Price Controls in a Multi-Sided Market[*]

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Abstract

This paper evaluates caps on the commissions that food delivery platforms charge to restaurants. Commission caps may lead restaurants to join platforms and to post lower prices on platforms, thereby benefitting consumers. But caps may also lead platforms to raise their consumer fees, thereby reducing ordering on platforms and consequently platforms' value to restaurants. The net welfare effects of caps are thus uncertain. To quantify these effects, I estimate a model of pricing and platform adoption in a multi-sided market using data on consumer restaurant orders, restaurants' platform adoption, and platform fees. Counterfactual simulations imply that commission caps reduce overall welfare, bolstering restaurant profits at the expense of platforms and especially consumers.

1 Introduction

The effects of policies on platform markets generally depend on equilibrium responses of all market participants connected by the affected platforms. This paper provides an empirical evaluation of a particular class of policies targeting a platform market: commission caps in the food delivery industry. Many US cities have capped the commissions that food delivery platforms (e.g., DoorDash) charge to restaurants. Commission caps have effects on the welfare of restaurants and consumers that depend on countervailing responses of these two groups of market participants. These responses, which reflect the multi-sided nature of the food delivery industry, complicate the analysis of commission caps relative to that of price controls in standard one-sided markets. Caps may entice restaurants to join platforms, which would benefit consumers who value the breadth of platforms' restaurant networks. Restaurants may also reduce their prices in response to a reduction in commissions. But commission caps may lead platforms to raise the fees that they charge to consumers. This would harm consumers. It would also reduce consumer ordering on platforms and consequently the value of platform membership to restaurants. An increase in platforms' fees, though, could lead consumers to switch from ordering from restaurants using food delivery platforms to ordering directly from restaurants. This benefits restaurants, who pay no commissions on sales made directly to consumers. Due to the presence of offsetting effects of commission caps on restaurant profits and consumer welfare as outlined above, the net effects of caps on the welfare of platform participants are uncertain.

This paper empirically assesses the net effects of commission caps on consumer welfare, restaurant profits, and platform profits. To this end, I assemble data characterizing the US food delivery industry. 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 monthly data on estimated ZIP-level platform sales and average platform fees and on all restaurants listed on each major delivery platform. Last, 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.

As a first pass, I compute difference-in-differences estimates of caps' effects. Estimates exploiting the staggered rollout of caps across municipalities suggest that caps raised fees by 7–20% across platforms, reduced the number of orders placed on platforms by 7%, and raised the share of restaurants that join at least one platform by 3.9%. 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 platform fee hikes, but that these harms are mitigated by an increase in the selection of restaurants available on platforms. They also suggest that restaurants benefit from a diversion away from platform ordering and towards direct ordering.

I subsequently develop a model of the food delivery industry with which to quantify welfare effects, to assess mechanisms contributing to these effects, and to evaluate alternative policies

intended to bolster restaurant profitability. In the model, platforms first set commission rates. Next, restaurants choose which platforms to join to optimize profits in a discrete game of incomplete information. After joining platforms, restaurants set profit-maximizing prices that may differ between direct-from-restaurant orders and orders placed on platforms. Platforms at the same time set fees charged to consumers 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 network externalities affecting both sides of the platform market: consumers are more likely to choose a platform with a wide variety of restaurants, and restaurants earn higher profits from joining a platform that is more popular among consumers (all else equal) because their incremental sales are higher from joining such a platform. Heterogeneity in consumer tastes for platforms influences how consumers substitute between platforms and the alternative of ordering directly from a restaurant. Consumers who are highly polarized in their tastes for platform ordering, for example, are unlikely to substitute between ordering from a platform and ordering directly from a restaurant. This would imply that platforms could lead consumers who would not otherwise order from restaurants to do so using a platform, thus boosting overall restaurant sales.

Estimation proceeds in multiple steps. The first step is maximum likelihood estimation of consumer preferences. Next, I estimate platforms' and restaurants' 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 costs of platform adoption to match (i) market-specific platform adoption frequencies and (ii) the covariance of the profitability of platform adoption with platform adoption.

The main parameters of interest in the consumer choice model are those that govern price sensitivity, network externalities, and substitution patterns. The endogeneity of platform fees and restaurant networks—both of which depend on local 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 local commission cap policies. My approach for estimating substitution patterns exploits the data's panel structure, which characterizes how consumers switch between alternatives across orders.

I use the estimated model to compare equilibria with and without a 15% commission cap. Counterfactual simulations imply that commission caps raise restaurant profits, reduce consumer welfare, and reduce platform profits. The sum of caps' effects on these components of total welfare is negative. The increase in restaurant profits across metro areas is 3.0% of the sum of participant surplus (i.e., the effect of platforms' availability on the sum of consumer welfare and restaurant profits, which is positive). The total welfare loss is 6.2% of participant surplus. Consumer welfare falls by 5.3% of participant surplus; this welfare loss exceeds the platform profit losses from a cap of 3.9% of participant surplus. Although consumers pay more for food delivery orders under commission caps, they benefit from the increased selection of

restaurants available on platforms and restaurant price reductions. Failing to account for increased restaurant adoption of platforms due to commission cap leads to an overstatement of caps' harms to consumers of over 60%. Absent any restaurant price response to caps, consumer losses would be ten times greater. These results reflect the broader principle that multi-sided markets feature numerous prices and quantities that may respond to policies in a manner that dampens their direct effects.

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 may obtain the increases in restaurant profits from a cap without negative effects on total welfare. One such policy is a cap on commissions combined with a cap on platforms' consumer fees. I find that such a policy does in fact raise total welfare, but it may hurt restaurants by inducing consumers to switch from direct-from-restaurant ordering to ordering through platforms; such substitution reduces restaurant profits because restaurants do not pay any commission on sales made directly to consumers. This result relates to another broader principle — in digital platform markets, substitution between online and offline channels may imply that, counterintuitively, 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 appropriately selected tax rate, this policy achieves the increase in restaurant profitability associated with a commission cap without a significant reduction in total welfare. Although a tax induces platforms to reduce commissions and raise consumer fees, it is less distortionary than a cap.

In addition to evaluating commission caps, I evaluate a common premise for commission caps: that platforms reduce restaurant profits. Platforms help restaurants by boosting overall restaurant sales, but hurt them by charging commission. A counterfactual simulation suggests that roughly half of restaurant orders placed on platforms would not be placed if platforms were eliminated. Additionally, platforms provide significant value to consumers; eliminating them reduces consumer welfare by almost $70 annually per capita on average across metro areas. Restaurant profits, however, increase by over $18 per capita a year on average across markets when platforms are abolished. 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. This result explains the paradoxical coincidence of restaurants' voluntary platform membership with complaints that platforms reduce restaurant profitability.

1.1 Related literature

This article makes several contributions to the empirical platforms literature.[1] Its primary contribution is to estimate effects of price controls in a platform market. There is extensive research on price controls,[2] but limited research on their application in multi-sided markets other than payment card markets. As noted in the introduction, responses of the multitudes of prices and quantities in multi-sided markets complicates the analysis of price controls in these markets. See Schmalensee and Evans (2005) for an overview of payment card interchange fee regulation, and Rysman (2007), Carbó-Valverde et al. (2016), and Huynh et al. (2022) for empirical studies of payment cards as platforms. Evans et al. (2015), Manuszak and Wozniak (2017), Kay et al. (2018), Wang (2012), Chang et al. (2005), Carbó-Valverde et al. (2016), Li et al. (2020), and Wang (2023) are examples of papers studying study payment card fees and their regulation. I add to this literature by developing and estimating a model to study the welfare effects of price controls in multi-sided setting with distinct features. A major part of my contribution is the analysis of seller prices and platform adoption responses to caps and of substitution between the online and offline channels of ordering, which I find to be important determinants of caps' effects. Futhermore, seller responses and online/offline substitution feature in many digital platform markets (e.g., e-commerce). Economic research on food-delivery commission caps is, to the best of my knowledge, limited to Li and Wang (2021). Li and Wang (2021) study the effects of caps on restaurant sales and delivery fees using a difference-in-differences research design. I complement their work by additionally estimating effects of caps on welfare and other outcomes (including sales, other fees, and platform adoption by restaurants).

Another contribution of my article is in evaluating the impacts of food delivery platforms on the restaurant industry. A recent literature assesses the welfare implications of digital platforms and their effects on established industries; see, for example, Castillo (2022), Calder-Wang (2022), Schaefer and Tran (2020), and Farronato and Fradkin (2022) for analyses of the ride-hailing and short-term accommodations industries. I contribute to this literature by assessing the impacts of food delivery platforms on the restaurant industry. Estimates of network externalities are important inputs in this assessment; my works draws from a literature on the modelling and estimation of 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—in the food delivery context—Natan 2022).

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 menu prices.[3] Robles-Garcia (2022) models decentralized pricing in

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[1] This literature often calls these markets two-sided markets or platform markets. I use these terms interchangeably. For overviews of the theory of multi-sided markets, see Rochet and Tirole (2006), Rysman (2009), and Jullien et al. (2021).

[2] 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).

[3] The most popular US ride-hailing platforms (Uber and Lyft) use centralized pricing. See Chen et al. (2019), Rosaia (2020), Buchholz et al. (2020), Cook et al. (2021), Cohen et al. (2016), Ming et al. (2020) for analysis of ride-hailing platforms with centralized pricing, and Gaineddenova (2022) for analysis of a ride-hailing platform

a two-sided market, but in a setting without an online/offline price distinction. Other papers 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 the food delivery industry 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 food ordering platform.[4] My paper also relates to work on 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 menu prices.

1.2 Roadmap

The remainder of my paper proceeds as follows. Section 2 provides background on the US food delivery industry and introduces my data. Section 3 presents empirical facts that inform my modelling choices. Section 4 develops the model. Section 5 outlines my estimation procedure. Section 6 reports estimation results. Section 7 describes the counterfactual analyses.

2 Data and background

2.1 Industry background

The major US food delivery platforms in 2020–2021 were DoorDash, Uber Eats, Grubhub, and Postmates.[5] 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,

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

where p is restaurant's menu-item price, c is the fee, and r is the commission. Average basket subtotals before fees, tips, and taxes were slightly below \$30 across platforms in Q2 2021.[6]

Throughout this article, I assume that the commission rates for all leading platforms were 30% in areas without active caps. Both Uber Eats and Grubhub charged 30% commissions in 2021. DoorDash's full-service membership tier featured a commission rate of 30% in April 2021.[7] Postmates did not publicly disclose its commissions. I cannot rule out the possibility of

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with decentralized pricing.

[4]Additional papers analyzing Yelp include Luca and Reshef (2021) and Luca (2016).

[5]Uber acquirer Postmates in December 2020, but did not immediately integrate Postmates into Uber Eats.

[6]Online Appendix Figure O.1 shows that order sizes were similarly distributed across platforms. About half of all orders are between \$15 and \$35 before fees, tips, and taxes.

[7]Restaurants belonging to the other tiers, which had commission rates of 15% and 25%, received limited marketing services and smaller delivery areas.

restaurants negotiating commissions rates below those publicly advertised, but I do not analyze such negotiation because I do not observe contracts between restaurants and platforms.

Each platform charges various fees that together constitute the overall consumer fee c. One such fee is the delivery fee, which varies across restaurants, time, and location. Delivery fees do not, however, depend on the consumer's selected menu items. Other fees include service fees and regulatory response fees that vary across municipalities. An example of a regulatory response fee is DoorDash's "Chicago Fee" of $2.50 per order introduced in Chicago when that city enacted its 15% commission cap. Service fees are often proportional to order value, but the other fees do not depend on order value. In addition, platforms have responded to commission caps by adjusting fixed fees rather than service fees. These observations motivate my choice to treat platform consumer fees as fixed amounts rather than *ad valorem* rates.

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, restaurants typically make an active choice to be listed on platforms.[8] It is common for restaurant locations belonging to the same chain to belong to different combinations of online platforms.

Some other features of US food delivery warrant mention. 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 are intended to capture courier compensation. Additionally, some platforms offer subscription plans that allow users to pay fixed fees to reduce per-transaction delivery fees. Given that modelling subscription plans would complicate the analyis and also that these plans do not protect subscribers from platforms' regulatory response fees, I abstract away from subscriptions in the model. I also abstract away from the recommendation and search algorithms that delivery platforms use to direct consumers toward restaurants.

Many local governments introduced commission caps in a staggered fashion after the beginning of the US COVID-19 pandemic. Figure 1 displays the share of the US population residing in a jurisdiction subject to a commission cap. Over 70 local governments representing about 60 million people had enacted commission caps by June 2021. Most caps limited commissions to 15%, although some limited commissions to other levels between 10% and 20%. The first commission caps were introduced as temporary measures, but several jurisdictions later made their caps permanent.[9]

Figure 2 reports monthly spending on delivery platforms in 2020–2021, indexed to January 2020. Usage of online food delivery platforms tripled between January and May 2020 as the US COVID-19 outbreak began and remained elevated thereafter even as governments relaxed public

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[8]Some food delivery platforms list restaurants without their consent. This practice has decreased in popularity in recent years, and has been outlawed in several jurisdictions including California and Seattle. See Mayya and Li (2021) for a study of nonconsensual restaurants listings.

[9]These include San Francisco (July 2021), New York City (August 2021), and Minneapolis (December 2021). The leading platforms brought legal action against San Francisco and New York City in response to their permanent caps.

health measures.[10] As shown by Figure 3, restaurant membership of food delivery platforms also grew during 2020–2021.[11]

Online Appendix Figure O.5 plots the average fees and commission charges over time in regions that had and that did not have a commission cap in place as of May 1, 2021. Platform price structures consistently skewed toward commissions in places without caps, but the disparity in charges paid by consumers and restaurants contracted in placed that adopted caps.

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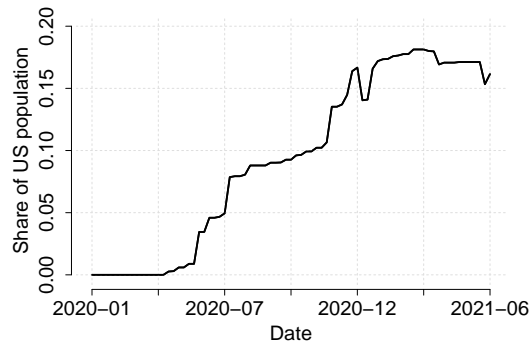

2.2 Data

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 often the restaurant from which the order was placed. At the menu-item level, they report item identifiers 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 more information regarding this comparison. The market definition that I use throughout this paper 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 — these are the metro areas 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.[12]

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[10]Oblander and McCarthy (2021) analyze the effects of the COVID-19 pandemic on consumer ordering.

[11]For each platform, I plot only restaurants that are partnered with the platform. In addition, I consider only restaurants that are partnered with a platform as having adopted that platform in my empirical analysis.
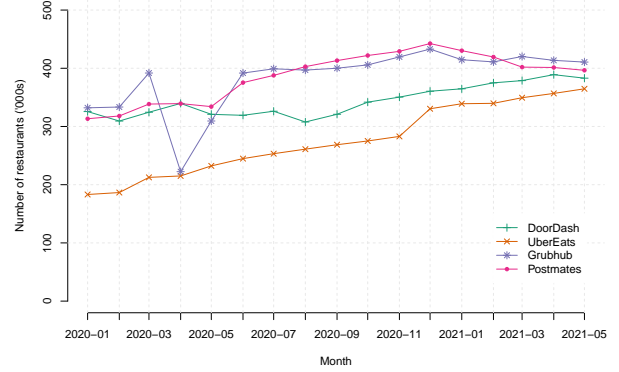
[12]See Table O.1 in the Online Appendix for sample sizes by metro.

Figure 2: Delivery platform sales, 2020–2021

Figure 3: Restaurant membership by platform
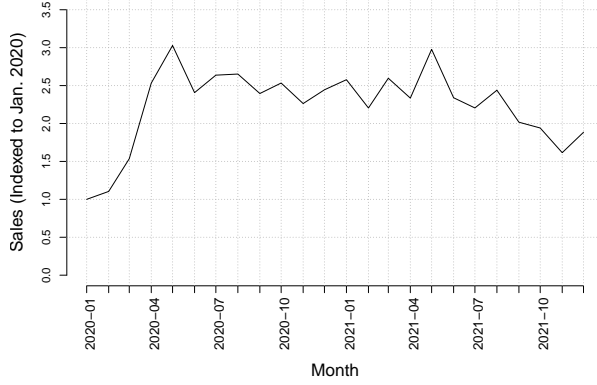
Notes: this plot reports indexed average monthly spending on orders placed on DoorDash, Uber Eats, Grubhub, and Postmates in the Numerator panel described in Section 2.2.

Notes: this figure shows the number of restaurants that belong to each major food delivery platform in each month from January 2020 to May 2021.

I supplement the Numerator data with platform/ZIP-level estimates of order volumes and average fees for each month from January 2020 to May 2021.[13] Edison provides these estimates, which are based on a large panel of email receipts.[14] This dataset also includes estimates of average basket subtotals (i.e., dollar values of orders before fees, tips, and taxes), average delivery fees, average service fees, average taxes, and average tips. I use these estimates to scale predicted orders in the Numerator panel to the market level and in my difference-in-differences analysis. The Edison data match well external data sources including the Consumer Expenditure Survey (CEX), DoorDash earnings reports, and an external payment card panel.[15]

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.[16] I obtain data on offline-only restaurants from Data Axle, which provides dataset of a comprehensive listing of US business locations for 2021.

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 large US metropolitan areas in the listed in Table O.1. The address is obtained by reverse geocoding the geographical coordinates of the ZIP's centroid into a street address. Other variables that I record while collecting data on these fees include the

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[13]I use ZIP rather than ZCTA as shorthand for "ZIP code tabulation area" in this paper.

[14]The panel includes 2,516,994 orders for an average of about 148,000 orders a month.

[15]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.

[16]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.

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Table 1: Description of platform pricing data, Q2 2021

Platform	Delivery fees data			Service/reg. response fees data		
	# obs.	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.

time of delivery, the delivery address, the restaurant's address, restaurant characteristics, and the estimated waiting time. I followed an analogous procedure to collect data on service fees and regulatory response fees; this procedure involves entering delivery addresses near the centroid of ZIPs in the markets listed by Table O.1, randomly choosing a restaurant from the landing page displayed after entering the delivery address, and inquiring about terms of a delivery from the restaurant to the chosen delivery address. 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 manually construct a dataset of commission cap policies including start and end dates. I conducted a search of online news articles to construct this dataset. This dataset includes 72 distinct caps active on March 28, 2021, the same date that NBC News reported that it had discovered 68 commission caps across the United States.

Also, I use ZIP-level data from five-year American Community Survey (ACS) from 2014–2019 to study the dependence of platform fees and usage on local demographics. To characterize places that adopt commission caps, I regress an indicator for a commission cap on local characteristics; the results, which appear in Online Appendix Table O.2, reveal that places with a higher Democratic vote share in the 2016 presidential election, with a higher population density, and with a more educated population are more likely to enact commission caps.

2.3 Fee indices

I construct measures of platform 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

$$c_{fz} = DF_{fz} + SF_{fz} + RR_{fz}, \tag{1}$$

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. The delivery fee measure DF_{fz} is the expected delivery fee charged by platform f in ZIP z conditional on a set of fixed order characteristics:

$$DF_{fz} = \mathbb{E}[df_{kfz}|x_k = \bar{x}, f, z], \tag{2}$$

where df_{kfz} is the delivery fee charged on order k on platform f in ZIP z, x_k are observable characteristics of order k, and $\bar{x}$ is a fixed vector of characteristics. Variation in DF_{fz} reflects systematic differences in fees across platforms and regions for an order with the same x_k characteristics.[17] It is important to include a rich set of order characteristics in x_k so that the fee indices do not reflect differences in the selection of restaurants across platforms and regions. In practice, the observable characteristics that I include in x_k are time of day and day of week, a cubic in the delivery distance, and indicator variables for various restaurant cuisines and restaurant chain indicators. I estimate (2) using a k-fold cross-validated Lasso (with $k = 10$), which is a penalized regression estimator intended to prevent overfitting in the presence of high-dimensional regressors. The high-dimensional regressors in my setting include a rich set of controls for geography. Appendix A discusses my procedure for estimating (2) in detail. I apply this procedure to the expected waiting times data as well to obtain waiting time indices W_{fz} analogous to the DF_{fz} delivery fee indices.

The service and regulatory response fee measures SF_{fz} and RR_{fz} are straightforwardly defined. 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 in practice, given that average subtotals are close to \$30 in my data. 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.[18] It does, however, limit my information on Grubhub's service fees. I use the Edison transactions data to overcome this limitation. These data include the average service fee, average order value before taxes and fees, and estimated sales at the level of a ZIP/platform. 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. I therefore use 10% as Grubhub's service fee in computing SF_{fz}. Regulatory response fees apply to entire municipalities, so I compute RR_{fz} by identifying all regulatory response fees in my data and then taking the sum of such fees charged by platform f in ZIP z's municipality. See Table O.4 in the appendix for a decomposition of each platform's average fee index across ZIPs into the delivery fee, service fee, and regulatory response fee components.

3 Four empirical findings

3.1 Commission caps raise platforms' consumer fees

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

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[17]In practice, delivery fees vary widely within CBSAs. Tables O.9 and O.10 report estimates from regressions of delivery fees df_{kfz} on various order characteristics and geographical characteristics. The results show that there remains a high level of unexplained variation in delivery fees within a CBSA or county, and they indicate meaningful variation in average fees across places within a CBSA.

[18]Grubhub introduced this fee in response to a state mandate that platforms provide certain benefits to couriers.

estimating equation

$$\underbrace{y_{fzt}}_{\text{Fees}} = \underbrace{\psi_{fz} + \phi_{ft}}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\delta_f x_{zt}}_{\text{Treatment}} + \underbrace{w'_{zt}\beta}_{\text{Controls}} + \epsilon_{fzt}, \quad (3)$$

where f denotes a platform, y_{fzt} is the log of platform f's average fees in ZIP z for month t, ψ_{fz} are platform/ZIP fixed effects, ϕ_{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 ϵ_{zft} is an unobservable assumed mean independent of x_{zt}. Here, δ_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 severity of COVID-19. The treatment variable x_{zt} is an indicator for z having a commission cap of 15% or lower.[19] In addition to estimating (3), I estimate a variant of the model in which caps' effects depend on the time since their imposition.[20] The primary identifying assumption underlying the TWFE approach is that, conditional on controls, the outcome variable in places that enacted commission caps would have followed the same trend as in places that never enacted commission caps if caps had not been imposed.

Recent research in econometrics—e.g., de Chaisemartin and D'Haultfœuille (2020)—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 difference-in-differences approaches may suffer from an endogeneity problem owing to unobserved heterogeneity that correlates with both adoption of a treatment and the outcomes of interest. This endogeneity problem may give rise to pre-trends, i.e., non-zero effects of interventions before treatment. The fact that I generally do not estimate statistically significant pre-trends may reflect a lack of statistical power rather than a lack of pre-trends; thus, I additionally compute the proxy-based estimator that Freyaldenhoven et al. (2019) develop to address potential endogeneity problems. This estimator requires proxies for unobserved heterogeneity that correlates with both the outcome of interest and the adoption of commission caps — as proxies, I use the COVID-19-related controls w_{zt}. I additionally control for these variables in computing the IW estimator. The qualitative conclusions from my analysis are robust to the

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[19]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.

[20]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 commission cap was first imposed in ZIP z in month $t-\tau$. I set $\bar{\tau} = 7$ in practice.

choice of estimator. See Online Appendix O.7 for technical 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	0.249	0.170	0.207	0.215
	(0.019)	(0.041)	(0.095)	(0.121)	(0.121)
Uber	0.070	0.069	0.209	0.061	0.055
	(0.019)	(0.040)	(0.126)	(0.039)	(0.041)
GH	0.127	0.127	0.275	0.106	0.110
	(0.062)	(0.142)	(0.148)	(0.060)	(0.060)

Notes: this table reports estimates of the effects of a commission cap of 15% or less on either log average fees. Each estimator is computed on a ZIP/month level panel, and each ZIP is weighted by its population. "TWFE" is a standard two-way fixed effects estimator. "IW" is the interaction weighted estimator of Sun and Abraham (2021). "Proxy" is the estimator of Freyaldenhoven et al. (2019). "CS" is the estimator of Callaway and Sant'Anna (2021), which I compute using not-yet-treated and never-treated units as control groups in distinct estimations. I control for various COVID-19-related variables in computing these estimators; see the main text for details. 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 4: Effects of commission caps on DoorDash fees

(a) TWFE   (b) IW (Sun and Abraham 2021)
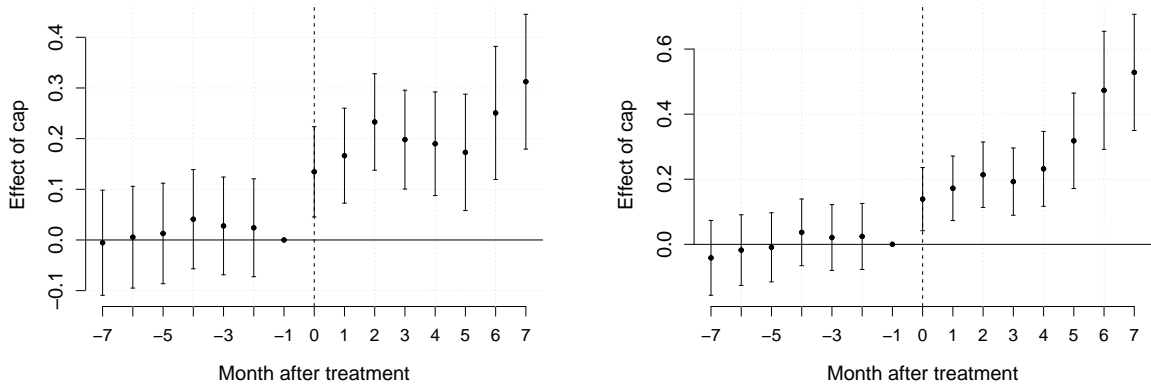
Notes: this figure reports estimates of the effects of commission caps of 15% or less on DoorDash's log average fees from a variant of (3) wherein the effect δ_f varies by the month relative to the implementation of a commission cap. The figure reports estimates from both the standard two-way fixed effects (TWFE) estimator and from the interaction weighted (IW) estimator. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

Table 2 provides estimated effects of commission caps for each of DoorDash (DD), Uber Eats (Uber), and Grubhub (GH). For the TWFE estimator, the table reports estimates of δ_f in (3). For the other estimators, the table reports estimates of average dynamic effects across time periods following the imposition of caps.[21] The TWFE results suggest that commission caps raised fees by 7%–20% across platforms. Moreover, the estimated effects on fees are positive and between 5.5% and 32% across platform/estimator pairs.[22] The non-TWFE estimates are

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[21] In computing these average dynamic effects, I weight the effect for τ periods after the introduction of a cap by the number of observations in the panel for which the unit in question adopted a cap τ periods ago.

[22] The panel's inclusion of fewer orders for Uber and Grubhub, which made fewer sales than DoorDash in

generally similar to the TWFE estimates, although often less precise. Figure 4 provides TWFE and IW estimates of dynamic effects of commission caps on the fees charged by DoorDash, the largest platform. There is not evidence of pre-trends in DoorDash's fees or order volumes in places that introduced commission caps. Additionally, Figure 4 suggests that platforms responded to commission caps with fee hikes almost immediately. Online Appendix O.7 provides event study plots for other estimators and platforms. These plots similarly show positive effects of caps on fees and a lack of fee pre-trends.

Online Appendix O.7 provides results for alternative specifications, including those with a continuous treatment variable, with fees entering in levels rather than in logs, excluding observations for months before July 2020 (in which laws prohibiting on-premises dining still applied), with proportional service fees and fixed delivery and regulatory response 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.7 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 raise fees by less in response to caps in markets in which they were historically dominant, although the interactions are imprecisely estimated. Last, Table O.15 in the Online Appendix reports estimates of (3) with the log average basket subtotal as the outcome. I do not find significant effects on basket subtotals.

3.2 Caps lead consumers to order less from platforms, more directly from restaurants

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. Indeed, if 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. If the channels were not substitutable, caps would reduce overall restaurant spending and consequently reduce restaurant revenues. To assess the substitutability of direct and platform ordering, I apply the difference-in-differences 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 of caps' effects on platforms 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 dependent variables.

Figure 5 reports results of the analysis for the log of platform sales and the log of direct sales as outcomes. For platform sales, it provides estimates from both the Numerator and Edison data. Across estimators and datasets, every estimated effect on log platform orders except one is between 0.05 and 0.10 (5–11%). Additionally, the estimated effects on direct-from-

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the sample period, contributes to fact that the estimates for these two platforms are less precise than those for DoorDash.

Figure 5: Effects of commission caps on restaurant sales

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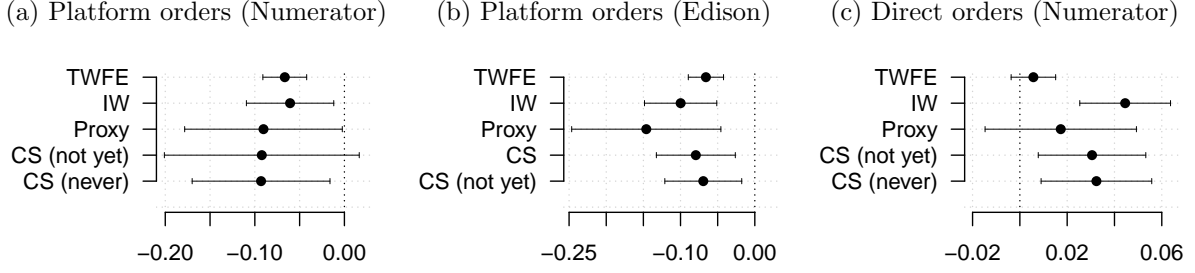
Notes: this figure reports difference-in-differences estimates of the effects of commission caps of 15% or less on the log number of restaurant orders placed (i) on delivery platforms and (ii) directly at restaurants. See the notes for Table 2 for an explanation of each estimator. The dots indicate point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

Figure 6: Effects of commission caps on order volumes (dynamic event study)

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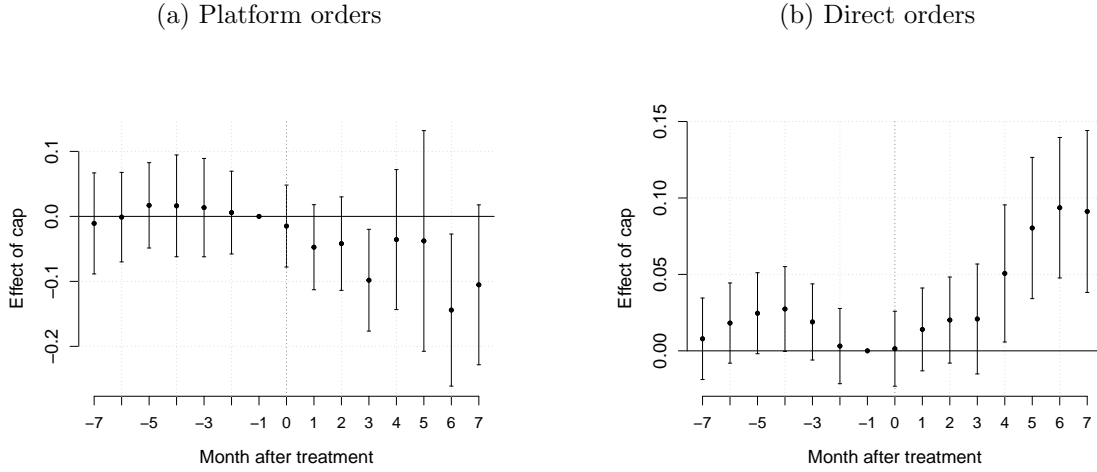
Notes: this figure plots interaction weighted (IW) estimates of the effects of commission caps on (i) the log number of orders placed on food delivery platforms and (ii) the log number of orders placed directly from restaurants. The dots indicate point estimates and the bars around each point indicate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

restaurant orders are all positive and range 0–5%. Figure 6 plots dynamic effects obtained from the IW estimator. There are not significant pre-trends in either direct or platform orders, although some pre-trends in direct ordering systematically differ from zero. This may reflect the presence of 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 O.7 (Figure O.15), effects from this estimator are similar to those plotted in Figure 5c.

The estimated positive response of direct-from-restaurant spending to caps suggests that direct ordering and platform ordering are highly substitutable. In fact, I fail to reject the hypothesis that caps affected overall restaurant spending (before fees, tips, and taxes). Figure O.18 in the Online Appendix provides results for difference-in-differences analysis of caps' effects on log overall spending — the estimated effects range from -0.012 to 0.020, and none of the estimated effects are significant at the 5% level. This finding suggests that commission caps' negative effects on platform ordering are unlikely to hurt restaurants, who may instead benefit from

consumer diversion to direct ordering.

Modelling implication. Consumers in the model substitute between restaurant meals ordered through platforms, restaurant meals ordered directly, and home-prepared meals.

3.3 Commission caps induce restaurant uptake of platforms

Commission caps may also affect restaurants' platform membership decisions. I next use difference-in-differences methods to estimate restaurants' platform adoption responses to caps. Although my data record all restaurants on delivery platforms at a monthly frequency, the data on all US restaurants—including those that do not belong to a platform—are at an annual frequency. I therefore estimate TWFE regressions at an annual level with platform adoption measures as outcomes. The time periods here are January 2020 (t_0) and January 2021 (t_1). The estimating equation is

$$y_{zt} = \underbrace{\psi_z + \phi_t}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\delta x_{zt}}_{\text{Treatment}} + \underbrace{\mathbb{1}\{t = t_1\}w_{zt}'\beta}_{\text{Controls}} + \varepsilon_{zt}, \tag{4}$$

where ψ_z are ZIP fixed effects, ϕ_t are time-period fixed effects, and x_{zt} is an indicator for whether a commission cap of 15% or lower is active in ZIP z during time period t. Additionally, the vector w_{zt} includes the number of new and cumulative COVID-19 per capita in January 2021; both of these per capita case counts interacted with the Democratic vote share in the 2020 US presidential election; and average value of the Hallas et al. (2020) index of local COVID-19 policy stringency in 2020. The interaction of these controls with an indicator for the January 2021 time period allows places with different exposure to COVID-19 and different COVID-19 policy responses to experience different trends in the outcomes of interest. The two outcomes y_{zt} are (i) the share of restaurants belonging to at least one platform and (ii) the average number of platforms that a restaurant in the ZIP joins. The sample includes (i) treated ZIPs where commission caps of 15% or lower were imposed between January and June 2020 and (ii) control-group ZIPs that did not have commission caps by the second period. Online Appendix O.7 provides results for platform-specific adoption shares as outcome variables and for a continuous treatment variable.

Table 3: Effects of commission caps on restaurants' platform uptake

Estimator	Share online	# platforms joined
Diff-in-diff	0.039	0.077
	(0.003)	(0.007)
Within-metro	0.040	0.124
	(0.004)	(0.010)

Notes: "Diff-in-diff" reports OLS estimates of δ in (4) in which the outcomes are either (i) the share of restaurants that belong to at least one platform or (ii) the average number of platforms joined among restaurants in the ZIP. In the regression, each ZIP is weighted by its total number of restaurants in January 2020. "Within-metro" reports estimates from cross-sectional regressions of outcomes (i) and (ii) on an indicator for an active commission cap of 15% or less, various COVID-19-related controls, and metro area fixed effects. In the regression, each ZIP is weighted by its number of restaurants. Asymptotic standard errors appear in parentheses.

The "Diff-in-diff" row of Table 3 provides OLS estimates of δ. These results suggest that commission caps led to a 3.9 percentage-point increase in the share of restaurants belonging to at least one delivery platform and an increase of 0.077 in the average number of delivery platforms joined. To assess the robustness of the estimates, I also estimate the effects of caps using cross-sectional variation between municipalities within a metro area that differ in their commission cap policies. The underlying identification assumption is that the unobservable propensity for restaurants to join platforms does not differ within a metro area between places with and without commission cap conditional on controls w_{zt} that may vary within metros. Here, w_{zt} includes the same covariates as in (4). I estimate effects of commission caps using within-metro variation by regressing the share of restaurants in a ZIP belonging to at least one platform on metro fixed effects and on an indicator for a cap of 15% or less being effect. The "Within-metro" row of Table 3 provides the results for May 2021. The results are similar to those from the difference-in-differences approach.

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.[23] A listing here is a restaurant/platform pair — if, for instance, there were two restaurants in a ZIP, one of which belonged to DoorDash and Uber Eats and another that belonged only to DoorDash, then the ZIP3 would have three listings.[24] As in Section 3.1, I control for COVID-19-related variables and focus on caps of 15% or lower. Figure 7a plots estimates of dynamic effects of a commission cap 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 restaurant 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 restaurant listings on platforms by between 2.5% and 14% (relative to the number of listings in April 2020) 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, which addresses unobserved heterogeneity giving rise to pre-trends using a proxy approach. The results are similar to the IW estimates.

Table O.19 in the Online Appendix reports estimates of aggregate effects of caps for each estimator and platform. The estimated average increases in restaurant listings on platform are between 10% and 11% across estimators, and the estimated effects are positive for each platform/estimator pair. Online Appendix O.7 provides other supplementary results as well, including results for specifications in which restaurant listing counts are not analyzed relative to local population. This appendix also provides and dynamic event study plots for alternative outcomes and estimators. These results are all consistent with positive effects of commission

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[23]I choose ZIP3s as the units of analysis because the number of listings per capita in a ZIP3 is a better measure of the number of listings available to consumers in an area than listings per capita in a ZIP. This is because ZIPs are much smaller than ZIP3s, and are thus less likely to include both the restaurants that service a local population and the local population itself.

[24]Online Appendix O.7 provides platform-specific results.

Figure 7: Dynamic effects of commission caps on restaurants' platform adoption

(a) IW (Sun and Abraham 2021)　　　　　(b) Proxy (Freyaldenhoven et al. 2019)
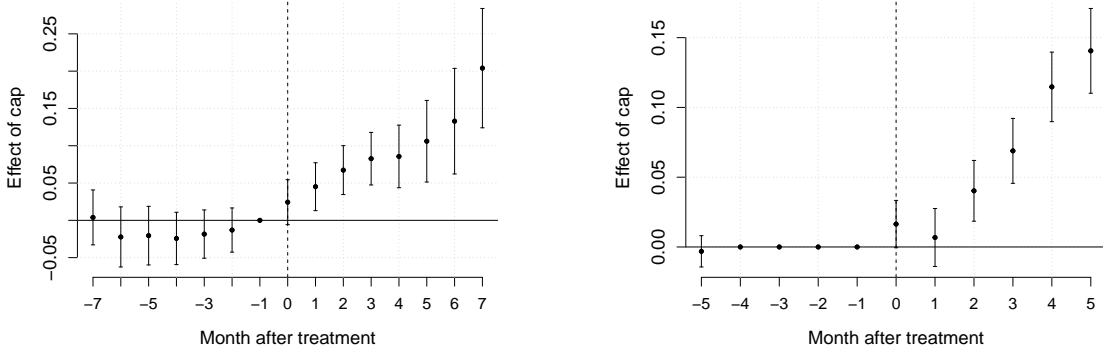
Notes: the plot provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents relative to the population-weighted mean number of listings in April 2020 (which was 2642). The estimates derive from the Callaway and Sant'Anna (2021) estimator with never-treated units constituting the control group. The bars around each point provide 95% pointwise confidence intervals.

caps on restaurants' platform adoption.

Modelling implication. Platform adoption by restaurants is endogenous and depends on commission rates.

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

Each leading delivery platform allows restaurants to post prices on the platform that differ from the restaurant's prices for direct orders and from the restaurant's prices on other platforms. I use my item-level transactions data to estimate the average markups of restaurant menu items on delivery platforms relative to their direct-from-restaurant prices. This procedure involves estimating

$$\underbrace{\log p_{\iota f t}}_{\text{Log price}} = \underbrace{\varphi_\iota}_{\text{Item fixed effect}} + \underbrace{\vartheta_f}_{\text{Mean markup}} + \varepsilon_{\iota f t}, \tag{5}$$

where ι is a menu item, f is a platform, and t is a transaction. Additionally, $p_{\iota f t}$ is an observed menu price, φ_ι are menu-item fixed effects, and $\varepsilon_{\iota f t}$ captures both measurement error and item-level deviations from the mean log markup ϑ_f of prices on platform f. I normalize $\vartheta_0 = 0$ for the platform $f = 0$, which represents direct-from-restaurant ordering. To understand why I interpret ϑ_f as a mean log markup of prices on platform f, note that

$$\mathbb{E}[\log(p_{\iota f t}/p_{\iota 0 t}) \mid \iota, f] = \vartheta_f.$$

I estimate (5) by OLS on data from Q2 2021. Table 4 reports estimates of ϑ_f when (i) $\vartheta_f = \vartheta$ for a constant ϑ across all platforms f and (ii) when ϑ_f varies across platforms. This table implies that prices on online platforms are about 27% higher than those for direct orders on average, and that this markup does not vary considerably across platforms. Online Appendix

Table 4: Markups of restaurant prices on food delivery 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 ϑ_f parameters in (5). I estimate the equation via an OLS regression of log menu prices on platform indicator variables after transforming both variables by the fixed-effects transformation (i.e., by subtracting off their within-item ι mean values across transactions) to purge the fixed effects φ_ι from (5). The estimation sample includes item-level transactions in Q2 2021. Standard errors appear in parentheses.

O.6 describes price differentials between platform orders and direct-from-restaurant orders in greater detail; it shows that markups are concentrated between 0% and 50%, and that price variation among platforms is small.

To obtain the menu price measures that I use in estimating my model, I estimate mean differences in menu items' prices across platforms and restaurant locations using a Lasso regression with item fixed effects. The regression equation differs from (5) in that it allows markups of restaurants' prices on platforms to vary across markets and restaurant locations belonging to different subsets of platforms. Appendix B details this procedure. The price measures I obtain systematically vary between the direct and platform-intermediated ordering channels, but not between platforms.

I also find suggestive evidence that commission caps led restaurants to reduce their prices on platforms. This evidence comes from a regression of prices on month, ZIP3, and item category fixed effects computed on the Numerator receipts panel. The estimating equation is

$$\log p_{r\iota zt} = \psi_z + \phi_t + \gamma_{\text{cat}(\iota)} + \delta x_{zt} + w'_{\iota zt}\beta + \epsilon_{r\iota zt}, \tag{6}$$

where r is a receipt, ι is a menu item, z is a ZIP3, t is a month, and $\text{cat}(\iota)$ is the category of menu item ι. Here, ψ_z are ZIP3 fixed effects, ϕ_t month fixed effects, $\gamma_{\text{cat}(\iota)}$ are item-category fixed effects, x_{zt} is an indicator for a commission cap of 15% of less having effect, and $w_{\iota zt}$ are control variables. These controls include the number of new COVID-19 cases, the COVID-19 policy stringency index, the number of new COVID-19 cases interacted with the Democrat vote share in the 2020 US presidential election, and 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., "bone-in chicken" or "chicken tenders"). In running the regression, I use only observations with a valid subcategory. I also only use receipts from major food delivery platforms. My regression approach estimates δ by comparing trends in the average log price of items within a particular category across places that enacted

commission caps and places that did not, conditional on various controls. Given that changes in the average prices could owe to substitution across products, I consider evidence from the regression to be suggestive rather than conclusively causal.[25] Table 5 reports the estimate of δ, which suggests that restaurants passed on their savings from commission caps to consumers via price reductions of 6%. Figure O.21 in Online Appendix O.7 plots estimates from a dynamic variant of (6). This figure shows a lack of price pre-trends and that prices fell immediately in the three months following the introduction of caps before slightly rebounding, falling by about 14% at their nadir.

Table 5: Restaurant price changes upon commission cap adoption

Variable	Estimate
Cap	-0.060
	(0.012)
N	117309

Notes: this table reports the OLS estimate of δ in (6), the asymptotic standard error of this estimate, and the sample size used in estimation.

Modelling implication. I model restaurant price-setting for both direct orders and platform-intermediated orders. This pricing model allows for incomplete pass-through of commissions.

3.5 Additional findings

Online Appendix O.2 presents five additional empirical findings that inform my modelling choices. The first such finding is that both restaurants and consumers multihome. Over half of restaurants on DoorDash belong to Uber and Grubhub, and consumers often switch between platforms across consecutive platform orders. Next, consumers are more likely to order from a platform with more local restaurants, and that consumers respond similarly to new chain and independent restaurants on a platform. The model correspondingly features a positive relationship between the number of restaurants on a platform and consumer ordering on the platform. The third additional finding is that restaurants that join a platform tend to stay on the platform, which motivates my decision to account for the value of restaurants in generating future profitability for platforms in platforms' commission-setting problem. I subsequently show that market shares vary across metros, which my model rationalizes through differences in local restaurant listings on each platform as well as metro-specific tastes for platforms. Last, I find that young consumers are more likely to use platforms, and that restaurants in places with relatively young populations are more likely to join platforms. This suggests that restaurants respond to the profitability of platform adoption.

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[25]I additionally tried a differences-in-differences-style regression with menu item fixed effects, although controlling for menu item left too little variation to precisely estimate the effects of commission caps.

4 Model

4.1 Summary of model

To analyze the welfare effects of commission caps and the economic forces shaping these effects, I develop a model of the food delivery industry. This model features consumers who place orders from nearby restaurants either through platforms or directly from the restaurant. Each consumer and each restaurant belongs to a metro m, each of which is further partitioned into ZIPs z. Each ZIP contains a fixed number of consumers and of restaurants.

Formally, I develop a sequential game equipped with a perfect Bayesian equilibrium solution concept. Competition in each metro area is a separate game played by platforms and restaurants. Platforms' strategic variables are consumer fees and restaurant commission rates. Restaurants differ in their locations and in costs of platform adoption decisions. Their strategic variables are platform adoption and prices. The model has four stages. In the first stage, platforms simultaneously choose their commission rates to maximize their profits. Restaurants subsequently choose which platforms to join. Upon joining platforms, restaurants choose prices to charge for direct orders and for orders from each platform. Platforms set their consumer fees concurrently as restaurants set prices. Last, consumers place orders. I specify that platforms set commissions first because delivery platforms advertise commission rates to restaurants considering membership. Platforms often change their fees after restaurants have joined platforms (e.g., in response to commission caps) — this underlies the assumption that platforms set consumer fees after restaurants join platforms.

Although the model captures numerous features of the food delivery industry with my model, I abstract away from other features. First, restaurants in the same ZIP do not systematically differ in their appeal to consumers or their costs of platform adoption. Reducing restaurant heterogeneity is necessary for tractability, although the model could be straightforwardly extended to feature multiple discrete types of restaurants (e.g., chain versus independent restaurants, downmarket versus upscale restaurants). Additionally, my model is static whereas platforms face dynamic pricing incentives in reality. I capture these dynamic incentives in a reduced-form way by including the size of a platform's restaurant network—which affects future platform profitability—in the platform's objective function.

The remainder of this section details the stages summarized above in backwards order.

4.2 Consumer choice

Consumer i contemplates ordering a restaurant meal at T occasions each month. In each occasion $t \in \{1, \ldots, T\}$, 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 consumer i's ZIP of residence and (ii) $f \in \mathcal{G}_j$ to maximize

$$v_{ijft} = \begin{cases} \psi_{if} - \alpha_i p_{jf} + \eta_i + \phi_j + \nu_{ijt}, & j \neq 0 \\ \nu_{i0t}, & j = 0, \end{cases}$$

where ψ_{if} is consumer i's taste for platform f, p_{jf} is restaurant j's price on platform f, η_i is the consumer's taste for restaurant dining, ϕ_j is the quality of restaurant j, and ν_{ijt} is consumer i's idiosyncratic taste for restaurant j in ordering occasion t. I impose that restaurant quality ϕ_j is equal across restaurants up to a restaurant type $\tau(j)$, and that there is a finite number of types. The types that I consider are independent and chain restaurants, although it is conceptually straightforward to introduce additional types (e.g., fast food versus fine dining). The idiosyncratic tastes ν_{ijt} are assumed iid Type 1 Extreme Value. Additionally, α_i is consumer i's price sensitivity, which I specify as

$$\alpha_i = \alpha + \alpha_{\text{LowInc}} \text{LowInc}_i,$$

where LowInc_i is an indicator for whether the consumer's household income is below \$40,000.

I specify consumer i's tastes ψ_{if} for platform f as

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

for $f \neq 0$. I normalize $\psi_{i0} = 0$ for all i. Here, δ_{fm} is a parameter governing the mean taste of consumers in market m for platform f; c_{fz} is platform f's fee to consumers in ZIP z; W_{fz} is a waiting-time index; and d_i is a vector of consumer characteristics. The characteristics included in d_i are indicators for the consumer being younger than 35 years of age and for being married. Additionally, the ζ_{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. The $\zeta_i^\dagger$ unobservable governs consumer i's taste for the online ordering channel whereas $\tilde{\zeta}_{if}$ governs consumer i's particular taste for platform f.[26]

I specify consumer i's taste for restaurant meals η_i as

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

where μ_m^η 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 assume that $\eta_i^\dagger \sim N(0, \sigma_\eta^2)$ independent of all else. Consumer tastes for restaurant ordering become increasingly heteroge-

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[26]Note that the parameters $\sigma_{\zeta 1}$ and $\sigma_{\zeta 2}$ are random coefficients in the style of Berry et al. (1995) on channel and platform indicators.

neous as σ_η is increased, which limits the substitutability of ordering and at-home dining.

4.3 Restaurant pricing and platform fee setting

Each restaurant sells a standardized menu item, whose price it selects after all restaurants have joined platforms. Restaurants simultaneously set their prices across platforms to maximize their profits. Platforms concurrently set their consumer fees c_{fz} to maximize profits with restaurant prices and platform fees together constituting a Nash equilibrium.

First consider restaurant pricing. Let $p^*_{jf}(\mathcal{G}_j, \mathcal{J}_{m,-j})$ denote the equilibrium price set by restaurant j on platform f when $\mathcal{J}_m$ denotes the platform adoption choices of all restaurants in metro m. The equilibrium prices solve

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

where κ_{jf} is restaurant j's marginal cost of fulfilling an order on platform f, p_{-j} are the prices of other restaurants, and S_{jf} are restaurant j's sales on platform f.[27]

The multi-sided markets literature—e.g., Rochet and Tirole (2006)—recognizes that transfers between platform users can make the division of a platform's prices between sides of users irrelevant, a situation known as neutrality of the price structure. Restaurant price adjustments, however, do not imply neutrality here, and restaurants do not perfectly pass through commission increases into prices. This reflects that consumer fees are fixed whereas restaurant commissions are proportional to restaurant prices. See Online Appendix O.14 for additional discussion of restaurant pricing and commission pass-through.

Next consider platform fee setting. Each platform f's profits in a ZIP z depend on their marginal costs mc_{fz}, which represent compensation to couriers. Platform marginal costs may vary across locations due to differences in going rates for couriers across regions due to, e.g., local labour demand and supply conditions as well as local regulation of benefits owed to couriers. I assume that platforms are price-takers in local labour markets and that, consequently, their marginal costs do not depend on orders volumes. A platform f's profits from sales in ZIP z are

$$\Lambda_{fz} = \underbrace{\jmath_{fz}(c_z, \mathcal{J}_m)}_{\text{Sales}} \times \left(\underbrace{c_{fz}}_{\substack{\text{Consumer} \\ \text{fee}}} + \underbrace{r_{fz}}_{\substack{\text{Restaurant} \\ \text{commission}}} \underbrace{\bar{p}^*_{fz}}_{\substack{\text{Average restaurant} \\ \text{price in } z \text{ on } f}} - \underbrace{mc_{fz}}_{\substack{\text{Marginal} \\ \text{cost}}} \right), \qquad (7)$$

where $\jmath_{fz}$ 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 Λ_{fz}, whereas Uber Eats and Postmates set their fees in ZIP z to maximize $\Lambda_{fz} + \Lambda_{f'z}$, where f denotes Uber Eats and f' denotes Postmates.

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[27]Sales also depend on platform fees, which I suppress in the notation. Online Appendix O.10 provides an expression for sales S_{jf}.

4.4 Restaurants' platform adoption choice

Restaurants choose which platforms to join in a positioning game in the spirit of Seim (2006). In this model, restaurants simultaneously choose which platforms to join. Each restaurant makes its choice to maximize the sum of its expected profits and a choice disturbance representing misperceptions of the profitability or non-pecuniary motives for platform adoption. A restaurant j's expected profits from joining platforms $\mathcal{G}$ are

$$\Pi_j(\mathcal{G}, P_m) = \underbrace{\mathbb{E}_{\mathcal{J}_{m,-j}} \left[\sum_{f \in \mathcal{G}} [(1 - r_{fz}) p_{jf}^*(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_{jf}] S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*) \mid P_m \right]}_{:=\bar{\Pi}_j(\mathcal{G}, P_m)} - K_m(\mathcal{G}). \quad (8)$$

The expectation in (8) 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 each platform set $\mathcal{G}$. Additionally, $K_m(\mathcal{G})$ is j's fixed cost of joining platforms $\mathcal{G}$. Restaurants correctly anticipate the prices p_{jf} and fees c_{fz} that arise in the model's downstream stages.

Restaurant fixed costs $K_m(\mathcal{G})$ do not represent payments to platforms. Instead, they include fixed costs undertaken in contracting with platforms; in maintaining the restaurant's menu on platforms; in interacting with platforms regarding payments and customer service; in processing online orders; and in training staff to interface with platforms. By specifying a separate cost for each subset of platforms $\mathcal{G}$, I allow for diminishing costs of joining additional platforms. Additionally, I normalize $K_m(\{0\})$ to zero in each market.

Restaurant j's choice of platforms maximizes the sum of its expected profits and a disturbance $\omega_j(\mathcal{G})$ that represents either restaurant misperceptions of the profitability of platform adoption or non-pecuniary motives for platform adoption:

$$\mathcal{G}_j = \arg \max_{\mathcal{G}:0 \in \mathcal{G}} \left[\Pi_j(\mathcal{G}, P_m) + \omega_j(\mathcal{G}) \right]. \quad (9)$$

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

An equilibrium in the platform adoption game is a sequence of probabilities $P_m^* = \{P_j^*(\mathcal{G}) : j, \mathcal{G}\}$ such that

$$P_j^*(\mathcal{G}) = \Pr \left(\mathcal{G} = \arg \max_{\mathcal{G}'} \Pi_j(\mathcal{G}', P_m^*) + \omega_j(\mathcal{G}') \right) \quad (10)$$

for all restaurants j in market m and for all platform subsets $\mathcal{G}$. The right-hand side of (10) 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 defined as a sequence of choice probabilities that arise when restaurants' best responses to each other's choice probabilities give rise to these choice probabilities. Condition (10) defines P_m^* as a fixed point, and Brouwer's fixed point theorem ensures the existence of an equilibrium.[28] Although equilibrium existence is ensured, an equilibrium may not be unique. In practice, I do not find multiple equilibria at my estimated

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[28]The equilibrium can be interpreted as a quantal response equilibrium (McKelvey and Palfrey 1995).

parameters.[29]

I specify restaurants' platform adoption disturbances as

$$\omega_j(\mathcal{G}) = \sum_{f \in \mathcal{G}} \sigma_{rc} \omega_{jf}^{rc} + \sigma_\omega \tilde{\omega}_j(\mathcal{G}), \tag{11}$$

where $\omega_j(\mathcal{G})$ are mean-zero type 1 extreme value random variables drawn independently across j and $\mathcal{G}$. Additionally, the ω_{jf}^{rc} are standard normal random variables drawn independently across restaurants and platforms. The parameter σ_ω governs the variability of platform-subset-specific idiosyncratic disturbances, whereas σ_{rc} governs the extent to which platform subsets are differentially substitutable based on their constituent platforms. The specification in (11) makes the choice model a random coefficients logit model in the style of Berry et al. (1995).

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 non-uniqueness in the identities of players that take particular actions. These problems that do not arise in my model. One critique of positioning games in the spirit of Seim (2006) is that they give rise to *ex post* regret: after players have realized their actions, some players would generally like to change their actions in response to other players' actions. This is not a considerable problem in my setting because the large number of restaurants leaves little uncertainty in each restaurant's payoffs from joining platforms $\mathcal{G}_j$.[30]

4.5 Platform commission setting

The first stage of the model is platform commission setting. Each platform's commission rate maximizes a weighted sum of (i) the platform's expected profits and (ii) the expected size of the platform's network of restaurants. This second term addresses the omission of dynamic pricing incentives from my measure of platform profits. If restaurants exhibit state dependence in the platforms they join, then a platform's future profitability increases when it induces a restaurant to join a platform. Rather than account for this effect in a fully structural manner, I take a reduced-form approach that has precedent in the literature. Castillo (2022) and Gutiérrez (2022) specify platform objective functions including terms representing user surplus, which capture unmodelled dynamic considerations. Additionally, Wang et al. (2022) propose a restaurant-recommendation system that has been adopted by Uber Eats and that accounts for restaurants'

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[29] In each metro area in my data, I compute equilibria using the algorithm outlined in Online Appendix O.14 from the following initial choice probabilities: (i) the ZIP-specific empirical frequencies of restaurants' platform choices, (ii) probability one of restaurants choosing not to join any platform, (iii) probability one of restaurants choosing to join 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 initial choice probabilities.

[30] 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.

interests in making recommendations, suggesting that platforms value user interests in addition to short-run profits.

The expected profits of platform f in metro m at the time of commission setting are

$$\bar{\Lambda}_{fm}(r_m) = \sum_{z \in \mathcal{Z}_m} \mathbb{E}_{\mathcal{J}_m} \left[\Lambda_{fz} \mid P_m^*(r_m) \right], \tag{12}$$

where Λ_{fz} are the ZIP-specific profits defined in (7) and $\mathcal{Z}_m$ is the set of all ZIPs in metro m. 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 restaurants 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

$$\max_{r_{fm}} \left[\bar{\Lambda}_{fm}(r_m) + h_{fm} J_f(r_m) \right], \tag{13}$$

where $J_f(r_m)$ is the expected number of restaurants that adopt platform f in metro m and h_{fm} are model parameters. The problems of Uber Eats and Postmates, which are jointly owned, differ from (13) in that these platforms' objective functions are sums of $\bar{\Lambda}_{fm}(r_m) + h_{fm} J_f(r_m)$ over $f \in \{\text{Uber Eats}, \text{Postmates}\}$.

5 Estimation

5.1 Estimation of the consumer choice model

My estimation procedure features a step for each stage of the model. The estimator of the consumer choice model maximizes the likelihood of consumers' observed sequences of platform choices conditional on observed covariates. In tis model, each consumer i places $T_i \leq T$ orders from restaurants, with T_i varying across i. Recall that T is the maximum number of ordering occasions in my model. In practice, I treat each panelist/month pair as a separate consumer, and I set $T = 20$ to the 99th percentile of the number of monthly orders placed by a panelist in Q2 2021. The sample includes consumers who place at least one restaurant order in Q2 2021, excluding consumers who place over T orders in a month. The objective function is

$$\text{Ł}(\theta, Y_n, X_n) = \sum_{i=1}^n \log \left(\int \prod_{t=1}^{T_i} \ell(f_{it} \mid x_i, w_{m(i)}, \Xi_i; \theta) \times \prod_{t=T_i+1}^T \ell_0(x_i, w_{m(i)}, \Xi_i; \theta) dH(\Xi_i; \theta) \right), \tag{14}$$

where n is the sample size, $Y_n = \{f_{it} : i, 1 \leq t \leq T_i\}$ contains each consumer's selected platform f_{it} across ordering occasions t. Similarly, $X_n = \{x_i, w_{m(i)} : 1 \leq i \leq n\}$ contains observable consumer characteristics x_i and characteristics $w_{m(i)}$ of the consumer's metro area $m(i)$. The x_i vector includes consumer i's ZIP, age, marital status, and household income. The w_m vector includes restaurants' platform adoption choices, platform fees c_{fz}, waiting times W_{fz}, and restaurant prices p_{jf}. The random vector Ξ_i, which is distributed according to H, includes the persistent channel tastes $\zeta_i^\dagger$, the persistent platform tastes $\tilde{\zeta}_{if}$, and the unobservables $\eta_i^\dagger$ govern-

ing tastes for restaurant orders. Additionally, $\ell(f \mid x, \Xi; \theta)$ is the probability that a consumer chooses to order from platform f conditional on explanatory variables x, taste unobservables Ξ, and model parameters θ, whereas $\ell_0(x, \Xi; \theta)$ is the conditional probability that the consumer does not order from a restaurant. Online Appendix O.10 provides expressions for ℓ and ℓ_0.

Under my chosen parametric assumptions, ℓ and ℓ_0 have closed forms but the integral in (14) does not. I approximate this integral by simulation with 300 draws of Ξ_i for each consumer i in my sample. Last, estimating my model on data from all markets and including platform/metro fixed effects δ_{fm} and metro-specific tastes μ_m^η for restaurant orders is computationally difficult due to the large number of parameters involved. I limit the number of parameters by estimating the model on data from the largest three metros: those of New York City, Los Angeles, and Chicago. I subsequently estimate the δ_{fm} and μ_m^η parameters for each remaining metro m by maximizing (14) as computed on data from metro m with respect to these parameters, holding fixed the other parameters at their estimated values.

Identification. A primary identification concern in demand estimation is price endogeneity, i.e., that unobserved demand shifters affect both consumer demand and prices. In the model, these unobserved demand shifters are the platform/metro fixed effects δ_{fm}. My solution to the endogeneity problem is to estimate the δ_{fm} as parameters, a solution that relies on the assumption that unobserved demand shifters affect platform demand at the metro level but not at more granular levels of geography. With platform/metro fixed effects specified, estimation of consumer responsiveness to fees (i.e., α_i) relies on within-market variation in fees, which is partly attributable to variation in commission cap policies and in local demographics. A concern related to price endogeneity is the endogeneity of platforms' networks. This problem arises in my setting because unobservable demand shifters affect both consumer demand and restaurants' platform adoption decisions. Platform/metro fixed effects also address this endogeneity problem. I estimate effects of restaurants' platform adoption decisions on consumer ordering using variation in platform networks within a metro.

The panel structure of my data permits the identification of the scale parameters $\sigma_{\zeta 1}$, $\sigma_{\zeta 2}$, and σ_η 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 $\zeta_i^\dagger \sim N(0, \sigma_{\zeta 1})$ and $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta 2})$. 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 delivery platforms. Thus, repetition in platform choice is informative about the value of $\sigma_{\zeta 2}$. Last, σ_η controls polarization among consumers in tastes for restaurant dining. When consumers are highly polarized in their tastes

for restaurant meals, they tend to either frequently order from restaurants or rarely order from restaurants. Thus, heterogeneity across consumers in the number of orders placed from restaurants is informative about the value of σ_η. Note that state dependence alternatively explains persistence in consumer ordering; my model rules out this possibility.

Market size. The model of Section 4.2 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 sales estimates. Appendix C explains this procedure in detail.

5.2 Estimation of restaurant marginal costs

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

$$\sum_{f \in \mathcal{G}_j} \left[(1 - r_f) p_{j0} - \kappa_{jf} \right] S_{jf}(\mathcal{J}_m, p), \tag{15}$$

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 the prices of all restaurants. For expositional convenience, I introduce $r_0 = 0$ as the commission rate for direct-from-restaurant ordering. The first-order condition for restaurant profit maximization is

$$\underbrace{\begin{bmatrix} (1 - r_{f_1}) S_{jf_1} \\ (1 - r_{f_2}) S_{jf_2} \\ \vdots \\ (1 - r_{f_k}) S_{jf_k} \end{bmatrix}}_{= \tilde{S}_j} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial p_{jf_1}} & \frac{\partial S_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_1}} \\ \frac{\partial S_{jf_1}}{\partial p_{jf_2}} & \frac{\partial S_{jf_2}}{\partial p_{jf_d}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial p_{jf_k}} & \frac{\partial S_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{= \Delta_p} \left(\underbrace{\begin{bmatrix} (1 - r_{f_1}) p_{jf_1} \\ (1 - r_{f_2}) p_{jf_2} \\ \vdots \\ (1 - r_{f_k}) p_{jf_k} \end{bmatrix}}_{= \tilde{p}_j} - \underbrace{\begin{bmatrix} \kappa_{jf_1} \\ \kappa_{jf_2} \\ \vdots \\ \kappa_{jf_k} \end{bmatrix}}_{= \tilde{\kappa}_j} \right) = 0, \tag{16}$$

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

$$\tilde{\kappa}_j = \tilde{p}_j + \Delta_p^{-1} \tilde{S}_j. \tag{17}$$

Equation (17) provides the basis of my estimation of restaurant marginal costs — I compute the right-hand side of (17) at estimated parameters and observed prices for each restaurant j in a market m. In addition, I assume that

$$\kappa_{jf} = \begin{cases} \kappa_z^{\text{direct}}, & f = 0 \\ \kappa_z^{\text{platform}}, & f \neq 0, \end{cases}$$

where κ_z^{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 preparing platform orders may differ from those for direct orders due to differences in the packaging and to and to costs of communicating with platforms. The costs κ_{jf} that I recover from (17) 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 κ_{j0} costs recovered from (17) as my estimator of κ_z^{direct}. I similarly use the average κ_{jf} recovered from (17) across pairs of platforms $f \neq 0$ and restaurants j locating on these platforms 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 the optimality of platform consumer fees. This procedure follows the standard approach for estimating marginal costs in the differentiated products literature following Berry et al. (1995). Within a ZIP z, platforms' consumer fees solve the following system of first-order conditions:

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

where c_z is a vector containing each platform's consumer fee in ZIP z, r_m is a vector containing each platform's commission rate, p_z is a vector including the sales-weighted average restaurant price in the ZIP on each platform f, and mc_z is a vector containing each platform f's marginal cost mc_{fz}. The vector $\jmath_z$ similarly contains each platform f's sales in z. The $\odot$ operator denotes entry/component-wise multiplication.[31] Letting F denote the number of online platforms, Δ_c is an $F \times F$ matrix whose (f, f') entry is $\partial \jmath_f / \partial c_{f'z}$. The $\mathcal{H}$ matrix also has dimension $F \times F$; its (f, f') entry indicates whether f and f' have the same owner.[32] Therefore,

$$mc_z = c_z + r_m \odot p_z + (\mathcal{H} \odot \Delta_c)^{-1}\jmath_z. \tag{18}$$

I estimate mc_z by substituting the observables c_z, r_m, and p_z and Δ_c and $\jmath_c$ as evaluated at the estimated consumer choice model parameters into the right-hand side of (18).

5.4 Estimation of parameters governing platform adoption by restaurants

I estimate the parameters K_m and $\Sigma = (\sigma_\omega, \sigma_{rc})$ governing restaurants' platform adoption decisions using a two-step generalized method of moments (GMM) estimator. Recall that, as stated by (9), restaurants choose platforms to join to maximize their profits given beliefs that are consistent with actual choice probabilities. The first stage of my estimation procedure involves estimating restaurants' conditional choice probabilities (CCPs) as a function of state variables affecting their profits. The second stage involves setting restaurants' choice probabilities to the estimated CCPs and subsequently fitting the model's prediction of restaurants choices to observed choices.[33]

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[31]My exposition follows Conlon and Gortmaker (2020).

[32]When the platforms are ordered as DoorDash, Uber Eats, Grubhub, and then Postmates, $\mathcal{H}$ is given by

$$\mathcal{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix}.$$

[33]Singleton (2019) similarly uses a CCP estimator to estimate a Seim (2006)-style positioning model.

In the first stage, I specify platform adoption CCPs as a multinomial logit and estimate the parameters of this logit by maximum likelihood. The included covariates are: the population within five miles of the restaurant; the number of restaurants within five miles; municipality fixed effects; an indicator for an active local commission cap; and the shares of the population within five miles that are under 35 years of age, married, both under 35 years of age and married, and that have a household income under $40,000. I also include interactions of the overall population with the of demographic group shares and with the total number of restaurants.

Given first-stage CCPs $\hat{P}_m$, it is straightforward to compute each restaurant's probability of joining platforms $\mathcal{G}$ for a trial value of parameter values θ^{adopt}, where θ^{adopt} includes the common fixed costs of platform adoption $\{K_m(\mathcal{G})\}_{\mathcal{G},m}$ as well as the Σ parameters. As noted, I estimate θ^{adopt} using a GMM estimator.[34] Defining this estimator requires new notation. Let n_J be the number of restaurants in the sample, and let G_{n_J} denote the n_J-vector of observed platform adoption choices. Additionally, let $\Pi^e_{n_J}$ denote a $n_J \times n_{\mathcal{G}}$ matrix whose (j,k) entry is equal to restaurant j's expected variable profits from selecting the kth platform subset $\mathcal{G}_k$, where $n_{\mathcal{G}}$ is the number of platform subsets $\mathcal{G}$. 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.

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

$$g_{m\mathcal{G}}(\mathcal{G}_j, \Pi^e_j, D_j; \theta^{\text{adopt}}) = \mathbb{1}\{m(j) = m\} \left(Q(\mathcal{G}, \Pi^e_j; \theta^{\text{adopt}}) - \mathbb{1}\{\mathcal{G}_j = \mathcal{G}\} \right) \qquad \forall m, \mathcal{G},$$

where $m(j)$ is restaurant j's market and

$$Q(\mathcal{G}, \Pi^e_j; \theta^{\text{adopt}}) = \Pr \left(\mathcal{G} = \arg \max_{\mathcal{G}'} \left[\bar{\Pi}_j(\mathcal{G}', \hat{P}_m) - K_m(\mathcal{G}) + \omega_j(\mathcal{G}) \right] \mid \theta^{\text{adopt}} \right)$$

is the probability that restaurant j chooses platforms $\mathcal{G}$. Note that, when θ^{adopt}_0 are the true model parameters and Π^e_j is computed using restaurants' true conditional choice probabilities, the law of iterated expectations implies $\mathbb{E}[g_{m\mathcal{G}}(\mathcal{G}_j, \Pi^e_j, D_j; \theta^{\text{adopt}}_0)] = 0$. The corresponding sample moment conditions are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{m\mathcal{G}}(\mathcal{G}_j, \Pi^e_j, D_j; \hat{\kappa}) = 0 \qquad \forall m, \mathcal{G}. \tag{19}$$

I target the Σ parameters that govern substitution patterns with additional moment conditions. Each of these moment conditions equalizes the covariance of D_j and a measure of platform adoption as computed on the estimation sample and as predicted by the model. The two measures of platform adoption that I use are (i) an indicator for whether the restaurant joins

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[34]I do not use a maximum likelihood estimator on account of the finite-sample problems of maximum likelihood estimation, which are well documented in the industrial organization literature on entry games; see Pakes et al. (2007) and Collard-Wexler (2013) for more detailed explanations.

any online platform and (ii) the number of online platforms that a restaurant joins. These moment conditions are based on the functions

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

$$g_{\omega,2}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) = D_j \times \left(|\mathcal{G}_j| - \sum_{\mathcal{G}} |\mathcal{G}| \times Q(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) \right),$$

where $|\mathcal{G}|$ is the cardinality of set $\mathcal{G}$. When θ_0^{adopt} are the true model parameters that generate $\mathcal{G}_j$, and when Π_j^e is computed using the true CCPs,

$$\mathbb{E}[g_\omega(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0. \tag{20}$$

The sample moment conditions corresponding to (20) are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{\omega,k}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0, \qquad k \in \{1, 2\}. \tag{21}$$

Increasing σ_ω and σ_{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 σ_ω and σ_{rc}.[35] A natural alternative to using the moment condition (20) in the GMM estimation 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 sample moment condition corresponding to (20) is

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_\omega(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0. \tag{22}$$

My estimator $\hat{\kappa}$ is the vector of parameter values that solves equations (19) and (22). Given that that the number of equations across (19) and (22) is equal to the number of parameters, it is generally possible to solve these equations exactly.

5.5 Estimation of restaurant-network weights in platform objective functions

I solve for the h_{fm} weights on restaurant-network sizes in platform objective functions from first-order conditions for optimal commission rates, substituting in estimates for true parameters in

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[35]Responses of the share of restaurants on platforms and of the average number of platforms joined differentially depend on σ_ω and σ_{rc}. Increasing σ_{rc} makes platform subsets with more overlap more substitutable, and subsets with less overlap less substitutable. This means that, when σ_{rc} is high, restaurants that do not belong to any platform are more likely to substitute to a platform subset with one platform than to one with multiple platforms. Thus, for a fixed increase in the share of restaurants belonging to at least one online platform, the average number of platforms joined increases by less when σ_{rc} is larger.

these conditions. See Online Appendix O.13 for a detailed explanation of the procedure.

6 Estimation results

6.1 Parameter estimates for consumer choice model

Table 6 reports estimates of consumer choice model parameters. Several estimates are noteworthy. First, the scale parameter $\sigma_{\zeta 1}$ of persistent tastes for online ordering is large, indicating dispersion across consumers in tastes for online ordering. The scale parameter of platform-specific tastes $\sigma_{\zeta 2}$ is smaller but also sizeable, suggesting that consumers are divided by both overall taste for online ordering and by tastes for specific platforms. Additionally, the estimated demographic effects λ^f_{age} and $\lambda^f_{\text{married}}$ imply that young and unmarried consumers prefer delivery platforms relative to older and married consumers. The parameters $\lambda^\eta_{\text{young}}$ and $\lambda^\eta_{\text{married}}$ govern differences in tastes for restaurant orders between demographic groups; we see that young consumers and unmarried consumers have lower tastes for restaurant orders that are not placed on platforms. In addition, the fact that α_{LowInc} is positive indicates that low-income consumers are more price-sensitive than their higher-earning counterparts, although the difference is small. Estimated own-price elasticities in the Chicago metro range from -0.96 to -3.05 across platforms.[36] Consumers are estimated to prefer platforms with lower waiting times, as the estimated disutility ρ of waiting time (in hours) is positive and statistically significant. The large estimate of σ_η suggests limited substitutability between restaurant ordering and at-home dining. Last, platform sales responds to the number of restaurants on the platform — the estimated elasticities of platform sales with respect to platform network size range from 0.48 to 1.10 across platforms in the Chicago metro.[37]

To evaluate the estimates and understand their implications for ordering behaviour, I compute substitution patterns predicted by the model. First, Table 7 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 25% and 40% of platforms' consumers who substitute away from ordering on a platform no longer place any restaurant order. An additional 24–34% switch to ordering directly from a restaurant whereas the remainder switch to a different platform.

Figure O.27 in Online Appendix O.15 describes sales differences between restaurants that belong and do not belong to online platforms. The figure shows that, on average across ZIPs and relative to restaurants that do not belong to any platform, the sales of a restaurant that joins DoorDash, the most popular platform, are 29% higher.

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[36]Note that, unlike in the case of one-sided markets, elasticities under one in absolute value do not contradict profit maximization under non-negative marginal costs. This is because the effective marginal cost that platforms consider in setting consumer fees are marginal costs net of restaurant commissions. See Online Appendix Table O.25 for cross-price elasticity estimates.

[37]See Online Appendix Table O.26 for details on the computation of these elasticities.

Table 6: Selected estimates of consumer choice model parameters

Parameter	Estimate	SE
α	0.228	0.003
α_{LowInc}	0.009	0.001
$\sigma_{\zeta 1}$	3.38	0.02
$\sigma_{\zeta 2}$	1.67	0.01
τ	0.97	0.08
$\lambda^{\text{DD}}_{\text{young}}$	1.19	0.02
$\lambda^{\text{DD}}_{\text{married}}$	-0.87	0.02
$\lambda^{\text{Uber}}_{\text{young}}$	1.06	0.02
$\lambda^{\text{Uber}}_{\text{married}}$	-1.07	0.02
$\lambda^{\text{GH}}_{\text{young}}$	0.70	0.02
$\lambda^{\text{GH}}_{\text{married}}$	-0.63	0.02
$\lambda^{\text{PM}}_{\text{young}}$	0.89	0.03
$\lambda^{\text{PM}}_{\text{married}}$	-1.98	0.03
σ_η	2.110	0.005
$\lambda^{\eta}_{\text{young}}$	-0.68	0.01
$\lambda^{\eta}_{\text{married}}$	0.18	0.01

Notes: this table reports estimates of the parameters of the consumer choice model. Estimates of the platform/metro fixed effects δ_{fm} and the metro fixed effects μ^{η}_m in consumer tastes for restaurant dining are omitted.

Table 7: Between-platform diversion ratios for the Chicago metro

Platform	Quantity response for...					
	No purchase	Direct	DD	Uber	GH	PM
DD	0.40	0.34	-1.00	0.17	0.07	0.02
Uber	0.38	0.31	0.21	-1.00	0.07	0.02
GH	0.30	0.29	0.22	0.17	-1.00	0.02
PM	0.25	0.24	0.24	0.19	0.09	-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. Formally, the table reports

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

where $c_{f'm}$ is a vector of the consumer fees charged by f' across all ZIPs within m; $\jmath_{fm}$ 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 8 describes the restaurant markups implied by my estimates of κ_{jf}. Restaurants' markups on platforms are much larger where commission caps are in effect. Their markups for direct orders are about a fifth of their prices. Additionally, the estimated costs for direct orders and platform-intermediated orders differ by only one cent on average across ZIPs.[38]

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[38]Figure O.25 in Online Appendix O.9 reports the distribution of the estimated difference $\kappa^{\text{platform}}_z - \kappa^{\text{direct}}_z$, which concentrates in [-\$2.00, \$2.00].

Table 8: Restaurant markups ($)

Means ± std. dev. across ZIPs by channel, policy

Channel	No cap	Cap
Direct	4.34±0.02	4.33±0.02
Platform	1.96±0.15	3.60±0.12

Notes: the table describes markups $(1 - r_f)p_{jf} - \kappa_{jf}$ across ZIPs separately for direct orders (for which the commission rate is $r_0 = 0$) and platform-intermediated orders, and also separately for ZIPs with commission caps and those without caps. Note that the average price for a direct-from-restaurant order is $21.89 (standard deviation: $1.17).

6.3 Estimates of platform marginal costs

Table 9 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"; ("Dashers" is DoorDash's name for its couriers).[39] This level of courier pay lines up well with the estimated interquartile range of DoorDash's marginal costs of $7.08 to $9.72.

Table 9: Estimates of platforms' marginal costs ($)

Platform	Marginal costs				Markup			
	Mean	25th %ile	Median	75th %ile	Mean	25th %ile	Median	75th %ile
DD	8.20	7.08	8.79	9.72	5.90	5.38	5.86	6.43
Uber	8.08	6.95	8.04	9.13	5.83	5.44	5.84	6.22
GH	9.39	7.40	9.87	10.94	4.52	4.26	4.58	4.91
PM	13.98	11.86	14.21	15.72	4.79	4.27	4.80	5.37

6.4 Estimates of the restaurant platform adoption model

Table 10 reports estimates of the parameters governing platform adoption by restaurants. In interpreting these parameters, note that the average expected variable profits of a restaurant that joins no online platform across ZIPs in my sample is roughly $12,500 a month. The fixed cost estimates are at a monthly level. The three lowest of the estimated fixed costs $K_m(\mathcal{G})$ are those for platform subsets including a single platform, which is to be expected if joining multiple platforms is more costly than joining a single one. I compute the standard errors reported by Table 10 using the bootstrap procedure described in Appendix D. The estimated scale parameter of restaurants' idiosyncratic $\tilde{\omega}_j(\mathcal{G})$ disturbances of joining the platforms in $\mathcal{G}$ is about $650, which implies a standard deviation of about $834. This is smaller than the fixed costs of joining platform subsets. The parameter σ_{rc}, which controls the variance of random coefficients on platform membership of subsets, is statistically significant.

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[39]See https://help.doordash.com/consumers/s/article/How-do-Dasher-earnings-work.

Table 10: Estimates of restaurant platform adoption parameters ($'000s/month)

Parameter	Estimate	SE
σ_ω	0.65	0.04
σ_{rc}	0.34	0.03
Fixed cost: DD	1.45	0.07
Fixed cost: Uber	1.52	0.07
Fixed cost: GH	2.34	0.10
Fixed cost: PM	1.56	0.08
Fixed cost: DD, Uber	2.32	0.11
Fixed cost: DD, GH	2.33	0.11
Fixed cost: DD, PM	2.00	0.08
Fixed cost: Uber, GH	2.29	0.12
Fixed cost: Uber, PM	3.04	0.15
Fixed cost: GH, PM	2.97	0.14
Fixed cost: DD, Uber, GH	2.68	0.11
Fixed cost: DD, Uber, PM	3.12	0.15
Fixed cost: DD, GH, PM	3.05	0.14
Fixed cost: Uber, GH, PM	2.99	0.14
Fixed cost: All	1.89	0.06

Notes: the table reports estimates of parameters governing restaurants' platform adoption decisions and, in the "SE" column, their standard errors. The "Fixed cost" parameters are cross-metro averages of fixed costs of joining the various platform subsets.

6.5 Estimates of restaurant-network weights in platform objective functions

Table 11 describes estimates of the weights h_{fm} that platforms place on their restaurant networks in setting commissions. These estimates suggest that dynamic considerations in commission-setting are significant — beyond the benefit of a restaurant on a platform's contemporaneous profits, platforms value the addition of a restaurant to their network by $850–$1044 on median across metros.

Table 11: Estimates of restaurant-network weights ($)

(a) Cross-metro distribution of estimated weights

Platform	Quantile		
	25%	Median	75%
DD	740	850	979
Uber	550	606	671
GH	966	1059	1066
PM	992	1044	1195

(b) Standard errors for cross-metro median weights

Platform	SE
DD	44
Uber	30
GH	34
PM	67

Notes: this table reports quantiles of the estimated h_{fm} weights taken across metros m for each leading platform.

7 Counterfactual analysis

This section uses my model to evaluate commission caps. It also evaluates alternative policies intended to bolster restaurant profitability, and the impact of delivery platforms on the restaurant industry. I evaluate commission caps by comparing baseline equilibria without commission caps to equilibria under caps. Rather than perform this section's counterfactual analyses on full metro areas, I perform them on the core municipality of each metro area and, in the case of New

York's metro area, on Manhattan. Limiting attention to metro areas' core subregions reduces the computational cost of computing equilibria. I compute equilibria using a combination of algorithms described by Online Appendix O.14.

7.1 Evaluation of commission caps

Figure 8 reports aggregate welfare effects of commission caps as shares of participant surplus from delivery platforms.[40] Caps achieve their intended objective of boosting restaurant profits, but they reduce total welfare. Both consumers and platforms suffer from commission caps, although consumer losses exceed those of platforms despite the fact that the policymakers intended caps to benefit restaurants at platforms' expense. The welfare loss here reflects that commission caps impede platforms from balancing consumer fees and restaurant commissions to encourage both sides' participation on platforms; limits on commissions lead platforms to rely more heavily on consumers for revenue, thus reducing consumers' platform usage. Indeed, consumers lose from commission caps because—as shown by Table 12—platforms raise their fees in response to caps by more than restaurants lower their prices. This positive net change in the consumer's cost of ordering from platforms outweighs the benefit of expansions in platforms' restaurant networks owing to caps. Figure 8 shows that commission caps reduce consumer surplus by over 5% of participant surplus from food delivery platforms, raise restaurant profits by about 3% of participant surplus, and reduce platform profits by about 4% of participant surplus. Summing over these effects, total welfare falls by over 6% of participant surplus. Figure O.28 in the Online Appendix shows that young and unmarried consumers experience especially high losses from commission caps, which reflects that these consumers are especially likely to use delivery platforms.

Figure 8: Welfare effects of 15% commission cap relative to participant surplus from platforms
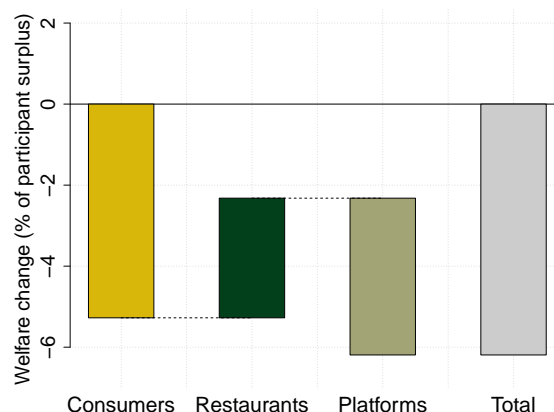
Notes: this figure plots ratios of welfare effects and the participant surplus from delivery platforms aggregated across metro areas. Note that the figure provides cumulative welfare changes when consumers' changes are considered first, then restaurants, and then platforms.

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[40]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. Online Appendix O.9 provides an analogue of Figure 8 that reports caps' welfare effects as a share of the sum of participant surplus and variable platform profits.

Table 12: Fee and price effects of a 15% commission cap

Outcome	Mean	Median	Min.	Max.
Fee	5.25	5.36	4.48	5.74
Restaurant price	-4.72	-4.83	-5.22	-3.94
Net change	0.52	0.53	0.50	0.55
Fees (fixed prices)	4.28	4.34	3.68	4.68

Notes: the table reports average effects of a commission cap on platform fees and restaurants prices on platforms. The "Fees (fixed prices)" row reports average effects of a 15% commission cap on fees in a scenario in which restaurants cannot adjust their prices upon the imposition of the cap.

Table 13: Welfare effects of 15% commission cap (% of platform revenue)

(a) Restaurant price response

Outcome	Mean	SE	Median	SE	Min.	Max.
Consumer welfare (fees/prices only)	-3.62	0.06	-3.83	0.07	-4.18	-2.67
Consumer welfare (total)	-2.24	0.06	-2.30	0.09	-2.68	-1.45
Restaurant profits	1.25	0.04	1.13	0.08	0.04	2.65
Platform variable profits	-1.64	0.05	-1.66	0.07	-2.05	-1.01
Total welfare	-2.63	0.10	-2.31	0.11	-3.83	-1.77

(b) No restaurant price response

| Outcome	Mean	SE	Median	SE	Min.	Max.
Consumer welfare (fees/prices only)	-25.88	0.08	-28.75	0.23	-31.73	-18.47
Consumer welfare (total)	-22.40	0.09	-24.78	0.32	-28.58	-14.48
Restaurant profits	9.20	0.08	7.81	0.21	4.07	15.60
Platform variable profits	-18.34	0.12	-21.00	0.45	-23.09	-11.51
Total welfare	-31.54	0.20	-33.48	0.62	-41.48	-21.80

Notes: all welfare and profit figures are expressed as shares of platform revenues without caps. I compute the means and medians across regions wherein I simulate commission caps, and I weight each region by its population. I compute standard errors using a bootstrap procedure with 100 replicates.

The effects of commission caps are dampened by responses related to the multi-sided nature of the food delivery market. Table 13, which summarizes welfare effects of caps as shares of platform revenue, illustrates this point. Whereas Table 13a reports results for the case in which restaurant prices respond to caps, Table 13b reports results for the case in which restaurant prices are held fixed. Whereas "Consumer welfare (fees/prices only)" reports effects that do not account for changes in platforms' restaurant networks, "Consumer welfare (total)" reports effects that do take account of these responses. A comparison of these rows shows that consumer losses from commission are mitigated by the fact that caps lead additional restaurants to join platforms. Indeed, when restaurant prices respond to caps, consumer losses are over 60% greater when caps' effects on platform restaurant networks are ignored. These losses are mitigated to an even greater extent by restaurant price adjustments: the average effect of a cap on consumer welfare is over 10 times greater when restaurant prices do not respond to the cap. Other components of total welfare are similarly larger in magnitude absent price responses.

Figure 9 plots commission caps' effects on (i) the number of orders placed on platforms and

(ii) the share of restaurants joining a platform across metros. Note that the predicted effects of caps on sales and restaurant platform adoption are similar to the difference-in-differences estimates of commission caps' effects reported by Section 3. Additionally, the figure shows that differences in caps' effects on restaurant uptake of platforms largely explain differences in effects on ordering across metros.

Figure 9: Cross-metro comparison of commission caps' sales and platform adoption effects
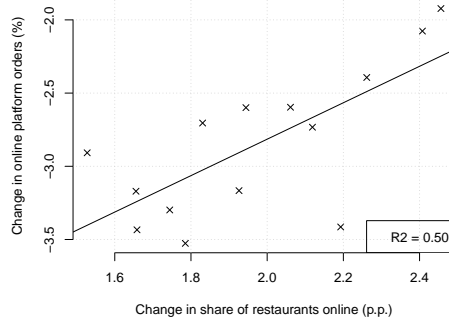

Notes: each point provides the estimated effect of a 15% commission cap on the share of restaurants that join at least one online platform and on overall online platform sales. The solid lines are ordinary least squares regression lines, and the R^2 of the regression is displayed in the lower right corner.

7.2 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 0% to 29% and compare them to the baseline equilibrium wherein commission rates equal 30%. Figure 10 provides results for the Los Angeles. Lowering the cap level monotonically raises restaurant profits while lowering platform profits, consumer welfare, and total welfare. This finding applies to all metro areas. Thus, the signs of the estimated welfare effects of the 15% commission cap do not depend on the 15% level of the cap, but instead broadly apply to commission caps.

Figure 10: Welfare effects of alternative commission caps in Los Angeles
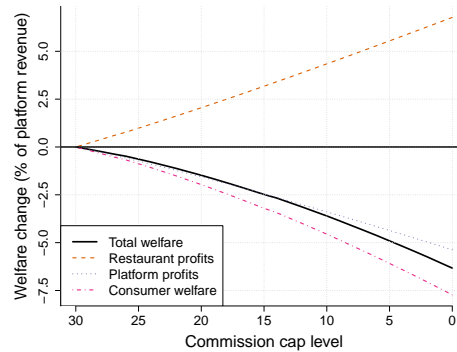
Notes: this plot provides welfare effects of capping commissions at levels between 30% and 0% as a share of total platform revenue in the baseline equilibrium.

Figure 11: Welfare effects of two-sided cap relative to participant surplus from platforms
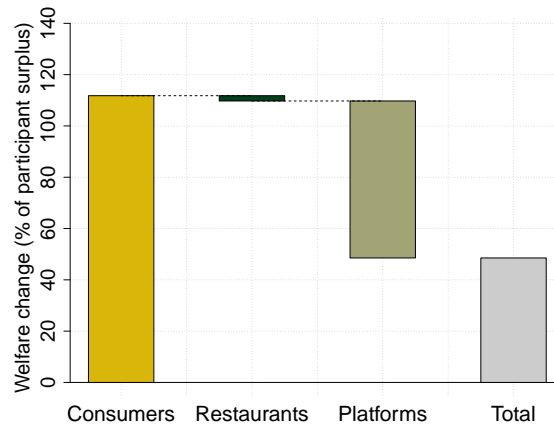
Notes: this figure plots aggregate welfare effects of a 15% commission cap combined with a $1.00 cap on consumer fee increases relative to participant surplus.

7.3 A two-sided cap

Given that commission caps boost restaurant profits at the expense of consumers, 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 consider a counterfactual in which governments prohibit platforms from raising their consumer fees by more than $1.00 upon the imposition of commission caps.

Figure 11 provides the welfare effects of such a two-sided cap aggregated across markets. Although the two-sided cap raises overall welfare and participation on platforms—the share of restaurants on a platform rises by 10 percentage points and the number of restaurant orders rises by 6%—restaurants are slightly worse off from the two-sided cap. This is because the policy makes platforms more attractive to consumers by increasing the variety of restaurants available to consumers through platforms and by reducing restaurant prices on platforms. Thus, the two-sided cap leads consumers to switch from ordering from restaurants directly to using food delivery platforms, thus undermining the profitability of restaurants who pay no commissions on direct-to-consumer orders. Indeed, the share of orders placed directly by consumers falls by 12% under the two-sided cap. This result justifies why restaurants have lobbied for a cap on commissions rather than a cap on platforms' overall price levels (i.e., sums of consumer fees and restaurant commissions). The result also illustrates a counterintuitive fact of digital platform markets — measures that bring more online business to platform sellers (e.g., consumer fee caps) may undermine seller profitability due to substitution between online and offline channels.

7.4 Taxing commissions

Commission caps lower welfare by distorting platforms' balance of consumer fees and restaurant commissions and thereby reducing consumer platform usage. I investigate whether a tax on commission charges could avoid this distortionary impact, and increase restaurant profits

without entailing large consumer losses. Revenues from this tax are assumed to be remitted to restaurants. Besides directly providing revenue to restaurants, a commission tax penalizes commissions as a revenue source for platforms relative to consumer fees, which could lead platforms to reorient their price structures away from commissions and toward fees. The tax that I consider is a share $\mathribk{t}$ of a platform's commission earnings. Recalling the expression for platform f's profits in (12), platform f's tax obligations are

$$\mathbb{t} \times \sum_{z \in \mathcal{Z}_m} r_{fz} \bar{p}^*_{fz} \eta_{fz}.$$

I set the tax rate $\mathbb{t}$ so that government revenue from the tax absent a pricing response by platforms is equal to restaurants' profit gains from a 15% commission cap. This yields $\mathbb{t} = 1.8\%$ for Los Angeles, the city on which I focus my analysis of a commission tax.

Table 14 reports effects of both a 15% commission cap and the commission tax for Los Angeles. Note that the sum of the 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 small relative to that of cap; responses in fees and commissions to a tax are relatively small. Consequently, reductions in consumers' platform orders and consumer welfare are small.

Table 14: Comparison of commission cap and commission tax

Change in...	Cap	Tax
Avg. consumer fee ($)	5.62	0.60
Avg. commission rate (p.p.)	-15.00	-1.36
Avg. platforms adopted (%)	4.58	0.43
Shr. adopting a platform (p.p.)	1.93	0.18
Platform orders (%)	-3.17	-0.26
Restaurant profits ($ p.c.)	3.18	0.26
Platform profits ($ p.c.)	-2.45	-2.10
Consumer welfare ($ p.c.)	-3.25	-0.25
Government revenue ($ p.c.)	0.00	2.79
Total welfare ($ p.c.)	-2.53	0.69

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.

7.5 Role of multihoming

Restaurants multihome across food delivery platforms. The freedom of restaurants to multihome across food delivery platforms may reduce restaurant profits in two ways. First, platforms have a greater competitive pressure to lower commission rates when the restaurants that the low commissions attract are exclusive to the platform. Second, a prohibition on multihoming would directly reduce restaurant membership on delivery platforms and thereby weaken restaurants'

competitive pressures to join platforms, which entails fixed adoption costs and commission charges. In Online Appendix O.16, I find that—for the above reasons—multihoming reduces restaurant profits.

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 *a priori* ambiguous. This is because platforms have countervailing market expansion and cannibalization effects — platforms raise restaurant sales, but sales on platforms cannibalize restaurants' commission-free sales made directly to consumers. 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 are equal to zero, and (ii) platform fixed costs are 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 platform fixed costs are non-negative.

My estimates of the welfare effects of eliminating platforms account for differences between deliveries made by restaurants' own delivery services and those delivered by online platforms. Consumer preferences to order from platforms rather than directly from restaurants (e.g., because deliveries from platforms are more reliable) are captured by the δ_{fm} fixed effects and ζ_{if} idiosyncratic tastes in the consumer utility model. Additionally, restaurants may face differential costs of fulfilling orders that they deliver themselves versus those delivered through platforms. The model accounts for these differential costs through the $K_m(\mathcal{G})$ costs of platform adoption and differential marginal costs between direct and platform-intermediated orders.

Figure 12 plots reductions in restaurant ordering across metros; it shows that in about half of cases, a restaurant order placed on a platform is no longer placed when platforms are eliminated. Thus, platforms have a substantial market expansion effect. Table 15 summarizes the welfare effects of eliminating food delivery platforms.[41] 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.

8 Conclusion

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

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[41]See Online Appendix O.15 for market-specific results.

Figure 12: Effects of eliminating delivery platforms on restaurant orders

Change in restaurant orders (%)
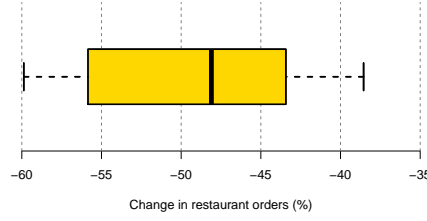
Notes: this figure reports the effects of eliminating delivery platforms on restaurant orders across metros. The reported changes are relative to platform orders in the baseline equilibrium. The plotted points are the cross-metro minimum effect, the 0.25, 0.50, and 0.75 quantiles of the effects across metros, and the cross-metro maximum effect.

Table 15: Welfare effects of eliminating delivery platforms (dollars per capita, annual)

Outcome	Mean effect
Consumer welfare	-66.98
Restaurant profits	17.88
Platform variable profits	-58.06
Total welfare: lower bound	-107.16
Total welfare: upper bound	-49.10

Notes: this table summarizes effects of abolishing food delivery platforms across markets. All welfare figures are in annualized dollar-per-capita terms.

sponses in shaping the effects of policies affecting prices in multi-sided markets. I make this assessment using a model of platform competition and a rich collection of datasets characterizing the US food delivery industry. 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. 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. Additional analyses of a two-sided price cap and of the elimination of platforms 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.

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Appendices

A   Delivery fee measures

I estimate the conditional expectation in (2) using a linear regression of the form

$$df_{kfz} = x'_k \beta_f + w'_z \mu_f + \phi x_k^{\text{dist}} w_z^{\text{dens}} + \epsilon_{kfz}, \tag{23}$$

where w_z are characteristics of ZIP z and x_k^{dist} and w_z^{dens} are scalar components of x_k and w_z, respectively, that are explained at the end of this paragraph. Additionally, ϵ_{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.[42] Last, x_k^{dist} is the delivery distance for order k and w_z^{dens} is the local density of z; I included variables' interaction in (23) to capture the possibility that the cost of increasing an order's distance depends on

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[42]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.

population density due to traffic congestion. It is important to include a rich set of geographical features so that the fee indices flexibly capture fee differences across geography.

There are several problems in estimating (23) 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, and I therefore use it to estimate (23).[43] The Lasso minimizes the sum of squared residuals plus the L_1 norm of the coefficient vector times a penalization parameter. 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. I select the value of the penalization parameter using k-fold cross validation, with $k = 10$.

Upon estimating the parameters (β_f, μ_f, ϕ_f) of (23) with a Lasso estimator separately for each platform f, I compute the delivery fee measure $\widehat{DF}_{fz}$ as

$$\widehat{DF}_{fz} = \bar{x}'\hat{\beta}_f + w_z'\hat{\mu}_f + \hat{\phi}_f \bar{x}_k^{\text{dist}} w_z^{\text{dens}}.$$

I set $\bar{x}$ to the average x_k across all orders in my sample. Additionally, I estimate each regression on observations recorded in the second quarter of 2021.

B   Restaurant price measures

This appendix describes the construction of restaurant price measures used in model estimation. I define such a measure $p_{f\mathcal{G}z}$ for each combination of a platform f, a platform subset $\mathcal{G}$, and a ZIP z. Variation in the $p_{f\mathcal{G}z}$ measures across platforms, platform subsets, and ZIPs reflects variation in the price of a fixed menu item offered by a restaurant chain across platforms, across ZIPs z, and across restaurant locations adopting different platforms $\mathcal{G}$. I estimate a menu item's relative price across platforms, locations on different platform subsets, and locations in different regions using a Lasso regression with item fixed effects and log price as the dependent variable. The Lasso selects which interactions of platform, platform subset, and geography are empirically relevant in explaining prices. With relative prices in hand, I obtain absolute prices by fixing the price of an order from Uber Eats in the New York City metro area from a restaurant that belongs only to Uber Eats to the average size of an Uber Eats order in New York before fees and taxes.

The Lasso is based on

$$\log p_{\iota f\mathcal{G}mt} = \varphi_\iota + \vartheta_{f\mathcal{G}m} + \epsilon_{\iota f\mathcal{G}mt}, \tag{24}$$

where ι denotes a menu item, t denotes a transaction, $p_{\iota f\mathcal{G}mt}$ is the observed transaction price of the item ι, φ_ι are item fixed effects, and $\vartheta_{f\mathcal{G}m}$ are platform/platform subset/metro fixed effects. Here, f and m are the the platform and metro of the transaction in question, and $\mathcal{G}$ is the set of platforms that the restaurant has joined. I interpret the $\epsilon_{\iota f\mathcal{G}mt}$ as measurement error. When

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[43]See Tibshirani (1996) for explication of the Lasso.

$\epsilon_{\iota t} = 0$ yields, we have (suppressing the transaction subscript)

$$\frac{p_{\iota f \mathcal{G} m}}{p_{\iota f' \mathcal{G}' m'}} = e^{\vartheta_{f \mathcal{G} m} - \vartheta_{f' \mathcal{G}' m'}}. \tag{25}$$

Thus, the ϑ parameters imply relative prices of a menu item on a particular combination of platform, platform subset, and metro.

Defining price indices in levels at the level of a platform, platform subset, and metro triple requires fixing one of the $p_{\iota f \mathcal{G} m}$ prices; once such a price is fixed, (25) and the ϑ fixed effects imply $p_{\iota f \mathcal{G} m}$ for all remaining $(f, \mathcal{G}, m)$ triples. In practice, I fix the price of an order on Uber Eats from a restaurant that belongs only to Uber Eats in New York City's metro area to the average basket size for an order from Uber Eats in New York City's metro area. Note that Uber Eats is the largest delivery platform in New York City's metro area, which is the largest metro area in the United States. This average basket size is \$29.50.

In estimating the Lasso, I specify ϑ as a linear combination of fixed effects for interactions of platforms, platform subsets, and metros:

$$\vartheta_{f \mathcal{G} m} = \Upsilon_f + \Upsilon_{\mathcal{G}} + \Upsilon_m + \Upsilon_{f\mathcal{G}} + \Upsilon_{fm} + \Upsilon_{\mathcal{G}m} + \Upsilon_{f\mathcal{G}m}. \tag{26}$$

The collinearity of fixed effects does not preclude the application of the Lasso, which selects the granularity of fixed effects to manage a bias/variance trade-off. I select the penalization parameter entering the Lasso objective function using 10-fold cross-validation. Rather than estimate (24) directly, I estimate the equation after applying a fixed-effects transformation to both sides of the equation to removes the item-level fixed effects φ_ι from (24). The estimation sample includes all transactions in the Numerator data in Q2 2021 placed in one of the 14 metro areas that this article analyzes. My restaurant price indices are then

$$p_{f \mathcal{G} m} = p_{f_0 \mathcal{G}_0 m_0} e^{\hat{\vartheta}_{f \mathcal{G} m} - \hat{\vartheta}_{f_0 \mathcal{G}_0 m_0}},$$

where f_0 denotes Uber Eats, $\mathcal{G}_0$ denotes the platform subset containing no online platform other than Uber Eats, and m_0 is the New York City metro area. In addition, the $\hat{\vartheta}$ are estimates of the ϑ parameters. As suggested above, $p_{f_0 \mathcal{G}_0 m_0} = \$29.50$.

I now discuss several caveats in the computation of the indices. First, I lack item-level data on Postmates orders. Consequently, I set the price indices for Postmates equal to those for Uber Eats. In particular, when f_1 is Postmates and f_0 is Uber Eats, I set $p_{f_1 \mathcal{G} m} = p_{f_0 \mathcal{G}^* m}$, where $\mathcal{G}^*$ is equal to $\mathcal{G}$ with membership of Postmates and Uber Eats interchanged. That is, $\mathcal{G}^*$ includes Postmates (Uber Eats) if and only if $\mathcal{G}$ includes Uber Eats (respectively, Postmates), and $\mathcal{G}$ and $\mathcal{G}^*$ each contain DoorDash and Grubhub if and only if the other set does. Another concern is that restaurant prices depend on the presence of a commission cap. I do not detect a difference in menu items' prices on online platforms between areas with and without commission caps. This could owe to the fact that most of the items for which I observe purchases across platforms are sold by chain restaurants that may practice uniform or zone pricing; that is, they

Figure 13: Restaurant price indices (medians and interquartile ranges)

(a) Level

(b) Relative to direct price
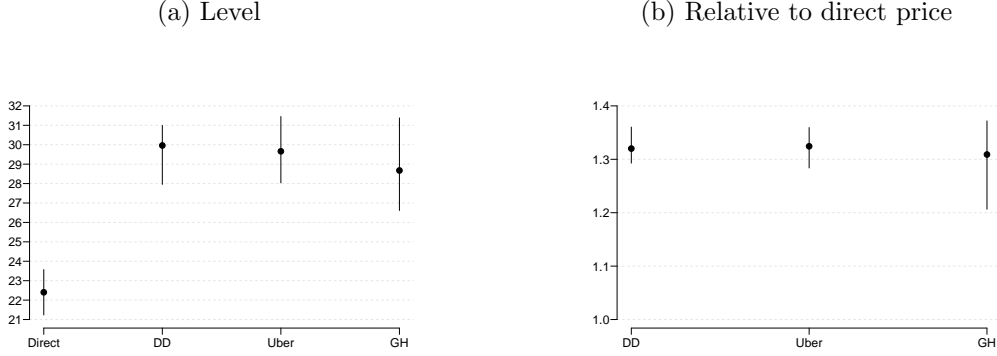
Notes: Panel (b) reports the median and interquartile range of each platforms' price indices divided by the respective direct price indices.

may not condition their prices on local commission cap policies.[44] I alternatively check for a difference between restaurants' prices on platforms between areas with and without commission caps by manually collecting data on restaurant prices. In particular, I randomly drew 20 and 10 restaurants on each of DoorDash and Uber Eats in each CBSA, respectively and found the price of an item from their menu on each delivery platform to which they belong. I also found the price of the same item for direct-from-restaurant orders. Collecting these data manually between July 21 and August 18, 2021 yielded a dataset of 593 prices for menu items on platforms for which a direct-from-restaurant price is available. A platform/menu item level regression of the ratio of the platform-intermediated price to the direct-from-restaurant price on an indicator for a commission cap being in place with platform and CBSA fixed effects included yields a coefficient of -7.02% (standard error: 2.94%) on the commission cap indicator. I adjust my estimated markup of platform-intermediated prices over direct-from-restaurant prices by this amount in computing my restaurant price measures. In particular, I set the restaurant price index for online platform f, platform subset $\mathcal{G}$, and metro m to

$$
p_{f\mathcal{G}m}^{\text{cap}} = p_{0\mathcal{G}m}\left[\frac{p_{f\mathcal{G}m}}{p_{0\mathcal{G}m}} - 0.0702\right]
$$

for ZIPs z where commission caps are in effect.

Figure 13 displays the median and interquartile range of restaurant price indices across metros m and subsets $\mathcal{G}$ for each platform f. This figure shows that that there is a systematic difference between direct-order prices and online platform prices, but not between the prices charged by restaurants across different online platforms.

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[44]See DellaVigna and Gentzkow (2019) and Adams and Williams (2019) for discussions of uniform and zone pricing.

C Market size

I set the number of consumers in each ZIP and distribution of these consumers' demographic types (i.e., their ages, marital statuses, and incomes) using a combination of the Edison platform/ZIP-level estimates of sales volumes, the Numerator panel, and the ACS. For each metro m, 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 residing in the ZIP. For ZIPs with fewer than 10 Numerator panelists, I instead set the distribution equal to that in the collection of ZIPs within five miles of the ZIP in question. Next, I compute an equilibrium in restaurant prices conditional on observed platform adoption decisions, fees, and commissions in April 2021. The ratio of the number of platform orders in the market from the Edison transactions dataset for April 2021 to the expected number of platform orders in this equilibrium provides the factor by which I multiply each ZIP's number of consumers. After scaling up the tentative number of consumers in each ZIP by this market-level factor, my model's predictions of metro-level sales align with the Edison estimates. As noted in Section 2.2, the Edison sales estimates align with DoorDash's earnings reports and the Consumer Expenditure Survey.

D Bootstrap procedure

This appendix describes the bootstrap procedure that I use to compute standard errors. This procedure has features of the parametric bootstrap and of the nonparametric bootstrap. The parametric part involves drawing from the estimated asymptotic distribution of the consumer choice model estimates and using these draws as inputs in later stages of estimation. The nonparametric part primarily involves sampling with replacement from the population of restaurants. Recall that I estimate my consumer choice model via maximum likelihood. I estimate the asymptotic variance of my maximum likelihood estimator using the outer product of the gradients estimator. I then take $B = 100$ draws from the associated estimate of the asymptotic distribution of $Z = \sqrt{n}(\hat{\theta}^{\mathrm{cons}} - \theta_0^{\mathrm{cons}})$, where θ_0^{cons} is the true choice model parameter vector, $\hat{\theta}^{\mathrm{cons}}$ is the maximum likelihood estimator, and n is the sample size. Let Z^b denote the bth draw, and let $\hat{\theta}^{\mathrm{cons},b} = \hat{\theta}^{\mathrm{cons}} + n^{-1/2}Z^b$. I estimate restaurants' and platforms' marginal costs, call them $\hat{mc}^b$ under each $\hat{\theta}^{\mathrm{cons},b}$. For each b, I also take a standard bootstrap draw of restaurants within each market, where each market is defined by its ZIP and its platform subset choice. Let $\mathcal{J}^b$ denote the bth draw. I proceed to estimate the parameters of restaurants' platform adoption game at $\{\hat{\theta}^{\mathrm{cons},b}, \mathcal{J}^b, \hat{mc}^b\}$ for each b. This procedures yields estimates $\hat{\theta}^{\mathrm{adopt},b}$ of the parameters of restaurants' platform adoption game for each bootstrap replicate 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 $\{\hat{\theta}^b, \hat{mc}^b, \hat{\theta}^{\mathrm{adopt},b}\}$ for each b, which yields estimates $\hat{h}_{fm}^b$ of these weights for each b. Last, I solve for equilibria at each b and take the standard deviation of outcomes across replicates b to obtain the standard errors for results from counterfactual simulations.