

# Price Controls in a Multi-Sided Market\*

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## Abstract

This article evaluates caps on the commissions that food delivery platforms charge to restaurants. Caps may lead platforms to raise consumer fees, thereby reducing ordering and consequently platforms' value to restaurants. Restaurant responses to caps, though, may counteract fee hikes: caps may boost restaurants' platform adoption and reduce restaurant prices, thereby benefitting consumers. The net welfare effects of caps are thus uncertain. To quantify these effects, I estimate a model of platform competition using data on ordering, platform adoption, and fees. Counterfactual simulations imply that caps reduce overall welfare, bolstering restaurant profits at the expense of platforms and especially consumers.

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## 1 Introduction

The effects of platform regulations depend on equilibrium responses of all market participants connected by the affected platforms. These responses may counteract or amplify policies' direct effects, thus complicating analysis of platform regulation. Although the rise of digital platforms has piqued policymakers' interest in multi-sided markets, platform regulation is often difficult to empirically study due to the rarity of settings with comparable but distinct platform markets that are differentially subject to regulation; indeed, platform markets are often national in scope, impeding comparisons of geographically distinct markets. An additional practical problem is that data characterizing multiple competing platforms in a market are typically limited.

This article empirically evaluates a particular class of platform regulations: commission caps in the food delivery industry. Many US cities have capped the commissions that delivery platforms (e.g., DoorDash) charge to restaurants with the goal of safeguarding restaurant profitability against the rise of platforms. Commission caps' effects on restaurant and consumer welfare depend on countervailing platform and user responses. Caps directly raise restaurant profits, but they impede platforms from balancing consumer fees and restaurant commissions to encourage both sides' participation on platforms. Deprived of commission revenue, platforms may raise the fees that they charge to consumers. This would harm consumers. It would also reduce ordering on platforms and consequently the value of platform membership to restaurants. But equilibrium restaurant responses to caps may counteract the effects of fee hikes — caps may entice restaurants to join platforms, which would benefit variety-loving consumers. Restaurants may also reduce their prices in response to a reduction in commissions. In addition, an increase in platform fees could lead consumers to switch from ordering from restaurants using platforms to ordering directly from restaurants. This would benefit restaurants, who pay no commissions on direct sales. Given that caps have offsetting effects on both restaurant profits and consumer welfare, their net effects on the welfare of platform participants are theoretically uncertain. Empirical work is required to ascertain the relative magnitudes of pricing, platform adoption, and ordering responses that shape these welfare effects. Commission caps' effects on total welfare are also ambiguous. Although caps can worsen platforms' balance between consumer fees and restaurant commissions from an efficiency standpoint, they may also limit platforms' exercise of market power and raise restaurant uptake of platforms. Uptake may be inefficiently low in competitive equilibrium because platforms fail to internalize inframarginal consumers' tastes for restaurant variety when setting commissions.

In this article, I estimate the net effects of commission caps on consumer welfare, restaurant profits, and platform profits. I do so by assembling data on all major US food delivery platforms. These data include a panel of consumer restaurant orders that provides consumer locations at the ZIP-code level as well as item-level prices. I supplement this panel with data on all restaurants listed on each major delivery platform. Additionally, I collect data on platform orders from delivery platform websites. These data characterize platform fees and estimated waiting times for hundreds of thousands of potential deliveries across 14 large US metropolitan areas.

I begin by computing difference-in-differences (DiD) estimates of caps' effects that exploit the staggered rollout of caps. The estimates suggest that caps raised consumer fees by 7–20%

across platforms, reduced platforms sales by 7%, and raised the share of restaurants that join a platform by 3.9 p.p. I additionally find that increases in direct-from-restaurant orders largely offset lost sales on platforms. These estimates suggest that commission caps harm consumers by prompting fee hikes, but that increased restaurant uptake of platforms mitigates these harms. They also suggest that restaurants benefit from a shift towards direct ordering.

To conduct detailed policy analysis, I develop a model. In the model, platforms first set commission rates. Next, restaurants adopt platforms in an incomplete information entry game. Restaurants vary by geographical location and type (chain versus independent). After joining platforms, restaurants set profit-maximizing prices that may differ between direct-from-restaurant orders and platform orders. Platforms concurrently set consumer fees to maximize their profits given constant marginal costs for fulfilling orders. Finally, each consumer chooses whether to order a restaurant meal, from which nearby restaurant to order, and whether to use a platform in ordering. This model captures interrelations between consumers' and restaurants' platform usage decisions; consumers are more likely to choose a platform with more restaurant listings, and restaurants earn higher profits from joining a platform that is more popular among consumers, all else equal. Heterogeneity in tastes for platforms influences how consumers substitute between platforms and the alternative of ordering directly from a restaurant.

Estimation proceeds in steps. The first step is maximum likelihood estimation of consumer preferences. Next, I estimate platform and restaurant marginal costs from first-order conditions for optimal pricing. The subsequent step is generalized method of moments (GMM) estimation of the restaurant platform adoption model. This GMM estimator selects parameters governing adoption costs to match (i) market-specific platform adoption frequencies and (ii) the covariance of the profitability of platform adoption with platform adoption.

The parameters of interest in the consumer choice model govern price sensitivity, tastes for restaurant variety, and substitution patterns. The endogeneity of fees and restaurant networks—both of which depend on unobserved tastes for platforms—poses an identification problem. I address this problem using platform/metro-area fixed effects; consequently, I rely on variation in fees and restaurant locations within a metro area to estimate price sensitivity and network externalities. This variation owes in part to variation in commission cap policies. My approach for estimating substitution patterns exploits the data's panel structure, which characterizes how consumers switch between alternatives. The estimated model replicates empirical relationships between restaurants' platform adoption, platform sales, and local demographics well. It also yields estimates of caps' effects that are similar to those obtained in the DiD analysis.

I use the model to compare equilibria with and without 15% commission caps. Counterfactual simulations imply that caps raise restaurant profits, reduce platform profits, and especially reduce consumer welfare. The sum of caps' effects on these components of total welfare is negative, and stands at 8% of participant surplus (i.e., consumers' and restaurants' joint surplus from platforms)—caps in aggregate render platforms' balance of consumer fees and restaurant commissions less efficient. With that said, commissions are sometimes inefficiently high relative to fees: less dramatic commission caps above 15% boost total welfare in some regions. But

these gains are negligible relative to caps' distributional effects. Further, caps' effects on each of consumer and restaurant welfare are not evenly distributed — places with more young people, more unmarried people, more high-income people, and greater population density suffer greater consumer losses from caps given that platforms are especially popular in these areas.

Equilibrium seller responses dampen the effects of platform regulation in my setting — although consumers pay higher fees under caps, they enjoy an increased selection of restaurants and lower prices on platforms. Restaurants' failure to adjust their adoption decisions would raise consumer gains and restaurant losses from caps by 67% and 58%. When restaurants do not change their prices, consumer gains and restaurant losses are 6.1 and 3.8 times greater.

One distributional rationale for caps is that they transfer surplus from platforms to local restaurants; this rationale is well founded in that caps boost restaurant profits at the expense of platform profits, but it does not acknowledge that consumers in large part pay for caps' benefits to restaurants. Alternative policies could plausibly raise restaurant profits without markedly reducing total welfare. One such policy is a cap on both commissions and consumer fees. I find that such a policy can raise total welfare, but may hurt restaurants by inducing consumer substitution from commission-free direct orders to platform orders. This result relates to another broader principle — in digital platform markets, substitution between online and offline channels may imply that more online business for platform sellers undermines seller profitability. Another alternative policy is a tax on platform commission revenues whose proceeds are remitted to restaurants. Under an appropriate tax rate, this policy achieves the increase in restaurant profitability associated with a cap with a smaller reduction in total welfare. Although a tax distorts how platforms balance consumer fees and restaurant commissions in a manner that reduces total welfare, this distortion is less than that of caps.

I additionally evaluate a common premise for commission caps: that platforms reduce restaurant profits. Platforms boost restaurant profits due to a market expansion effect—they raise the total number of restaurant orders—but they also cannibalize restaurants' commission-free direct sales. A counterfactual simulation indicates that, across ZIP codes, the median share of platform orders that are replaced by direct-from-restaurant orders when platforms are eliminated is only 55%, indicating significant market expansion. This market expansion effect, though, is not large enough to eclipse the cannibalization effect — abolishing platforms raises restaurant profits by about \$29 per capita annually. With that said, eliminating platforms reduces consumer welfare by about \$48 annually per capita. This exercise reveals that platform membership is a prisoner's dilemma for restaurants: restaurants would collectively prefer to stay off platforms, but they individually gain from joining platforms and consequently stealing business from rivals.

### 1.1 Related literature

This article's main contribution is to estimate effects of platform price controls.<sup>1</sup> There is extensive research on pricing regulation,<sup>2</sup> but limited research on its application in multi-sided

<sup>1</sup>I use the terms two-sided, multi-sided, and platform markets interchangeably. Surveys of the multi-sided markets literature include Rochet and Tirole (2006), Rysman (2009), and Jullien et al. (2021).

<sup>2</sup>See, for example, Chapelle et al. (2019) and Diamond et al. (2019) (rent controls); Giberson (2011) (price gouging laws); and Ghosh and Whalley (2004) (price controls on an agricultural staple).

markets. A theme of Rochet and Tirole (2003) is that, as would a planner setting socially efficient Ramsey prices, profit-maximizing oligopolistic platforms balance prices charged to platform buyers and sellers to encourage both sides' participation. Restricting price structures could then undermine participation and reduce total welfare. The potential for efficiency gains from pricing regulation reflects that profit-maximizing platforms set a total price level (sum of both sides' fees) that is too high and they fail to internalize inframarginal users' tastes for users on the other side of the market, leading to an inefficient ratio of one side's fee to the other's. Weyl (2010) explores this latter source of suboptimality, calling it the Spence distortion after Spence (1975). When, e.g., marginal consumers are highly sensitive to fees whereas inframarginal consumers care more about restaurant variety, the platform may set suboptimally high commissions—which discourage restaurant uptake—to subsidize low consumer fees. It is equally possible for marginal consumers to be relatively fee sensitive and for commission rates to consequently be too low. Whether commission caps can correct the Spence distortion depends on the nature of consumer heterogeneity. One contribution of this article then is the estimation of a model with rich consumer heterogeneity that is capable of capturing Spence distortions.

Empirical work on platform pricing regulation is largely limited to payment card markets — see Schmalensee and Evans (2005), Rysman (2007), Carbó-Valverde et al. (2016), Huynh et al. (2022), Wang (2023), Evans et al. (2015), Manuszak and Wozniak (2017), Kay et al. (2018), Wang (2012), Chang et al. (2005), and Li et al. (2020). I add to this literature by estimating a model to study price controls in a multi-sided setting with (i) rich seller responses to caps and (ii) substitution between online and offline purchasing. These features appear in many platform markets and, in my setting, are important determinants of caps' effects. Economic research on commission caps is (to the best of my knowledge) limited to Li and Wang (2021), who study effects on ordering and fees using DiD methods. I complement their work by estimating caps' effects on welfare and other outcomes using a structural model.

Another contribution is the evaluation of how delivery platforms impact the restaurant industry. By making this evaluation, the article joins a literature that assesses digital platforms' effects on established industries; see, e.g., Castillo (2022), Calder-Wang (2022), Schaefer and Tran (2020), and Farronato and Fradkin (2022) for analyses of ride-hailing and short-term accommodations. Estimates of network externalities are important inputs in evaluating platforms' welfare effects. A literature on estimating network externalities—including Farronato et al. (2020), Cao et al. (2021), Lee (2013), Sokullu (2016), Kaiser and Wright (2006), Fan (2013), Ivaldi and Zhang (2020), and Natan (2022)—informs my work.

The article's third contribution is to analyze decentralized pricing by platform sellers who set separate prices on and off platforms. Pricing on food delivery platforms is decentralized in that sellers—not platforms—set prices.<sup>3</sup> Robles-Garcia (2022) models decentralized pricing in a two-sided market, but in a setting without an online/offline price distinction. Other studies

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<sup>3</sup>The popular ride-hailing platforms Uber and Lyft use centralized pricing. See Rosaia (2020) and Buchholz et al. (2020) for analysis of ride-hailing platforms with centralized pricing and Gaineddenova (2022) for analysis of a ride-hailing platform with decentralized pricing.

that empirically analyze prices in multi-sided settings are Argentesi and Filistrucchi (2007), Ho and Lee (2017), and Jin and Rysman (2015).

There is little economic research on food delivery other than that mentioned above; other articles include Chen et al. (2022), Lu et al. (2021), and Feldman et al. (2022). Reshef (2020) studies network externalities on Yelp’s ordering platform.<sup>4</sup> My article also relates to restaurant cost pass-through. Allegretto and Reich (2018) and Cawley et al. (2018) find that, in different settings, restaurants largely pass through cost increases into prices.

## 2 Data and background

### 2.1 Industry background

The major US food delivery platforms in 2020–2021 were DoorDash, Uber Eats, Grubhub, and Postmates; their market shares in Q2 2021 were 59%, 26%, 13%, and 2%.<sup>5</sup> These platforms facilitate deliveries of meals from restaurants to consumers, earning revenue from prices charged to both consumers and restaurants. I refer to the prices that platforms charge to consumers and restaurants as “fees” and “commissions,” respectively, and the prices that restaurants charge for menu items simply as “prices.” In summary,

$$\begin{aligned} \text{Consumer Bill} &= p + c \\ \text{Restaurant Revenue} &= (1 - r)p \\ \text{Platform Revenue} &= rp + c, \end{aligned}$$

where  $p$  is restaurant’s price,  $c$  is the fee, and  $r$  is the commission rate. Average order values before fees, tips, and taxes were slightly below \$30 across platforms in Q2 2021. Throughout this article, I take it that the commission rates for all leading platforms were 30% in areas without caps — Uber Eats and Grubhub advertised 30% commissions in 2021 and DoorDash’s full-service membership tier featured 30% commissions in April 2021. Postmates did not publicly disclose its commissions. It is possible that restaurant chains negotiated lower commissions, although I do not observe their contracts with platforms. I do, though, perform analysis under the alternative assumption that chains’ commission rates were under 30% absent caps.

Each platform charges various fees that together constitute the consumer fee  $c$ . These include delivery, service, and regulatory response fees (e.g., the “Chicago Fee” of \$2.50 per order that DoorDash introduced in response to Chicago’s commission cap). Service fees—unlike the other fees—are often proportional to order value. The fact that platforms responded to commission caps by adjusting fixed rather than proportional fees explains my choice to specify consumer fees as fixed amounts rather than *ad valorem* rates. As discussed later, platforms’ use of fixed consumer fees make their division of total per-order revenue between platform fees and restaurant commissions non-neutral (i.e., relevant for equilibrium allocations).

Restaurants that adopt delivery platforms control their menus on these platforms. Their prices on platforms need not equal their prices for direct-from-restaurant orders. Additionally, restau-

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<sup>4</sup> Additional articles analyzing Yelp include Luca and Reshef (2021) and Luca (2016).

<sup>5</sup> Uber acquired Postmates in 2020, but did not immediately integrate Postmates into Uber Eats.

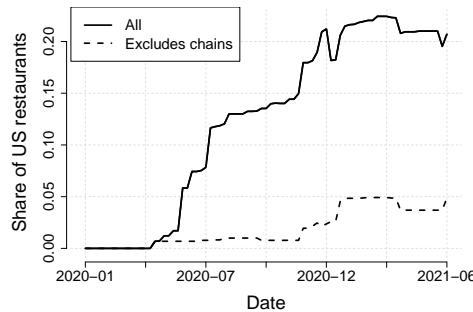
rants typically make an active choice to be listed on platforms.<sup>6</sup> It is common for restaurant locations belonging to the same chain to belong to different combinations of online platforms.

I abstract away from some features of the US food delivery industry due to data limitations and in order to focus on aspects of greater importance in shaping the effects of commission caps. Although I focus on consumers and restaurants, delivery orders also involve couriers. I do not explicitly model couriers, and instead specify platform marginal costs of fulfilling deliveries that capture courier compensation. Additionally, some platforms offer subscription plans that allow users to pay fixed fees to reduce per-transaction delivery fees. Given that these plans do not reduce regulatory response fees that platforms added in response to caps, their importance is not likely first order and I abstract away from them. I also abstract away from the recommendation and search algorithms that delivery platforms use to direct consumers toward restaurants, focusing instead on platform pricing decisions.

Many local governments introduced commission caps in a staggered fashion after the beginning of the COVID-19 pandemic. Figure 1 displays the share of the US restaurants located in a jurisdiction subject to a cap. Over 70 local governments representing about 60 million people had enacted commission caps by June 2021. Most caps—78% of those introduced before 2022—limited commissions to 15%, although some limited commissions to other levels between 10% and 20%. The first caps were introduced as temporary measures, but several jurisdictions later made their caps permanent.<sup>7</sup> Some commission caps (19% of those introduced before 2022) excluded chain restaurants; the dotted curve in Figure 1 shows the share of US restaurants subject to such caps. I take these caps’ exemption of chains into account in estimating the article’s model, although I focus on the more popular form of cap that does not exempt chains in the counterfactual analysis.

Online Appendix Figure O.2 plots the average fees and commission charges over time. Commission revenue consistently exceeded consumer fee revenue in places without caps, but the disparity in consumers and restaurant charges contracted in places with caps.

Figure 1: Share of US restaurants in jurisdictions with commission caps



<sup>6</sup>Some platforms list restaurants without their consent, although this practice has decreased in popularity and has been outlawed in several jurisdictions. See Mayya and Li (2021) for a study of nonconsensual listing.

<sup>7</sup>These include San Francisco, New York, and Minneapolis. Platforms sued San Francisco and New York City in response to their permanent caps.

## 2.2 Data

**Transactions data.** This article uses several data sources, the first of which is a consumer panel provided by the data provider Numerator covering 2019–2021. Panelists report their purchases to Numerator through a mobile application that (i) integrates with email applications to collect and parse email receipts and (ii) accepts uploads of receipt photographs. I use Numerator records for restaurant purchases whether placed through platforms or directly from restaurants (including orders placed on premises, pick-up orders, and delivery orders). At the panelist level, these data report ZIP code of residence and demographic variables. At the transaction level, they report basket subtotal and total, time, delivery platform used (if any), and the restaurant from which the order was placed. At the menu-item level, they report menu item names (e.g., “Bacon cheeseburger”), numeric identifiers, categories (e.g., “hamburgers”), and prices. The demographic composition of Numerator’s core panel is close to that of the US adult population as measured with census data. In addition, market shares computed from these data are similar to those computed from an external dataset of payment card transactions; see Online Appendix O.4 for details. The market definition that I use throughout this article is a metropolitan area, formally a Core-Based Statistical Area (CBSA). I focus on the fourteen large metro areas for which I have detailed fee data — those of Atlanta, Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York, Philadelphia, Phoenix, Riverside/San Bernardino County, San Francisco, Seattle, and Washington. In Q2 2021, there are 58,208 unique consumers and 447,846 transactions in the sample for these metros.

I supplement the Numerator data with platform/ZIP/month-level estimates of order volumes and average fees for January 2020 to May 2021.<sup>8</sup> Edison provides these estimates, which are based on a panel of email receipts.<sup>9</sup> This dataset also includes estimates of average basket subtotals (before fees, tips, and taxes), delivery fees, service fees, taxes, and tips. I use these estimates in the DiD analysis. The Edison data match well external data sources including the Consumer Expenditure Survey (CEX), earnings reports, and a payment card panel.<sup>10</sup>

**Platform adoption** I obtain data on restaurants’ platform adoption decisions from the data provider YipitData. These data record all US restaurants listed on each major platform in each month from January 2020 to May 2021.<sup>11</sup> I obtain data on offline-only restaurants from Data Axe, which provides dataset of a comprehensive listing of US business locations for 2021. In the 14 large metros on which I focus, there were 69,245 restaurants belonging to chains with at least 100 US locations and 354,614 independent restaurants in 2021.

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<sup>8</sup>I use ZIP rather than ZCTA as shorthand for “ZIP code tabulation area” in this article.

<sup>9</sup>The panel includes 2,516,994 orders for an average of about 148,000 orders a month.

<sup>10</sup>The Edison estimates of expenditures at the leading platforms sum to \$33.6 billion for 2020. These platforms account for 11.2% of restaurant spending by Numerator panelists with linked email applications. These estimates together imply restaurant spending of \$2296 per CEX consumer unit, close to the 2020 CEX estimate of food spending away from home of \$2375. The Edison data, which imply DoorDash revenues of \$935 million and \$1.2 billion in Q4 2020 and Q1 2021, also matches DoorDash’s earning reports, which claim revenues of \$970 million and \$1.1 billion in these quarters. See Online Appendix O.4 for additional validation of the data.

<sup>11</sup>Note that I estimate my consumer choice model on data from Q2 2021. Because I do not have data on restaurant platform adoption decisions in June 2021, I use the May 2021 platform adoption data for both May 2021 and June 2021.

Table 1: Description of platform pricing data, Q2 2021

Platform	# obs.	Delivery fees data		Service/reg. response fees data		
		Avg. delivery fee (\$)	Avg. wait time (mins)	# obs.	Avg. service fee (%)	Avg. regulatory response fee (\$)
DD	40437	2.18	29.16	3066	0.14	0.41
Uber	48062	1.93	41.64	4838	0.15	0.55
GH	688428	2.93	41.71	-	-	-
PM	2915	4.95	41.43	2915	0.20	0.53

Notes: the order-level dataset of fees charged by Postmates includes information on both delivery fees and fixed fees. This explains why the number of observations for these two sort of fees coincide in the table.

**Platform pricing** I collect data on platform fees in 2021. My procedure for collecting these data involves drawing from the set of restaurants in a ZIP and inquiring about terms of a delivery to an address in the ZIP for ZIPs in the 14 metros listed above. The address is obtained by reverse geocoding the coordinates of the ZIP’s centre into a street address. Other variables that I record include time of delivery, delivery address, restaurant characteristics, and estimated waiting time. I followed an analogous procedure to collect data on service fees and regulatory response fees; this procedure involves entering a delivery address near the centre of a ZIPs, randomly choosing a restaurant from the landing page displayed after entering this address, and inquiring about terms of a delivery from the restaurant. Table 1 provides observation counts and sample means for the platform pricing datasets for Q2 2021. Section 2.3 describes how I address my lack of data on Grubhub’s service and regulatory response fees.

I construct a dataset of commission caps including start and end dates based on a review of news articles. The dataset includes 72 caps active in March 2021. Online Appendix Table O.1 characterizes predictors of adoption, revealing that high Democratic vote share, population density, and educational attainment predict cap adoption. Last, I use demographic data from the American Community Survey (ACS, 2014–2019 estimates).

### 2.3 Fee indices

I construct indices of platforms’ consumer fees to analyze platform pricing. The consumer fee index  $c_{fz}$  for each pair of a platform  $f$  and a ZIP  $z$  is defined by

$$c_{fz} = DF_{fz} + SF_{fz} + RR_{fz},$$

where  $DF_{fz}$  is a measure of platform  $f$ ’s delivery fees in ZIP  $z$ ,  $SF_{fz}$  is a measure of platform  $f$ ’s service fee in  $z$ ’s municipality, and  $RR_{fz}$  is the regulatory response fee charged by  $f$  in  $z$ . Given that delivery fees vary across orders placed within the same municipality at the same time, I defined  $DF_{fz}$  as a hedonic price index. This index, formally defined in Appendix A, captures systematic differences in delivery fees across geography and platforms conditional on delivery distance, restaurant characteristics, day-of-week, and time-of-day. I define  $SF_{fz}$  as platform  $f$ ’s median service fee in ZIP  $z$ ’s municipality. Service fees are generally proportional to order subtotals; I use a subtotal of \$30 to compute service fees. Recall that the fee data does not include service fees for Grubhub. This omission is not critical given that Grubhub did not enact regulatory response fees aside from a fee of \$1 per order in California. It does,

however, limit information on Grubhub's service fees. I use the Edison dataset to overcome this limitation. The median and the sales-weighted mean of ZIPs' ratios of average service fees to average order value before taxes and fees are both 0.10 for Grubhub in this dataset; I therefore use 10% as Grubhub's service fee. Regulatory response fees apply to entire municipalities, so I compute  $RR_{fz}$  by taking the sum of such fees charged by platform  $f$  in ZIP  $z$ 's municipality. See Online Appendix Table O.3 for a decomposition of fee indices into their components.

### 3 Four empirical findings

#### 3.1 Commission caps raise platform consumer fees

This section describes empirical findings that inform my modelling decisions. The first such finding is that commission caps raised platform consumer fees. I estimate the effects of caps on fees using various difference-in-differences (DiD) methods and the Edison panel of average fees. The first such method is two-way fixed effects (TWFE) regression with estimating equation

$$\underbrace{y_{fzt}}_{\text{Fees}} = \underbrace{\psi_{fz} + \phi_{ft}}_{\text{ZIP and month fixed effects}} + \underbrace{\delta_f x_{zt}}_{\text{Treatment}} + \underbrace{w'_{zt}\beta}_{\text{Controls}} + \epsilon_{fzt}, \quad (1)$$

where  $f$  denotes a platform,  $y_{fzt}$  is the log of platform  $f$ 's average fees in ZIP  $z$  for month  $t$ ,  $\psi_{fz}$  are platform/ZIP fixed effects,  $\phi_{ft}$  are platform/month fixed effects,  $x_{zt}$  is a measure of ZIP  $z$ 's commission cap policy during  $t$ ,  $w_{zt}$  are control variables, and  $\epsilon_{fzt}$  is an unobservable. Here,  $\delta_f$  is the effect of commission caps on log fees.

I control for variables  $w_{zt}$  related to COVID-19 that may affect both governments' decisions to enact commission caps and the outcomes of interest. These include the number of new COVID-19 cases per capita in ZIP  $z$ 's county in month  $t$ , a measure of the stringency of state government responses to COVID-19 (Hallas et al. 2020), and the number of new COVID-19 cases per capita interacted with the Democrat vote share in the 2020 US presidential election. I include this interaction because places with different political proclivities may differentially respond to the local COVID-19 severity. The treatment variable  $x_{zt}$  is an indicator for  $z$  having a commission cap of 15% or lower.<sup>12</sup> In addition to estimating (1), I estimate a version of the model in which caps' effects dynamically vary.<sup>13</sup> The primary identifying assumption underlying the TWFE approach is that, conditional on controls, the outcome in places that enacted caps would have followed the same trend as in places that never enacted caps if caps had not been imposed.

Recent research in econometrics highlights problems affecting TWFE estimators in settings with heterogeneous effects and staggered interventions. To address these problems, I additionally compute the interaction weighted (IW) estimator (Sun and Abraham 2021) and the estimator of Callaway and Sant'Anna (2021), both of which are robust to heterogeneous treatment effects. In addition, Freyaldenhoven et al. (2019) argue that DiD estimators may suffer from an endo-

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<sup>12</sup>I focus on caps of 15% or lower because 15% is the most common level of caps. I exclude ZIPs with caps greater than 15% from the analysis.

<sup>13</sup>This variant is

$$y_{fzt} = \psi_{fz} + \phi_{ft} + \sum_{\tau=-\bar{\tau}}^{\bar{\tau}} \delta_{f\tau} x_{z,t-\tau} + \delta_f^+ \sum_{\tau>\bar{\tau}} x_{z,t-\tau} + \delta_f^- \sum_{\tau<-\bar{\tau}} x_{z,t-\tau} + w'_{zt}\beta + \epsilon_{fzt},$$

The treatment variable  $x_{z,t-\tau}$  equals one if and only if a cap was first imposed in ZIP  $z$  in month  $t - \tau$ .

ogeneity problem owing to unobserved heterogeneity that correlates with both treatment and the outcomes of interest. I additionally compute the Freyaldenhoven et al. (2019) proxy-based estimator that addresses this problem. This estimator requires proxies for unobserved heterogeneity — as proxies, I use the controls  $w_{zt}$ . I additionally control for these variables in computing the IW estimator. The qualitative conclusions from my analysis are robust to estimator. See Online Appendix O.5 for details regarding the computation of each estimator.

Table 2: Fee responses to commission caps

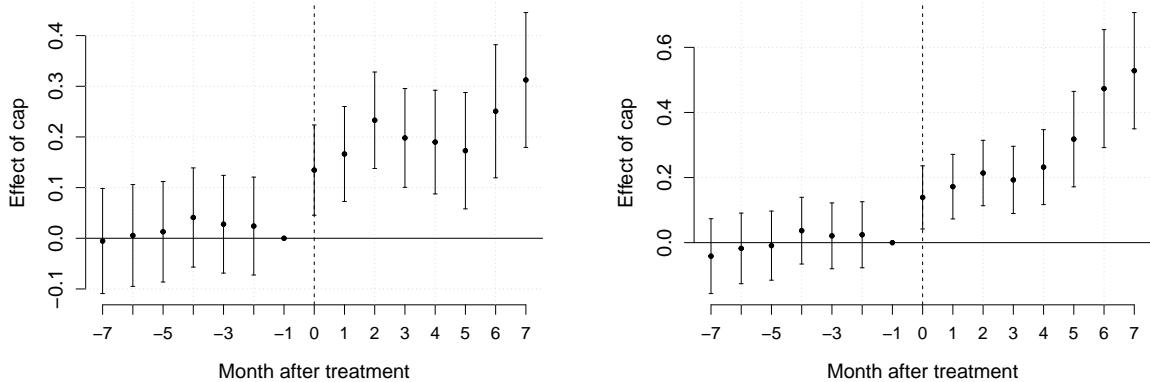
Platform	TWFE	IW	Proxy	CS (not yet)	CS (never)
DD	0.186 (0.019)	0.249 (0.041)	0.170 (0.095)	0.207 (0.121)	0.215 (0.121)
Uber	0.070 (0.019)	0.069 (0.040)	0.209 (0.126)	0.061 (0.039)	0.055 (0.041)
GH	0.127 (0.062)	0.127 (0.142)	0.275 (0.148)	0.106 (0.060)	0.110 (0.060)

Notes: this table reports estimates of the effects of commission caps on log fees. Each estimator is computed on a ZIP/month level panel, and each ZIP is weighted by its population. “TWFE” is the two-way fixed effects estimator. “IW” is the interaction weighted estimator. “Proxy” is the Freyaldenhoven et al. (2019) estimator. “CS” is the Callaway and Sant’Anna (2021) estimator (with not-yet-treated and never-treated units as controls). I control for COVID-19-related variables (see main text). I do not include results for Postmates because I lack data on Postmates fees across the sample period. Asymptotic standard errors appear in parentheses.

Figure 2: Effects of commission caps on DoorDash fees

(a) TWFE

(b) IW (Sun and Abraham 2021)



Notes: this figure reports estimates of the effects of commission caps on DoorDash’s log average fees. The figure reports estimates from both the standard two-way fixed effects (TWFE) estimator and from the interaction weighted (IW) estimator. The bars around each point indicate 95% confidence intervals.

Table 2 provides estimates of commission caps’ effects on the fees charged by DoorDash (DD), Uber Eats (Uber), and Grubhub (GH). For the TWFE estimator, the table reports estimates of  $\delta_f$  in (1). For the other estimators, the table reports estimates of average dynamic effects across time periods following the imposition of caps.<sup>14</sup> The TWFE results suggest that commission caps raised fees by 7%–20% across platforms. Moreover, the estimates are positive and between

<sup>14</sup>In computing average dynamic effects, I weight the effect for  $\tau$  periods after cap introduction by the number of observations for which the unit in question adopted a cap  $\tau$  periods ago.

5.5% and 32% across platform/estimator pairs.<sup>15</sup> The non-TWFE estimates are similar to the TWFE estimates but often less precise. Figure 2 provides TWFE and IW estimates of dynamic effects on the fees of DoorDash, the largest platform. There is no evidence of pre-trends in places that introduced caps. Additionally, Figure 2 suggests that platforms responded to caps with fee hikes almost immediately.

Online Appendix O.5 provides results for other platforms, estimators, and specifications, including those with caps exempting chain restaurants excluded from the estimation sample, with a continuous treatment variable, with fees entering in levels, excluding months before July 2020 (in which laws prohibiting on-premises dining still applied), with proportional service fees and fixed fees as separate outcomes, and in which places with any cap constitute the treatment group. The estimates are similar to those in the main text, and provide evidence that commission caps raised fixed fees but not service fee rates. Online Appendix O.5 also provides results from specifications in which the commission cap treatment indicator is interacted with platforms' market shares and measures of concentration. These results suggest that platforms raised fees by less in response to caps in markets in which they were historically dominant, although the interactions are imprecisely estimated. Last, Table O.14 in the Online Appendix reports estimates of effects on basket subtotals. I do not find significant effects on subtotals.

### **3.2 Caps reduce platform ordering, boost direct ordering**

The harms that restaurants suffer from increased consumer fees depends on the extent to which ordering with platforms and ordering directly from a restaurant are substitutable from the consumer's perspective. If, for example, these channels were highly substitutable, consumers would switch from platform ordering to restaurant ordering due to platform fee hikes, which could help benefit restaurants given that they do not pay commission on direct sales. To assess the substitutability of direct and platform ordering, I apply the DiD methods deployed in Section 3.1 to a panel of ZIP3/month-level estimates of order volumes derived from the Numerator panel. I use the Numerator data here as they characterize both platform and direct ordering. Given that the Edison data analyzed in Section 3.1 contain data on platform sales, I check the robustness of my estimates using those data, repeating the analysis of platform fees described in Section 3.1 but with log orders taking the place of log fees as the outcome.

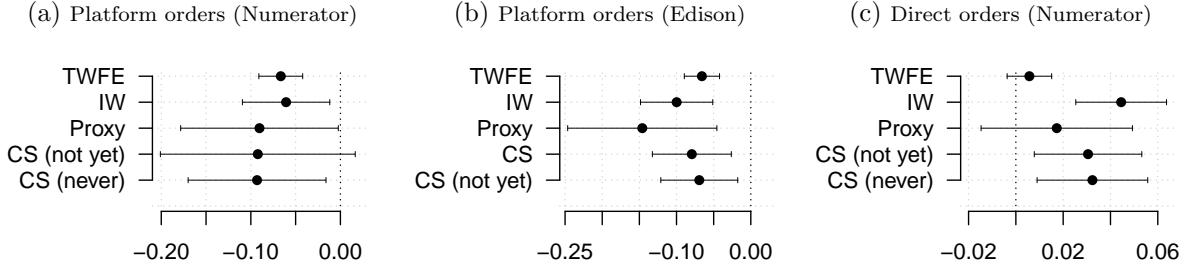
Figure 3 reports results of the analysis for log platform sales and log direct sales as outcomes and Figure 4 plots dynamic effects from the IW estimator.<sup>16</sup> Across estimators and datasets, every estimated effect on platform orders except one is between 0.05 and 0.10 (5–11%). Additionally, the estimated effects on direct orders are all positive and range 0–5%. The estimated positive response of direct-from-restaurant spending to caps suggests that direct ordering and platform ordering are reasonably substitutable. In fact, I fail to reject the hypothesis that caps

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<sup>15</sup>The panel's inclusion of fewer orders for Uber and Grubhub, which made fewer sales than DoorDash in the sample period, contributes to fact that the estimates for these two platforms are less precise than those for DoorDash.

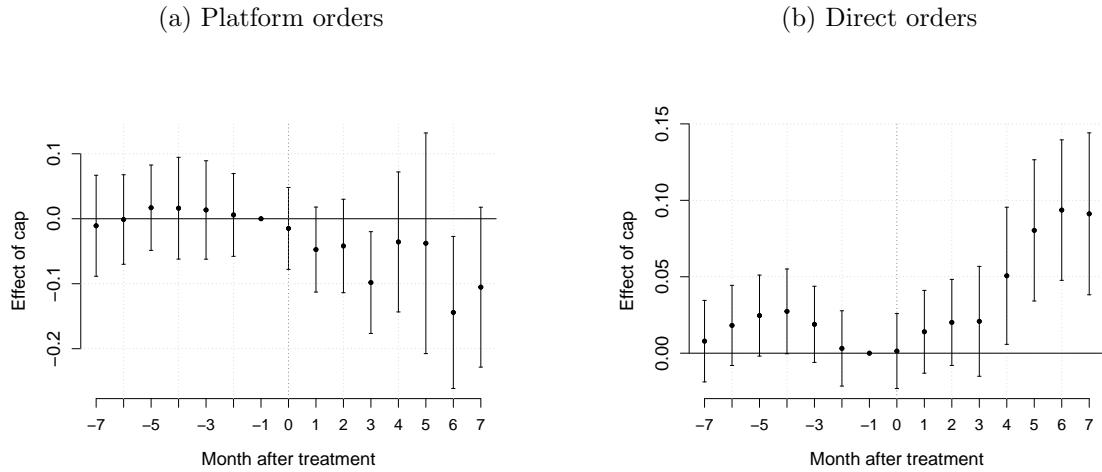
<sup>16</sup>There are not significant pre-trends, although some pre-trends in direct ordering systematically differ from zero. This may reflect unobserved heterogeneity affecting both cap adoption and order volumes. I assess this endogeneity concern by comparing the IW estimates to those from the estimator of Freyaldenhoven et al. (2019). As shown in Online Appendix Figure O.12, effects from this estimator are similar to those plotted in Figure 3c.

Figure 3: Effects of commission caps on restaurant sales



Notes: this figure reports DiD estimates of the effects of commission caps of 15% or less on the log number of restaurant orders placed (i) on delivery platforms and (ii) directly at restaurants. See the notes for Table 2 for an explanation of each estimator. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

Figure 4: Effects of commission caps on order volumes (dynamic event study)



Notes: this figure plots interaction weighted (IW) estimates of the effects of commission caps on (i) the log number of orders placed on food delivery platforms and (ii) the log number of orders placed directly from restaurants. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

affected overall restaurant spending (before fees, tips, and taxes). Figure O.15 in the Online Appendix provides results for DiD analysis of caps' effects on overall spending — the estimated effects range from -0.012 to 0.020, and none of the estimates are significant at the 5% level. This suggests that commission caps' negative effects on platform ordering are unlikely to hurt restaurants, who instead benefit from diversion to direct ordering.

### 3.3 Commission caps induce restaurant uptake of platforms

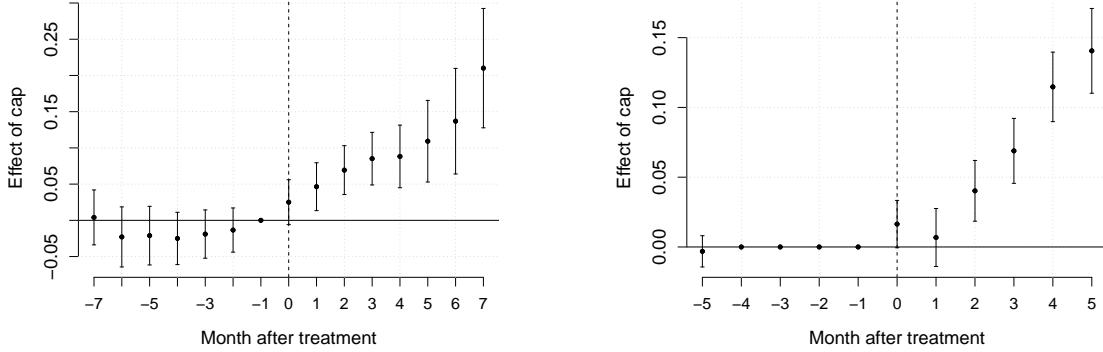
Commission caps may also affect restaurants' platform membership decisions. I assess this possibility using DiD methods. The monthly data on restaurant listings on platforms facilitates estimation of caps' dynamic effects on the number of such listings. I estimate these effects on a monthly panel of 3-digit ZIP code areas (ZIP3), and analyze the number of restaurant listings on platforms both in levels and per million residents as outcomes.<sup>17</sup> A listing here is a

<sup>17</sup>I choose ZIP3s as the units of analysis because ZIP3s are large enough to likely include both the restaurants that service a local population and the local population itself, which is important given that the outcome is a per capita measure.

Figure 5: Dynamic effects of commission caps on restaurants' platform adoption

(a) IW (Sun and Abraham 2021)

(b) Proxy (Freyaldenhoven et al. 2019)



Notes: the plot provides estimates of the effects of commission caps on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents relative to the population-weighted mean number of listings in April 2020 (which was 2642). The bars around each point provide 95% pointwise confidence intervals.

restaurant/platform pair — e.g., between one restaurant listed on DoorDash and another listed on both DoorDash and Uber Eats, there would be three listings. As in Section 3.1, I control for COVID-19-related variables and focus on caps of 15% or lower. Figure 5a plots estimates of effects of caps on the total number of restaurant listings per capita from the IW estimator. Here, the estimates are divided by the population-weighted mean number of listings per capita in April 2020 so that the effects may be interpreted as changes relative to this mean. I find that commission caps raised the number of listings on platforms by between 2.5% and 14% within six months of taking effect. Although the pre-trends are not statistically distinguishable from zero at a 95% confidence level, they systematically fall below zero for the periods leading up to cap implementation. Thus, I compute estimates from the Freyaldenhoven et al. (2019) estimator; the results are similar to the IW estimates. Online Appendix O.5.3 provides supplementary results, including those for individual platforms, for alternative estimators, for specifications in which listing counts are not analyzed relative to local population, and for an estimation sample that excludes places with caps that exempted chain restaurants. These results are consistent with positive effects on platform adoption. In addition, Online Appendix O.5.3 provides results for specifications in which the share of restaurants that have joined at least one platform and the average number of platforms joined by restaurants are the outcomes. I find that the 15% caps increased the share of restaurants belonging to at least one platform by 3.9–4.0 p.p.

### 3.4 Restaurants charge higher prices for platform than for direct orders

Each leading platform allows restaurants to post prices on the platform that differ from the restaurant's prices for direct orders or orders on other platforms. I use item-level transactions data to estimate the average markups of prices on platforms above in-restaurant prices. This

Table 3: Markups of restaurant prices on platforms

Platform	Common markup	Platform-specific markups
Online	0.24 (0.01)	- -
DD	- -	0.28 (0.09)
Uber	- -	0.27 (0.01)
GH	- -	0.23 (0.01)

Notes: this table reports estimates of the  $\vartheta_f$  parameters in (2). The sample includes item-level transactions in Q2 2021. Standard errors appear in parentheses.

procedure involves estimating by OLS

$$\underbrace{\log p_{\iota ft}}_{\text{Log price}} = \underbrace{\varphi_\iota}_{\text{Item fixed effect}} + \underbrace{\vartheta_f}_{\text{Mean log markup}} + \varepsilon_{\iota ft}, \quad (2)$$

where  $\iota$  is a menu item,  $f$  is a platform, and  $t$  is a transaction. Additionally,  $p_{\iota ft}$  is an observed price,  $\varphi_\iota$  are menu-item fixed effects, and  $\varepsilon_{\iota ft}$  captures both measurement error and deviations from the mean log markup  $\vartheta_f$  of prices on platform  $f$ . I normalize  $\vartheta_0 = 0$  for  $f = 0$ , which represents direct ordering. I estimate (2) on data from Q2 2021. Table 3 reports estimates when  $\vartheta_f$  is (i) constant across platforms and (ii) varies across platforms. I find that implies that prices on platforms are about 27% higher than those for direct orders on average, and that this markup is similar across platforms.

I also find suggestive evidence that commission caps led restaurants to reduce their prices on platforms. This evidence comes from a regression with equation

$$\log p_{r\iota zt} = \psi_z + \phi_t + \gamma_{\text{cat}(\iota)} + \delta x_{zt} + w'_{\iota zt} \beta + \epsilon_{r\iota zt}, \quad (3)$$

where  $r$  is a receipt,  $\iota$  is a menu item,  $z$  is a ZIP3,  $t$  is a month, and  $\text{cat}(\iota)$  is the category of menu item  $\iota$ . Here,  $p_{r\iota zt}$  is price,  $\psi_z$  are ZIP3 fixed effects,  $\phi_t$  month fixed effects,  $\gamma_{\text{cat}(\iota)}$  are item-category fixed effects,  $x_{zt}$  is an indicator for a commission cap of 15% or less, and  $w_{\iota zt}$  are controls. These controls include the COVID-19-related variables described above as well as the average price of menu items purchased offline in ZIP3  $z$ , month  $t$ , and category  $\text{cat}(\iota)$ . Some items in the panel have high-level categories (e.g., “chicken entree”) but not subcategories (e.g., “chicken tenders”); I include only observations with a valid subcategory. This approach estimates  $\delta$  by comparing trends in the average price of items within a category across places that enacted caps and places that did not, conditional on controls. Given that price changes could owe to substitution across products in a category, I consider evidence from the regression to be suggestive.<sup>18</sup> The estimate of  $\delta$ , reported in Table 4, suggests that caps led restaurants to reduce their prices on platforms by 6%. Figure O.19 in Online Appendix O.5 plots estimates

<sup>18</sup>I additionally tried a DiD-style regression with menu item fixed effects, although controlling for menu item left too little variation to precisely estimate the effects of commission caps.

of dynamic effects. This figure shows an absence of pre-trends and that prices fell immediately upon the introduction of caps before rebounding, falling by about 14% at their nadir.

### 3.5 Additional findings

Online Appendix O.2 presents five additional findings. First, both restaurants and consumers multihome: over half of restaurants on DoorDash belong to Uber Eats, and consumers sometimes switch between platforms across orders. The model features flexible multihoming. Next, consumers are more likely to order from a platform with more local restaurants. The model replicates this relationship. The third finding is that restaurants that join a platform tend to remain on the platform, which motivates my decision to account for dynamic commission-setting incentives in the model. I next find that young consumers and unmarried are more likely to use platforms; I thus enter age and marital status variables in consumer preferences. Last, I analyze differences in waiting times between places with and without caps conditional on calendar day, metro area, delivery distance, local population density, and time of day. The results are inconclusive: the estimated differences in waiting times vary in sign across platforms and are small in magnitude. I therefore choose to hold waiting times fixed in the model.

## 4 Model

### 4.1 Summary of model

To analyze the welfare effects of commission caps, I develop a model that captures the responses to caps and behaviour documented in Section 3.<sup>19</sup> Competition in each metro area  $m$  is a separate game played by platforms and restaurants. The model’s treatment of platforms is detailed whereas its treatment of restaurants is stylized — restaurants systematically differ only in their location (ZIP  $z$ ) and type (chain versus independent). Each platform, though, has fees, restaurant networks, waiting times, and consumer demand shocks that vary richly across geography. When it comes to estimation, I match consumers’ choices of platforms rather than restaurants. Further, I use detailed platform-specific fee data but restaurant price indices that apply to types of restaurants rather than individual establishments.

The model has four stages. In the first stage, platforms choose commission rates to maximize profits. Restaurants subsequently join platforms. Upon joining platforms, restaurants set prices. Platforms concurrently set their consumer fees. Last, consumers choose what to eat. I specify that platforms set commissions first because, in practice, they advertise commission rates to restaurants considering membership. Platforms often change their fees after restaurants have joined platforms — this underlies the assumption that platforms set consumer fees after restaurants join platforms. Although the model captures numerous features of the food delivery industry, I abstract away from other features: I do not model the market for courier services, consumers have full information of alternatives, and the set of restaurants is fixed. The remainder of this section details the model stages in reverse order.

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<sup>19</sup>Formally, I develop a sequential game with a perfect Bayesian equilibrium solution concept.

## 4.2 Consumer choice

Consumer  $i$  contemplates ordering a restaurant meal at  $T$  occasions each month. In each occasion  $t$ , the consumer chooses whether to order a meal from a restaurant  $j$  or to otherwise prepare a meal, an alternative denoted  $j = 0$ . A consumer who orders from a restaurant chooses both (i) a restaurant and (ii) whether to order from a platform  $f \in \mathcal{F}$  or directly from the restaurant, denoted  $f = 0$ . Let  $\mathcal{G}_j \subseteq \mathcal{F}$  denote the set of platforms on which restaurant  $j \neq 0$  is listed; I call  $\mathcal{G}_j$  restaurant  $j$ 's platform subset. The consumer chooses a restaurant/platform pair  $(j, f)$  among pairs for which (i) restaurant  $j$  is within five miles of the consumer's ZIP and (ii)  $f \in \mathcal{G}_j$  to maximize

$$v_{ijft} = \begin{cases} \psi_{if} - \alpha_i p_{jf} + \eta_i + \phi_{i\tau(j)} + \nu_{ijt}, & j \neq 0, f \neq 0 \quad (\text{Restaurant order via platform}) \\ -\alpha_i p_{j0} + \eta_i + \phi_{i\tau(j)} + \nu_{ijt}, & j \neq 0, f = 0 \quad (\text{Direct-from-restaurant order}) \\ \nu_{i0t}, & j = 0 \quad (\text{Home-prepared meal}). \end{cases}$$

Here,  $\psi_{if}$  is consumer  $i$ 's taste for platform  $f$ ,  $p_{jf}$  is restaurant  $j$ 's price on platform  $f$ ,  $\eta_i$  is the consumer's taste for restaurant dining,  $\phi_{i\tau(j)}$  is consumer  $i$ 's tastes for a restaurant of type  $\tau(j)$ , and  $\nu_{ijt}$  is consumer  $i$ 's idiosyncratic taste for restaurant  $j$  in ordering occasion  $t$  (assumed iid Type 1 Extreme Value). The types  $\tau(j)$  that I consider are independent and chain restaurants, although it would be straightforward to add types (e.g., fast food versus fine dining). Additionally,  $\alpha_i$  is consumer  $i$ 's fee/price sensitivity, which I specify as

$$\alpha_i = \alpha + \alpha'_d d_i,$$

where  $d_i$  are observable consumer characteristics including indicators for age under 35 years, for being married, and for having a household income above \$40k. The prices  $p_{jf}$  that I take to the data are hedonic price indices capturing systematic variation in restaurant prices across platforms, restaurant types, and geography; see Section 5 for details.

Consumer  $i$ 's tastes  $\psi_{if}$  for platform  $f$  are

$$\psi_{if} = \delta_{fm} - \alpha_i c_{fz} - \rho W_{fz} + \lambda'_f d_i + \zeta_{if}.$$

for  $f \neq 0$ . Here,  $\delta_{fm}$  is a parameter governing the mean taste of consumers in metro  $m$  for platform  $f$ ;  $c_{fz}$  is platform  $f$ 's fee to consumers in ZIP  $z$ ; and  $W_{fz}$  is a hedonic waiting time index. Additionally, the  $\zeta_{if}$  are persistent idiosyncratic tastes for platforms, specified as

$$\zeta_{if} = \zeta_i^\dagger + \tilde{\zeta}_{if},$$

where  $\zeta_i^\dagger \sim N(0, \sigma_{\zeta_1}^2)$  and  $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta_2}^2)$  independently of all else. Here,  $\zeta_i^\dagger$  governs tastes for the online ordering channel in general whereas  $\tilde{\zeta}_{if}$  governs tastes for particular platforms  $f$ . The  $\sigma$  scale parameters govern substitution patterns. As  $\sigma_{\zeta_1}^2$  grows large, e.g., consumers become polarized in their tastes for food delivery platforms. This reduces the substitutability of platform ordering and direct ordering.

I specify consumer  $i$ 's taste for restaurant meals  $\eta_i$  as

$$\eta_i = \mu_m^\eta + \lambda_\eta' d_i + \eta_i^\dagger,$$

where  $\mu_m^\eta$  governs average tastes for restaurant dining in metro  $m$ ,  $d_i$  are consumer characteristics, and  $\eta_i^\dagger$  is consumer  $i$ 's idiosyncratic taste for restaurant dining. I specify that  $\eta_i^\dagger \sim N(0, \sigma_\eta^2)$

independent of all else. Last, I specify  $\phi_{i\tau} = \bar{\phi}_\tau + \tilde{\phi}_{i\tau}$ , where  $\tilde{\phi}_{i\tau} \sim N(0, \sigma_\phi^2)$ .

### 4.3 Restaurant pricing and platform fee setting

Each restaurant sells a standardized menu item. It selects this item's prices across platforms to maximize its profits after all restaurants have joined platforms. Let  $p_{jf}^*(\mathcal{G}_j, \mathcal{J}_{m,-j})$  denote the equilibrium price set by restaurant  $j$  on platform  $f$  when  $\mathcal{J}_{m,-j}$  denotes the platform adoption choices of all restaurants in metro  $m$  except  $j$ . Equilibrium prices solve

$$p_j^* = \arg \max_{p_j} \sum_{f \in \mathcal{G}_j} [(1 - r_f)p_{jf} - \kappa_{jf}] S_{jf}(\mathcal{J}_m, p_j, p_{-j}^*),$$

where  $\kappa_{jf}$  is restaurant  $j$ 's marginal cost of fulfilling an order on platform  $f$ ,  $p_{-j}$  are other restaurants' prices, and  $S_{jf}$  are restaurant  $j$ 's sales on platform  $f$ .<sup>20</sup>

The multi-sided markets literature—e.g., Rochet and Tirole (2006)—recognizes that transfers between platform users can render the division of platform fees/commissions between sides of the market irrelevant, a situation known as price structure neutrality. That neutrality does not arise here follows from the fact that consumer fees are fixed whereas restaurant commissions are proportional to price. See Online Appendix O.10 for additional discussion of this point.

Platforms concurrently set their consumer fees to maximize local profits. Each platform  $f$ 's profits in a ZIP  $z$  depend on its marginal costs  $mc_{fz}$ , which represent compensation to couriers. Platform marginal costs may vary across locations due to cross-regional differences in local labour demand and supply conditions. I assume that platforms are price-takers in local labour markets and that their marginal costs do not depend on order volumes. A platform  $f$ 's profits from sales in ZIP  $z$  are

$$\Lambda_{fz} = \underbrace{\vartheta_{fz}(c_z, \mathcal{J}_m)}_{\text{Sales}} \times (\underbrace{c_{fz}}_{\text{Consumer fee}} + \underbrace{r_{fz}}_{\text{Restaurant commission}} - \underbrace{\bar{p}_{fz}^*}_{\text{Average restaurant price in } z \text{ on } f} - \underbrace{mc_{fz}}_{\text{Marginal cost}}), \quad (4)$$

where  $\vartheta_{fz}$  are platform  $f$ 's sales in ZIP  $z$ . The quantity  $\bar{p}_{fz}^*$  is the sales-weighted average price charged by a restaurant for a sale on  $f$  in ZIP  $z$ . DoorDash and Grubhub choose  $c_{fz}$  in each ZIP  $z$  to maximize  $\Lambda_{fz}$ , whereas Uber Eats and Postmates set their fees in ZIP  $z$  to maximize  $\Lambda_{\text{Uber Eats},z} + \Lambda_{\text{Postmates},z}$ .

### 4.4 Restaurants' platform adoption choice

Restaurants simultaneously choose which platforms to join in a positioning game in the spirit of Seim (2006). A restaurant  $j$ 's expected profits from joining platforms  $\mathcal{G}$  are

$$\Pi_j(\mathcal{G}, P_m) = \mathbb{E}_{\mathcal{J}_{m,-j}} \left[ \underbrace{\sum_{f \in \mathcal{G}} [(1 - r_{fz})p_{jf}^*(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_{jf}] S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*)}_{:= \bar{\Pi}_j(\mathcal{G}, P_m)} \mid P_m \right] - K_{\tau(j)m}(\mathcal{G}). \quad (5)$$

The expectation in (5) is taken over rivals' platform adoption decisions  $\mathcal{J}_{m,-j}$ , which are unknown to restaurant  $j$  when it chooses which platforms to join. Rival restaurants' decisions are determined by the probabilities  $P_m = \{P_k(\mathcal{G}) : k, \mathcal{G}\}$  with which rival restaurants  $k$  choose

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<sup>20</sup>Online Appendix O.6 provides an expression for sales  $S_{jf}$ .

each platform subset. Additionally,  $K_{\tau(j)m}(\mathcal{G})$  is the fixed cost of joining platforms  $\mathcal{G}$  for a restaurant of type  $\tau(j)$  in metro  $m$ . Restaurants correctly anticipate the prices  $p_{jf}$  and fees  $c_{fz}$  that arise in the model's downstream stages. The fixed costs  $K_{\tau(j)m}(\mathcal{G})$  do not represent payments to platforms. Instead, they include costs of contracting with platforms; in maintaining a menu on platforms; and in training staff to interface with platforms. By specifying a separate cost for each platform subset  $\mathcal{G}$ , I allow for diminishing costs of joining additional platforms. Additionally, I normalize  $K_{\tau m}(\{0\})$  to zero for each type  $\tau$  and for each metro  $m$ .

Restaurant  $j$ 's adoption decision maximizes the sum of expected profits and a disturbance  $\omega_j(\mathcal{G})$  representing misperceptions or non-pecuniary motives for adoption:

$$\mathcal{G}_j = \arg \max_{\mathcal{G}: 0 \in \mathcal{G}} [\Pi_j(\mathcal{G}, P_m) + \omega_j(\mathcal{G})]. \quad (6)$$

In welfare analysis, I do not count the  $\omega_j(\mathcal{G})$  toward restaurant profits.

A platform adoption equilibrium is a sequence of probabilities  $P_m^* = \{P_j^*(\mathcal{G})\}_{j,\mathcal{G}}$  such that

$$P_j^*(\mathcal{G}) = \Pr \left( \mathcal{G} = \arg \max_{\mathcal{G}'} \Pi_j(\mathcal{G}', P_m^*) + \omega_j(\mathcal{G}') \right) \quad (7)$$

for all restaurants  $j$  in market  $m$  and for all platform subsets  $\mathcal{G}$ . The right-hand side of (7) is the probability that restaurant  $j$ 's best response to rivals' choice probabilities  $P_m^*$  is to join platform subset  $\mathcal{G}$ . Thus, an equilibrium is a sequence of choice probabilities that arise when restaurants' best responses to each other's choice probabilities give rise to these choice probabilities. Condition (7) defines  $P_m^*$  as a fixed point, and Brouwer's fixed point theorem ensures the existence of an equilibrium.<sup>21</sup> Although existence is ensured, an equilibrium may not be unique. In practice, I do not find multiple equilibria at my estimated parameters.<sup>22</sup>

I specify restaurants' platform adoption disturbances as

$$\omega_j(\mathcal{G}) = \sum_{f \in \mathcal{G}} \sigma_{rc} \omega_{jf}^{rc} + \sigma_\omega \tilde{\omega}_j(\mathcal{G}), \quad (8)$$

where  $\omega_j(\mathcal{G})$  are Type 1 Extreme Value deviates drawn independently across  $j$  and  $\mathcal{G}$ . Additionally, the  $\omega_{jf}^{rc}$  are standard normal deviates drawn independently across restaurants and platforms. The parameter  $\sigma_\omega$  governs the variability of platform-subset-specific idiosyncratic disturbances, whereas  $\sigma_{rc}$  governs the extent to which platform subsets are differentially substitutable based on their constituent platforms.

My use of a Seim (2006) positioning game is justified by the facts that (i) equilibria of the game are easier to find than Nash equilibria in complete information games and (ii) complete information entry games suffer from problems related to multiplicity of Nash equilibria reflecting

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<sup>21</sup>The equilibrium can be interpreted as a quantal response equilibrium (McKelvey and Palfrey 1995).

<sup>22</sup>In each metro area, I compute equilibria using the algorithm outlined in Online Appendix O.10 from the following initial choice probabilities: (i) the ZIP-specific empirical frequencies of restaurants' platform choices, (ii) probability one of restaurants not joining any platform, (iii) probability one of restaurants joining all platforms, and (iv) the ZIP-specific empirical frequencies of restaurants' platform adoption choices randomly shuffled between platform subsets within each ZIP. I find the same equilibrium in each market using each of these starting points.

non-uniqueness in the identities of players that take particular actions. These problems do not arise in my model. One critique of Seim (2006)-style positioning models is that they give rise to *ex post* regret: after players realize their actions, some players would generally like to change their actions in response to other players' actions. This is not a considerable problem here because the large number of restaurants leaves little uncertainty in restaurant payoffs.<sup>23</sup>

#### 4.5 Platform commission setting

Platforms set commission rates in the first stage. Each platform's commission rate maximizes a weighted sum of (i) expected profits and (ii) the expected profits of restaurants belonging to the platform. Platforms may value the interests of their users in addition to static profits for dynamic reasons; this second term accounts for such valuation.<sup>24</sup> The expected profits of platform  $f$  in metro  $m$  when setting commissions are

$$\bar{\Lambda}_{fm}(r_m) = \sum_z \mathbb{E}_{\mathcal{J}_m} [\Lambda_{fz} \mid P_m^*(r_m)], \quad (9)$$

where  $\Lambda_{fz}$  are the ZIP-specific profits defined in (4). The  $r_m$  vector includes all platforms' commissions in metro  $m$ , and  $P_m^*(r_m)$  are choice probabilities from an equilibrium in restaurants' platform adoption. The expectation is taken over the equilibrium distribution of platform adoption choices  $\mathcal{J}_m$ , which are governed by the  $P_m^*(r_m)$  probabilities. The problem of a single-platform firm  $f$  is then

$$\max_{r_{fm}} [\bar{\Lambda}_{fm}(r_m) + h_{fm}R_f(r_m)], \quad (10)$$

where  $R_f^c(r_m)$  are the expected profits of restaurants that adopt platform  $f$ . The  $h_{fm}$  weights are model parameters. Uber Eats and Postmates instead maximize the sum of  $\bar{\Lambda}_{fm}(r_m) + h_{fm}R_f(r_m)$  over  $f \in \{\text{Uber Eats, Postmates}\}$ .

### 5 Estimation

#### 5.1 Estimation of the consumer choice model

Estimation proceeds in steps. The estimator of consumer preferences maximizes the likelihood of consumers' observed sequences of platform choices conditional on covariates. In this model, each consumer  $i$  places  $T_i \leq T$  orders from restaurants. Recall that  $T$  is the maximum number of orders per month in my model. In practice, I define each panelist/month pair as a separate consumer, and set  $T = 17$  to the 99th percentile of the number of monthly orders placed by a panelist. The sample includes consumers who place at least one order in Q2 2021, excluding consumers who place over  $T$  orders. In addition, I restrict the sample to panelists who linked

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<sup>23</sup>Formally, for any sequence of choice probabilities  $\{P_{J,m}\}_{J=1}^\infty$  indexed by the number of restaurants  $J$ , the difference between the share of restaurants joining each platform subset (as encoded in  $\mathcal{J}_m$ ) and  $P_z(\mathcal{G}_j)$  converges to zero almost surely due to the strong law of large numbers. This suggests that for a large number of restaurants, the integrand in the definition of  $\bar{\Pi}_j$  is approximately constant across  $\mathcal{J}_{m,-j}$  draws, thus leaving little scope for *ex post* regret.

<sup>24</sup>This approach has precedent in the literature: Castillo (2022) and Gutiérrez (2022) specify platform objective functions including terms representing user surplus. Additionally, Wang et al. (2022) propose a recommendation system that accounts for restaurant interests that Uber Eats has adopted, suggesting that Uber values user interests in addition to short-run profits.

their e-mail accounts to the application that the data provider used to collect e-mail receipts. This leaves a sample of 29,958 panelist/month pairs. The objective function is

$$L(\theta, Y_n, X_n) = \sum_{i=1}^n \log \left( \int \prod_{t=1}^{T_i} \ell(f_{it} | x_i, w_{m(i)}, \Xi_i; \theta) \times \prod_{t=T_i+1}^T \ell_0(x_i, w_{m(i)}, \Xi_i; \theta) dH(\Xi_i; \theta) \right), \quad (11)$$

where  $n$  is the sample size,  $Y_n = \{f_{it} : 1 \leq t \leq T_i, 1 \leq i \leq n\}$  contains each consumer's selected platform  $f_{it}$  across ordering occasions. Similarly,  $X_n = \{x_i, w_{m(i)}\}_{i=1}^n$  contains consumer characteristics  $x_i$  (age, martial status, and income) and characteristics  $w_{m(i)}$  of the consumer's metro area  $m(i)$ , including fees, waiting times, and prices. The restaurant price measures that I use are hedonic price indices that capture systematic variation in the price of a menu item across platforms, restaurant types, and geography. Appendix B details the computation of these indices. The random vector  $\Xi_i$ , which is distributed according to  $H$ , includes the platform tastes  $\zeta_i$ , restaurant dining tastes  $\eta_i$ , and restaurant-type tastes  $\tilde{\phi}_{it}$ . Additionally,  $\ell(f | x, \Xi; \theta)$  is the conditional probability that a consumer orders using  $f$  (either a platform or  $f = 0$ , the direct-from-restaurant option) whereas  $\ell_0(x, \Xi; \theta)$  is the conditional probability that the consumer does not place an order. Online Appendix O.6 provides expressions for  $\ell$  and  $\ell_0$ .

As the integral in (11) does not have a closed form, I approximate it by simulation with 500 draws of  $\Xi_i$  for each consumer. Last, estimation on data from all markets is computationally difficult due to the large number of fixed effects. I therefore estimate the model on data from the largest three metros: those of New York, Los Angeles, and Chicago. I subsequently estimate  $\delta_{fm}$  and  $\mu_m^\eta$  for each remaining metro  $m$  by maximizing (11) on data from metro  $m$  with respect to these parameters, holding fixed the other parameters at their estimated values.

**Identification.** A primary endogeneity problem is that unobserved demand shifters affect both demand and fees. My solution is to estimate the demand shifters  $\delta_{fm}$  as fixed effects, a solution that relies on the assumption that the demand shifters affect demand at the metro level but not at more granular levels of geography. With platform/metro fixed effects specified, estimation of consumer fee sensitivity relies on within-metro fee variation. Fee variation owes to variation in commission cap policies and in local demographics. Note that platform/metro fixed effects similarly address the endogeneity of platforms' restaurant networks.

The panel structure of my data permits the identification of the scale parameters  $\sigma_{\zeta 1}$ ,  $\sigma_{\zeta 2}$ , and  $\sigma_\eta$  governing heterogeneity in consumer tastes for platforms and restaurant dining. Recall that consumer  $i$ 's persistent unobserved tastes for platform  $f$  are  $\zeta_{if} = \zeta_i^\dagger + \tilde{\zeta}_{if}$ , where  $\zeta_i^\dagger \sim N(0, \sigma_{\zeta 1}^2)$  and  $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta 2}^2)$ . When  $\sigma_{\zeta 1}$  is large, consumers are polarized in their tastes for ordering through platforms. This leads consumers to either repeatedly order meals through platforms or repeatedly order meals directly from restaurants. Repetition in the choice to order through a platform is consequently informative about the value of  $\sigma_{\zeta 1}$ . Similarly, a large value of  $\sigma_{\zeta 2}$  implies that consumers are highly polarized in their tastes for individual platforms. This leads consumers to repeatedly choose the same food delivery platform when using a platform to order a meal. Conversely, when  $\sigma_{\zeta 2}$  is low, consumers do not have strong idiosyncratic preferences for

platforms, and are more likely to switch between platforms. Thus, repetition in platform choice is informative about the value of  $\sigma_{\zeta 2}$ . Heterogeneity across consumers in the number of orders placed from restaurants is similarly informative about the value of  $\sigma_\eta$ . Note that the model rules out state dependence as an alternative explanation for persistence in ordering.

**Market size.** The model yields predictions of sales given counts of consumers in each ZIP. I set the number of consumers in each ZIP so that the model implies platform sales equal to overall sales. Appendix C explains this procedure.

## 5.2 Estimation of restaurant marginal costs

The profits of a restaurant  $j$  that adopts platforms  $\mathcal{G}_j$  are

$$\sum_{f \in \mathcal{G}_j} [(1 - r_f)p_{j0} - \kappa_{jf}] S_{jf}(\mathcal{J}_m, p), \quad (12)$$

where  $S_{jf}$  are restaurant  $j$ 's sales on platform  $f$ ,  $\mathcal{J}_m$  are the platform adoption decisions of all restaurants in market  $m$ , and  $p$  contains all restaurant prices. For expositional convenience, I introduce  $r_0 = 0$  as the commission rate for direct-from-restaurant orders. The first-order condition for profit maximization is

$$\underbrace{\begin{bmatrix} (1 - r_{f_1})S_{jf_1} \\ \vdots \\ (1 - r_{f_k})S_{jf_k} \end{bmatrix}}_{=\tilde{S}_j} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial p_{jf_1}} & \frac{\partial S_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_1}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial p_{jf_k}} & \frac{\partial S_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{=\Delta_p} \left( \underbrace{\begin{bmatrix} (1 - r_{f_1})p_{jf_1} \\ \vdots \\ (1 - r_{f_k})p_{jf_k} \end{bmatrix}}_{=\tilde{p}_j} - \underbrace{\begin{bmatrix} \kappa_{jf_1} \\ \vdots \\ \kappa_{jf_k} \end{bmatrix}}_{=\tilde{\kappa}_j} \right) = 0, \quad (13)$$

where  $\mathcal{G}_j = \{f_1, \dots, f_k\}$ . Solving for marginal costs yields

$$\tilde{\kappa}_j = \tilde{p}_j + \Delta_p^{-1} \tilde{S}_j. \quad (14)$$

Equation (14) provides the basis of my estimation of restaurant marginal costs — I compute the right-hand side of (14) at estimated parameters and observed prices for each restaurant  $j$  in a market  $m$ . In addition, I assume that  $\kappa_{jf} = \kappa_z^{\text{direct}}$  for  $f = 0$  and  $\kappa_{jf} = \kappa_z^{\text{platform}}$  for  $f \neq 0$ , where  $\kappa_z^{\text{direct}}$  is a restaurant's cost of preparing a meal for a direct order and  $\kappa_z^{\text{platform}}$  is the cost of preparing a meal for a platform order. Marginal costs of platform orders may differ from those of direct orders due to differences in the packaging and logistical costs. The costs  $\kappa_{jf}$  that I recover from (14) generally differ across restaurants within a particular platform  $f$  due to sampling error. In light of these differences, I use the cross-restaurant average of the  $\kappa_{j0}$  costs recovered from (14) as my estimator of  $\kappa_z^{\text{direct}}$ . I similarly use the average  $\kappa_{jf}$  recovered from (14) across platform/restaurant pairs as my estimator of  $\kappa_z^{\text{platform}}$ .

### 5.3 Estimation of platform marginal costs

I estimate platform marginal costs from first-order conditions for consumer fee optimality. Within a ZIP  $z$ , platforms' consumer fees solve the following first-order conditions:

$$(\mathcal{H} \odot \Delta_c)(c_z + r_m \odot p_z - mc_z) + s_z = 0,$$

where  $c_z$  is a vector containing platform consumer fees in  $z$ ,  $r_m$  is a vector containing platforms' commission rates,  $p_z$  is a vector including sales-weighted average restaurant prices on each platform  $f$ , and  $mc_z$  is a vector containing each platform  $f$ 's marginal cost  $mcf_z$ . The vector  $s_z$  similarly contains each platform  $f$ 's sales. The  $\odot$  operator denotes entry/component-wise multiplication.<sup>25</sup> Letting  $F$  denote the number of platforms,  $\Delta_c$  is an  $F \times F$  matrix whose  $(f, f')$  entry is  $\partial s_f / \partial c_{f'z}$ . The  $\mathcal{H}$  matrix also has dimension  $F \times F$ ; its  $(f, f')$  entry indicates whether  $f$  and  $f'$  have the same owner.<sup>26</sup> Therefore,

$$mc_z = c_z + r_m \odot p_z + (\mathcal{H} \odot \Delta_c)^{-1} s_z. \quad (15)$$

I estimate  $mc_z$  by substituting the observables  $c_z$ ,  $r_m$ , and  $p_z$  and  $\Delta_c$  and  $s_z$  as implied by the estimated consumer choice model into (15).

### 5.4 Estimation of restaurant platform adoption model

I estimate the parameters  $K_{\tau m}(\mathcal{G})$  and  $\Sigma = (\sigma_\omega, \sigma_{rc})$  governing restaurants' platform adoption decisions using a two-step generalized method of moments (GMM) estimator. Recall that restaurants adopt platforms to maximize perceived profits given beliefs regarding rivals' choices that are consistent with actual choice probabilities. The first stage of estimation involves estimating restaurants' conditional choice probabilities (CCPs) as a function of variables affecting their profits. The second stage involves setting restaurant beliefs to the estimated CCPs and then fitting model predictions to observed choices.<sup>27</sup>

In the first stage, I specify platform adoption CCPs as a multinomial logit whose parameters I estimate by maximum likelihood. The covariates include: population within five miles of the restaurant; the number of restaurants within five miles; municipality fixed effects; an indicator for an active commission cap; and the shares of the population within five miles that are under 35 years old, married, both under 35 years old and married, and with household income under \$40k. I also include interactions of the nearby population with the of demographic shares and with the number of nearby restaurants.

The first-stage CCPs  $\hat{P}_m$  permit computation of each restaurant's probability of joining platforms  $\mathcal{G}$  for under parameter values  $\theta^{\text{adopt}}$ . As noted, I estimate  $\theta^{\text{adopt}}$  using a GMM estimator.<sup>28</sup> Defining this estimator requires new notation. Let  $n_J$  be the number of restaurants in the sam-

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<sup>25</sup>My exposition follows Conlon and Gortmaker (2020).

<sup>26</sup>Here,  $\mathcal{H}_{i,j} = \mathbb{1}\{i = j \text{ or } i, j \in \{\text{Uber, Postmates}\}\}$ .

<sup>27</sup>Singleton (2019) uses a similar estimator to estimate a Seim (2006)-style positioning model.

<sup>28</sup>I do not use a maximum likelihood estimator on account of finite-sample problems of maximum likelihood estimation that are well documented in the literature on entry games; see, e.g., Pakes et al. (2007) and Collard-Wexler (2013).

ple, and let  $G_{n_J}$  denote the  $n_J$ -vector of observed platform adoption choices. Additionally, let  $\Pi_{n_J}^e$  denote a  $n_J \times n_G$  matrix whose  $(j, k)$  entry is equal to restaurant  $j$ 's expected variable profits from selecting the  $k$ th platform subset  $\mathcal{G}_k$ , where  $n_G$  is the number of subsets. Last, let  $D_j$  be the log of the population under age 35 within five miles of  $j$ ; I use  $D_j$  as a shifter of the profitability of platform adoption.

The GMM estimator is based on moment conditions that match model predictions to the data. The first set of moments match model predictions of aggregate choice probabilities to empirical frequencies. These conditions involve the functions

$$g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) = \mathbb{1}\{m(j) = m, \tau(j) = \tau\} \left( Q_{\tau m}(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) - \mathbb{1}\{\mathcal{G}_j = \mathcal{G}\} \right),$$

for all  $\tau, m$ , and  $\mathcal{G}$ , where  $\tau(j)$  and  $m(j)$  are restaurant  $j$ 's type and market, respectively. Additionally,

$$Q_{\tau m}(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) = \Pr \left( \mathcal{G} = \arg \max_{\mathcal{G}'} \left[ \bar{\Pi}_j(\mathcal{G}', \hat{P}_m) - K_{\tau m}(\mathcal{G}) + \omega_j(\mathcal{G}) \right] \mid \theta^{\text{adopt}} \right)$$

is the probability that restaurant  $j$  chooses platforms  $\mathcal{G}$ . Under the true model parameters  $\theta_0^{\text{adopt}}$ , profits  $\Pi_j^e$ , and CCPs,  $\mathbb{E}[g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0$ . The corresponding sample moment conditions are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0 \quad \forall \tau, m, \mathcal{G}. \quad (16)$$

I target the  $\Sigma$  parameters that govern substitution patterns with additional moments. Each moment equalizes the covariance of  $D_j$  and a measure of platform adoption as computed on the data and as predicted by the model. The two measures of platform adoption that I use are (i) an indicator for whether the restaurant joins any online platform and (ii) the number of online platforms joined. These moments are based on

$$\begin{aligned} g_{\omega,1}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) &= D_j \times \left( \mathbb{1}\{\mathcal{G}_j \neq \{0\}\} - (1 - Q(\{0\}, \Pi_j^e; \theta^{\text{adopt}})) \right) \\ g_{\omega,2}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) &= D_j \times \left( |\mathcal{G}_j| - \sum_{\mathcal{G}} |\mathcal{G}| \times Q(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) \right), \end{aligned}$$

where  $|\mathcal{G}|$  is the cardinality of set  $\mathcal{G}$ . Under the true model parameters  $\theta_0^{\text{adopt}}$ ,  $\mathbb{E}[g_{\omega}(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0$ . The corresponding sample moment conditions are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{\omega,k}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0, \quad k \in \{1, 2\}. \quad (17)$$

Increasing  $\sigma_\omega$  and  $\sigma_{rc}$  make restaurants less responsive to expected profits when choosing which platforms to join. Given that a higher population of young people—who are especially likely to enjoy platforms—boosts the profit gains from joining platforms, a larger covariance between  $D_j$  and platform adoption suggests smaller values of  $\sigma_\omega$  and  $\sigma_{rc}$ . An alternative approach would be to replace the profit shifter  $D_j$  with estimated profits. I choose to use demographics  $D_j$  rather

than estimated profits because the latter are more likely to suffer from measurement error due to sampling error or misspecification error, which would introduce bias.

The estimator  $\hat{\kappa}$  is the vector of parameter values that solves (16) and (17). Given that the model is just-identified, one problem that arises is that exactly computing restaurants' expected profits given beliefs about a large number of rivals' decisions is computationally prohibitive. Two approximations that reduce the computational burden are available: (i) approximation of the integral defining expected profits by simulation and (ii) an alternative approximation that involves computing profits at the expected number of restaurants of each type and ZIP that adopt each platform subset. These approximations yield near-identical results: a regression of expected profits from the first on those from the second yields a coefficient of 1.001 and an  $R^2$  of one up to three decimal places. The latter approximation, which ignores Jensen's inequality, introduces minimal bias because variability in the realized distribution of restaurants across platform subsets is low due to the large number of competing restaurants; the median number of restaurants within five miles of a particular restaurant is 1448 in the metros that I study. Given that this latter approximation involves a lower computational burden than simulation, I use it in estimation and in solving counterfactuals. See Online Appendix O.10 for details.

## 5.5 Estimation of restaurant-network weights in platform objective

I solve for the  $h_{fm}$  weights in platform objective functions from first-order conditions for optimal commission rates, substituting in estimates for true parameters in these conditions. See Online Appendix O.9 for a detailed explanation.

# 6 Estimation results

## 6.1 Parameter estimates for consumer choice model

Table 5 reports estimates of consumer choice model parameters. Several estimates are noteworthy. First, the estimated scale parameters  $\sigma_{\zeta_1}$  and  $\sigma_{\zeta_2}$  are both sizeable, suggesting that consumers are divided by both overall taste for online ordering and by tastes for specific platforms. Additionally, the estimated  $\lambda$  demographic effects on platform tastes imply that young and unmarried consumers prefer delivery platforms relative to older and married consumers. The large estimate of  $\sigma_\eta$  suggests limited substitutability between restaurant ordering and at-home dining. In addition, the  $\alpha$  parameter estimates indicate that married and higher income consumers are less price sensitive. Figure 6 plots the distribution of estimated own-fee elasticities across metros; these elasticities range from 0.5 to 2.5 for DoorDash, Uber Eats, and Grubhub, the three platforms with sizeable national market shares. Last, platform sales respond to restaurant variety on platforms — the estimated elasticities of platforms' orders with respect to their restaurant listing counts range from 0.57 to 0.97 across platforms in the New York metro.<sup>29</sup> Price sensitivity  $\alpha_i$  governs the extent to which consumers value low fees relative to restaurant variety. The mean  $\alpha_i$  for DoorDash across metros is 0.209 when weighting by sales and 0.220 when weighting by the change in sales when fees are infinitesimally reduced. The

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<sup>29</sup>See Online Appendix Table O.23 for details on the computation of these elasticities and for cross-elasticity estimates.

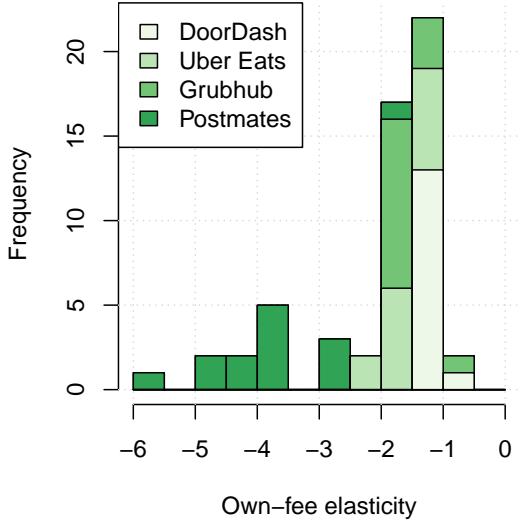
similarity of average fee sensitivity and marginal consumers' fee sensitivities here casts doubt on the presence of a Spence distortion that commission caps could correct.

Table 5: Consumer choice model parameter estimates

Parameter	Estimate	SE
$\alpha$	0.28	0.01
$\alpha_{\text{young}}$	0.01	0.01
$\alpha_{\text{married}}$	-0.07	0.01
$\alpha_{\text{high inc}}$	-0.06	0.01
$\sigma_{\zeta 1}$	2.02	0.04
$\sigma_{\zeta 2}$	1.28	0.02
$\rho$	0.51	0.19
$\phi_{\text{chain}}$	-0.84	0.11
$\sigma_{\phi}$	1.02	0.06
$\lambda_{\text{DD}}^{\text{young}}$	0.71	0.14
$\lambda_{\text{DD}}^{\text{married}}$	-1.29	0.15
$\lambda_{\text{DD}}^{\text{high income}}$	-0.16	0.15
$\lambda_{\text{Uber}}^{\text{young}}$	0.82	0.13
$\lambda_{\text{Uber}}^{\text{married}}$	-1.62	0.14
$\lambda_{\text{Uber}}^{\text{high income}}$	-0.35	0.14
$\lambda_{\text{GH}}^{\text{young}}$	0.54	0.16
$\lambda_{\text{GH}}^{\text{married}}$	-1.14	0.15
$\lambda_{\text{GH}}^{\text{high income}}$	-0.32	0.16
$\lambda_{\text{PM}}^{\text{young}}$	0.80	0.19
$\lambda_{\text{PM}}^{\text{married}}$	-1.40	0.21
$\lambda_{\text{PM}}^{\text{high income}}$	-1.03	0.20
$\sigma_{\eta}$	2.03	0.01
$\lambda_{\text{young}}^{\eta}$	-0.35	0.20
$\lambda_{\text{married}}^{\eta}$	-1.12	0.21
$\lambda_{\text{high income}}^{\eta}$	-1.23	0.21

Notes: this table reports estimates of the parameters of the consumer choice model. Estimates of the platform/metro fixed effects  $\delta_{fm}$  and the metro fixed effects  $\mu_m^\eta$  are omitted.

Figure 6: Distribution of own-fee elasticities across markets



Notes: this figure plots stacked histograms of platform-specific own-fee elasticity estimates across metro areas.

To evaluate the estimates and understand their implications for ordering behaviour, I compute substitution patterns predicted by the model. First, Table 6 provides the shares of consumers substituting to each platform and to making no purchase among those who substitute away from a platform  $f$  upon a uniform increase in  $f$ 's consumer fees. The estimates show that, across platforms, between 21% and 34% of platforms' consumers who substitute away from ordering on a platform no longer place any restaurant order. An additional 33–40% switch to ordering directly from a restaurant whereas the remainder switch to a different platform. The estimates additionally suggest that cannibalization is an important consideration for restaurants in determining whether to join platforms. On average across markets, the loss of direct sales by a restaurant that has previously not joined any platform from joining DoorDash equals 25% of the restaurant's overall gain in sales from joining this platform. Although joining platforms raises a restaurant's overall sales, it also shifts sales from the commission-free direct channel to

the commission-subject platform channel.

Table 6: Between-platform diversion ratios for the New York metro

Platform	Quantity response for...					
	No purchase	Direct	DD	Uber	GH	PM
DD	0.29	0.39	-1.00	0.20	0.11	0.01
Uber	0.35	0.43	0.10	-1.00	0.11	0.01
GH	0.29	0.39	0.10	0.20	-1.00	0.01
PM	0.20	0.34	0.12	0.22	0.12	-1.00

Notes: this table reports the share of consumers who substitute to each platform and to making no purchase among those who substitute away from a platform  $f$  upon a uniform increase in  $f$ 's consumer fee across the New York City metro area. Formally, the table reports

$$d_{ff'} = \left( \frac{\partial \beta_{fm}(c_{f'm} + h)}{\partial h} \Big|_{h=0} \right) / \left( - \frac{\partial \beta_{f'm}(c_{f'm} + h)}{\partial h} \Big|_{h=0} \right)$$

where  $c_{f'm}$  is a vector of the consumer fees charged by  $f'$  across all ZIPs within  $m$ ;  $\beta_{fm}$  are alternative  $f$ 's sales in  $m$ . Each column provides diversion ratios  $d_{ff'}$  for a particular alternative  $f$  whereas each row provides diversion ratios  $d_{ff'}$  for a particular platform  $f$  whose consumer fees increase across  $m$ .

## 6.2 Estimates of restaurant marginal costs

Table 7 describes restaurant markups implied by the  $\kappa_{jf}$  estimates. Independent restaurant markups for direct orders are about a sixth of their prices. Further, markups on platform orders are larger under commission caps. Markups, however, do not vary substantially between chain and independent restaurants. Nor do they vary much between direct orders placed from restaurants subject and not subject to commission caps.

Table 7: Restaurant markups (means and standard deviations, \$)

(a) Chain restaurants			(b) Independent restaurants		
Channel	No cap	Cap	Channel	No cap	Cap
Direct	4.67±0.42	4.51±0.27	Direct	4.86±0.40	4.74±0.31
Platform	3.51±0.32	3.93±0.25	Platform	3.79±0.32	4.17±0.35

Notes: the table describes markups  $(1 - r_f)p_{jf} - \kappa_{jf}$  across ZIPs separately for direct orders ( $r_0 = 0$ ) and platform-intermediated orders, and also separately for ZIPs with commission caps and those without caps. The averages are taken over restaurants. Note that the average direct-from-restaurant price is \$18.08 for independent restaurants and \$16.27 for chain restaurants.

## 6.3 Estimates of platform marginal costs

Table 8 describes the estimated cross-ZIP distribution of platform marginal costs—which reflect courier compensation—and platform markups. As of September 2022, DoorDash's website stated that “Base pay from DoorDash to Dashers ranges from \$2–\$10+ per delivery depending on the estimated duration, distance, and desirability of the order” (DoorDash calls its couriers “Dashers”).<sup>30</sup> This level of courier pay lines up well with the estimated interquartile range of DoorDash's marginal costs of \$7.08 to \$9.72. Additionally, McKinsey & Company found platform marginal costs of \$8.20 per delivered order in a 2021 analysis of the US food delivery

<sup>30</sup>See <https://help.doordash.com/consumers/s/article/How-do-Dasher-earnings-work>.

industry (Ahuja et al. 2021); this figure is close to my mean marginal cost estimates for the leading three platforms.

Table 8: Estimates of platforms’ marginal costs (\$)

	Marginal costs				Markup			
	Quantiles			Mean	Quantiles			
	Mean	0.25	0.50	0.75	0.25	0.50	0.75	
DD	8.10 (0.18)	6.87 (0.19)	8.48 (0.20)	9.35 (0.19)	4.84 (0.18)	4.42 (0.16)	4.96 (0.18)	5.70 (0.19)
Uber	8.37 (0.27)	7.23 (0.28)	8.21 (0.26)	9.40 (0.26)	4.12 (0.27)	3.71 (0.22)	4.33 (0.26)	5.10 (0.32)
GH	8.93 (0.14)	7.69 (0.16)	9.09 (0.14)	10.29 (0.14)	3.91 (0.14)	3.57 (0.12)	4.05 (0.14)	4.55 (0.16)
PM	13.93 (0.24)	12.47 (0.24)	13.90 (0.25)	15.15 (0.24)	3.24 (0.24)	2.90 (0.20)	3.60 (0.25)	4.31 (0.30)

Notes: this table describes the estimated distribution of platforms’ marginal costs across ZIPs. Standard errors obtained from the bootstrap procedure of Appendix D appear in parentheses.

#### 6.4 Estimates of the restaurant platform adoption model

Table 9 reports estimates of the parameters governing platform adoption by restaurants in the scale of thousands of dollars. In interpreting the estimates, note that the average expected variable profits of a restaurant that joins no online platform in my sample is roughly \$12,500. The fixed cost estimates are at a monthly level. Panel 9c displays average costs by the number of platforms joined across platform subsets and metros. This plot shows that costs increase at a diminishing rate as restaurants join more platforms and level off considerably at two platforms joined. The estimated scale parameter  $\sigma_{rc}$  of restaurants’ platform-specific normal choice disturbances is \$350 whereas the estimated scale parameter  $\sigma_\omega$  of the platform-subset-specific disturbance is \$290, which maps to a standard deviation of \$372.

#### 6.5 Estimates of restaurant-profit weights in platform objective functions

Table 10 describes estimates of the weights  $h_{fm}$  that platforms place on the profits of restaurants belonging to their platform in setting commissions. The median weights vary from 0.07 to 0.15 across platforms.

#### 6.6 Model fit

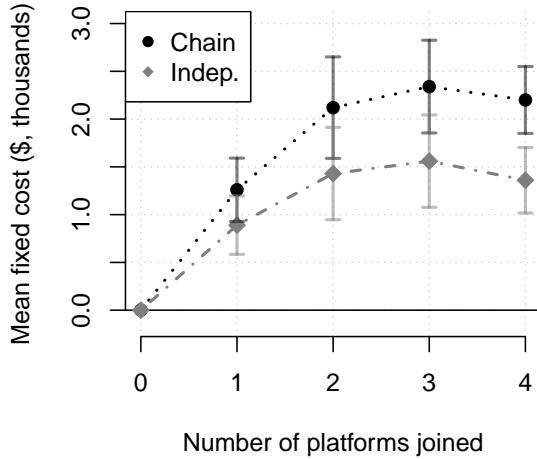
To assess model fit, I compare results from regressions computed on the estimation sample (“Data”) to those computed on data simulated from the estimated model (“Model”). Table 11a displays results from regressions of the share of restaurant orders placed on platforms in a ZIP on the demographic characteristics of the ZIP. In both the raw data and the model predictions, platform orders account for a greater share of restaurant sales in ZIPs with more young people, more unmarried people, and more people with household incomes above \$40k. In addition, the coefficients are similar in magnitude between the two regressions. This indicates that the model does well in capturing patterns of geographical heterogeneity in platform usage.

Table 9: Estimates of restaurant platform adoption parameters

(a) Parameters governing choice disturbance

Parameter	Estimate	SE
$\sigma_\omega$	0.29	(0.07)
$\sigma_{rc}$	0.35	(0.03)

(c) Average cost by platform subset size



(b) Mean fixed costs by restaurant type

Platform subset	Chain	Indep.
DD	1.76 (0.15)	0.80 (0.11)
Uber	0.86 (0.16)	0.79 (0.15)
GH	2.28 (0.23)	1.31 (0.20)
PM	1.23 (0.19)	0.81 (0.14)
DD, Uber	2.68 (0.28)	1.26 (0.19)
DD, GH	1.68 (0.26)	1.22 (0.22)
DD, PM	2.32 (0.20)	1.26 (0.18)
Uber, GH	1.21 (0.23)	1.15 (0.22)
Uber, PM	2.38 (0.27)	1.63 (0.28)
GH, PM	1.75 (0.33)	1.51 (0.29)
DD, Uber, GH	2.33 (0.24)	1.62 (0.25)
DD, Uber, PM	1.95 (0.31)	1.64 (0.30)
DD, GH, PM	2.69 (0.27)	1.77 (0.28)
Uber, GH, PM	2.03 (0.32)	1.59 (0.29)
All	2.20 (0.18)	1.36 (0.17)

Notes: Panel 9a reports estimates of the parameters governing the disturbance affecting restaurants' platform adoption decisions. Panel 9b reports estimates of the mean  $K_{\tau m}(\mathcal{G})$  fixed costs across markets  $m$  for each platform subset  $\mathcal{G}$  and restaurant type  $\tau$ . Panel 9c reports the mean  $K_{\tau m}(G)$  across markets  $m$  and platform subsets  $\mathcal{G}$  with a given number of constituent platforms for each restaurant type. I compute the standard errors appearing in parentheses using the bootstrap procedure described in Appendix D.

Table 10: Estimates of restaurant-profit weights in platform objective functions

Platform	Quantile		
	25%	Median	75%
DD	0.05 (0.018)	0.12 (0.024)	0.15 (0.023)
Uber	0.10 (0.015)	0.12 (0.017)	0.13 (0.020)
GH	0.12 (0.017)	0.15 (0.020)	0.17 (0.026)
PM	0.06 (0.011)	0.07 (0.016)	0.08 (0.014)

Notes: this table reports quantiles of the estimated  $h_{fm}$  weights taken across metros  $m$  for each leading platform. I compute standard errors using the bootstrap procedure described in Appendix D.

Table 11b displays results from additional regressions. First, I regress the share of restaurants in a ZIP that join at least one online platform on the share of the nearby population (within five miles) under 35 years old. I then regress this same outcome on the log population within five miles, a measure of local population density. For each of these regressions, the coefficients for the data and model regressions are similar in magnitude, with the model-regression coefficient lying within the 95% confidence interval for the data-regression's coefficient. The subsequent regressions feature the mean number of platform orders per consumer as the outcome and

Table 11: Model fit

(a) Regression of platform sales share on local demographics

Value	Model	Data	SE
Share < 35yo	0.11	0.11	(0.04)
Share married	-0.07	-0.17	(0.03)
Share HH inc. > 40k	0.10	0.08	(0.03)

(b) Other regressions

Value	Model	Data	SE
Restaurant adoption ~ young share	0.139	0.129	(0.046)
Restaurant adoption ~ population density	0.032	0.029	(0.002)
Platform sales ~ restaurant adoption	1.527	2.094	(0.519)
Platform sales ~ population density	0.323	0.274	(0.050)

Notes: Table 11a displays estimates from a ZIP-level regression of the share of restaurant orders placed on food delivery platforms on various local demographic characteristics both (i) data simulated from the estimated model (“Model”) and (ii) the estimation sample (“Data”), as well as standard errors from the latter regression. The included local demographics are (i) the share of the population under 35 years old, (ii) the share that is married, and (iii) the share with household income over \$40k.

Table 11b displays estimates from ZIP-level regressions of (i) the share of restaurants in the ZIP that belong to at least one online platform on the share of the population within five miles that is under 35 years old, (ii) the share of restaurants that belong to at least one online platform on the log population within five miles, (iii) the mean number of platform orders placed by a consumer in a ZIP on the share of restaurants belonging to at least one platform, and (iv) the mean number of platform orders on the log population within five miles.

the share of restaurants on a platform as the regressor. Last, I regress the mean number of platform orders per consumer on the population density measure. The coefficients are similar across regressions for both specifications, and the model-regression coefficients lie within their corresponding data-regression coefficients’ 95% confidence intervals. These results suggest that the model captures empirical relationships between restaurants’ platform adoption, consumers’ platform usage, and local demographics well. Note that the model predicts greater platform usage by consumers in denser areas because (i) their demographics are favourable to platform ordering, as denser areas tend to have more young, unmarried, and high income consumers, and (ii) platforms offer greater variety of restaurants in denser areas. Greater consumer tastes for platform ordering in dense areas leads more restaurants to join platforms in these areas. Additionally, the estimated model implies effects of commission caps similar to those estimated using DiD methods in Section 3. I elaborate on this comparison in the proceeding section.

## 7 Counterfactual analysis

### 7.1 Evaluation of commission caps

With the estimated model in hand, I turn to the evaluation of commission caps. I evaluate commission caps by comparing equilibria in each metro with and without 15% caps on platforms’ commission rates. Table 12 reports effects of commission caps on platform usage and prices. As expected from the DiD evidence presented in a preceding section, caps boost restaurant adoption of platforms, lead platforms to raise their fees, and lead restaurants to reduce their prices on platforms. Platforms’ fee increases are larger than restaurants’ price reductions, and

the increase in the total cost of ordering from platforms is sufficiently large to reduce platform sales despite the increase in restaurants' participation on platforms. These estimated effects are quantitatively similar to those obtained through DiD analysis. The DiD estimate of the effect of 15% commission caps on the share of restaurants online is 3.90 p.p., whereas the model estimate (in terms of p.p. rather than the percentage change) is 3.74; the DiD estimate of the effects on the number of restaurant listings on platforms is 10.00% compared to the model-based estimate of 8.36%; and the DiD estimate of DoorDash's fee change is 78.98% compared to the model-based estimate of 79.17%. The fit for price is somewhat less close: the DiD estimate of restaurant price reduction on platforms is 6.18% compared to the model-based estimate of 14.73%.<sup>31</sup> A caveat in this comparison is that the DiD estimates are for average effects across places that factually adopted caps in the US at large in 2020–2021, whereas the model-based estimates apply to the 14 large metros on which the model was estimated in Q2 2021, irrespective of their historical commission cap policies.

Figure 7 describes the welfare implications of equilibrium responses to commission caps. The plot displays a cumulative addition of the effects of caps on consumer surplus, restaurant profits, and platform profits to obtain the total welfare effect of caps. The effects are displayed as shares of participant surplus, i.e., the joint surplus of consumers and restaurants from platforms.<sup>32</sup> There are several notable welfare effects. First, as intended, restaurants benefit from caps, and their benefit is about 18% of participant surplus from platforms. Most of the benefit to restaurants accrues to independent restaurants—the bar with “I” indicates independent restaurants’ gains, whereas the bar with “C” indicates chain restaurants’ gains—suggesting that governments that introduced caps accomplished their objective of helping local independent restaurants via commission caps. However, this aid to restaurants primarily comes at the expense of consumers. The leftmost dark yellow bar shows consumer losses from caps, which amount to about 18% of participant surplus. Consumer losses from caps need not equal restaurant gains — in some metros, the former is larger than the latter, and in others the reverse holds. These two quantities, though, are close to equal in aggregate under the estimated model; this means that 15% caps imposed uniformly across the metros under analysis would transfer surplus from consumers to restaurants essentially one-for-one. Given that platform profits fall by about 8% of participant surplus, commission caps ultimately reduce total welfare.

Consumer losses and overall efficiency losses from caps are mitigated by equilibrium restaurant responses. First, the light yellow bar in Figure 7 shows the additional welfare reduction the consumers suffer when the researcher does not account for increased restaurant uptake of platforms. This additional amount equals 59% of consumer loss from caps. This result indicates both the importance of accounting for participation on the seller side of the market in comput-

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<sup>31</sup>I list here the DiD analyses that generated the results mentioned in the main text. The DiD estimate of the effect of caps on the share of restaurants online is the two-period DiD whose results appear in Online Appendix Table O.15a. The DiD estimate of the effect of caps on the number of restaurant listings on platforms is from a static variant of the dynamic DiD whose results appear in Figure 5a. The DiD estimate of the effect of caps on fees is the terminal effect from the dynamic IW estimator as plotted in Figure 2b. The DiD estimate of the effect on restaurant prices is that displayed in Table 4, converted from log points to percentage.

<sup>32</sup>As detailed in Section 7.6, I use my model to estimate the participant surplus associated with delivery platforms, i.e., the sum of consumer and restaurant surplus from platforms.

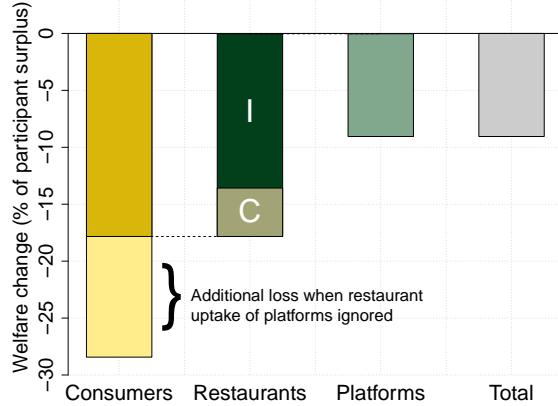
Table 12: Aggregate effects of 15% commission caps

Outcome	Effect	SE
Share of restaurants online (pct)	5.82	(0.31)
Number of restaurant listings (pct)	8.36	(0.42)
Average consumer fee (dollars)	4.69	(0.05)
Average price on platforms (dollars)	-4.10	(0.04)
Platform-intermediated sales (pct)	-3.37	(0.27)

Notes: this table reports estimated effects of 15% commission caps on outcomes aggregated across metros. I obtain the standard errors using the bootstrap procedure described in Appendix D.

ing welfare on the buyer side in multi-sided settings and the role of seller responses in driving the effects of policies in platform markets. I additionally compute equilibria in which restaurants are barred from either changing their prices or changing their platform adoption decisions from the baseline equilibria without caps. Table 13 provides aggregate welfare results in terms of dollars per resident of the analyzed markets on an annual basis. Restaurant responses to caps markedly reduce their profit gains from caps, but limit consumers’ and platforms’ losses in addition to the overall efficiency loss from caps — that is, restaurants compete away their direct gains from caps in a manner that benefits consumers. This result establishes the importance of seller responses in dampening the direct effects of policies in a multi-sided market.

Figure 7: Welfare effects of 15% commission cap relative to participant surplus from platforms



Notes: this figure plots aggregate welfare effects of 15% commission caps as a share of participant surplus from delivery platforms, proceeding cumulatively from consumers to restaurants and then platforms. “I” indicates the effect on independent restaurants’ profits whereas “C” indicates the effect on chain restaurants’ profits.

Although I do not explicitly model couriers, the assumption that platforms’ marginal costs represent courier compensation permits analysis of caps’ effects on courier pay. Commission caps reduce aggregate courier pay across markets by 3.6%, or \$2.52 per capita annually. Fisher (2023), who studies courier surplus in the UK food delivery industry, finds that couriers’ surplus amounts to 70–80% of their pay. This result suggests that commission caps significantly harm couriers in addition to consumers. In addition, I rule out platform quality adjustments to commission caps based on my finding of minimal waiting time variations between places with and without caps. But it is plausible that platforms could respond to commission caps

Table 13: Welfare effects of 15% commission cap under alternative restaurant responses (\$, per capita, annual)

Outcome	No adoption response	No pricing response	All responses
Consumer surplus	-5.59 (0.36)	-20.38 (1.36)	-3.35 (0.30)
Restaurant profit	5.29 (0.27)	12.66 (1.11)	3.35 (0.27)
Platform profit	-3.93 (0.24)	-19.36 (1.18)	-1.70 (0.21)

Notes: this table reports effects of 15% commission caps on welfare outcomes aggregated across metros under (i) no responses of restaurants' platform adoption decisions, (ii) no response of restaurant prices, and (iii) under all equilibrium restaurant responses to caps. The figures are reported on an annual dollar basis, divided by the combined population of the metros in question.

by reducing spending on platform quality (e.g., by adding advertisements or reducing courier compensation, thus raising wait times), harming consumers in a manner similar to fee hikes. Last, I additionally rule out an effect of caps on restaurant survival or entry. A cap's potential effect in raising the number of active restaurants in equilibrium would further mitigate caps' harms to consumers.

I conduct an analysis of caps with alternative baseline equilibria in which chain restaurants pay commissions of 25% rather than 30% to gauge how chains negotiating lower commissions than independent restaurants would affect the results. Online Appendix Tables O.24 and O.25 report the results. As in the primary analysis with 30% chain commissions in the baseline, caps benefit restaurants while reducing platform profits, consumer surplus, and total welfare. One difference from the primary analysis is that, although independent restaurants enjoy a \$5.24 per capita profit increase from caps annually, chain restaurants' profits fall by \$1.60 per capita annually. This reflects that, when chains face lower commission rates in the baseline, caps reduce their commission rates by less than they do for independents; this strengthens the competitive position of independents relative to chains. Independents' deeper commission reductions lead them to reduce their prices more so than chains, inducing consumers to substitute from chain restaurants to independent restaurants, thus reducing chains' profits.

## 7.2 Distributional effects of commission caps

The effects of commission caps vary across consumer demographic groups and geography. I assess spatial heterogeneity in caps' effects via a ZIP-level regression of mean consumer welfare loss on various ZIP characteristics, including the share of the ZIP's population that is under 35 years old, the share that is married, the share with an income over \$40k, and the population within five miles of the ZIP ("Pop density"). Table 14 provides the results. First, note that the limited set of ZIP characteristics included as regressors explains a significant share of spatial heterogeneity in caps' effects; the  $R^2$  of the regression is 0.36. In addition, places that have more young people, more unmarried people, and more people with household incomes over \$40k suffer more from commission caps. This reflects that these groups use platforms more in the

baseline, thus exposing them to greater adverse effects of platform fee hikes. In addition, places with greater population density suffer more from commission caps. Figure 8, which displays a nonparametric ZIP-level regression of consumer welfare changes on log population density, elaborates on this finding. People in denser areas tend to use delivery platforms more than those in less dense areas both in the model and the raw data (see Table 11b), thus exposing them to greater harms from platform fee hikes.

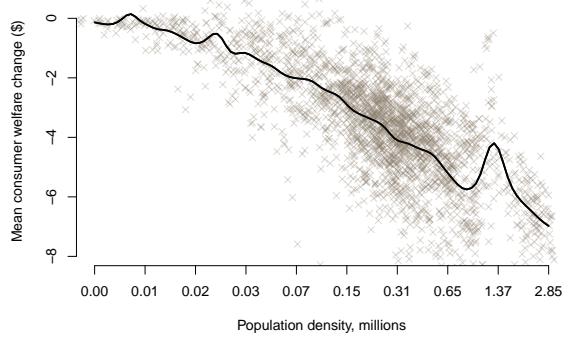
Restaurant profit effects of caps also vary spatially. Figure 9 displays nonparametric ZIP-level regressions of 15% commission caps' restaurant profit effects on population density for chain and independent restaurants separately. The effects are similar for the two types of restaurants, and they are greater in areas with higher population density. This is because restaurant uptake of platforms is higher in dense areas and a greater share of orders are placed on platforms in these areas. This disproportionately exposes restaurants in dense places to caps.

Table 14: Correlates of consumer welfare effects

Variable	Coef.	SE
Constant	-2.63	0.19
Share under 35yo	-0.66	0.27
Share married	1.92	0.21
Share income over \$40k	-1.41	0.23
Pop density	-1.83	0.06
$R^2$	0.36	
N	2423	

Notes: this table reports results from a ZIP-level regression of the mean dollarized consumer welfare loss in a ZIP on (i) the share of the ZIP's population that is under 35 years old, (ii) the share of the population that is married, (iii) the share of the ZIP with a household income over \$40k, and (iv) the population density, defined as population (in millions) within 5 miles of ZIP.

Figure 8: Consumer welfare and population density



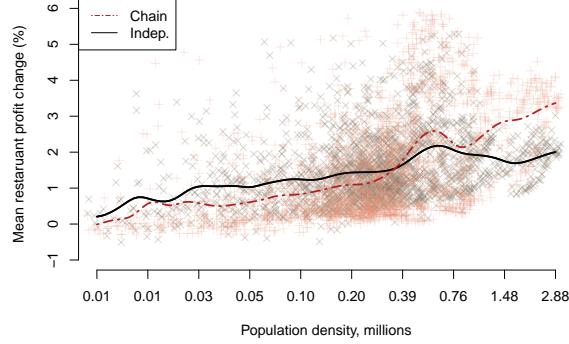
Notes: this figure displays results from a ZIP-level Nadaraya-Watson kernel regression of mean consumer welfare changes (annual) from 15% commission caps on the log population (in millions) of the area within five miles of a ZIP. I use a Gaussian kernel and bandwidth of 0.1 in the regression. The "x" points represent ZIPs.

### 7.3 Alternative commission caps

Negative effects of 15% commission caps on consumer welfare and total welfare do not rule out positive effects of capping commissions at higher or lower levels. To determine how the effects of alternative caps compare to those of 15% caps, I compute equilibria under caps from 2% to 29% and compare them to the baseline equilibrium wherein commission rates equal 30%. Figure 10 provides results for Chicago and Philadelphia.<sup>33</sup> Caps have monotonic effects on each component of total welfare in Chicago. In Philadelphia, however, levels of caps higher than 20% slightly boost total welfare. This result confirms the theoretical possibility under the model of welfare improvements from caps. Although platforms' commissions are suboptimally high in Philadelphia, the extent of suboptimality is small; gains from capping commissions are slight relative to caps' distributional effects. Platforms seem to balance consumer fees and

<sup>33</sup>I select Chicago and Philadelphia for illustrative purposes; the other market follow the qualitative pattern of either the former or the latter.

Figure 9: Restaurant profits and population density

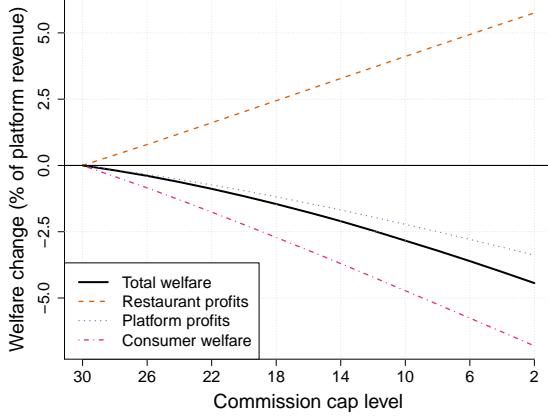


Notes: this figure displays results from ZIP-level Nadaraya-Watson kernel regressions of mean relative restaurant profit changes from 15% commission caps on the log population (in millions) of the area within five miles of a ZIP. I use a Gaussian kernel and bandwidth of 0.1 in the regressions. The “+” and “x” points represent ZIPs for chain and independent restaurants, respectively.

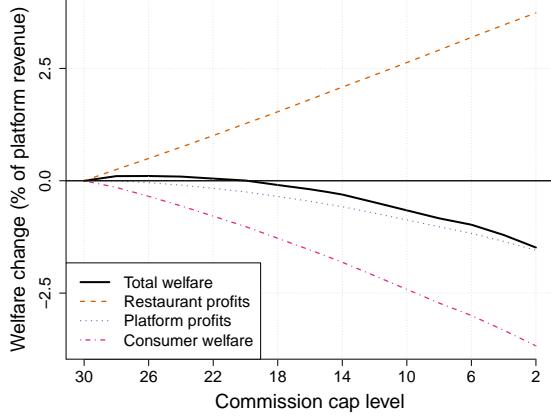
restaurant commissions fairly efficiently; there is little scope for commission caps to correct Spence distortions.

Figure 10: Welfare effects of alternative commission caps

(a) Chicago metro



(b) Philadelphia metro

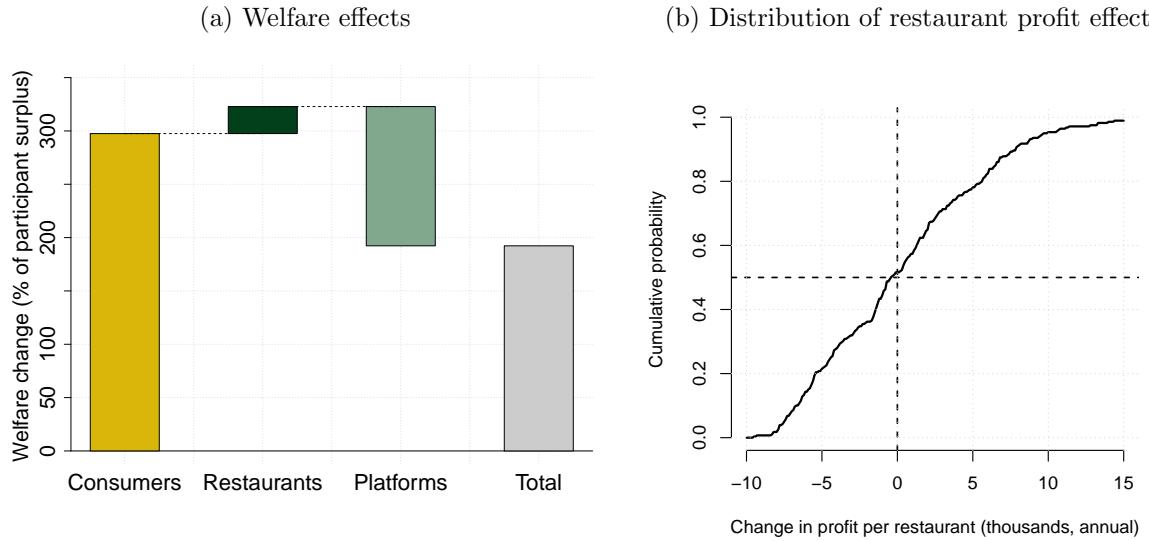


Notes: this plot provides welfare effects of capping commissions at levels between 30% and 0% as a share of total platform revenue in the baseline equilibrium.

#### 7.4 A two-sided cap

Commission caps boost restaurant profits at the expense of consumers, but it is plausible that a cap on both restaurants commissions and on consumer fees could make both sides of the market better off. To evaluate this possibility, I simulate a 15% commission cap combined with a cap of \$1.00 on platform consumer fee increases relative to the baseline. This analysis comes with the caveat that excess caps on platform revenue may induce platform exit or changes in platforms’ business models. Figure 11a provides the welfare effects of such a two-sided cap aggregated across markets. Although the two-sided cap raises overall welfare and participation on

Figure 11: Welfare effects of two-sided cap relative to participant surplus from platforms



Notes: Panel 11a plots aggregate welfare effects of a 15% commission cap combined with a \$1.00 cap on consumer fee increases relative to participant surplus. Panel 11b plots the distribution of restaurant profit effects of this two-sided cap.

platforms—the share of restaurants on a platform rises by 18 p.p. and the number of restaurant orders rises by 7.1%—aggregate restaurant profit gains are small relative to the total welfare gain. Furthermore, about half of restaurants are less profitable due to the cap. Figure 11b, which displays the distribution of restaurant profit effects of the two-sided cap, highlights this finding. A two-sided cap can make restaurants worse off because it makes platforms more attractive to consumers — it expands the variety of restaurants available on platforms and reduces restaurant prices on platforms. Thus, a two-sided cap induces switching from direct ordering to platform ordering, thus undermining restaurant profitability. Indeed, the share of orders placed directly by consumers falls by 18% under the two-sided cap. This result rationalizes restaurant lobbying for a cap on only commissions and not one that also applies to consumer fees. It also illustrates a counterintuitive fact of digital platform markets — measures that bring more online business to platform sellers may undermine seller profitability due to substitution between online and offline channels.

## 7.5 Taxing commissions

Commission caps lower welfare by distorting platforms’ balance of consumer fees and restaurant commissions in a manner that reduces consumer platform usage. I investigate whether a tax on platforms’ commission revenue could avoid this distortionary impact. Revenues from this tax are assumed to be remitted to all restaurants irrespective of their platform adoption decisions in a lump sum. Besides directly providing revenue to restaurants, a commission tax penalizes commissions as a revenue source for platforms; thus, commission taxes could lead platforms to reorient their price structures away from commissions and toward fees. Table 15 reports effects of both a 15% commission cap and a 2% commission tax for Miami.<sup>34</sup> Note that the sum of the

<sup>34</sup>I choose 2% as it yields a similar gain in restaurant profits between the cap and tax.

change in restaurant profits and the change in government revenue is similar for each policy. Consumers and platforms, however, are better off under the tax. Although a tax alters platform pricing incentives, its distortion of platforms' price structures is smaller than that of the cap. Consequently, reductions in consumers' platform orders and consumer welfare are smaller. The results for other markets are similar to those for Miami.

Table 15: Comparison of 15% commission cap and 2% commission tax, Miami

Change in...	Cap	Tax
Avg. ordering cost (\$)	0.55	0.35
Avg. commission rate (p.p.)	-15.00	-9.52
Shr. adopting a platform (p.p.)	2.45	1.66
Platform orders (%)	-4.86	-2.91
Restaurant profits (\$ p.c.)	2.56	2.61
Platform profits (\$ p.c.)	-2.74	-2.69
Consumer welfare (\$ p.c.)	-4.85	-3.01

Notes: welfare changes are reported in dollars per market resident over the age of 18 on an annual basis, denoted “\$ p.c.” “Avg. consumer fee” and “Avg. commission rate” are averages weighted by sales in the baseline equilibrium. “Avg. platforms adopted” gives the change in the average number of online platforms that a restaurant in the market adopts. “Shr. adopting a platform” gives the percentage point change in the share of restaurants that join at least one online platform. The symbol “(%)” indicates a percentage rather than absolute change.

## 7.6 Effects of online platforms on the restaurant industry

Although delivery platforms offer a valuable service to consumers, the effect of platforms on restaurant profitability is theoretically ambiguous. This is because platforms have countervailing market expansion and cannibalization effects — platforms raise restaurant sales, but sales on platforms may cannibalize restaurants' commission-free direct sales. Platform membership also entails fixed costs. To evaluate the effects of platforms on the restaurant industry, I consider a counterfactual in which platforms are eliminated. Savings on platform fixed costs should be accounted for in an analysis of the overall welfare effects of eliminating platforms. Rather than estimate fixed costs, I compute welfare outcomes under two scenarios: (i) platform fixed costs equal zero, and (ii) platform fixed costs equal to platform variable profits. Changes in total welfare under these scenarios provide sharp lower and upper bounds on the total welfare effects of eliminating platforms when both platform profits and fixed costs are non-negative.

The analysis of eliminating platforms is intended to illustrate the fundamental trade-off between market expansion and cannibalization in shaping platforms' effects on restaurant profits rather than to yield detailed, realistic estimates of the overall effects of abolishing platforms. Indeed, the analysis does not account for changes in the business model of food delivery that would occur upon the elimination of platforms — restaurants may begin to offer their own delivery service, or contracting services may take the place of platforms in fulfilling deliveries.

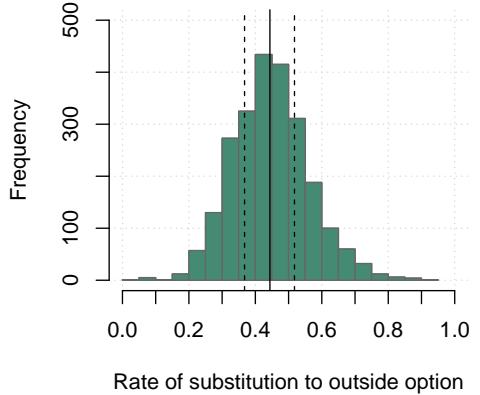
Figure 12 provides a histogram across ZIPs of the share of platform orders that divert to the outside option of not ordering from any restaurant when platforms are eliminated. This histogram characterizes the market expansion effects of platforms. Indeed, if all orders diverted to the outside option, then every order on platforms would represent market expansion. In this

Figure 12: Market expansion effects

Table 16: Welfare effects of eliminating platforms (\$ per capita, annual)

Outcome	Effect	SE
Consumer welfare	-48.05	(9.05)
Restaurant profits	29.21	(6.52)
Platform variable profits	-47.36	(4.12)
Total: lower bound	-66.20	(13.37)
Total: upper bound	-18.84	(13.17)

Notes: this table reports aggregate welfare effects of abolishing platforms across the analyzed markets in annualized dollar-per-capita terms. “Total: lower bound” is the total welfare effect when platforms have no fixed costs. “Total: upper bound” is the total welfare effect when platforms’ fixed costs equal their variable profits.



Notes: this figure displays a histogram across ZIPs of diversion ratios, each of which is defined as a ZIP’s increase in direct-from-restaurant orders divided by the ZIP’s reduction in platform-intermediated orders upon the elimination of platforms. The solid vertical line indicates the median diversion ratio whereas the dotted vertical lines indicate the 25th and 75th quantiles.

case, the histogram would concentrate at one. Conversely, a rate of substitution of zero would imply that all orders placed on platforms cannibalize orders placed directly from restaurants. The median share is about 45%; most platform orders cannibalize direct orders, but platforms also markedly increase the overall number of restaurant orders placed.

The market expansion effect of platforms, though, is not large enough to make platforms a boon for restaurants. Table 16 summarizes the welfare effects of eliminating food delivery platforms.<sup>35</sup> Even though platforms boost restaurant order volumes, they reduce restaurant profits. This reflects that platform adoption boosts a restaurant’s profits largely at the expense of its rivals. This situation is analogous to a firm’s ability to profit from undercutting its rival’s prices despite the fact that an industry-wide agreement to sustain high prices could raise the sum of firm profits. These results suggest that restaurant collusion against platform membership would be profitable for restaurants.

Although restaurants lose out platforms, consumers enjoy considerable surplus from them. This surplus is larger than restaurants’ profit losses from platforms. Given that—as discussed earlier—platform ordering is especially popular in areas with high population density, it is not surprising that consumer surplus is especially high in urban areas and much lower in rural areas. Figure 13 includes maps of mean consumer surplus in selected ZIPs surrounding Boston and San Francisco. In both maps, surplus is much higher in urban centres than in outlying areas.

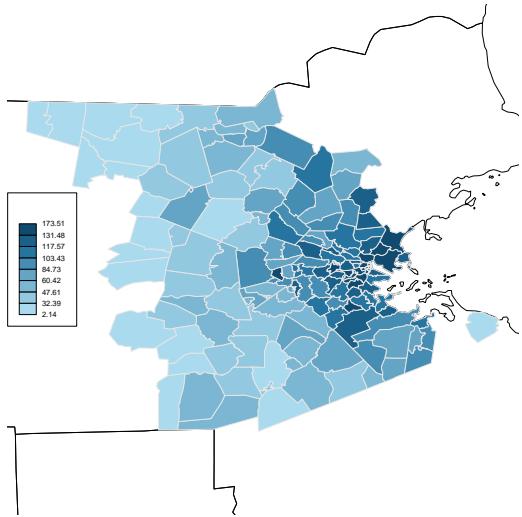
## 8 Conclusion

This article evaluates caps on food delivery platforms’ commission charges to restaurants. The primary contribution is to assess the role of simultaneous platform and seller responses in shap-

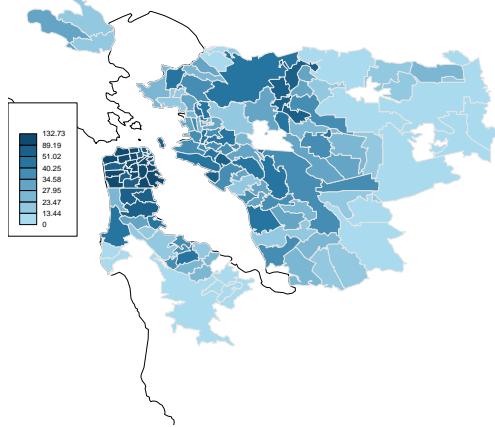
<sup>35</sup>See Online Appendix O.11 for market-specific results.

Figure 13: Spatial heterogeneity in consumer surplus from platforms

(a) Boston



(b) San Francisco



Notes: this figure plots annual per capita consumer surplus from food delivery platforms by ZIP in selected regions nearby Boston and San Francisco.

ing the effects of policies affecting platform commissions in multi-sided markets. One main finding is that commission caps benefit restaurants but undermine overall welfare and especially hurt consumers. This reflects that caps impede platforms from balancing restaurant commissions and consumer fees to induce both sides' participation — caps prompt consumer fee hikes that undermine ordering on platforms. Caps especially help restaurants and especially hurt consumers in places with high population density, where favourable demographics and a high variety of available restaurants make platforms more popular. With that said, responses of restaurants' prices and platform adoption decisions significantly blunt consumer harms, as restaurants reduce their prices on platforms and join more platforms as a result of caps. The result that seller responses may dampen the effects of platform price changes more generally applies to platform markets. Although I find that 15% caps reduce total welfare in the markets that I study, caps above 20% boost total welfare in some markets. Limits on commissions may generally boost efficiency in multi-sided markets when platforms' inframarginal consumers highly value restaurant variety and caps are effective in inducing seller entry onto the platform. In assessing commission caps in other platform markets, it is thus crucial to ascertain the participation responses of platform sellers and the possibility of caps to correct a Spence distortion. The article's additional analyses of a two-sided price cap and of platforms' elimination illustrate another general fact about digital platform markets: increased business on a digital platform may harm platform sellers when consumers substitute between online and offline purchasing. In assessing whether a platform regulation is likely to aid platform sellers, it is thus important to understand how the regulation will shift buyers' and sellers' interactions between online and offline channels.

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## APPENDICES

### A Delivery fee measures

In analyzing platform fees, I use hedonic indices  $DF_{fz}$  defined as expected delivery fees charged by platforms  $f$  in ZIPs  $z$  conditional on a set of fixed order characteristics:

$$DF_{fz} = \mathbb{E}[df_{kfz}|x_k = \bar{x}, f, z], \quad (18)$$

where  $df_{kfz}$  is the delivery fee charged for order  $k$  on platform  $f$  in ZIP  $z$ ,  $x_k$  are observable characteristics of order  $k$ , and  $\bar{x}$  is a fixed vector of order characteristics. I estimate (18) using a 10-fold cross-validated Lasso with delivery fee data from Q2 2021, and set  $\bar{x}$  to the average  $x_k$  across all orders in my sample. The estimating equation is

$$df_{kfz} = x'_k \beta_f + w'_z \mu_f + \phi x_k^{\text{dist}} w_z^{\text{dens}} + \epsilon_{kfz}, \quad (19)$$

where  $w_z$  are characteristics of ZIP  $z$  and  $\epsilon_{kfz}$  is an unobservable that is mean-independent of  $x_k$  and  $w_z$ ,  $f$ , and  $z$ . The observable characteristics included in  $w_z$  are municipality indicators; county indicators; CBSA indicators; local density defined as the population within five miles of ZIP  $z$ ; and several variables measuring the demographic composition of the area within five miles of  $z$ .<sup>36</sup> Note that I include indicators for multiple levels of geography because it is important for my empirical analysis to flexibly capture fee differences across geography. Last,  $x_k^{\text{dist}}$  is the delivery distance for order  $k$  and  $w_z^{\text{dens}}$  is the local density of  $z$ ; I include their interaction to capture the possibility that the cost of increasing an order’s distance depends on density due to traffic congestion.

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<sup>36</sup>These variables include the shares of the population in various age groups, the share of the population over 15 years of age that is married, and the shares of the population over 18 years of age having achieved various levels of educational attainment.

There are several problems in estimating (19) by OLS: OLS is prone to overfitting in settings with many regressors, and using OLS would require a somewhat arbitrary selection of a non-collinear set of geographical indicators to include in  $w_z$ . The Lasso does not suffer from these problems.<sup>37</sup> In my setting, the Lasso provides a data-driven method for selecting geographical indicators for inclusion in  $w_z$  based on their relevance in predicting delivery fees. It is only the coefficients for geographical characteristics  $w_z$  that I penalize in estimation. I apply the procedure explained above with delivery-fee records substituted for waiting-time records to compute hedonic indices of expected waiting times.

## B Restaurant price measures

I use hedonic restaurant price indices at the platform/region level in estimating the model. Variation in the indices reflects variation in the prices of restaurant menu items with the same characteristics across platforms and places. The hedonic indices are based on the following hedonic regression:

$$\log p_{ifzt} = \vartheta_f + \beta_{\text{cap}} \text{cap}_z + \beta_{\text{cap}/\text{online}} \text{cap}_z \times \text{online}_f + x'_{ift} \beta + \varepsilon_{ifzt}, \quad (20)$$

where  $i$  denotes a menu item,  $f$  denotes a platform,  $z$  denotes a ZIP, and  $t$  denotes an order. Additionally,  $\vartheta_f$  is a platform fixed effect,  $\text{cap}_z$  is an indicator for a commission cap in ZIP  $z$ ,  $\text{online}_f$  is an indicator for  $f$  being an online platform (i.e.,  $f \neq 0$ ),  $x_{ift}$  are observed item/order characteristics, and  $\varepsilon_{ifzt}$  is a regression disturbance. The observed item/order characteristics included in  $x_{ift}$  are category fixed effects (e.g., French fries, fountain soda), brand fixed effects (e.g., McDonald's, Pizza Hut), and—for independent restaurants—characteristics extracted from the restaurant name. I generate these latter characteristics by identifying the 100 most common words appearing in the names of independent restaurants and constructing indicator variables equal to one if the word appears in the restaurant's name and zero otherwise. I run regressions separately for each market and, within each market, separately for chain and for independent restaurants.

The hedonic price index for  $(f, z)$  is

$$p_{fz} = \bar{p} \times \exp(\vartheta_f + \text{cap}_z + \beta_{\text{cap}} \text{cap}_z + \beta_{\text{cap}/\text{online}} \text{cap}_z \times \text{online}_f),$$

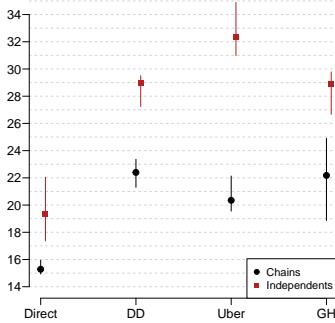
where  $\bar{p}$  is a factor that determines the absolute magnitude of the price indices (but does not affect their relative values across  $f$  and  $z$ ). I set  $\bar{p}$  so that the price index for DoorDash in a place without a commission cap equals the average basket subtotal for DoorDash. It is possible to estimate indices specific to platform subsets  $\mathcal{G}$  to which restaurants belong, but this significantly raises the variance of the estimated price indices in practice. It is for this reason that I do not estimate separate indices for each  $(f, \mathcal{G}, z)$  triple. Figure 14 displays the median and interquartile range of restaurant price indices across metros  $m$  for each platform  $f$  in places without commission caps.<sup>38</sup>

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<sup>37</sup>See Tibshirani (1996) for explication of the Lasso.

<sup>38</sup>In the Seattle metro area, all ZIPs had commission caps. Therefore, the indices for ZIPs in Seattle with caps were used in constructing the figure.

Figure 14: Restaurant price indices (medians and interquartile ranges)



Notes: the figure displays the median and interquartile range of price indices for each platform across metro areas in places.

## C Market size

I set the number of consumers in each ZIP and the distribution of their demographic types (i.e., ages, marital statuses, and incomes) using a combination of the Edison, Numerator, and ACS data. I tentatively set the number of consumers in each ZIP to the ACS estimate of the ZIP’s population. I then set the distribution of consumers across demographic types equal to the distribution among Numerator panelists in the ZIP. For ZIPs with fewer than 10 panelists, I instead set the distribution equal to that in the sets of ZIPs within five miles. Next, I compute an equilibrium in prices conditional on observed restaurant platform adoption, fees, and commissions in April 2021. The ratio of the number of platform orders in the metro from the Edison sales estimates dataset for April 2021 to the expected number of orders in this equilibrium provides a factor by which I multiply each ZIP’s tentative number of consumers. After scaling by this factor, the model’s predictions of metro-level sales align with the Edison estimates.

## D Bootstrap procedure

This appendix describes the article’s bootstrap procedure. The procedure has, first, a parametric part that involves drawing from the estimated asymptotic distribution of the consumer choice model estimator. I estimate the asymptotic variance of this estimator using the outer product of the gradients estimator. I then take  $B = 100$  draws from the associated estimate of the asymptotic distribution of  $Z = \sqrt{n}(\hat{\theta}^{\text{cons}} - \theta_0^{\text{cons}})$ , where  $\theta_0^{\text{cons}}$  is the true choice model parameter vector,  $\hat{\theta}^{\text{cons}}$  is the maximum likelihood estimator, and  $n$  is the sample size. Let  $Z^b$  denote the  $b$ th draw, and let  $\hat{\theta}^{\text{cons},b} = \hat{\theta}^{\text{cons}} + n^{-1/2}Z^b$ . I estimate restaurants’ and platforms’ marginal costs, call them  $\hat{mc}^b$ , under each  $\hat{\theta}^{\text{cons},b}$ . For each  $b$ , I also take a bootstrap draw of restaurants within ZIP and type. Let  $\mathcal{J}^b$  denote the  $b$ th draw. I proceed to estimate the parameters of the platform adoption game at  $\{\hat{\theta}^{\text{cons},b}, \mathcal{J}^b, \hat{mc}^b\}$  for each  $b$ , obtaining estimates  $\hat{\theta}^{\text{adopt},b}$  for each  $b$ . The standard errors that I report for these parameters are the standard deviations of the parameters across bootstrap replicates. I similarly estimate the weights  $h_{fm}$  at  $\{\hat{\theta}^b, \hat{mc}^b, \hat{\theta}^{\text{adopt},b}\}$  for each  $b$ , yielding estimates  $\hat{h}_{fm}^b$ . Last, I solve for equilibria at each  $b$  and take the standard deviation of outcomes across replicates  $b$  to obtain standard errors.