regulatory debates (Jacobides and Lianos 2021).

Powerful platforms may also set restrictive pricing clauses and exclusive policies that limit third-party producers' options to operate outside the platform (Mantovani et al. 2021). For instance, online travel agencies (e.g., Booking.com) impose price parity clauses (PPCs) that make sure hotels provide the lowest prices for reservations made through the platform compared with other distribution channels, including the hotels' direct channel (Mantovani et al. 2021). Online retail platforms (e.g., Amazon.com) have also imposed similar policies on third-party sellers, raising antitrust concerns (Evans 2013, Baker et al. 2019).

2.2. Regulation of Powerful Platforms

The growing prominence of digital platforms has sparked heated debates on whether and how to regulate these platforms to protect societal welfare (Biggar and Heimler 2021). Although no prior research has investigated on-demand delivery platforms, several studies in different contexts have investigated regulatory issues such as market power, privacy protection, and social welfare (Evans and Schmalensee 2013). Deriving results from a game-theoretical approach, Zhu et al. (2021) suggest that regulators should consider the network structures to better understand the market power of the incumbent platforms and their competitive strategies against new entrants. Goldfarb and Tucker (2012) investigate the influence of privacy regulation in the European Union on the effectiveness of online advertising.

A stream of theoretical studies has investigated interchange fee regulation in credit/debit card payment networks (Evans and Schmalensee 2005, Rochet and Tirole 2006). Tremblay (2023) develops analytical models and finds that banning commission fee discrimination can benefit social welfare, whereas banning commission fees may harm social welfare. Wang (2016) builds analytical models and shows some unintended consequences of commission fee regulation: although the regulation intended to lower merchants' card acceptance costs by capping the maximum interchange fee, the fee for small-ticket transactions rose postregulation.

2.3. Platforms and Firms' Response to Commission Fee Regulation

Regulations may create both intended and unintended consequences depending on how platforms and participants respond to them. Imposing a commission fee cap can help small businesses gain a larger cut of the profit from collaborating with the platforms, especially for small businesses that have little bargaining power over the platforms (Plambeck and Taylor 2005).

Modeling a restaurant as a congested service system, Feldman et al. (2023) develop a stylized analytical model to understand relationships between restaurants and delivery platforms to maximize joint profits, and suggest that capping the commission fee is ineffective at coordinating the system. Prior studies have also investigated the behavior of businesses in response to changes in revenue. For instance, businesses that receive a larger cut of the revenue (i.e., a larger slice) may exert higher efforts to increase sales (Krishnan et al. 2004, Jiang et al. 2011, Sun and Zhu 2013, Hagiu and Wright 2015).

Unlike primarily software-based platforms such as Google and Facebook that incur zero or negligible marginal cost for serving one additional customer, delivery businesses enjoy lower economies of scale because of the last-mile problem (Ho et al. 2017)—delivery to an individual consumer incurs considerable marginal costs (e.g., labor and fuel) for each order. This research adds to these theoretical studies by providing empirical insights into how platform owners may strategically respond to a reduced commission rate by shifting efforts to serve other businesses that pay higher rates.

3. Data and Methods

To support local restaurants during the pandemic, San Francisco was the first city to enact a cap of commission fees at 15% on April 13, 2020, quickly followed by other cities across multiple states in the United States. The commission fee caps apply to *independent restaurants only*. Although most of the regulations are imposed at the city level, on June 29, 2020, New Jersey became the first to impose a statewide policy to cap commission fees for *independent restaurants* (chain restaurants not included). As of March 2021, 68 localities (cities or states) had enacted similar regulations.[5] All commission cap regulations were imposed with the intention to help independent restaurants on delivery platforms.

With data availability and constraints, this research covers the period from March 16, 2020, to September 21, 2020. In this period, 14 localities enacted commission fee regulations at different times (Table 1). We also collect data from the other 54 localities that enacted similar regulations after the period we study (Table A3 in Online Appendix A), which serve as a potential control group (i.e., we call these unregulated cities during the period we study).

3.1. Data Sources

We compose a comprehensive panel data set from multiple sources, including restaurant-platform partnerships from food delivery platforms, customers' restaurant visit data from a mobile-device location tracking company,

Table 1. Localities with Commission Fee Caps

	Locality	Enactment date	Policy level	Source (link)
1	San Francisco (CA)	4/13/2020	City	Eater.com (https://sf.eater.com/2020/4/10/21216546/san-francisco-delivery-cap-doordash-grubhub-uber-eats-postmates-caviar)
2	Seattle (WA)	4/24/2020	City	National's Restaurant News (https://www.nrn.com/delivery-takeout-solutions/seattle-caps-third-party-delivery-fees-15-nyc-considers-10-cap)
3	Washington D.C.	5/5/2020	City	*Washington City Paper* (https://washingtoncitypaper.com/article/174585/dc-becomes-third-city-to-pass-law-temporarily-capping-food-delivery-commissions/)
4	Jersey City (NJ)	5/8/2020	City	NJ.com (https://www.nj.com/hudson/2020/05/uber-eats-slaps-surcharge-on-customers-of-jersey-city-eateries-in-response-to-10-commission-cap.html)
5	Santa Monica (CA)	5/26/2020	City	*Santa Monica Daily Press* (https://smdp.com/2020/05/20/santa-monica-caps-food-delivery-app-fees-for-restaurants/)
6	New York (NY)	5/26/2020	City	CBS Local News (https://www.cbsnews.com/newyork/news/city-council-capping-delivery-app-fees/)
7	Los Angeles (CA)	6/4/2020	City	Eater.com (https://la.eater.com/2020/6/4/21280511/morning-briefing-restaurant-news-los-angeles-delivery-fee-cap-15-percent-approved)
8	Philadelphia (PA)	6/25/2020	City	*The Philadelphia Inquirer* (https://www.inquirer.com/health/coronavirus/coronavirus-restaurants-delivery-fees-cap-grubhub-doordash-outdoor-dining-streeteries-20200625.html)
9	All other cities in NJ	6/29/2020	State	NorthJersey.com (https://www.northjersey.com/story/news/coronavirus/2020/06/26/coronavirus-nj-caps-food-delivery-app-fees-help-small-businesses/3267169001/)
10	Portland (OR)	7/8/2020	City	Oregonlive.com (https://www.oregonlive.com/portland/2020/07/portland-approves-10-cap-on-fees-that-food-delivery-apps-can-charge-restaurants.html)
11	San Leandro (CA)	7/13/2020	City	Eastbaytimes.com (https://www.eastbaytimes.com/2020/07/10/coronavirus-east-bay-city-limits-food-delivery-fee/)
12	Berkeley (CA)	7/13/2020	City	Eater.com (https://sf.eater.com/2020/7/10/21320201/berkeley-san-leandro-doordash-uber-eats-postmates-grubhub-delivery-costs)
13	Fremont (CA)	7/23/2020	City	*The Mercury News* (https://www.mercurynews.com/2020/07/22/fremont-to-limit-fees-food-delivery-apps-charge-restaurants-during-pandemic/)
14	Oakland (CA)	7/29/2020	City	CBS Local News (https://www.cbsnews.com/sanfrancisco/news/oakland-city-council-approves-cap-on-charges-for-food-deliveries/)

Table 2. Restaurants on Delivery Platforms

Restaurant type	Number of restaurants	Percentage on platforms
Independent restaurants	91,052 (74%)	37%
National chains	32,082 (26%)	49%
All	123,134	40%

Notes. Eighty-six percent of the independent restaurants are full-service restaurants. Eighty percent of the chain restaurants are limited-service fast-food chains.

and bank card transactions from a financial data provider.

3.1.1. Restaurants on Delivery Platforms. Restaurant-platform partnership data were collected from the three largest on-demand delivery platforms, that is, DoorDash, Grubhub, and Uber Eats, which together account for about 90% of the market share in the delivery businesses (Holland and Reed 2020). We used a Python script to download a complete list of partnered restaurants from each platform's website and through the platform's Application Programming Interface at the beginning of the period covered in this study. To create a balanced panel, this research does not include a small fraction of restaurants that joined the platforms during the period we study. As shown in Table 2, there are, in total, 123,134 restaurants in the 68 localities covered in this study. We classify these restaurants into two categories based on whether a restaurant is an independent restaurant or is affiliated with a chain (e.g., McDonald's and KFC). Among all the restaurants, the majority (74%) are independent restaurants. Overall, about 40% of the restaurants are on at least one of the delivery platforms, though the percentage is higher for chain restaurants (49%) than independent restaurants (37%).

3.1.2. Restaurant Foot Traffic Data. Data on foot traffic to restaurants were provided by our collaborator company, SafeGraph Inc. SafeGraph partners with mobile app services that have opt-in consent from users to collect their location data. SafeGraph tracks location data for approximately 35 million unique devices in the United States. Researchers from more than 1,000 organizations have used the foot traffic data to understand visit patterns.[6] Studies using SafeGraph data find the data to be generally representative of the U.S. population (Chen and Rohla 2018, Painter and Qiu 2021). To protect user privacy and preserve anonymity, the data are aggregated to the level of a point-of-interest, such as a restaurant. The data record weekly visits to each restaurant from March 16, 2020, to September 21, 2020.

SafeGraph further aggregates the visits into four buckets based on the duration of a visit: shorter than 20 minutes, 21–60 minutes, 61–240 minutes, and longer than 240 minutes. Therefore, for each restaurant, our

Table 3. Distribution of Visits by Duration of Stay Across Restaurants

Duration (minutes)	<20	20–60	60–240	>240	All
Median number of visits	10.699	4.511	3.646	2.481	21.337
Percentage of visits	50%	21%	17%	12%	100%

Note. The number of visits is based on approximately 35 million unique devices in the United States.

data set records the total number of visits and the number of visits that fall into each of these buckets (Table 3). The unique value of these foot traffic data is that it allows us to identify takeout visits, dine-in visits, and staff working in the restaurants based on the duration of a visit in a restaurant:

- Takeout 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 or pickup. 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.[7] Note that takeout visits could be by 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.[8]
- Dine-in visits (staying for 20–60 minutes). Dine-in customers normally stay for about half an hour if dining individually, and about one hour if with a small/medium group. Some diners may stay longer than 60 minutes. As a robustness check, we consider an alternative measure to also include staying for 60–240 minutes as dine-in visits.
- Staff (staying for longer than 240 minutes). Staff in a restaurant typically work longer than four hours. However, we also include visits of 60–240 minutes because some restaurants might have reduced hours of operation during the pandemic.

Table 3 shows that takeout visits account for the majority of visits to restaurants during the period we study (March 16, 2020, to September 21, 2020), whereas dine-in is limited because of the pandemic.

3.1.3. Transaction Data. We obtained anonymized, aggregate debit/credit card transaction data from a large financial data provider (Visa). The transaction data complement 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. Our collaborator company 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 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 (5,812 for independent restaurants and 5,814 for chain restaurants).[9] Therefore, the transaction data include weekly restaurant sales through the delivery platforms and the individual channels of independent or chain restaurants in each zip code.

3.2. Variables and Measurement

We construct the variables of interest from the data sources discussed above. The dependent variables are consumer demand measured by the number of visits to restaurants and net restaurant sales after subtracting commission fees paid to the platforms. The main variables listed in Table 4 are constructed as follows:

- The dates of regulatory policy enactment from local news (Table 1) are used to construct the main explanatory variable for treatment timing. We code a binary variable to capture the timing of a city's policy on a commission fee cap (Table 4: *CapPolicy* = 1 for any week after the policy enactment in a regulated city, and = 0 for any week if such a policy is not present before the policy is enacted).
- Platform partnership data from three major platforms provide information about whether a restaurant is partnered with the platforms or not. Combining data about cities with regulation, we can identify independent restaurants that are directly affected by the commission fee caps. We create a binary variable, *Independent*, to capture if a restaurant is an independent restaurant or a chain restaurant.
- The foot traffic data from SafeGraph provide information about consumer visits, which is used to measure consumer demand (dependent variable *TakeoutVisits* in Table 4).
- The transaction data allow us to calculate restaurant revenue. We then subtract the commission fees to calculate a restaurant's net total revenue (dependent variable *NetTotalSales* in Table 4). Online Appendix B provides the details on how we calculate the net total revenue.

Data from SafeGraph provide restaurant characteristics that are used in the matching process to construct comparable restaurants in the control and treatment groups. We use propensity score matching (PSM), with coarsened exact matching (CEM) as a robustness check, based on several variables, including city demographics (e.g., population and income) and restaurant characteristics (type of restaurant, size, staffing level, historical visit patterns). The list of variables (Table A1) and the matching outcomes (Table A2 and Table A4) are in Online Appendix A.

3.3. Empirical Model

Our empirical framework addresses two important identification challenges. First, it considers the temporal variations in treatment timing across cities in the staggered DiD framework. Second, it addresses the heterogeneity of cities and restaurants when constructing a comparable control group. The staggered DiD framework uses the principle of forward matching, that is, later-treated cities are used as the control group, which mitigates the concerns that the treatment and control groups are systematically different (cities that imposed the policies later are more similar to cities that imposed the policies slightly earlier, compared with cities that never imposed such policies). We use restaurants in the 54 localities which did not enact commission caps during the study period but imposed the regulation later as the proper control group (this list of localities is in Table A3 in Online Appendix A).

We use two approaches to address the heterogeneity of restaurants. First, independent restaurants can be systematically different from chain restaurants. Therefore,

Table 4. Definition of Variables

Variables	Definition	Sources
Dependent variables		
TakeoutVisits	The number of visits staying between 0 and 20 minutes in a given week (a proxy for drive-through or pickup visits).	SafeGraph
NetTotalSales	Net total revenue (USD) for the restaurant after subtracting commission fees.	SafeGraph, Visa
Key independent variables		
CapPolicy	A dummy variable that indicates whether a city in a given week is under regulation (= 1 if yes and = 0 otherwise).	Local news (Table 1)
Independent	A dummy variable that indicates whether a restaurant is an independent restaurant (= 1 if yes and = 0 otherwise).	SafeGraph, Delivery platforms

our empirical analyses compare independent restaurants on platforms in regulated cities with their counterparts in unregulated cities, rather than using chain restaurants in the same city as the control group. Second, we choose the unit of analysis to be at the restaurant level, which leverages the localized nature of restaurants and demographics across different regions in the cities (Bekkerman et al. 2023). With this granular unit of analysis, we use matching to identify a comparable control group of restaurants using both city and restaurant characteristics. We also conduct another subsample analysis of the spillover effects on chain restaurants by comparing chain restaurants on the platforms in regulated versus unregulated cities.

3.3.1. Staggered Difference-in-Differences. We adopt the staggered DiD framework by Callaway and Sant'Anna (2021). This framework has two main advantages compared with the two-way fixed effect framework. It avoids the problematic comparison of newly treated units relative to already-treated units, which biases the estimation (Callaway and Sant'Anna 2021). Moreover, the staggered DiD framework allows us to estimate not only the overall treatment effect but also the dynamic treatment effect based on the length of the exposure to the regulation, by aggregating cities that imposed the regulation at different time periods into different groups. The estimated dynamic effects can help policymakers evaluate how regulatory policies affect restaurants in the short run (early stage of the pandemic) and the longer run (middle/later stage of the pandemic).

Specifically, we create G_{ig}, a dummy variable, which equals to one if restaurant i first became treated at week g (i.e., when the regulation was first enacted at week g in the city where restaurant i is located). We observe the outcome of interest Y_{it}, for restaurant i at week t. We further use $Y_{it}(0)$ to denote restaurant i's untreated potential outcome and use $Y_{it}(g)$ to denote restaurant i's potential outcome at week t if it *first* became treated first at week g. Under the assumption of no anticipation of treatment, $Y_{it}(0) = Y_{it}(g)$ for all $t < g$. Therefore, for restaurants in the cities that enacted the regulation after our study period, we observe only their untreated outcomes, that is, $Y_{it}(0)$. We finally define the group-time treatment effect at week t ($t \geq g$) for the groups of observations that were first treated at time g as follows:

$$ATT(g,t) = \mathbb{E}[Y_{it}(g) - Y_{it}(0)] | G_{ig} = 1].$$

3.3.2. Overall Treatment Effect. The overall treatment effect is simply the average of all the identified group-time average treatment effects (ATT), that is, a weighted average of $ATT(g,t)$ for restaurants in regulated cities across all treated time periods (i.e., weeks). Specifically, we define $\overline{\theta}$, the overall treatment effect, as follows:

$$\overline{\theta} = \frac{1}{\kappa} \sum_{g} \sum_{t>g} \omega_g ATT(g,t),$$

where ω_g is the weight for group g that is proportional to the group size of the restaurants, which first became treated in week g; κ normalizes the weights so that the weights sum up to one.

3.3.3. Dynamic Treatment Effect by the Length of Exposure. We consider the treatment effect by the length of exposure to capture the dynamic effect over the posttreatment periods. That is, we aggregate $ATT(g,t)$ for the treated restaurants at the eth week relative to their first exposure to the regulation (i.e., $e = t - g$). Specifically, we define $\theta(e)$, the average treatment effect by length of exposure parameter, as follows:

$$\theta(e) = \frac{1}{\kappa_e} \sum_{g} \omega_g ATT(g, g+e),$$

where again, ω_g is the weight for group g and proportional to the group size of restaurants, which became treated first at week g; κ_e ensures that the weights sum up to one. We use $\theta(e)$ to capture the trend of the treatment effect of regulation for $e \geq 0$, and the preregulation trend for $e < 0$. Hence, $\theta(e)$ can be viewed as an event-study estimand (Bekkerman et al. 2023).

4. Empirical Analyses and Results

4.1. Direct Effects on Independent Restaurants

We first estimate the direct effects of the regulation on independent restaurants on delivery platforms by comparing these restaurants in regulated cities to their counterparts in unregulated cities before and after the regulation. Results of the overall treatment effects ($\overline{\theta}$) in Table 5 show that following the regulation, independent restaurants in regulated cities overall experience a 2.5% decrease in takeout orders and a 3.9% decrease in net total sales after subtracting commission fees paid to the platforms. The results are consistent when using the full sample and when using only the matched subsample. These negative effects of commission caps are a sharp deviation from the purpose of the regulation, which intends to protect independent restaurants' bottom line.

We further examine the dynamic treatment effect by the length of exposure ($\theta(e)$) for the treated independent restaurants. One challenge to calculate and interpret $\theta(e)$ is that different cities have different lengths of posttreatment periods because of their different times of enacting the regulation. For example, because the regulatory policy was enacted in Oakland, CA, on July 29, 2020, we can observe restaurants in Oakland for

Table 5. Overall Treatment Effect on Independent Restaurants

	TakeoutVisits		*NetTotalSales*	
	W/o matching	Matching	W/o matching	Matching
Overall treatment effect	−0.025***	−0.021***	−0.039***	−0.034***
	(0.006)	(0.007)	(0.006)	(0.007)
Restaurants	27,275	19,412	27,275	19,412
Observations	749,815	533,695	749,815	533,695

Notes. We implement the estimation based on the bootstrap method (n = 5,000) in R using the package *DID*. W/o, without. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance level).

only 6 posttreatment weeks. To ensure a relatively long posttreatment period (15 weeks), we construct our samples utilizing restaurants from cities that enacted the regulation in early June and earlier (the first seven cities in Table 1).

Figure 1 shows the dynamic treatment effects (and the 95% confidence interval) of the regulation on independent restaurants on delivery platforms. Figure 1(a) (on *TakeoutVisits*) and Figure 1(b) (on *NetTotalSales*) show that the regulation has persistent negative effects on independent restaurants on delivery platforms.

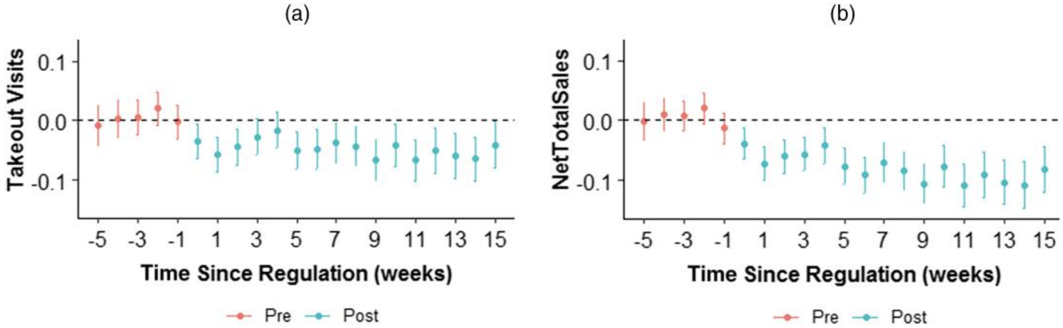
4.2. Spillover Effects on Chain Restaurants

Although the commission caps do not apply to chain restaurants, they may still impact chain restaurants that are also on delivery platforms. To examine the potential spillover effect, we compare chain restaurants in regulated cities to chain restaurants in unregulated cities before and after the regulation during our study period. Table 6 presents the estimates of the overall treatment effects ($\overline{\theta}$) regarding the two dependent variables. We see that following the regulation, chain restaurants in regulated cities overall experience an increase in takeout orders and in net total sales with the same magnitude (4.5%). These results suggest that the regulation had a positive impact on the performance of chain restaurants. We obtain consistent findings using the matched subsample of chain restaurants.

Figure 2 shows the dynamic treatment effects by the length of exposure for chain restaurants. We see that the positive treatment effects of the regulation on chain restaurants (both on *TakeoutVisits* and on *NetTotalSales*) slightly increase over the posttreatment periods. As we will discuss in Section 5, delivery platforms respond to the regulation by shifting their promotion efforts to favor chain restaurants over independent restaurants, which may explain why chain restaurants benefit from the regulation. The spillover effects on chain restaurants are stronger in areas with a higher proportion of chain restaurants, possibly because the platforms can easily find similar chain restaurants to replace independent restaurants without significantly compromising consumer preferences and causing delivery delays (Table C14 in Online Appendix C.8).

Comparing the results in Section 4.1 and those in Section 4.2, we see substantially heterogeneous effects for independent restaurants (i.e., restaurants paying reduced commission fees) versus chain restaurants not directly affected by the commission caps. These differential results show that the regulatory policies that intend to protect independent restaurants hurt independent restaurants but benefit chain restaurants. In Section 5, we explore potential mechanisms that drive

Figure 1. (Color online) Effects by Length of Exposure for Independent Restaurants



Notes. (a) Effect on *TakeoutVisits*. (b) Effect on *NetTotalSales*.

Table 6. Overall Treatment Effect on Chain Restaurants

	TakeoutVisits		*NetTotalSales*	
	W/o matching	Matching	W/o matching	Matching
Overall treatment effect	0.045***	0.034***	0.045***	0.038***
	(0.008)	(0.009)	(0.008)	(0.009)
Restaurants	13,218	7,420	13,218	7,420
Observations	365,864	205,288	365,864	205,288

Notes. Standard errors in parentheses. W/o, without.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance level).

the disparity between independent restaurants and chain restaurants.

4.3. Robustness Checks

4.3.1. Parallel Trend Test. The validity of the staggered DiD estimation relies on the parallel trend assumption, that is, the control and treatment groups (restaurants in regulated cities and unregulated cities) followed the same trend before the regulation was enacted (Meyer 1995). To test the assumption, we utilize the $\theta(e)$, the average treatment effect by the length of exposure, and calculate the aggregated pretreatment effects for $e < 0$. Results in Table C1 in Online Appendix C.1 show that the parallel trend assumption overall holds.

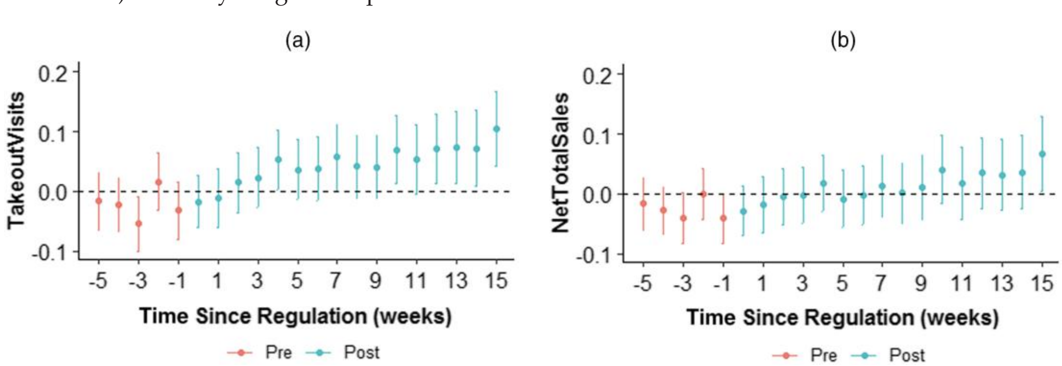
4.3.2. Extended Samples. In the main analysis, we use restaurants in cities that enacted commission caps after our study period as the control group (i.e., unregulated cities). In this robustness test, we expand the sample to include cities in the control group (e.g., Indianapolis and cities in Texas) that have proposed the same regulation but never enacted it. Compared with those cities that have never enacted or proposed commission caps, cities that have considered such regulations are more similar to the treated cities. These cities can therefore serve as an eligible control group. Moreover, as shown in Table A4 in Online Appendix A, the extended sample allows us to create a larger matched sample.

Table C2 in Online Appendix C.2 summarizes the estimates of the overall treatment effects. The results are consistent with those in the main analysis; that is, the regulation has a negative impact on independent restaurants' takeout demand and net total revenue, but a positive impact on chain restaurants.

4.3.3. Alternative Matching Approaches. In the main analysis, we use propensity score one-to-one matching (PSM 1:1) as the matching method. To evaluate the robustness of the findings, we also consider alternative matching methods, including propensity score one-to-many matching (PSM 1:3) and CEM. The estimated overall treatment effects using new matched subsamples are shown in Table C3 in Online Appendix C.3. Our main findings remain qualitatively the same.

4.3.4. Additional Matching Variables. The regulations took place amid the backdrop of the COVID-19 pandemic. Our staggered difference-in-differences analysis serves to alleviate the potential issues stemming from pandemic-related confounders. To further mitigate pandemic-related concerns, we incorporated three extra COVID-specific variables into the matching procedure. We first construct *NewCases_per1000_pre* to measure the pandemic severity by calculating the average value of weekly new COVID cases (noncumulative) per 1,000 people at a county level. A greater value of this

Figure 2. (Color online) Effects by Length of Exposure for Chain Restaurants



Notes. (a) Effect on *TakeoutVisits*. (b) Effect on *NetTotalSales*.

variable indicates a more severe condition of COVID transmission. Second, we consider the trend of the cumulative COVID cases, *CovidCases_Trend*, measured by the fitted linear coefficient. A positive and higher value indicates a faster spreading of the virus. Third, we construct a community mobility variable, which measures the proportion of residents in a county not completely staying at home. We constructed *CommunityMobility_pre* by calculating the average value of weekly *CommunityMobility* at a county level, which reflects how consumers responded to the pandemic. A greater value of this variable indicates a lower level of stay-at-home compliance. The findings remain consistent (Tables C4 and C5 in Online Appendix C.4).

4.3.5. Two-Way Fixed Effects Model (TWFE). The TWFE is one of the popular model specifications within the information systems (IS) literature, particularly in standard DiD settings. As the methodology of the DiD has evolved significantly in recent literature on econometrics, the CS method by Callaway and Sant'Anna (2021) represents one of the state-of-the-art approaches for handling staggered DiD settings. Compared with TWFE, the CS method has advantages in our staggered setting where commission caps were imposed at different times in different cities, and the effects of commission caps are likely to be heterogeneous across cities and time periods as platforms (and restaurants) respond to the changes in commission fees. We conduct additional analyses with TWFE and find the results to be mostly consistent. We justify why it is more appropriate to use the relatively new staggered difference-in-differences model (Online Appendix C.6).

4.4. Overall Impact on the Platforms

We conduct additional analysis regarding the overall impact on the platform orders and platform revenue. Empirical results below show that the total number of orders and the total revenue generated by the platform decrease. The platforms' commission fees earned from all restaurants combined also decrease.

4.4.1. Impact on Total Customer Orders and Sales. Using the bank card transaction data, we aggregate consumer orders and sales on a delivery platform to the platform-zip code level. Table 7 below shows that the total number of customer orders (measured by the number of unique bank cards and the number of transactions) and sales (total dollar amount customers spend on the platforms) via the platforms decrease after the regulation. This suggests that the regulation overall negatively affects the total revenue generated by the platforms.

Table 7. Overall Effect on Platforms

	#Cards	*#Transactions*	*#Spend*
Overall effect	−0.059***	−0.068***	−0.046**
	(0.017)	(0.019)	(0.021)
Zip codes	2,092	2,092	2,092
Observations	47,186	47,186	47,186

Notes. We implement the estimation based on the bootstrap method (n = 5,000). Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance level).

4.4.2. Commission Earned by Platforms. We further investigate the total commission fees that delivery platforms earn from restaurant sales. Table 8 shows that delivery platforms' total commission from all restaurants combined decreases. This suggests that the increase in commission from chain restaurants cannot compensate for the decrease in commission from independent restaurants.

5. Plausible Mechanisms

Section 4 reveals that imposing a cap on commission fees that on-demand delivery platforms can charge to independent restaurants may end up benefiting chain restaurants but hurting independent restaurants. This section explores plausible explanations of why this result happens. We provide empirical evidence that after regulation delivery platforms become more likely to promote chain restaurants over independent restaurants that are subject to the commission fee cap. Also, these platforms become less likely to advertise restaurants in regulated cities and instead promote restaurants in nearby cities. The changes in platform advertising efforts affect the exposure of the two types of restaurants: independent restaurants in regulated cities get less exposure and see a decrease in

Table 8. Overall Effect on Platform Commissions

	Total_Commission	*Commission_Independent*	*Commission_Chain*
Overall effect	−0.179***	−0.264***	0.023**
	(0.010)	(0.010)	(0.009)
Zip codes	2,175	2,081	1,841
Observations	60,704	58,048	51,462

Notes. We implement the estimation based on the bootstrap method (n = 5,000). Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance level).

demand because of reduced consumer awareness, whereas chain restaurants get more exposure and thus their demand increases.

We obtained additional data from one of the three largest delivery platforms in the United States to understand how delivery platforms may strategically respond to commission fee regulation. The platform's operational model is the same as the other two major delivery platforms. We obtain the complete list of cities, regulated or unregulated, where the platform operates restaurant delivery service. We devised a Python scraper to download the platform's landing page for each city on a weekly basis from March 2020 to September 2020. When consumers browse a city page on the platform's website, the platform displays a list of restaurants,[10] along with the delivery fee and estimated delivery time for each restaurant.[11] We, therefore, construct a panel data set including the list of restaurants recommended on the platform in each city, together with the delivery fee and estimated delivery time before and after the regulation.

5.1. Platforms' Changes in Promotion Strategies

Our city-level analysis shows that changes in delivery platforms' recommendation strategies may explain why independent restaurants in regulated cities experience a decline in pickup/delivery orders (i.e., visits shorter than 20 minutes).

5.1.1. Regulated Cities vs. Unregulated Cities. Delivery platforms may prioritize restaurants in unregulated cities, where they receive higher commission fees. To measure this effect, we compute the fraction of restaurants from unregulated cities that appear on a regulated city's page on the delivery platform (*FractionOtherCities*).[12] We specify the empirical model (DiD) as follows:

$$FractionOtherCities_{ct} = \alpha + \beta CapPolicy_{ct} + \eta_c + v_t + \varepsilon_{ct},$$

where c and t index a city and week, respectively, and η_c and v_t represent the fixed effect for city c and week t. The coefficient β captures the effect of regulation on the platform's promotion of restaurants from nearby cities.

Table 9 shows that after a city caps platforms' commission fees, delivery platforms become more likely to display to consumers restaurants from unregulated cities on the regulated city's platform page (the estimate of Model 1 shows a 3.5% increase in the fraction of restaurants from nearby cities). This finding suggests that delivery platforms strategically replace restaurants in regulated cities with restaurants from nearby cities.

5.1.2. Chains vs. Independent Restaurants. Delivery platforms may also prioritize chain restaurants over independent restaurants after a city caps the commission fees they can charge independent restaurants. To measure this effect, we compute the fraction of independent restaurants that appear on a regulated city's platform page (*FractionIndependent*). We conduct a similar DiD analysis as above. Table 9 shows that after a city caps platforms' commission fees, delivery platforms become more likely to recommend chain restaurants compared with independent restaurants (the estimate of Model 2 shows a 1.3% decrease in the fraction of independent restaurants listed on a regulated city's platform page). This finding suggests that delivery platforms are more likely to promote national chains that pay the original commission fees, instead of independent restaurants that pay the reduced commission fees.

Table 9. Changes in Platforms' Promotion Strategies

Variables	(1) *FractionOtherCities*	(2) *FractionIndependent*
CapPolicy	0.035***	−0.013***
	(0.003)	(0.003)
Control variables		
City fixed effect	Yes	Yes
Week fixed effect	Yes	Yes
Observations	34,963	34,963
Adjusted R^2	0.940	0.778

Notes. Analysis at the city-week level. Standard errors in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance level).

5.2. Changes in Delivery Fees and Customers' Waiting Time

Delivery platforms may increase the delivery fees customers pay as the regulation of commission fees reduces their revenue. To measure this effect, we compute the average delivery fees for all restaurants that appear on a city's page on a delivery platform (*DeliveryFee*). We conduct similar analyses as in Section 5.1. Table 10 shows that after a city caps platforms' commission fees, the average delivery fees charged by the delivery platforms also increase for restaurants in the regulated city (the estimate of Model 1 shows a \$0.4 increase for each order fulfilled by the platform). As platforms shift to recommending distant restaurants from other cities, the delivery time (i.e., customers' waiting time for delivery) may increase as well. To measure this effect, we compute the expected delivery time for restaurants that appear on a city's platform page (*DeliveryTime*). Table 10 shows that the average delivery time also increases slightly (the estimate of Model 3 shows a one-minute increase).

Models 2 and 4 in Table 10 provide evidence that the increase in delivery fees and time can be due to delivery platforms' strategies to recommend restaurants from other cities rather than a customer's focal city that is being regulated. Regulation pushes the platforms to promote more restaurants from other cities across the

Table 10. Changes in Delivery Fees and Customers' Waiting Time

Variables	(1) *Delivery Fee*	(2) *Delivery Fee*	(3) *Delivery Time*	(4) *Delivery Time*
CapPolicy	0.415***	0.332***	0.951***	0.860***
	(0.038)	(0.037)	(0.148)	(0.148)
FractionOtherCities		2.412***		2.723***
		(0.073)		(0.292)
Control variables				
City fixed effect	Yes	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes	Yes
Observations	34,963	34,963	34,963	34,963
Adjusted R^2	0.631	0.643	0.526	0.528

Notes. Analysis at the city-week level. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance).

border, which increases the delivery distance, delivery fees, and delivery time. Such a promotion strategy may have negative externalities on delivery for restaurants in the focal, regulated city as delivery drivers stretch to serve a wider area in and out of the city borders.

5.2.1. Mediation Analysis.

We examine whether the change in delivery time and fee each explains the impact of regulations on independent restaurants. Because the results are similar for the two key dependent variables, *TakeoutVisits* and *NetTotalSales*, our analysis focuses on *NetTotalSales*, which is the ultimate outcome restaurants care about. The mediation analysis (Online Appendix C.5) shows that *DeliveryTime* is a partial mediator, which suggests that the regulation leads to an increase in delivery time for independent restaurants, which negatively affects their sales. Similarly, *DeliveryFee* is a partial mediator, which suggests that the regulation leads to an increase in delivery fees, which hurts restaurant sales.

5.3. Impact of Reduced Consumer Awareness for Independent Restaurants

Delivery platforms may influence restaurant revenue from delivery sales via the platforms as well as other benefits thanks to increased consumer exposure on these platforms (e.g., spillovers to self-takeout or dine-in visits). In this section, we conduct additional analysis on various channels, such as net platform-driven takeout sales (*NetPlatformSales* = *PlatformSales* − *CommissionFees*) and net total takeout sales (*NetTotalTakeoutSales* = *NetPlatformSales* + *SelfTakeoutSales*. Table 11 highlights the two opposing effects of the regulation: it improves independent restaurants' profit from platform sales thanks to a lower commission rate, but it also reduces the orders through delivery platforms. A closer examination exposes more negative consequences: reduced consumer awareness because of platforms' behavior may hurt independent restaurants' sales through other channels such as self-takeout, ultimately reducing independent restaurants' net total takeout sales.

In addition, reduced consumer awareness of independent restaurants may especially affect younger consumers who rely more on online searches and recommendations on the platforms. The effect is also particularly noticeable for niche restaurants that need more exposure through platforms' recommendations. Our additional analyses show that niche restaurants in localities with a higher proportion of the young population experienced a larger decline in orders and sales (Online Appendix C.7).

5.4. Gain in Platforms' Commissions from their Strategic Responses

We investigate if the platforms are rational, that is, they are better off with their responses to the regulation compared with the counterfactual where the platforms

Table 11. Effects on Various Channels for Independent Restaurants

	PlatformSales		*NetPlatformSales*		*SelfTakeoutSales*		*NetTotalTakeoutSales*	
	W/o matching	Matching	W/o matching	Matching	W/o matching	Matching	W/o matching	Matching
Overall effect	−0.020***	−0.016***	0.042***	0.047***	−0.029***	−0.026***	−0.014***	−0.010
	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)	(0.009)	(0.004)	(0.009)
Restaurants	16,492	11,751	16,492	11,751	16,492	11,751	16,492	11,751
Observations	453,324	322,947	453,324	322,947	453,324	322,947	453,324	322,947

Notes. We implement the estimation based on the bootstrap method (n = 5,000). Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (significance level).

did not change their behavior. We compare platform commissions in the real scenario with platform responses and the counterfactual scenario without platform responses. Before the regulation, the composition of total platform sales was roughly about 60% from independent restaurants and 40% from chain restaurants. We assume that this composition remains the same in the counterfactual scenario as in the preregulation period. Following the regulation, the imposed caps would reduce platform commissions from independent restaurants by 50% (for cities with a cap of a 15% commission rate) in the counterfactual scenario but reduce platform commissions by 26.4% from independent restaurants in the real scenario shown in Table 8. The regulation would not affect platform commissions from chain restaurants in the counterfactual scenario but would increase platform commissions from chain restaurants by 2.3% in the real scenario shown in Table 8. Consequently, the regulation would reduce the overall platform commissions from all restaurants combined by 30% in the counterfactual scenario but reduce that by only 17.9% in the real scenario shown in Table 8. These back-of-the-envelope calculations suggest that the platforms are indeed better off with their strategic responses than if they did not respond.

6. Discussion and Conclusions

This research provides empirical evidence on how regulations that cap commission fees for independent restaurants on delivery platforms influence restaurant demand and revenue. We find that delivery platforms may shift to promoting chain restaurants over independent restaurants after the regulation is enacted. Such strategic responses from the platforms can overturn the intended benefits of the regulation. Our empirical findings have implications for policymakers when developing and evaluating regulatory policies for on-demand delivery platforms.

6.1. Theoretical Implications

The empirical findings deepen our understanding of market dynamics on multisided on-demand platforms (Chen and Wu 2013, Hu and Zhou 2020, Zhu et al. 2021, Gomes and Mantovani 2022). On-demand platforms provide flexible delivery services on a pay-per-use basis, and can quickly scale up if businesses need more capacity (Chen and Wu 2013). Small businesses may particularly benefit from such a flexible revenue-sharing scheme because they are financially more vulnerable (Raj et al. 2023). Our research highlights the sophisticated behavior on these platforms in the presence of governmental regulation. Imposing a fee cap can help small businesses gain a larger cut of the revenue from collaborating with on-demand platforms, especially for small businesses that have little bargaining power over the platforms (Cachon and Lariviere 2005, Plambeck and Taylor 2005). However, our findings show that this type of regulation may create unintended consequences. Platform owners may reduce efforts to serve small businesses that pay a reduced rate, which may end up hurting small businesses.

Our research adds to the ongoing conversations about whether platforms should offer a menu of commission rates rather than a uniform commission rate for all businesses (Bhargava et al. 2022). With differential commission rates, our empirical findings show that platform owners' incentives to discriminate against small businesses can be particularly strong when the platforms can switch to promote other businesses on the platforms that pay a higher rate. Also, these platforms may transfer some of the revenue loss to consumers by adding additional fees, which further reduce social welfare. These findings deepen our understanding of the second-order effects of regulating powerful platforms on small businesses. These findings extend the literature that focuses primarily on software-based platforms such as Google and Facebook that incur a negligible marginal cost for serving one more consumer.

6.2. Practical Implications

Dozens of cities have been experimenting with or are considering imposing caps on platform fees (see endnote 5). The empirical findings highlight the complexity of regulating delivery platforms because of the changes in equilibria within the platforms. Although a fee cap may protect restaurants' profit margins, such a policy regulation may end up hurting independent restaurants. Our findings on delivery platforms' shifting in promotion efforts to other restaurants should sound alarm bells about the consequences of imposing a fee cap. Policymakers should consider these second-order effects when developing regulatory policies. For instance, auditing on-demand delivery platforms' discriminatory promotion strategies may reduce the instances where independent restaurants are demoted. Also, cities can coordinate their regulatory policies with those of nearby cities so that a uniform policy across borders would help prevent on-demand delivery platforms from including restaurants in nearby cities while excluding those in regulated cities. Finally, federal and local governments may also step back and think about other options to support independent restaurants, such as providing stimulus loans for independent restaurants (Furnari 2020) or offering tax benefits to refund independent restaurants for the commission fees paid to delivery platforms.

Regulation of commission fees has also been observed in other platform markets such as Ticketmaster, Steam, and iOS/Android app markets. For instance, facing regulatory pressure in 2020, Apple reduced its commission rate to 15% for small app developers if they earned up to

$1 million in proceeds during the previous calendar year.[13] Our research highlights that a reduced commission rate does not necessarily help small businesses because the platform can seek other approaches to compensate for the loss of commission, and such discriminatory behaviors may end up hurting small businesses.

6.3. Future Research

This research is not without limitations, and thus we point out several avenues for future research. Our study focuses on restaurant demand and revenue. Future research can investigate the impact of commission caps on other stakeholders (e.g., independent drivers who fulfill delivery orders). A comprehensive analysis could provide more insights for policymakers to make informed decisions. Also, our data set covers less than seven months, which allows us to observe the immediate effect of regulation. These effects on independent restaurants and national chains are likely to permanently change the structure of the restaurant industry. Future research can investigate the long-term effects of commission fee regulation. On the consumer side, future research can investigate how consumer demand is affected by delivery time and fee. Lastly, the pandemic has put ongoing tensions between restaurants and delivery platforms under a microscope. Future research may also investigate these tensions during normal periods of operations, when restaurants rely less on delivery.

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Endnotes

[1] See https://www.protocol.com/delivery-commission-caps-uber-eats-grubhub (accessed January 30, 2024).

[2] See https://sf.eater.com/2020/4/10/21216546/san-francisco-delivery-cap-doordash-grubhub-uber-eats-postmates-caviar (accessed January 30, 2024).

[3] See https://thecounter.org/food-delivery-platform-fee-caps-grubhub-postmates-covid-19/ (accessed January 30, 2024).

[4] See https://pdx.eater.com/2020/7/29/21346985/portland-delivery-app-fee-cap-law-postmates-grubhub (accessed January 30, 2024).

[5] A complete list of localities is available at https://www.nbcnews.com/tech/tech-news/doordash-pushes-back-against-fee-delivery-commissions-new-charges-n1262088 (accessed January 30, 2024).

[6] See https://www.safegraph.com/blog/safegraph-provides-cdc-fed-and-1000-organizations-with-data-to-fight-the-covid-19-crisis (accessed January 30, 2024).

[7] See https://www.restaurantdive.com/news/chipotle-panera-starbucks-have-fastest-in-store-pickup-times-survey-find/566625/ (accessed January 30, 2024).

[8] 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 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.

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

[10] Viewing the restaurant list does not require a consumer to have an account. However, it is still likely that the platform may personalize the list for an individual based on other information. To address this issue and ensure the displayed list is representative of what an average consumer would see, we use the Python scraper on a Linux server with a dedicated IP address located in our institution's computing center, which minimizes the chance that the machine or IP address has been used to access the platform's website. When the Python scraper starts running each week, the program (Python Selenium package) launches a brand-new browser profile without any cookies or browsing history. The scraper simply downloads each city's landing page and does not click on any link on the page.

[11] The platform started to offer sponsored ads in November 2019. These restaurant listings have a "sponsored" tag added below the restaurant name. We noticed only a few such sponsored listings and removed them from our analysis.

[12] Before the regulations, about 60% of restaurants listed on a city's platform page are outside the city border.

[13] See https://www.apple.com/newsroom/2020/11/apple-announces-app-store-small-business-program/ (accessed January 30, 2024).

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