Online Appendix for "Fee Optimality in a Two-Sided Market"*

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Contents

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O.1 Consumer fee distortions in the full model

In Section 2, I developed an illustrative model of a monopolistic platform that yields the following decomposition of distortions in platform consumer fees:

$$c^{\text{pr}} - c^{\text{so}} = \underbrace{\mu_B^{\text{pr}}}_{\text{Market power}} - \underbrace{aD^{\text{so}}}_{\text{Offline business stealing}} + \underbrace{\left[\bar{b}_S^{\text{so}} - \tilde{b}_S^{\text{so}}\right]}_{\text{Spence distortion}} + \underbrace{\left[\tilde{b}_S^{\text{so}} - \tilde{b}_S^{\text{pr}}\right]}_{\text{Displacement distortion}}, \tag{1}$$

where the superscripts "pr" and "so" denote quantities associated with the allocations maximizing platform profits and total welfare, respectively. Throughout this appendix, I call equation (1) the *distortion decomposition formula*. Recall that c^{pr} is the profit-maximizing ("privately optimal") consumer fee, c^{so} is the total-welfare-maximizing ("socially optimal") consumer fee, a is a restaurant's benefit from a direct sale, D^{so} is the diversion rate from platform to direct sales under the socially optimal fees, and $\bar{b}_S^{\text{so}}$, $\tilde{b}_S^{\text{so}}$, $\tilde{b}_S^{\text{pr}}$ are terms related to network-externality-based distortions as defined in the main text. In the counterfactual analysis of Section 7, I apply this decomposition to the full structural model. Here, I detail this application.

First, applying the decomposition formula to the full model requires amending the formula to incorporate platform competition. This is because changes in the fee of platform f affect sales on rival platforms, which in turn impact restaurant profits and rival platform profits. I develop an extended version of the illustrative model that captures these impacts. In this extended model, I take the consumer fees c_g and commission rates r_g of rival platforms g as fixed and assess the optimality of platform f's fees conditional on rival fees.

Suppose that the focal platform faces competition from rival platforms $g \in \mathcal{F}$, a set of rival platforms, and that rival g's profits are

$$\Lambda_g = (c_g + r_g p_g - mc_g)S_g,$$

where p_g is the price charged by restaurants on platform g (assumed constant) and mc_g is platform g's marginal cost (also assumed constant). Last, S_g are platform g's sales, which I assume are a differentiable, decreasing function sales S_1 of the focal platform. In the extension of the illustrative model, total welfare is defined as

$$W = CS + RP + \Lambda + \sum_{g \in \mathcal{F}} \Lambda_g,$$

where CS is consumer surplus, RP are restaurant profits (defined in the next paragraph), Λ are the profits of the focal platform, and Λ_g are the profits of rival platform g.

Introducing rival platforms g changes the expression for restaurant profits recorded in Section 2 to:

$$RP = a_0 S_0 + \sum_{g \in \mathcal{F}} a_g S_g + ([1-r]p_1 - \bar{\kappa}_1(J))S_1 - KJ,$$

where a_0 is restaurant profit from a direct sale and a_g is restaurant profit from a sale on platform g, which in turn depends on prices, commissions, and costs on platform g (all of which are assumed constant).

The analogue of the distortion decomposition formula for the generalized model with platform competition is

$$c^{\text{pr}} - c^{\text{so}} = \underbrace{\mu_B^{\text{pr}}}_{\text{Market power}} - \underbrace{a_0 D_0^{\text{so}}}_{\substack{\text{Offline business}\\ \text{stealing}}} - \underbrace{\sum_{g \in \mathcal{F}} a_g D_g^{\text{so}}}_{\substack{\text{Online business}\\ \text{stealing}}} + \underbrace{\left[\bar{b}_S^{\text{so}} - \tilde{b}_S^{\text{so}}\right]}_{\substack{\text{Spence}\\ \text{distortion}}} + \underbrace{\left[\tilde{b}_S^{\text{so}} - \tilde{b}_S^{\text{pr}}\right]}_{\substack{\text{Displacement}\\ \text{distortion}}} - \underbrace{\sum_{g \in \mathcal{F}} (c_g + r_g - mc_g) D_g}_{\text{Rival profits distortion}}, \tag{2}$$

where $D_0 = -dS_0/dS_1$ and $D_g = -dS_g/dS_1$ are diversion ratios from ordering on the focal platform to ordering directly and on rival platform g, respectively.

I use the distortion decomposition formula (2) to separately quantify distortions affecting consumer fees in the structural model. In applying the formula, I consider one focal platform f at a time, holding rival platforms' fees fixed at the privately optimal levels when computing objects associated with platform f's profit-maximizing fees and at the socially optimal levels when computing objects associated with platform f's socially optimal fees.

Applying the distortion decomposition formula to the full model requires generalizing its constituent terms. Unlike the illustrative model, the full model incorporates heterogeneity across geography and restaurant type. To avoid excessive notation, I use z to denote a ZIP/restaurant type pair and let $\mathcal{Z}$ denote the set of all such pairs.

I extend each component of the decomposition by replacing quantities from the illustrative model with their analogues in the structural model. Although I do not formally re-derive the decomposition under the full model, these generalizations closely approximate the distortions computed by solving the full model directly for privately and socially optimal fees. This is shown later in Figure O.1.

As a preliminary, define $S_f = \sum_{z \in \mathcal{Z}} S_{fz}$ as platform f's total sales across ZIP/type pairs and

$$\bar{p}_f = \frac{\sum_{z \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} p_{z\mathcal{G}f} S_{f\mathcal{G}z}}{S_f}$$

as the sales-weighted price for a restaurant meal on platform f. Here, $p_{z\mathcal{G}f}$ is the price charged by a restaurant with ZIP/type z that belongs to the platform set $\mathcal{G}$ on ordering channel f (i.e., f is either a platform or the direct ordering channel, $f = 0$). These prices vary by $\mathcal{G}$ in equilibrium. Similarly, $S_{z\mathcal{G}f}$ are the sales of a restaurant of ZIP/type z belonging to the platform set $\mathcal{G}$ through ordering channel f. The corresponding sales-weighted marginal cost is $\bar{\kappa}_f = (\sum_z \kappa_{fz} S_{fz})/S_f$.

I now provide the full model distortions for a focal platform f. The full-model analogue of the market power distortion is

$$\mu_{B,f} = -\frac{S_f}{\partial S_f / \partial c_f}.$$

The offline business stealing distortion in the illustrative model is

$$-a_0 D_0 = a_0 \frac{dS_0}{dS_1}. \tag{3}$$

In the full model, this becomes

$$\sum_{z \in \mathcal{Z}} \sum_{\mathcal{G}} (p_{z\mathcal{G}0} - \kappa_{z0}) \frac{\partial S_{z\mathcal{G}0} / \partial c_f}{\partial S_f / \partial c_f}. \tag{4}$$

Here, κ_{zf} is the marginal cost of a restaurant with ZIP/type equal to z on platform f, which assumed constant within a ZIP/type cell.

The analogue of the online business stealing distortion is

$$\sum_{g \neq f} \sum_{z \in \mathcal{Z}} \sum_{\mathcal{G}: g \in \mathcal{G}} ([1 - r_g] p_{z\mathcal{G}g} - \kappa_{zg}) \frac{\partial S_{z\mathcal{G}g} / \partial c_f}{\partial S_f / \partial c_f}.$$

The mean gross (i.e., pre-commission) seller benefit from a platform transaction in the full model is

$$\bar{b}_{S,f} = \bar{p}_f - \bar{\kappa}_f.$$

The platform's additional commission revenue from an incremental consumer order is

$$\tilde{b}_{S,f} = r_f \bar{p}_1 \times (1 + \epsilon_f).$$

In the illustrative model,

$$\epsilon = \frac{S_1}{rp_1} \frac{d[rp_1]}{dS_1}$$

is the elasticity of per-transaction commission charges with respect to the number of consumer orders. This elasticity is positive when restaurants are willing to pay higher commissions in order to join a platform boasting a higher number of consumer orders. The first-order condition of platform profits with respect to S_1 is

$$c + rp_1 - mc + \left(\frac{\partial c}{\partial S_1} + \frac{d[rp_1]}{dc} \right) S_1 = 0,$$

or,

$$c + rp_1(1 + \epsilon) - mc - \mu_B = 0.$$

An alternative first-order condition with respect to c is

$$c + rp_1 - mc + \frac{S_1}{dS_1/dc} = 0,$$

which implies that

$$\epsilon = \frac{S_1 \left(\frac{1}{dS_1/dc} - \frac{\partial c}{\partial S_1} \right)}{rp_1}.$$

The numerator is the difference between the inverse total semi-elasticity of platform sales with respect to consumer fees—which reflects the dependence of restaurants' platform adoption J on consumer fees—and the inverse partial semi-elasticity of platform sales with respect to consumer fees. This latter elasticity measures the response of sales to changes in consumer fees holding fixed restaurant uptake of platforms. The difference between these inverse elasticities measures the extent to which the overall impacts of consumer fee increases on sales are explained by indirect effects on platform uptake among restaurants. The analogue of ϵ for platform f in the full model is

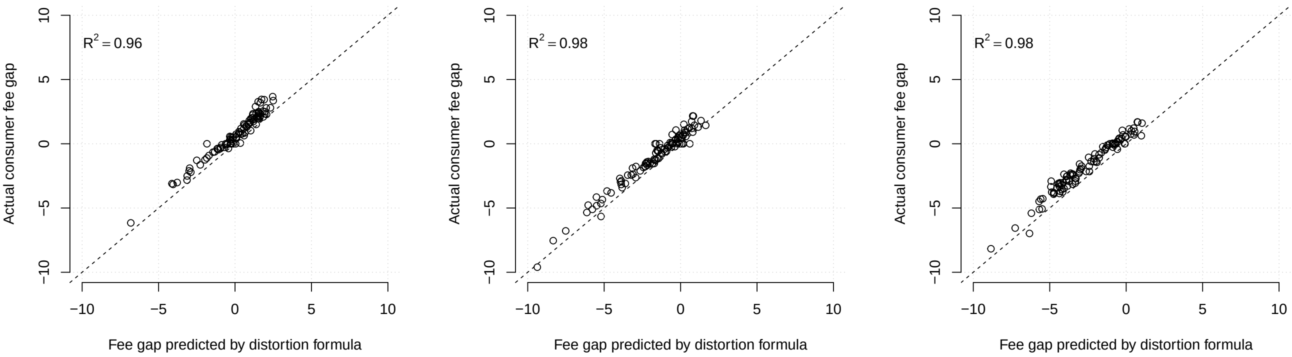
$$\epsilon_f = \frac{S_f \left(\frac{1}{dS_f/dc_f} - \frac{1}{\partial S_f/\partial c_f} \right)}{r_f \bar{p}_f}.$$

Here, dS_f/dc_f is the derivative of equilibrium sales with respect to consumer fees, which includes changes in sales due to restaurant platform adoption and pricing responses to fee changes. In contrast, $\partial S_f/\partial c_f$ is the partial derivative of sales with respect to consumer fees, holding fixed restaurant platform adoption decisions and prices.

Given the differences between the full structural model and the illustrative model (including geographical heterogeneity and the absence of insulating tariffs), the distortion decomposition formula provides only an approximation to the total distortion in consumer fees obtained by solving the full structural model for privately and socially optimal fees. To evaluate the accuracy of the approximation, I compare the full-model total distortion to the total distortion predicted by summing together individual distortion terms in the generalized decomposition formula (2). Figure O.1 plots these two quantities by county for each major platform. The two are highly correlated, with R^2 values ranging from 0.96 to 0.98 across the three leading platforms. When weighting county/platform observations by order volume under the privately optimal fees, the overall correlation between the model-generated and formula-predicted total distortions is 0.97. In addition to tracking variation closely, the formula-predicted distortions are similar

Figure O.1: Actual consumer fee gaps versus formula-predicted gaps

(a) DoorDash (b) Uber Eats (c) Grubhub



to the magnitudes of the actual distortions.

O.1.1 Sources of variation in overall consumer fee gap

I now investigate the sources of variation in the gap $c^{\text{pr}}_{fm} - c^{\text{so}}_{fm}$ between platform f's privately optimal platform fee in county m and its socially optimal fee gap in county m. To do so, I conduct two sorts of regression exercises. First, I regress the fee gap on each distortion individually, the distortions being market power, offline business stealing, online business stealing, Spence, displacement, rival profits, and other, which captures the part of the fee gap that is unexplained by the six distortions identified in the illustrative model as generalized to reflect platform competition. Table O.1 reports the R^2 from these bivariate regressions in tis R^2_k column. Next, for each distortion k, I regress the fee gap on all distortions except k and report the R^2 from this regression as R^2_{-k} in Table O.1. Lower values of R^2_{-k} indicate higher explanatory value conditional on the other distortions.

Table O.1 indicates that, in terms of R^2_{-k}, the network-externality-related Spence and displacement distortions best explain variation in the gap between privately and socially optimal consumer fees: excluding one of these variables reduces the R^2 from a regression of the fee gap on distortions from 1.00 to under 0.50. Although excluding market power reduces the R^2 only to 0.93, market power alone explains 38% of variation in the fee gap. Business stealing alone explains 21% of variation in the fee gap. The "Other" distortion arising from factors excluded from the illustrative model explains comparatively little of the fee gap.

O.2 Why do platforms charge fixed consumer fees?

Platforms can often charge either fixed fees that do not depend on seller prices or fees that are proportional to these prices. Each sort of fee has its advantages and disadvantages. The primary benefits of a proportional fee is that it makes the total fee paid by merchants increasing in merchant prices, which encourages merchants to reduce their prices, raising sales and thus platform revenue. This argument is developed by Shy and Wang (2011). Additionally, Wang and Wright (2017) and Wang and Wright (2018) argue that proportional fees allow platforms to practice third-degree price discrimination when the costs of goods sold on platforms are heterogeneous and consumer valuations from these goods are proportional to their costs.

A proportional fee, however, may distort consumer choices of menu items when the platform's cost of a delivery does not depend on the value of the ordered item. If the platform's cost is indeed fixed, the

Table O.1: Sources of variation in overall consumer fee distortion

Distortion (k)	R^2_k (only k)	R^2_{-k} (all but k)
Market power	0.38	0.94
Offline business stealing	0.00	0.98
Online business stealing	0.11	0.99
Spence	0.00	0.55
Displacement	0.03	0.53
Rival profits	0.08	0.99
Other	0.07	0.94

Notes: this table reports R^2 measures from regressions of the overall gap $c^{\text{pr}}_{fm} - c^{\text{so}}_{fm}$ between platform f's privately optimal consumer fee in county m and its socially optimal fee in market m on each of the constituent distortions contribution to this overall gap. In particular, R^2_k provides the R^2 from a regression of the overall gap on only the indicated distortion k whereas R^2_{-k} provides the R^2 from a regression of the overall gap on all distortions except the indicated distortion k. Each observation in the platform/county panel is weighted by platform f's order volume in county m. The sample size is $N = 416$.

socially optimal price structure involves restaurants pricing at marginal cost and platforms charging a fixed fee equal to the cost of facilitating a delivery. The fact that a fixed fee is reflective of cost relates to the argument of Wang and Wright (2017) that a fee structure including both fixed and proportional components is optimal when platforms have fixed costs of facilitating transactions (e.g., paying a courier to make a delivery). When the platform charges a proportional fee and merchants' goods are substitutable from the consumer's perspective, the platform inefficiently steers consumers toward ordering menu items with lower prices (and hence lower platform fees). This inefficiency leaves less social surplus available for the platform to capture. This argument is relevant in the food delivery industry wherein restaurants sell menu items with substantial variation in cost. Given that both fixed and proportional fees have relative advantages from the platform's perspective, it is ambiguous whether platforms should charge fixed or proportional fees.

In practice, food delivery platforms charge both fixed and proportional consumer fees. This may be a prudent way for the platform to both set prices corresponding to its cost structure (i.e., in which delivery costs do not depend on the prices of ordered items) while also encouraging merchants to set lower prices. I explore this possibility through a numerical exercise. In this exercise, a merchant sells two goods, goods 1 and 2, which have marginal costs κ_1 and $\kappa_2 \leq \kappa_1$. When $\bar{p}_1, \bar{p}_2$ are the post-fee prices for these two menu items, sales for the goods are $S_1(\bar{p}_1, \bar{p}_2)$ and $S_2(\bar{p}_1, \bar{p}_2)$. Assume that the merchant makes sales to consumers exclusively through the platform. Under fixed fees c, the platform's profits are

$$\Lambda = (c - mc)\left[S_1(\bar{p}_1(c), \bar{p}_2(c)) + S_2(\bar{p}_1(c), \bar{p}_2(c))\right]$$

where mc are the platform's marginal costs. Here, $\bar{p}_j(c) = p_j(c) + c$, where $p_j(c)$ denotes the merchant's price (excluding the fee) under a fee level c. I abstract away from commissions to focus on the optimal choice of consumer fee structure. The restaurant's profits are

$$\Pi = (p_1 - \kappa_1)S_1(\bar{p}_1(c), \bar{p}_2(c)) + (p_2 - \kappa_2)S_2(\bar{p}_1(c), \bar{p}_2(c)).$$

The restaurant's optimal prices satisfy the following first-order condition:

$$\begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \kappa_1 \\ \kappa_2 \end{bmatrix} - \begin{bmatrix} \frac{\partial S_1}{\partial p_1} & \frac{\partial S_2}{\partial p_1} \\ \frac{\partial S_1}{\partial p_2} & \frac{\partial S_2}{\partial p_2} \end{bmatrix}^{-1} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix}. \tag{5}$$

Under proportional fees levied at rate q against restaurant prices, the platform's profits are

$$\Lambda = (qp_1(q) - mc)S_1(\bar{p}_1(q), \bar{p}_2(q)) + (qp_2(q) - mc)S_2(\bar{p}_1(q), \bar{p}_2(q)).$$

Here, the post-fee prices are $\bar{p}_j(q) = p_j(q)(1+q)$. The restaurant's profits are

$$\Pi = (p_1 - \kappa_1)S_1(\bar{p}_1(q), \bar{p}_2(q)) + (p_2 - \kappa_2)S_2(\bar{p}_1(q), \bar{p}_2(q)).$$

The restaurant's optimal prices satisfy the following first-order condition:

$$\begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \kappa_1 \\ \kappa_2 \end{bmatrix} - \frac{1}{1+q} \begin{bmatrix} \frac{\partial S_1}{\partial p_1} & \frac{\partial S_2}{\partial p_1} \\ \frac{\partial S_1}{\partial p_2} & \frac{\partial S_2}{\partial p_2} \end{bmatrix}^{-1} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix}. \tag{6}$$

A comparison of (5) and (6) illustrates why proportional fees encourage restaurants to reduce their prices. When a restaurant facing fixed platform fees raises its price, the fee-inclusive price paid by consumers rises by the same amount. When the platform instead uses proportional fees, the fee-inclusive price paid by consumers rises by the amount of the increase times $(1+q)$; this, in effect, makes the demand curve faced by the restaurant $1+q$ times more elastic, putting downward pressure on prices.

To show why fixed fees may be preferable to the platform, I conduct a numerical exercise with the model above. In this exercise, I consider two cost structures: the first, which I call heterogeneous costs, has $(\kappa_1, \kappa_2) = (10, 30)$ whereas the second, which I call homogeneous costs, has $(\kappa_1, \kappa_2) = (20, 20)$. Under both merchant cost structures, the platform's marginal cost is $mc = 4$. Demand is given by

$$S_j(p_1, p_2) = \frac{e^{\delta_j - \alpha p_j}}{1 + \sum_{k=1}^{2} e^{\delta_k - \alpha p_k}},$$

where $\alpha = 0.6$ and (δ_1, δ_2) are selected so that the market shares of goods 1 and 2 are 15% and 75% under the socially efficient prices and fees. In addition to pure fixed fees and pure proportional fees, I consider a hybrid regime in which the platform may charge both of these sorts of fees.

Tables O.2 and O.3 contain results. First consider sales of each good under the heterogeneous cost structure, which are reported by Table O.2a. The table shows that, under fixed fees, the ratio of sales of the two goods is the same as under socially efficient pricing, but that the ratio is severely distorted under proportional fees ("Prop."). This is because proportional fees are higher for the more costly good 2, which leads consumers to inefficiently substitute toward the less costly good. Under the homogeneous cost structure, this problem does not arise as platform fees do not vary between the two goods; see Table O.2b. As shown by Table O.3, the fixed fee structure achieves greater platform profits and social welfare than the proportional fee structure under the heterogeneous cost structure because it does not induce inefficient substitution toward the low-cost good 1. In the homogeneous cost structure, however, the proportional fee structure outperforms the fixed fee structure given that it reduces restaurant markups. Under each cost structure, the hybrid fee structure delivers higher platform profits and social welfare than either the purely fixed or purely proportional fee structures. With that said, the improvement upon platform profits and total welfare is small under the heterogeneous cost structure.

The numerical exercise illustrates motivations for platforms to use both fixed and proportional fees. I ultimately specify fixed consumer fees because including multiple sorts of consumer fees would complicate the model and distract from the primary problem of the balance of fees between consumers and merchants that the article addresses. Additionally, platforms charge proportional fees to merchants, leaving the consumer side as the only place to incorporate potentially important fixed fees.

Table O.2: Sales by good under fixed and proportional platform fees

(a) Heterogeneous costs

Regime	Sales		Ratio
	Good 1	Good 2	Good 2/1
Fixed	0.044	0.221	5.000
Prop.	0.161	0.001	0.007
Hybrid	0.069	0.201	2.893
Efficient	0.150	0.750	5.000

(b) Homogeneous costs

Regime	Sales		Ratio
	Good 1	Good 2	Good 2/1
Fixed	0.044	0.221	5.000
Prop.	0.049	0.247	5.000
Hybrid	0.087	0.436	5.000
Efficient	0.150	0.750	5.000

Table O.3: Welfare under fixed and proportional platform fees

(a) Heterogeneous costs

Regime	Consumer surplus	Profits		Total welfare
		Rest	Plat	
Fixed	0.31	0.60	0.82	1.73
Prop.	0.18	0.21	0.36	0.75
Hybrid	0.31	0.59	0.84	1.74
Efficient	2.30	0.00	0.00	2.30

(b) Homogeneous costs

Regime	Consumer surplus	Profits		Total welfare
		Rest	Plat	
Fixed	0.31	0.60	0.82	1.73
Prop.	0.35	0.52	0.99	1.86
Hybrid	0.74	0.00	1.83	2.58
Efficient	2.30	0.00	0.00	2.30

Notes: "Rest" indicates restaurant profits whereas "Plat" indicates platform profits.

O.3 Additional data description

O.3.1 Platform fees

Figure O.2 plots time series of the average platform consumer fees and commission revenue per order. The figure includes separate time series for each platform and also for regions that adopted a commission cap by May 2021 and those that did not. The figure shows that, in early 2020, platforms collected more revenue from restaurants than from consumers. This pattern persevered in areas that did not adopt commission caps. In areas that did adopt commission caps, the gap in revenues from consumer fees and commissions shrank as these areas limited commissions.

O.3.2 Multi-homing patterns

I quantify multi-homing in the food delivery industry by computing measures of consumer and restaurant multi-homing. The measure of consumer multi-homing for a pair of platforms f and f' equals the share of pairs of consecutive orders placed on any platform made by the same consumer that contain a purchase from f among those that also contain a purchase from f'. This is not a measure of the extent to which consumers have adopted multiple platforms but instead to which they actively order from multiple platforms. To illustrate the measure, suppose that one consumer bought from DoorDash across two consecutive orders and a second consumer bought from DoorDash and then Uber Eats. Then, the multi-homing measure for f = Uber Eats and f' = DoorDash among these two consumers would be one half.[1] Table O.4a reports the results, which indicate that consumers do often switch between platforms despite typically ordering from the same platform across consecutive orders. For example, 13% of the

[1]Another measure of consumer multi-homing is the average Herfindahl–Hirschman Index (HHI) of a consumer's shares of orders made across platforms:

$$\bar{\text{HHI}} = \sum_i \frac{n_i}{\sum_{i'} n_{i'}} \sum_{f=1}^{F} s_{if}^2,$$

where n_i is the number of orders that consumer i placed on platforms and s_{if} is the share of those orders that the consumer placed on platform f. Among consumers residing in the 14 markets on which my study focuses during the second quarter of 2021, $\bar{\text{HHI}}$ equals 0.86, which indicates a high degree of purity in consumers' platform-choice sequences.

Table O.4: Multi-homing patterns

(a) Consumers of delivery platforms

Platform	Share of consecutive-order pairs including an order from...	Share of pairs also including an order from...			
		DD	Uber	GH	PM
DD	0.53	1.00	0.13	0.06	0.02
Uber	0.42	0.17	1.00	0.06	0.02
GH	0.16	0.21	0.16	1.00	0.01
PM	0.04	0.24	0.24	0.06	1.00

(b) Restaurants listed on delivery platforms

Platform	Share listed on platform	Share of restaurants also listed on...			
		DD	Uber	GH	PM
DD	0.34	1.00	0.55	0.50	0.33
Uber	0.27	0.68	1.00	0.57	0.39
GH	0.24	0.71	0.65	1.00	0.38
PM	0.14	0.79	0.76	0.65	1.00

Notes: Table O.4a reports, for each pair of platforms f and f', the share of pairs of consecutive orders placed by the same consumer in April 2021 that include an order from f' among those that contain an order from f. Table O.4b reports the share of restaurants on each major delivery platform that also belong to each other major delivery platform for April 2021. Note that the figures in the "Share listed on platform" column do not necessarily add up to one; they are the shares of restaurants on each platform considered individually.

consecutive-order pairs featuring a DoorDash order also feature an Uber Eats order.

I characterize restaurant multi-homing by computing the share of restaurants listed on each platform that are also listed on each other platform. Table O.4 reports the results, which show that both consumers and restaurants multi-home.

O.3.3 Time series patterns in ordering

One channel through which food delivery platforms could reduce direct ordering from restaurants is by encouraging consumers to over-order and consume leftovers in subsequent meals rather than dining again. To investigate this possibility, I estimate regressions of future ordering outcomes on contemporaneous ordering activity.

The analysis is based on a user/day panel constructed from Numerator data. I restrict the sample to core panelists who linked their email accounts with Numerator's data collection application. The study period runs from January 2019 to April 2021. I include users who placed at least one direct order and at least one platform order during this period.

For each user/day observation (i, t), I construct the following variables: (i) an indicator for whether user i placed a platform order on day t; (ii) an indicator for whether user i placed a direct order on day t; (iii) indicators for whether user i placed at least one platform order within the next 3 and 7 days; and (iv) indicators for whether user i placed at least one direct order within the next 3 and 7 days.

I estimate regressions of the form

$$y_{it} = \phi_{i,\text{month}(t)} + \psi_t + \beta_{\text{direct}}\text{direct}_{it} + \beta_{\text{platform}}\text{platform}_{it} + \varepsilon_{it},$$

where y_{it} is the outcome variable, which will be one of the variables characterizing short-term future ordering described above; $\phi_{i,\text{month}(t)}$ is a user/month fixed effect; ψ_t is a day fixed effect; platform_{it} is an indicator for user i placing a platform order on day t; and direct_{it} is an indicator for user i placing a platform order on day t. The user/month fixed effects are included to richly control for time-varying consumer preferences for online and offline ordering. The day fixed effects are included to flexibly control for time trends in ordering. With these controls, the β_{direct} and β_{platform} capture short-term changes in future ordering behaviour associated with placing a direct or platform order on day t

Table O.5 provides the results for each of the four outcome variables characterizing short-term future ordering. lt also provides the mean values of these outcome variables and the sample size N. The results indicate that consumers are less likely to order from a restaurant—either directly or through a platform—within either 3 or 7 days of placing an order from a restaurant directly or on a platform. Additionally, contemporaneous direct ordering subtracts more from future direct ordering than does contemporaneous platform ordering. Similarly, contemporaneous platform ordering subtracts more from platform direct ordering than does contemporaneous direct ordering. The results suggest that platform orders are not more likely than direct orders to become leftovers that discourage future direct ordering.

Table O.5: Results from time series patterns regressions

Regressor	Future direct ordering				Future platform ordering			
	Within 7 days		Within 3 days		Within 7 days		Within 3 days	
direct_{it}	-0.060	(0.0007)	-0.045	(0.0007)	-0.001	(0.0004)	-0.001	(0.0003)
platform_{it}	-0.004	(0.0018)	-0.002	(0.0017)	-0.112	(0.0010)	-0.069	(0.0008)
Mean outcome	0.345		0.193		0.066		0.033	
N	2947470							

Notes: see the text of Online Appendix O.3.3 for a description of the regressions.

O.4 Validation of transactions datasets

In this appendix, I argue that the Numerator data used in the article's analysis is representative of US consumers. First, I compare demographics of Numerator panelists to those of the US at large as measured via the US Census. Second, I compare market shares computed on the Numerator data to those measured using an external dataset based on payment card transactions.

As noted in the main text, Numerator selects a subset of users who upload receipts to form its core panel. It chooses this core panel to be representative of the US population. I find that the core panel matches the US census well on demographics, with a few exceptions. Table O.6 compares the demographics of Numerator core panelists who belonged to the panel throughout Q2 2021 (the sample period for model estimation) with those of the US adult population as computed using public use microdata from the American Community Survey (ACS) for 2021.[2] The first panel of the table compares the share of the Numerator panel and of the US population falling into various age groups. Numerator slightly underweights panelists under 35 years old and above 65 years old while overweighting middle-aged panelists. The next panel compares income groups. Here, I use the family income variable in the ACS to measure income of the US population. We see that the income group shares are close with the exception that Numerator has a smaller share of panelists with incomes over $125,000 (20% versus 29% in the US adult population). The following panel shows marital status shares. The shares are close, although Numerator somewhat overweights married people (57% in Numerator compared to 50% in the US adult population). Next comes a panel comparing the share of adults with children. I measure this variable in the ACS using the "number of children in the household" variable. The share is 36% in both Numerator and the

[2] I use one year estimates and, in computing population shares, use the ACS person weights.

ACS. The final panel shows shares of ethnic groups. The comparison is complicated by the fact that Numerator reports a single ethnicity variable whereas the ACS reports race and Hispanic status separately. I assign the "Hispanic/Latino" ethnicity to all ACS respondents with a response to the Hispanic status question other than "Not hispanic." This method of assignment may be responsible for the fact that the ACS share of Hispanic individuals is higher than in Numerator, and why the "White/Caucasian" share is lower (some White Hispanic individuals may primarily identify as "White/Caucasian" in Numerator's single race/ethnicity question). Otherwise, the ethnicity shares are similar across Numerator and the ACS.

Table O.6: Demographic composition of core Numerator panel (Q2 2021)

Group share	Numerator	ACS
18-34	0.21	0.29
35-44	0.22	0.17
45-54	0.21	0.16
55-64	0.24	0.17
65+	0.13	0.22
Under $20k	0.12	0.11
$20k-40k	0.15	0.13
$40k-60k	0.16	0.14
$60k-80k	0.14	0.12
$80k-125k	0.24	0.21
Over $125k	0.20	0.29
Divorced	0.11	0.11
Married	0.57	0.50
Never married	0.27	0.31
Separated	0.02	0.02
Widower	0.04	0.06
Has children	0.36	0.36
White/Caucasian	0.69	0.61
Black or African American	0.11	0.12
Hispanic/Latino	0.12	0.17
Asian	0.07	0.06
Other	0.02	0.05

Figure O.3 compares market shares for April 2021 computed from the Numerator transactions panel to those reported by the market research firm Second Measure, which estimates platforms' market shares based on payment card records, for March 2021. Market shares are similar across these two data sources. This similarity assuages worries that my primary consumer panel is not representative of the population on account of the fact that its records were collected through a mobile application.

O.5 Consumer fee indices

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

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

where DF_{fz} is a measure of platform f's delivery fees in ZIP z, SF_{fz} is a measure of platform f's service fee in z's municipality, and RR_{fz} is the regulatory response fee charged by f in z. Given that delivery fees vary across orders placed within the same municipality at the same time, I defined DF_{fz} as a hedonic price index. This index, formally defined below in Online Appendix O.5.1, captures systematic differences in delivery fees across geography and platforms conditional on delivery distance, restaurant characteristics, day-of-week, and time-of-day. I define SF_{fz} as platform f's median service fee in ZIP z's municipality. Service fees are generally proportional to order subtotals; I use a subtotal of $30 to compute service fees. Recall that the fee data does not include service fees for Grubhub. This omission is not critical given that Grubhub did not enact regulatory response fees aside from a fee of $1 per order in California. It does, however, limit information on Grubhub's service fees. I use the Edison dataset to overcome this limitation. The median and the sales-weighted mean of ZIPs' ratios of average service fees to average order value before taxes and fees are both 0.10 for Grubhub in this dataset; I therefore use 10% as Grubhub's service fee. Regulatory response fees apply to entire municipalities, so I compute RR_{fz} by taking the sum of such fees charged by platform f in ZIP z's municipality. See Online Appendix Table O.7 for a decomposition of fee indices into their components.

Table O.7: Decomposition of average fees

Fee	DoorDash	Uber Eats	Grubhub	Postmates
Delivery	1.87	1.58	2.91	3.43
Service	4.36	4.50	3.00	6.35
Regulatory Response	0.18	0.27	0.17	0.08

Notes: the table reports average components of platforms' fee indices in dollars. Each figure in the table is an unweighted average taken over ZIPs.

Table O.8 provides observation counts and sample means for the platform pricing datasets for Q2 2021.

O.5.1 Delivery fee measures

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

$$DF_{fz} = \mathbb{E}[df_{kfz} | x_k = \bar{x}, f, z], \tag{7}$$

where df_{kfz} is the delivery fee charged for order k on platform f in ZIP z, x_k are observable characteristics of order k, and $\bar{x}$ is a fixed vector of order characteristics. I estimate (7) using a 10-fold cross-validated Lasso with delivery fee data from Q2 2021, and set $\bar{x}$ to the average x_k across all orders in my sample. The estimating equation is

$$df_{kfz} = x_k' \beta_f + w_z' \mu_f + \phi x_k^{\text{dist}} w_z^{\text{dens}} + \epsilon_{kfz}, \tag{8}$$

where w_z are characteristics of ZIP z and 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;

Table O.8: Description of platform pricing data, Q2 2021

Platform	Delivery fees data: # obs.	Delivery fees data: Avg. delivery fee ($)	Delivery fees data: Avg. wait time (mins)	Service/reg. response fees data: # obs.	Service/reg. response fees data: Avg. service fee (%)	Service/reg. response fees data: Avg. regulatory response fee ($)
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.

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.[3] Note that I include indicators for multiple levels of geography because it is important for my empirical analysis to flexibly capture fee differences across geography. Last, x_k^{dist} is the delivery distance for order k and w_z^{dens} is the local density of z; I include their interaction to capture the possibility that the cost of increasing an order's distance depends on density due to traffic congestion.

There are several problems in estimating (8) by OLS: OLS is prone to overfitting in settings with many regressors, and using OLS would require a somewhat arbitrary selection of a noncollinear set of geographical indicators to include in w_z. The Lasso does not suffer from these problems.[4] In my setting, the Lasso provides a data-driven method for selecting geographical indicators for inclusion in w_z based on their relevance in predicting delivery fees. It is only the coefficients for geographical characteristics w_z that I penalize in estimation. I apply the procedure explained above with delivery-fee records substituted for waiting-time records to compute hedonic indices of expected waiting times.

O.6 Restaurant prices

I collected supplementary data on restaurant prices from platform and restaurant websites in December 2022 with the goal of measuring differences in restaurants' prices for direct and for platform orders. To do so, I randomly selected restaurants in various municipalities in the greater New York City metropolitan area: New York, NY (360 restaurants); Hoboken, NJ (40 restaurants); and Bridgeport, New Haven, Hartford, and Stamford, CT (250 restaurants). I drew these restaurants from the universe of restaurants in the Data Axle data for 2021, as I did not have access to the 2022 data at the time of sampling.

Whereas Hoboken had a commission cap of 15% and New York had a commission cap of 20%, none of the Connecticut municipalities had a commission cap. For each restaurant, I selected two menu items on the restaurant's website and recorded its price on the website. I then determined the price of the same menu item on the restaurant's listing on each food delivery platform to which the restaurant belonged. For each combination of a menu item j and a platform f, I compute the ratio y_{jf} of the menu item's price on platform f to its price as listed on the menu on the restaurant's website.

Some restaurants were closed at the time of data collection, did not have websites, did not have recent online menus, or had been mislabelled as restaurants in Data Axle despite not being restaurants. After dropping these restaurants, the sample includes 134 restaurants in New York, 18 restaurants in Hoboken, and 98 restaurants in Connecticut.

To assess the relationship between platform/direct pricing gaps and commission caps, I run the following regression:

$$y_{jf} = \alpha + \beta r_j + \varepsilon_{jf}, \tag{9}$$

where r_j is the commission cap applying to restaurant j, or $r_j = 0.30$ for restaurants j in areas without commission caps (i.e., Connecticut). Here, the parameter α governs the extent to which restaurants charge different prices on platforms than for direct orders independently of the commission level whereas r_j controls pass-through of commissions into platform prices. I cluster standard errors at the level of a menu item j.

Table O.9 reports the results of the regression. The bottom two rows of the table show the predicted ratios of platform to direct restaurant prices implied by the regression. The results suggest that a

[3] 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.

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

restaurants partially pass through platform commissions into their online prices: a restaurant facing 15% commissions is predicted to charge 7% higher prices on platforms than for direct orders, whereas a restaurant facing 30% commissions is predicted to charge 13% higher prices on platforms.

Table O.9: Restaurant prices and commission rates

Parameter	Estimate
α	1.01
	(0.04)
β	0.39
	(0.19)
N	554
$\hat{y}_{jf}(r_j = 0.30)$	1.13
$\hat{y}_{jf}(r_j = 0.15)$	1.07

Notes: this table reports results from a regression based on equation (9) as estimated on the restaurant/platform-level panel described in the main text. The $\hat{y}_{jf}(r_j = 0.30)$ row provides the predicted ratio of platform to direct prices under 30% commissions. The $\hat{y}_{jf}(r_j = 0.15)$ row provides the predicted ratio of platform to direct prices under 15% commissions. Asymptotic standard errors clustered at the menu item level are reported in parentheses.

O.7 Difference-in-differences analysis of commission caps

O.7.1 Implementation details

In this appendix, I describe details of the article's difference-in-differences (DiD) analysis and provide additional results. I conduct DiD analysis using three distinct datasets. The first is the ZIP/month/platform-level panel provided by Edison, the second is consumer panel provided by Numerator, and the third is data on the universe of restaurants on each food delivery platform as provided by YipitData. I estimate the effects of commission caps on platform fees using the Edison data. These data provide variables for (i) average order value including fees, tips, and taxes, (ii) average order value excluding fees, tips, and taxes, (iii) average tips, and (iv) average taxes. I compute average fees by subtracting the sum of (ii), (iii), and (iv) from (i). I use the Numerator panel to estimate the effects of commission caps on restaurant order volumes. Before analyzing these data, I process them in several ways. First, I keep only transactions made by a member of Numerator's core panel whose e-mail address was linked to Numerator's data-collection app at the time of the transaction. I then aggregate the data to the panelist/month level, keeping only panelist/month pairs for which the corresponding panelist had a linked e-mail address during the corresponding month. For each panelist/month pair, I compute the number of orders placed on each platform and not placed on any platform. Next, I aggregate to the ZIP3/month level, taking an average of panelist/month-level order counts across panelists residing in each ZIP3. This yields a ZIP3/month level panel of mean order counts among Numerator panelists. I use this panel to estimate overall order volumes at the ZIP3/month level. To estimate order volumes, I run a Lasso regression of mean order counts on ZIP3, state, and month fixed effects as well as interactions between (i) the ZIP3 and month fixed effects and (ii) the state and month fixed effects. Here, I choose the penalization parameter that minimizes 10-fold cross-validation prediction error. Then, I multiply the fitted values from this regression by ZIP3 populations to obtain estimated order volumes by ZIP3. This approach removes noise from the raw mean order counts, and it also resolves the problem of zero-valued mean order counts; this is a problem because it prevents the application of the log transformation to these order counts. The fitted mean order counts from the Lasso correlate strongly with the raw mean order counts: for non-platform orders and platform orders, the correlation coefficients are 0.986 and 0.942, respectively, across ZIP3/month pairs.

Multiple estimators appear in the literature on DiD research designs. The first is the standard two-way fixed effects (TWFE) estimator, which is an OLS estimator applied to linear equation with time fixed effects, panel unit fixed effects, and treatment indicators. The estimating equation is

$$\underbrace{y_{fzt}}_{\text{Outcome}} = \underbrace{\psi_{fz} + \phi_{ft}}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\delta_f x_{zt}}_{\text{Treatment}} + \underbrace{w'_{zt}\beta}_{\text{Controls}} + \epsilon_{fzt}, \tag{10}$$

where f denotes a platform, y_{fzt} is the outcome variable (in the analysis of consumer fees, e.g., the log of platform f's average consumer 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. Here, δ_f is the effect of commission caps on the outcome variable. The primary treatment variable x_{zt} that I specify is an indicator for z having a commission cap of 15% or lower.[5] I also consider, though, specifications with a continuous treatment variable equal to the commission rate applying in ZIP z. In addition to estimating (10), I estimate a version of the model in which caps' effects dynamically vary.[6] I describe the controls w_{zt} that I include later in this appendix. The primary identifying assumption underlying the TWFE approach is that, conditional on controls, the outcome in places that enacted caps would have followed the same trend as in places that never enacted caps if caps had not been imposed.

Recent research in econometrics highlights problems affecting TWFE estimators in settings with heterogeneous effects and staggered interventions. To address these problems, I additionally compute the interaction weighted (IW) estimator (Sun and Abraham 2021) and the estimator of Callaway and Sant'Anna (2021), both of which are robust to heterogeneous treatment effects. The IW estimator is an OLS estimator of an equation similar to (10) but including interactions of treatment indicators and cohort-membership indicators, wherein cohorts are defined by time of treatment. Another estimator that corrects problems affecting the TWFE estimator is that of Callaway and Sant'Anna (2021). The version of the Callaway and Sant'Anna (2021) estimator that I compute generalizes that of doubly robust DiD estimator of Sant'Anna and Zhao (2020). I compute this estimator using both not-yet-treated units and never-treated units as the control group.

In addition, Freyaldenhoven et al. (2019) argue that DiD estimators may suffer from an endogeneity problem owing to unobserved heterogeneity that correlates with both treatment and the outcomes of interest. I additionally compute the Freyaldenhoven et al. (2019) proxy-based estimator that addresses this problem. This estimator requires proxies for unobserved heterogeneity. As proxies, I use the controls w_{zt}. I additionally control for these variables in computing the IW estimator. The qualitative conclusions from my analysis are robust to estimator.

The TWFE, IW, and IV estimators permit the inclusion of time-varying covariates w_{zt}. I include as covariates (i) the Oxford Covid-19 Government Response Tracker (OxCGRT) measure of the stringency of local COVID-19 policy (Hallas et al. 2020), (ii) the number of new COVID-19 cases per capita in the ZIP's county, and (iii) the number of new COVID-19 cases per capita interacted with the Democrat vote share in the 2020 US presidential election. Additionally, I use data on COVID-19 cases by county from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (Dong et al. 2020) and county-level data on the results of the 2020 US presidential

[5] 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.

[6] 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.

election from MIT Election Data and Science Lab (2018). In addition, I use each of these variables as proxies for unobserved heterogeneity in computing the Freyaldenhoven et al. (2019) IV estimator. I do not use covariates in computing the Callaway and Sant'Anna (2021) estimator. Another way in which I use auxiliary variables in the analysis is in weighting. I weight geographical units by their populations in computing the TWFE, IW, and Callaway and Sant'Anna (2021) estimators. The implementation of the Freyaldenhoven et al. (2019) estimator that I used does not allow weights, and thus I instead emphasized larger geographies by dropping those below a population threshold of 10,000 from the analysis. To obtain a ZIP3-level version of each county-level COVID-19 and election variable, I compute a population-weighted average of the variable across ZIPs within the ZIP3, assigning each ZIP the value of its encompassing county.

Several tables and figures in the article report overall effects as opposed to effects varying in time relative to the imposition of caps. The manner in which I compute these overall effects differs somewhat by estimator. The overall effects estimated by TWFE are estimates of δ_f or δ in equation (10) or (11) as appropriate. For the other estimators, I aggregate across dynamic effects to obtain overall effects. The estimands of Callaway and Sant'Anna (2021) are average treatment effects on the treated (ATTs) specific to treatment cohorts g and calendar times t. I report a weighted average of cohort-time-specific ATTs across (g, t) pairs such that cohort g has been treated by t, with each cohort weighted by its size. For the IW estimator and IV estimators, I reported averages across dynamic treatment effects at τ periods since treatment for $\tau = 1, \ldots, \bar{\tau}$, weighting the effect for τ by the number of observations for which treatment occurred τ periods ago. Note that $\bar{\tau}$ is the number of periods before and after treatment for which I estimate effects. For the TWFE and IW estimator, I specify $\bar{\tau} = 7$. For the IV estimator, I specify $\bar{\tau} = 5$. I compute standard errors for each estimator that I compute. For the standard TWFE estimator, the IW estimator, and the IV estimator, I compute classical asymptotic standard errors. For the Callaway and Sant'Anna (2021) estimator, I compute robust asymptotic standard errors.

O.7.2 Consumer fee effects

I estimate the effects of caps on fees using various difference-in-differences (DiD) methods and the Edison panel of average consumer fees. The outcome variable y_{zt} in the analysis are log average consumer fees for one of the leading platforms. Table O.11 provides estimates of commission caps' effects on the fees charged by DoorDash (DD), Uber Eats (Uber), and Grubhub (GH). For the TWFE estimator, the table reports estimates of δ_f in (10). For the other estimators, the table reports estimates of average dynamic effects across time periods following the imposition of caps.[7] The TWFE results suggest that commission caps raised fees by 7%–20% across platforms. Moreover, the estimates are positive and between 5.5% and 32% across platform/estimator pairs.[8] The non-TWFE estimates are similar to the TWFE estimates but often less precise. Figure O.5 provides TWFE and IW estimates of dynamic effects on the fees charged by DoorDash, the largest platform. There is not evidence of pre-trends in places that introduced caps. Additionally, Figure O.5 suggests that platforms responded to 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 and a lack of pre-trends.

The following exhibits provide results for alternative specifications, including those with caps exempting chain restaurants excluded from the estimation sample (Table O.12), with a continuous treatment variable (Table O.13), with fees entering in levels (Table O.13), excluding months before July 2020 (in which laws prohibiting on-premises dining still applied) and before 2021 (Table O.14), with proportional service

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

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

fees and fixed fees as separate outcomes (Table O.15), and in which places with any cap constitute the treatment group (Table O.16). The estimates are similar to those in the main text, and provide evidence that commission caps raised fixed fees but not service fee rates.

Table O.10: 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 commission caps on log fees. Each estimator is computed on a ZIP/month level panel, and each ZIP is weighted by its population. "TWFE" is the two-way fixed effects estimator. "IW" is the interaction weighted estimator. "Proxy" is the Freyaldenhoven et al. (2019) estimator. "CS" is the Callaway and Sant'Anna (2021) estimator (with not-yet-treated and never-treated units as controls). I control for COVID-19-related variables (see main text). I do not include results for Postmates because I lack data on Postmates fees across the sample period. Asymptotic standard errors appear in parentheses.

Table O.11: Fee responses to commission caps (additional estimators)

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

Table O.12: Fee responses to commission caps, excluding caps that exempt chains

Platform	TWFE	IW	CS (not yet)	CS (never)
DD	0.175	0.336	0.272	0.274
	(0.022)	(0.048)	(0.165)	(0.165)
Uber	0.092	0.067	0.042	0.033
	(0.023)	(0.050)	(0.053)	(0.054)
GH	0.104	0.188	0.137	0.145
	(0.079)	(0.190)	(0.077)	(0.077)

Notes: this table reports results of the difference-in-differences analysis of commission caps' effects on platform consumer fees when areas that ever enacted a cap that exempted chain restaurants are excluded from the estimation sample.

Table O.13: Fee responses to commission caps, alternative treatment and outcome variables

Specification	DD	Uber	GH
Level fee and discrete treatment	0.67	0.23	0.58
	(0.10)	(0.12)	(0.11)
Level fee and continuous treatment (rate)	-4.44	-1.64	-3.70
	(0.67)	(0.81)	(0.74)
Log fee and continuous treatment (rate)	-1.25	-0.48	-0.80
	(0.13)	(0.13)	(0.41)
Log fee and continuous treatment (log rate)	-0.27	-0.10	-0.17
	(0.03)	(0.03)	(0.09)

Notes: the "continuous treatment" rows of this table report results of DiD analyses in which the treatment indicator x_{zt} is by a variable that is

1. equal to the level of the commission cap in place in ZIP z in month t, if a cap is in place, and
2. equal to 0.30, otherwise,

or the log of this continuous treatment variable. The table also reports results for specifications in which platform fees enter in levels rather than in logs. The estimation sample includes ZIPs with commission caps greater than 0.15.

Table O.14: Fee responses to commission caps (subsamples for later time periods)

(a) July 2020 to May 2021

Platform	TWFE	IW	CS (not yet)	CS (never)
DD	0.169	0.336	0.234	0.235
	(0.025)	(0.050)	(0.166)	(0.166)
Uber	0.109	0.053	0.132	0.130
	(0.021)	(0.041)	(0.042)	(0.042)
GH	0.091	-0.020	0.086	0.087
	(0.049)	(0.112)	(0.058)	(0.058)

(b) January 2021 to May 2021

Platform	TWFE	IW	CS (not yet)	CS (never)
DD	0.166	0.078	0.043	0.043
	(0.064)	(0.031)	(0.078)	(0.078)
Uber	0.026	0.001	0.254	0.254
	(0.070)	(0.034)	(0.158)	(0.158)
GH	0.068	0.010	-0.017	-0.017
	(0.112)	(0.075)	(0.171)	(0.171)

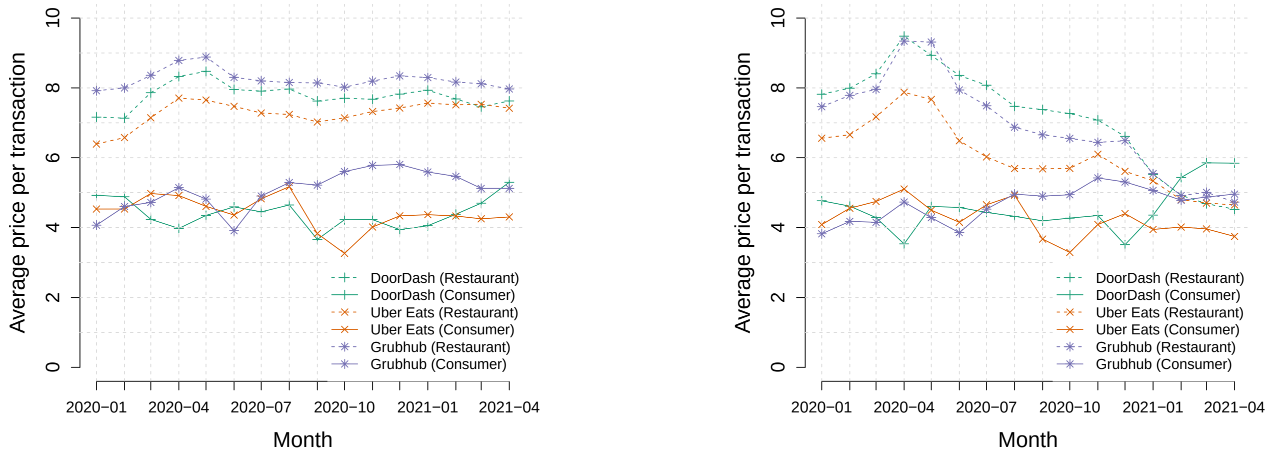
Notes: This table reports results of the DiD analyses of platform fees applied to data from subperiods of the sample period. See the notes of Table O.11 for additional details.

Table O.15: Responses of service fees and fixed fees to commission caps

Outcome	DD	Uber	GH
Service fee rate	-0.041	0.068	-0.018
	(0.019)	(0.030)	(0.044)
Log fixed fee	0.084	0.173	0.049
	(0.035)	(0.033)	(0.071)

Notes: the table reports TWFE estimates of the effects of commission caps on platforms' service fee rates and log fixed fees. I compute the service fee rate in a ZIP for a particular month by dividing the ZIP's average service fee amount in dollars by the average basket subtotal before fees, tips, and tax. I compute the average fixed fee by subtracting the average service fee from the average total fee. See the notes of Table O.11 for additional details.

Figure O.2: Platforms' average consumer fees and commissions in regions with and without a commission cap (May 2021)

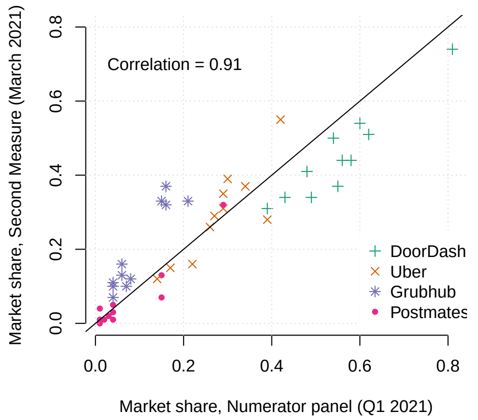


(a) Average prices per transaction: no cap

(b) Average prices per transaction: cap

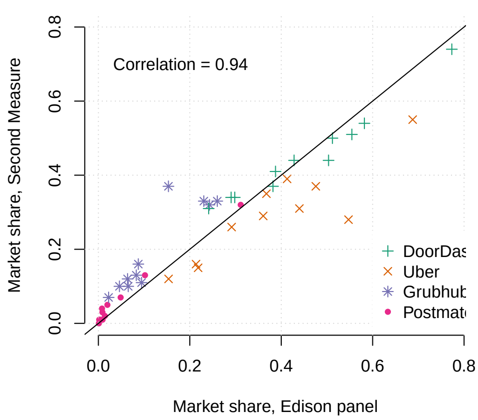
Notes: this figure describes the average per-order restaurant commission and the average per-order consumer fee charged by platforms. The average restaurant commissions are obtained by multiplying estimated average order subtotals at the ZIP level in the Edison transactions data by (i) 0.30 if no commission cap is in effect and (ii) the level of the active commission cap if a commission cap is in effect, and by then averaging across ZIPs, using the number of orders placed in each ZIP as weights. The figure plots average commissions and average consumer fees separately for regions with and without active commission caps in May 2021.

Figure O.3: Market shares: validation of Numerator panel



Note: This plot compares market shares (CBSA level) from the Numerator data to market shares based on payment card transactions (Second Measure data, March 2021). The Second Measure market shares are available here: https://dfdnews.com/2021/04/15/which-company-is-winning-the-restaurant-food-delivery-war/. The solid line is the 45° line.

Figure O.4: Market shares: validation of Edison panel

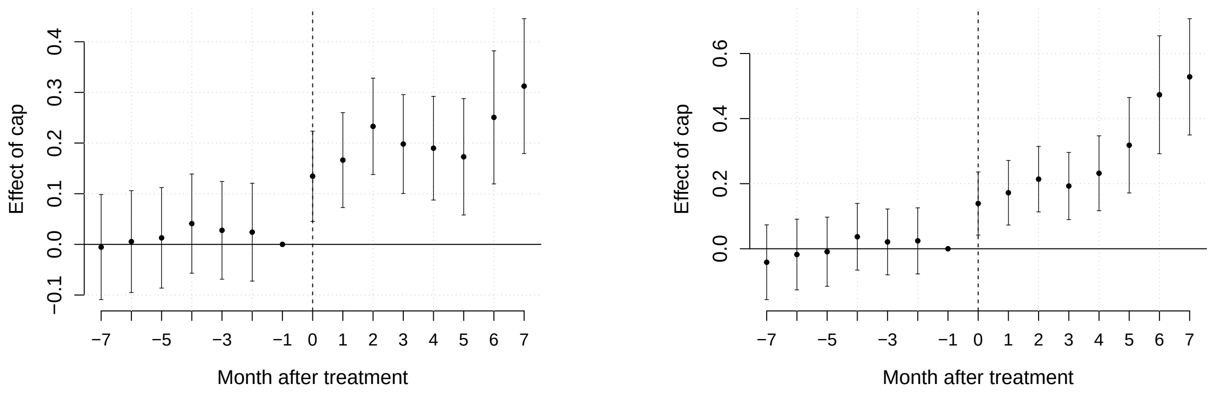


Note: This plot compares market shares (CBSA level) from the Edison data to market shares based on payment card transactions (Second Measure data, March 2021). See the notes for Figure O.3.

Figure O.5: Effects of commission caps on DoorDash fees

(a) TWFE

(b) IW (Sun and Abraham 2021)



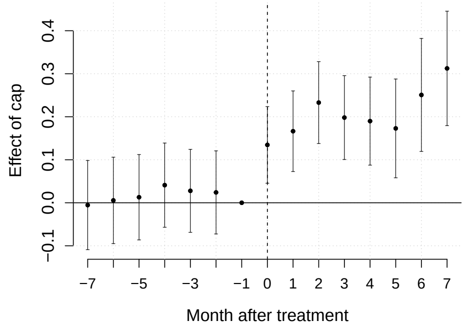
Notes: this figure reports estimates of the effects of commission caps on DoorDash's log average fees, The figure reports estimates from both the standard two-way fixed effects (TWFE) estimator and from the interaction weighted (IW) estimator. The dots indicate point estimates and the bars around each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

Table O.16: Fee responses to commission caps, alternative treatment/control groups

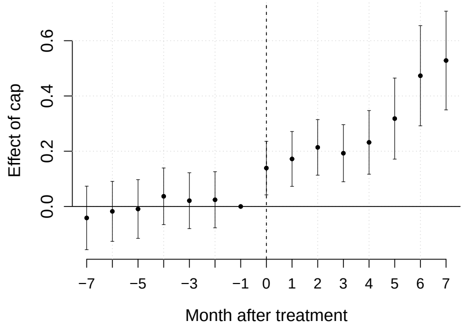
Platform	TWFE	IW	IV	CS (not yet)	CS (never)
DD	0.129	0.250	0.061	0.206	0.220
	(0.015)	(0.042)	(0.084)	(0.084)	(0.084)
Uber	0.037	-0.050	-0.064	-0.071	-0.051
	(0.014)	(0.037)	(0.095)	(0.040)	(0.037)
GH	0.171	0.111	0.135	0.045	0.042
	(0.054)	(0.203)	(0.139)	(0.064)	(0.064)

Notes: This table is an analogue of Table O.11 with the exception that the treatment group in the underlying analysis includes ZIPs with any cap (including those above 15%) and the control group includes all remaining ZIPs. See the notes of Table O.11 for additional details.

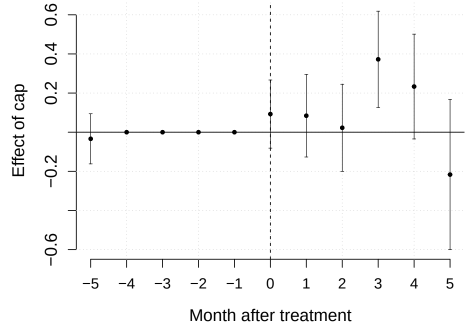
Figure O.6: Dynamic effects of commission caps on consumer fees



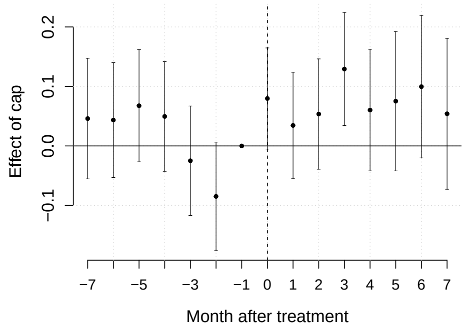
(a) DoorDash, TWFE



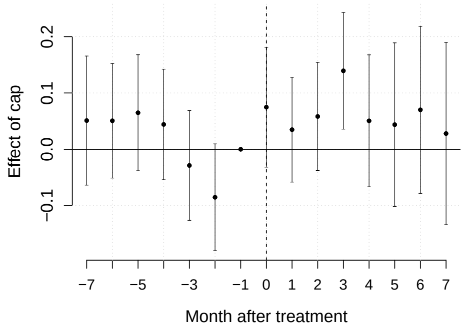
(b) DoorDash, IW



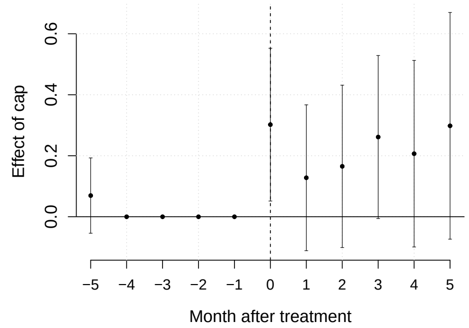
(c) DoorDash, IV



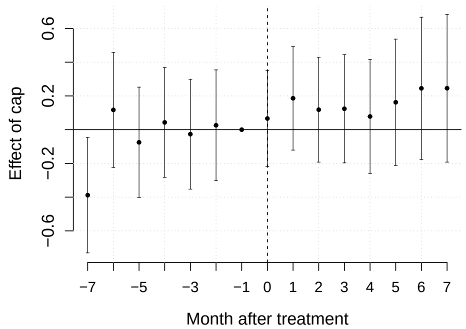
(d) Uber Eats, TWFE



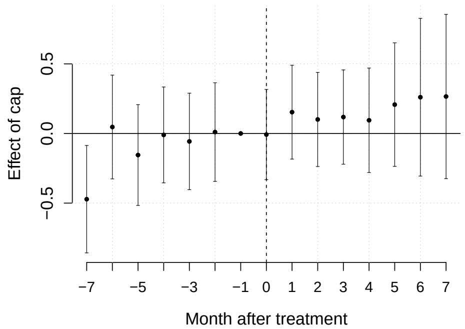
(e) Uber Eats, IW



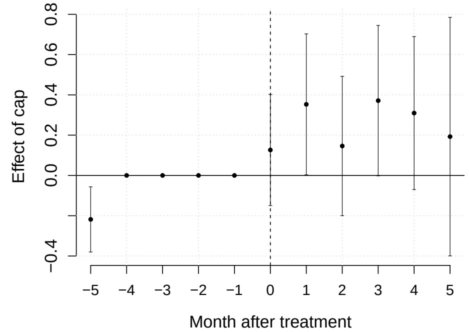
(f) Uber Eats, IV



(g) Grubhub, TWFE



(h) Grubhub, IW



(i) Grubhub, IV

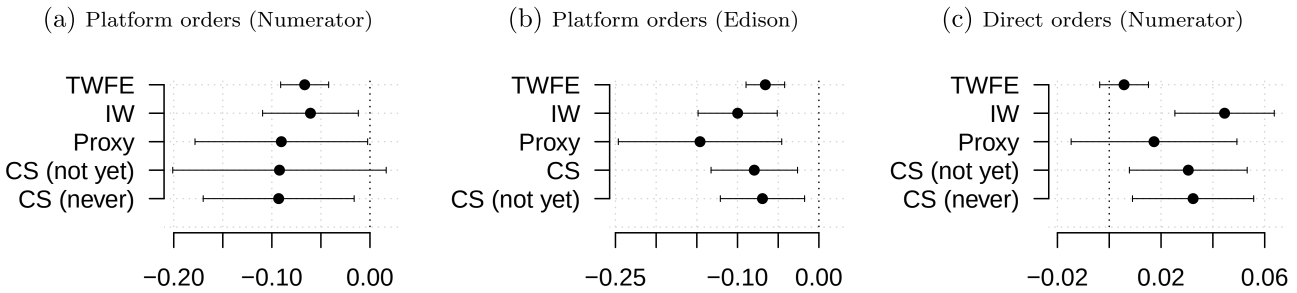
Notes: this figure plots estimates of dynamic effects of commission caps on platforms' consumer fees. These estimates were computed on the Edison ZIP/platform/month-level panel using three estimators described in the main text. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

O.7.3 Ordering effects

The effects of commission caps on restaurant profits depend on the extent to which ordering with platforms and ordering directly from a restaurant are substitutable from the consumer's perspective. If, for example, these channels were highly substitutable, consumers would switch from platform ordering to restaurant ordering due to platform fee hikes, benefitting restaurants given that they do not pay commission on direct sales. To assess the substitutability of direct and platform ordering, I apply the DiD methods deployed in Section O.7.2 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 O.7.2 contain data on platform sales, I check the robustness of my estimates using those data, repeating the analysis of platform fees described in Section O.7.2 but with log orders taking the place of log fees as the outcome.

Figure O.7 reports results of the analysis for log platform sales and log direct sales as outcomes and Figure O.8 plots dynamic effects from the IW estimator.[9] Across estimators and datasets, every estimated effect on platform orders except one is between -0.10 and -0.05 (a reduction of 5–11%). Additionally, the estimated effects on direct orders are all positive and range 0–5%. The estimated positive response of direct-from-restaurant spending to caps suggests that direct ordering and platform ordering are reasonably substitutable. In fact, I fail to reject the hypothesis that caps affected overall restaurant spending (before fees, tips, and taxes). Figure O.12 provides results for DiD analysis of caps' effects on overall spending — the estimated effects range from -0.012 to 0.020, and none of the estimates are significant at the 5% level.

Figure O.7: Effects of commission caps on restaurant sales

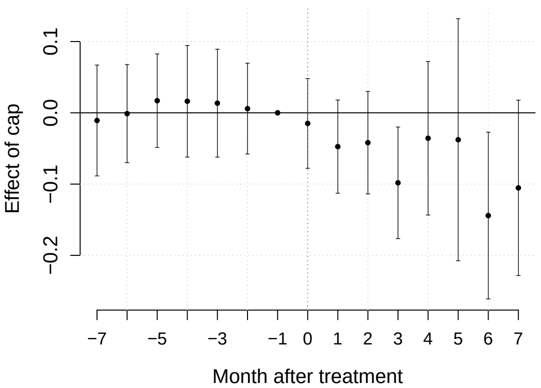


Notes: this figure reports DiD estimates of the effects of commission caps of 15% or less on the log number of restaurant orders placed (i) on delivery platforms and (ii) directly at restaurants. See the notes for Table O.11 for an explanation of each estimator. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

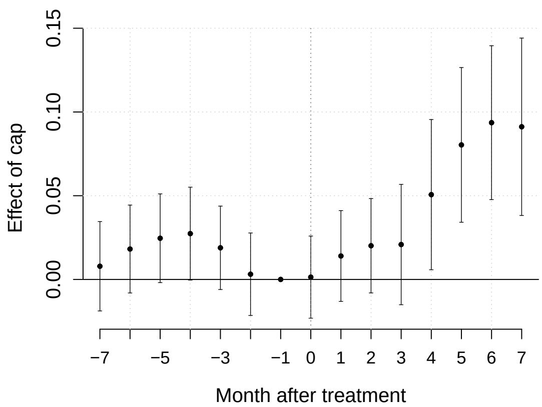
[9]There are not significant pre-trends, although some pre-trends in direct ordering systematically differ from zero. This may reflect unobserved heterogeneity affecting both cap adoption and order volumes. I assess this endogeneity concern by comparing the IW estimates to those from the estimator of Freyaldenhoven et al. (2019). As shown in Online Appendix Figure O.9, effects from this estimator are similar to those plotted in Figure O.13b.

Figure O.8: Effects of commission caps on order volumes (dynamic event study)

(a) Platform orders



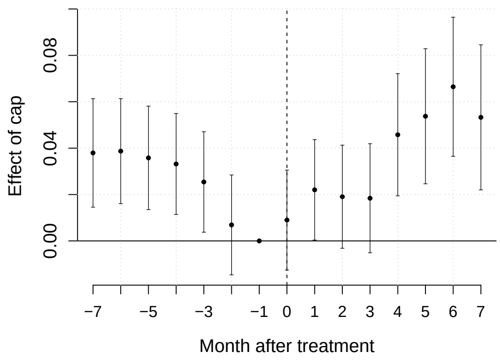
(b) Direct orders



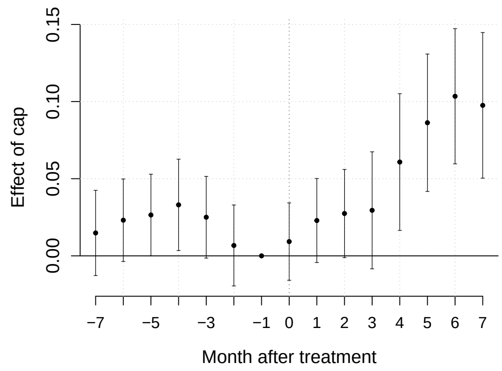
Notes: this figure plots interaction weighted (IW) estimates of the effects of commission caps on (i) the log number of orders placed on food delivery platforms and (ii) the log number of orders placed directly from restaurants. The dots indicate point estimates and the bars around each point indicate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

Figure O.9: Dynamic effects of commission caps on direct ordering (Numerator panel)

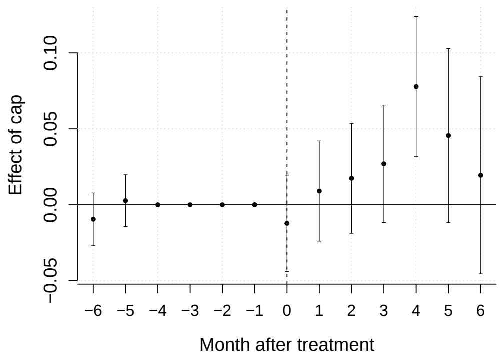
(a) TWFE



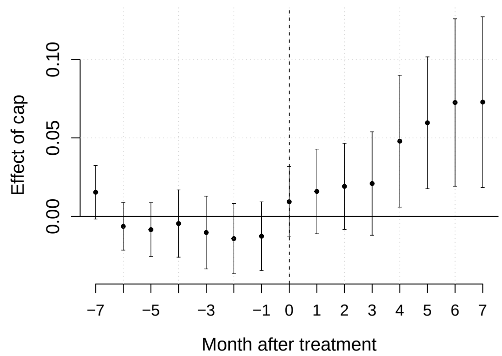
(b) IW, Sun and Abraham (2021)



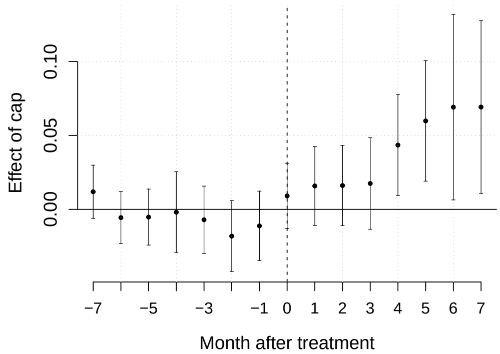
(c) IV, Freyaldenhoven et al. (2019)



(d) Callaway and Sant'Anna (2021) (never)



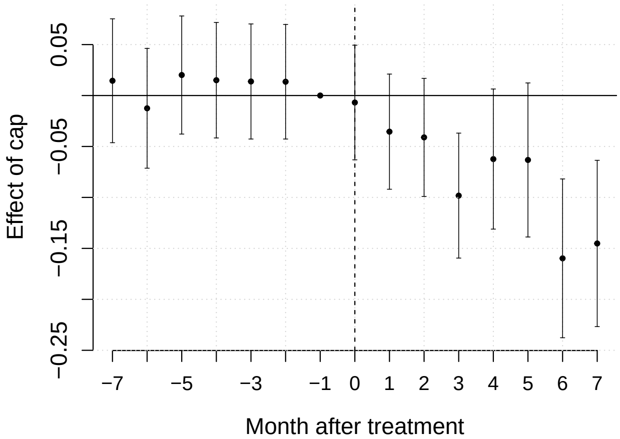
(e) Callaway and Sant'Anna (2021) (not yet)



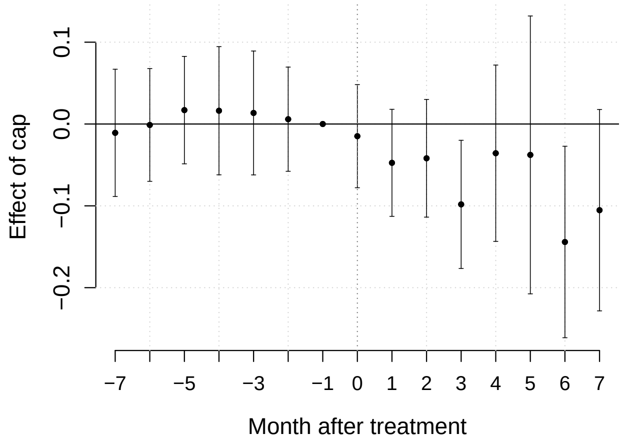
Notes: this figure includes plots of estimates of dynamically evolving effects of commission caps on the log of the total number direct-from-restaurant orders. Each unit in the analysis is a ZIP3, and each time period is a month. The figure includes estimates obtained from various estimators described in the main text. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

Figure O.10: Dynamic effects of commission caps on platform ordering (Numerator panel)

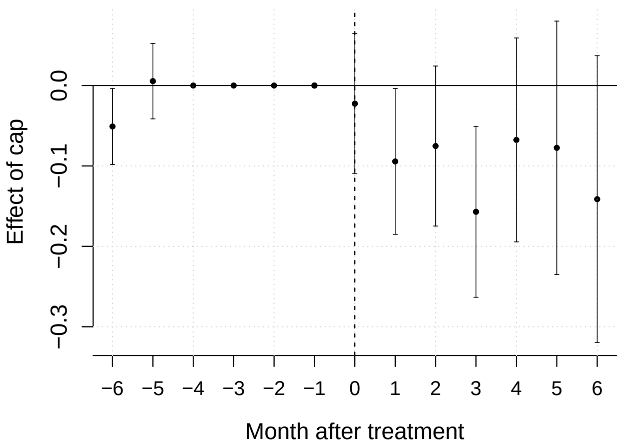
(a) TWFE



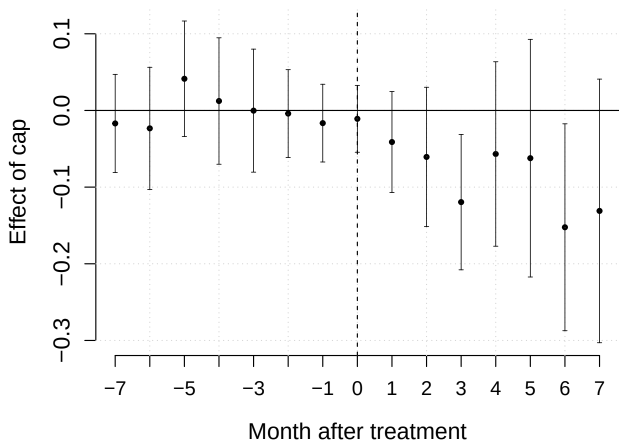
(b) IW, Sun and Abraham (2021)



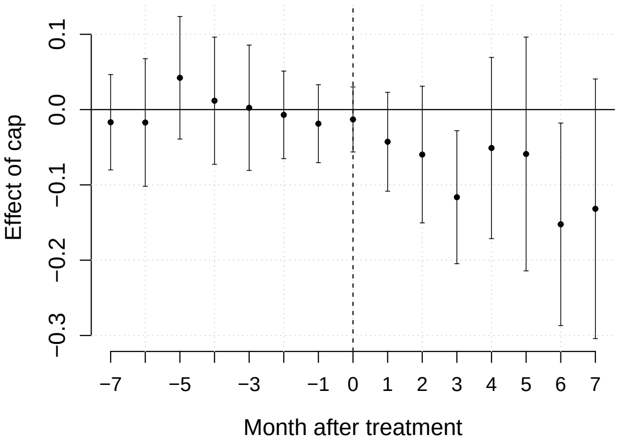
(c) IV, Freyaldenhoven et al. (2019)



(d) Callaway and Sant'Anna (2021) (not yet)



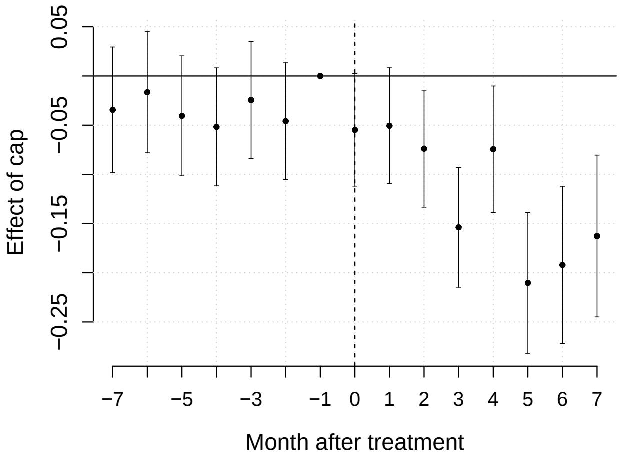
(e) Callaway and Sant'Anna (2021) (never)



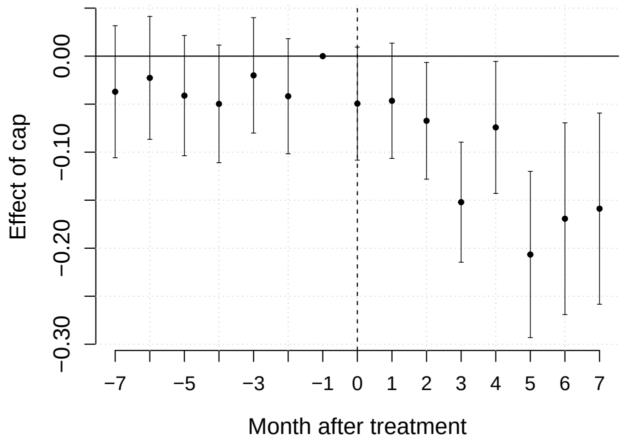
Notes: this figure includes plots of estimates of dynamic effects of commission caps on the log of the total number of restaurant orders placed on platforms. Each unit in the analysis is a ZIP3 and each time period is a month. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

Figure O.11: Dynamic effects of commission caps on platform ordering (Edison panel)

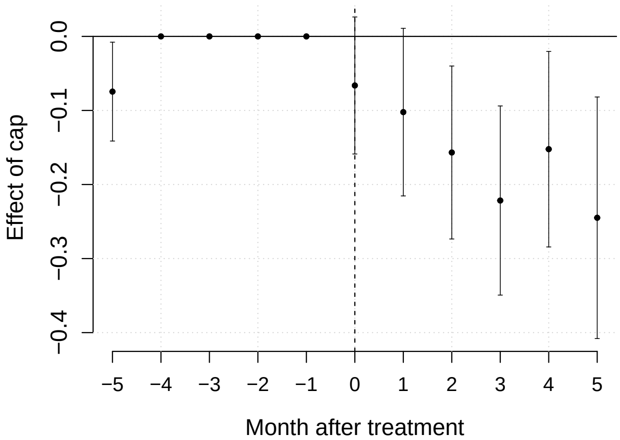
(a) TWFE



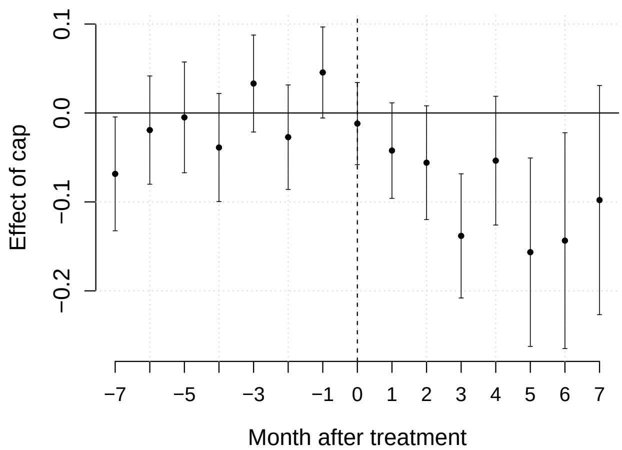
(b) IW, Sun and Abraham (2021)



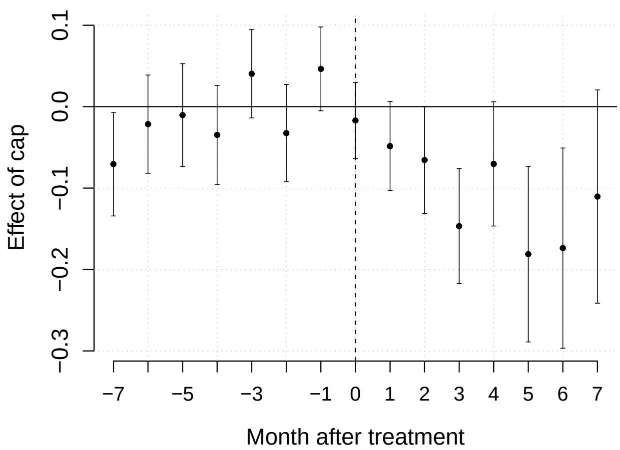
(c) IV, Freyaldenhoven et al. (2019)



(d) Callaway and Sant'Anna (2021) (not yet)



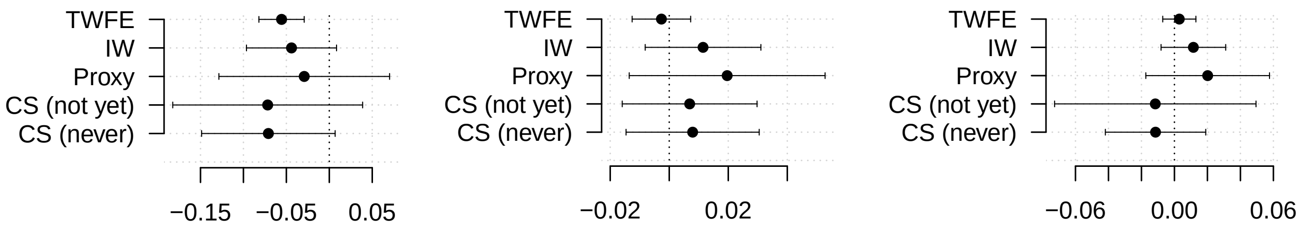
(e) Callaway and Sant'Anna (2021) (never)



Notes: this figure includes plots of estimates of dynamic effects of commission caps on the log of the total number of restaurant orders placed on platforms. These estimates were computed on the Edison panel. Each unit in the analysis is a ZIP and each time period is a month. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

Figure O.12: Effects of commission caps on restaurant sales (basket subtotals)

(a) Platform orders (b) Direct orders (c) All orders



Notes: this figure reports difference-in-differences estimates of the effects of commission caps of 15% or less on the log of aggregate basket subtotals (i.e., order values before fees, tips, and taxes) placed (i) on delivery platforms, (ii) directly at restaurants, and (iii) across both channels. See the notes for Table O.11 for an explanation of each estimator.

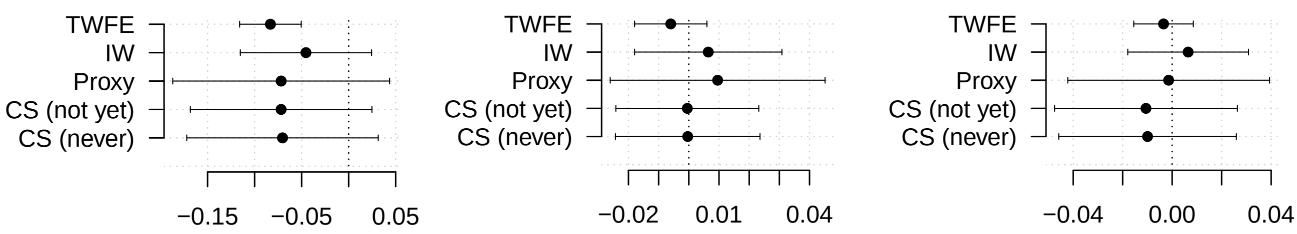
Figure O.13: Effects of commission caps on restaurant sales (January to May 2021)

(a) Platform orders (Numerator) (b) Direct orders (Numerator)

Notes: this figure reports DiD estimates of the effects of commission caps of 15% or less on the log number of restaurant orders placed (i) on delivery platforms and (ii) directly at restaurants. See the notes for Table O.11 for an explanation of each estimator. Both sets of results come from the Numerator data. The dots indicate point estimates and the bars around each point indicate 95% confidence intervals.

Figure O.14: Effects of commission caps on restaurant sales (basket subtotals), exclude caps that exempt chains

(a) Platform orders (b) Direct orders (c) All orders



Notes: this table reports results of the analysis described in the notes of Table O.12 but on a sample that excludes areas that ever had a commission cap that exempted chain restaurants.

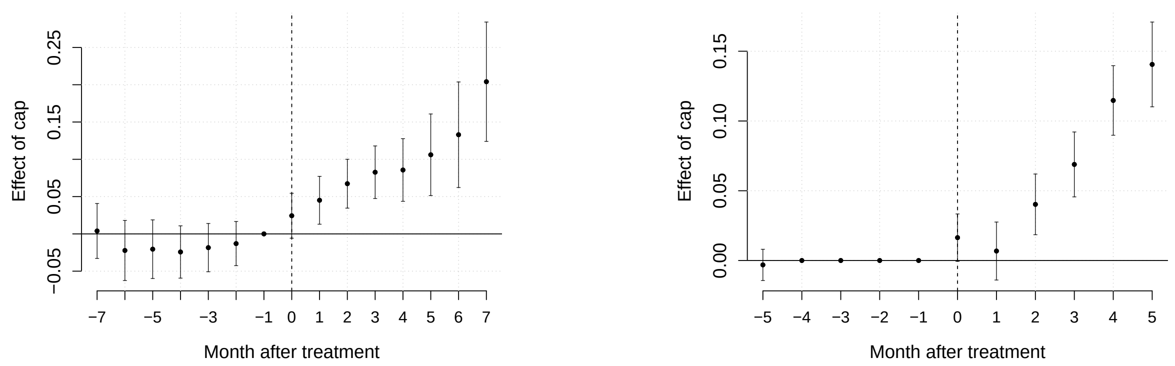
O.7.4 Restaurant platform adoption effects

Commission caps may also affect the intensity of restaurant platform adoption. I assess this possibility using DiD methods. The monthly data on restaurant listings on platforms facilitates estimation of caps' dynamic effects on the number of such listings. I estimate these effects on a monthly panel of 3-digit ZIP code areas (ZIP3), and analyze the number of restaurant listings on platforms both in levels and per million residents as outcomes.[10] A listing here is a restaurant/platform pair — e.g., between one restaurant listed on DoorDash and another listed on both DoorDash and Uber Eats, there would be three listings. As in Section O.7.2, I control for COVID-19-related variables and focus on caps of 15% or lower. Figure O.15a plots estimates of the effects of caps on the total number of restaurant listings per capita from the IW estimator. Here, the estimates are divided by the population-weighted mean number of 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 listings on platforms by between 2.5% and 14% within six months of taking effect. Although the pre-trends are not statistically distinguishable from zero at a 95% confidence level, they systematically fall below zero for the periods leading up to cap implementation. Thus, I compute estimates from the Freyaldenhoven et al. (2019) estimator; the results are similar to the IW estimates.

Figure O.15: Dynamic effects of commission caps on restaurants' platform adoption

(a) IW (Sun and Abraham 2021)

(b) Proxy (Freyaldenhoven et al. 2019)



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

The analysis above focuses on the number of restaurant listings on platforms as an outcome. Changes in this outcome could reflect changes in the extent to which existing restaurants join platforms and also changes in the set of active restaurants. I additionally conduct analyses that use the share of restaurants belonging to platforms and the mean number of platforms joined by restaurants as outcome measures. 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 the platform adoption measures described above as outcomes. The time periods here are January 2020 (t_0) and January 2021 (t_1). The estimating equation is

$$y_{zt} = \underbrace{\psi_z + \phi_t}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\delta x_{zt}}_{\text{Treatment}} + \underbrace{\mathbb{1}\{t = t_1\} w'_{zt}\beta}_{\text{Controls}} + \varepsilon_{zt}, \tag{11}$$

[10] I choose ZIP3s as the units of analysis because ZIP3s are large enough to include both the restaurants that service a local population and the local population itself, which is important given that the outcome is a per capita measure.

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 inclusion of these controls allows places differentially affected by COVID-19 to experience different trends in the outcomes. 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 caps by the second period.

Table O.17: Effects of commission caps on restaurants' platform uptake

(a) All commission caps of 15% or under

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)

(b) Exclude commission caps that exempt chains

Estimator	Share online	# platforms joined
Diff-in-diff	0.026	0.044
	(0.004)	(0.008)
Within-metro	0.031	0.101
	(0.005)	(0.011)

Notes: "Diff-in-diff" reports OLS estimates of δ in (11) 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 regressions, each ZIP is weighted by its number of restaurants. Whereas Table O.17a reports estimates from a sample that includes all areas that either had no commission cap or a cap of 15% or under, Table O.17b reports estimates from a sample that excludes areas that ever enacted a cap that exempted chain restaurants from the sample. Asymptotic standard errors appear in parentheses.

The "Diff-in-diff" row of Table O.17 provides OLS estimates of δ. These results suggest that caps led to a 3.9 percentage point increase in the share of restaurants belonging to at least one platform and an increase of 0.077 in the average number of 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 caps, conditional on the controls w_{zt}. I estimate effects of commission caps using within-metro variation by regressing outcomes on metro fixed effects and on an indicator for a cap. The "Within-metro" row of Table O.17 provides the results for May 2021. The results are similar to those from the DiD approach. Table O.18 provides estimates of platform-specific uptake effects. These estimates suggest a positive effect of caps on restaurants' probabilities of joining each platform. Table O.19 provides estimates of the effects of a continuous treatment variable that is defined to be equal to the level of the active commission cap in places where a cap is in effect and equal to 30% otherwise. The estimates are consistent with those from specifications with a binary treament: they suggest that commission reductions raise platform uptake among restaurants.

Table O.18: Effects of commission caps on restaurants' platform uptake, platform-specific estimates

Estimator	Share on			
	DD	Uber	GH	PM
Diff-in-diff	0.027	0.028	0.006	0.016
	(0.004)	(0.003)	(0.002)	(0.002)
Within-metro	0.010	0.040	0.035	0.038
	(0.004)	(0.003)	(0.003)	(0.002)

Notes: "Diff-in-diff" reports OLS estimates of δ in (11) in which the outcomes are the shares of restaurants in the ZIP that belong to the food delivery platform indicated by the columns. 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 the same outcomes 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.

Table O.19: Effects of commission caps on restaurants' platform uptake, continuous treatment

Estimator	Share online	# platforms joined
Diff-in-diff	-0.128	-0.119
	(0.020)	(0.044)
Within-metro	-0.275	-0.856
	(0.027)	(0.064)

Notes: see the notes for Table O.17. The treatment variable x_{zt} used in the regressions whose results are displayed above is equal to the level of ZIP z's commission cap in effect at time period t if a commission cap was in effect and equal to 0.30 otherwise. The sample includes ZIPs with commission caps exceeding 15%.

Table O.20: Effects of commission caps on platform restaurant listing counts (absolute listing counts)

Outcome	TWFE	IW	Proxy	CS (not yet)	CS (never)
Total listings	511.9	291.3	429.4	411.4	414.1
	(22.9)	(38.4)	(68.7)	(138.1)	(138.8)
DD listings	63.1	22.7	42.5	39.4	38.4
	(4.7)	(14.7)	(15.1)	(22.6)	(22.4)
Uber listings	166.5	85.8	152.2	148.7	150.2
	(7.7)	(10.9)	(23.2)	(46.5)	(46.8)
GH listings	139.2	83.8	117.7	115.3	116.7
	(6.8)	(9.7)	(20.3)	(37.7)	(38.0)
PM listings	143.1	99.0	117.1	107.9	108.9
	(5.5)	(10.1)	(16.8)	(39.4)	(39.5)

Notes: the table 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). The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2757 (total), 1037 (DoorDash), 734 (Uber Eats), 613 (Grubhub), and 373 (Postmates). The "TWFE" column provides results from a two-way fixed effects regression of the outcome variable on (i) ZIP3 fixed effects, (ii) month fixed effects, and (iii) an indicator for an active 15% or lower commission cap in the ZIP3. The "CS (not yet)" column provides estimates of the average treatment effect on the treated (ATT) across time periods and treatment cohorts from the Callaway and Sant'Anna (2021) estimator when not-yet-treated units constitute the control group. The "CS (never)" reports estimates of the ATT from the Callaway and Sant'Anna (2021) estimator when never-treated units constitute the control group. Asymptotic standard errors appear in parentheses.

Table O.21: Effects of commission caps on platform restaurant listing counts (relative effects)

Outcome	TWFE	IW	Proxy	CS (not yet)	CS (never)
Total listings	0.114	0.088	0.100	0.098	0.099
	(0.005)	(0.009)	(0.012)	(0.023)	(0.023)
DD listings	0.023	0.009	0.015	0.009	0.008
	(0.003)	(0.011)	(0.010)	(0.013)	(0.013)
Uber listings	0.156	0.106	0.146	0.151	0.153
	(0.006)	(0.012)	(0.017)	(0.029)	(0.029)
GH listings	0.153	0.120	0.129	0.133	0.135
	(0.006)	(0.012)	(0.016)	(0.026)	(0.027)
PM listings	0.253	0.250	0.228	0.215	0.217
	(0.009)	(0.021)	(0.026)	(0.055)	(0.055)

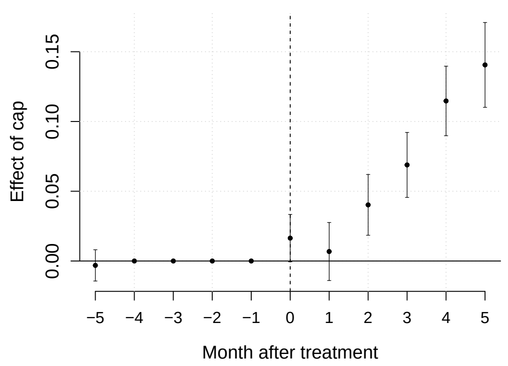
Notes: the table provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents relative to the population-weighted mean value of this quantity in April 2020. The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2642 (total), 1056 (DoorDash), 668 (Uber Eats), 587 (Grubhub), and 332 (Postmates). Each column provides results for a distinct estimator; see the notes for Table O.11 for a description of these estimators. Asymptotic standard errors appear in parentheses.

Table O.22: Effects of commission caps on platform restaurant listing counts (relative effects), excluding caps that exempt chains

Outcome	TWFE	IW	Proxy	CS (not yet)	CS (never)
Total listings	0.127	0.080	0.083	0.093	0.093
	(0.005)	(0.011)	(0.015)	(0.019)	(0.019)
DD listings	0.022	0.001	-0.009	-0.011	-0.012
	(0.004)	(0.013)	(0.012)	(0.011)	(0.011)
Uber listings	0.167	0.086	0.133	0.151	0.153
	(0.008)	(0.014)	(0.021)	(0.026)	(0.026)
GH listings	0.171	0.106	0.113	0.134	0.135
	(0.007)	(0.013)	(0.020)	(0.024)	(0.024)
PM listings	0.299	0.269	0.224	0.233	0.235
	(0.010)	(0.025)	(0.031)	(0.052)	(0.053)

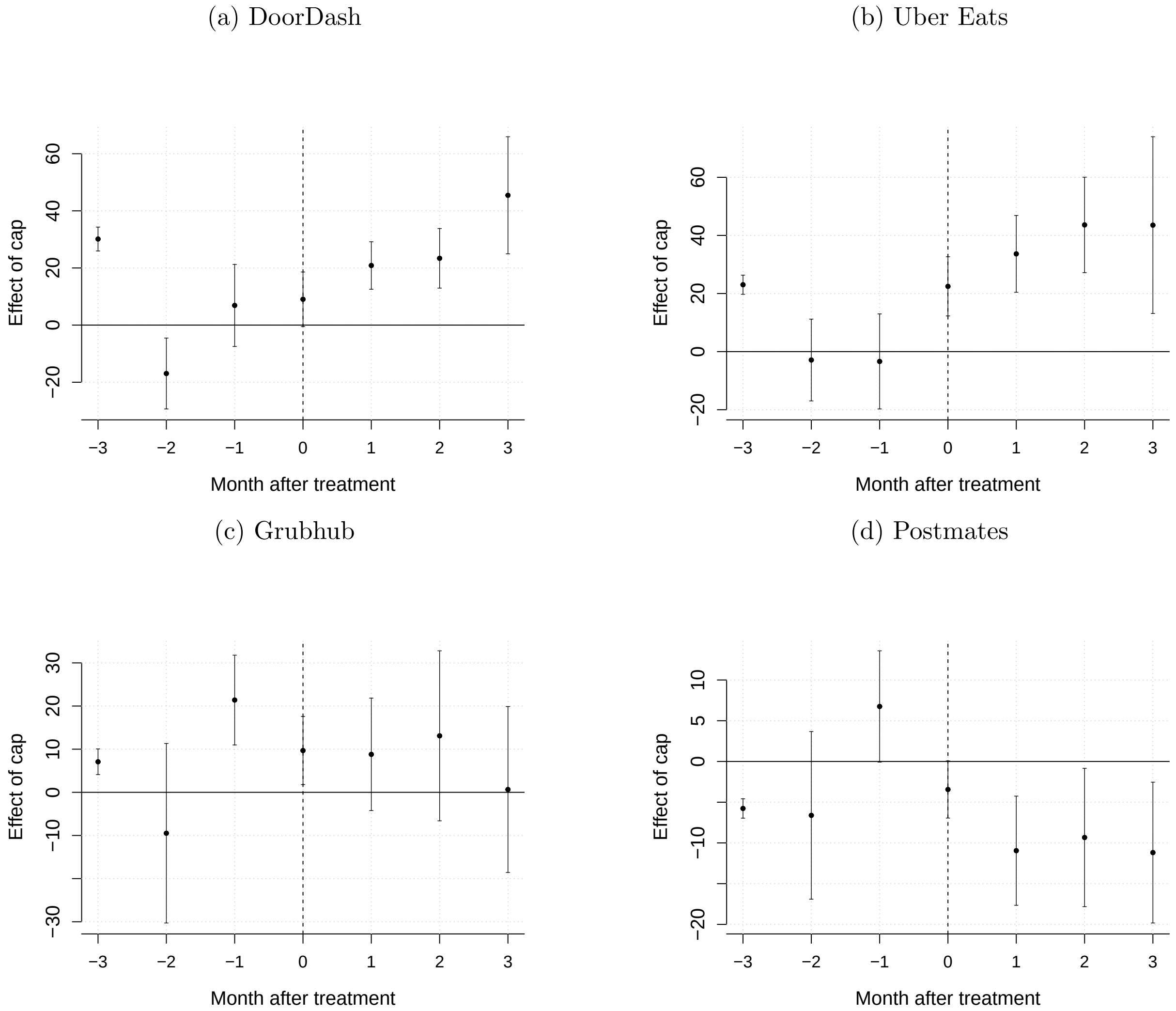
Notes: this table reports results of the analysis described in the notes of Table O.21 but with areas that ever had commission caps that exempted chains excluded from the estimation sample.

Figure O.16: Dynamic effects of commission caps on restaurants' platform adoption (Freyaldenhoven et al. 2019 proxy estimator)



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

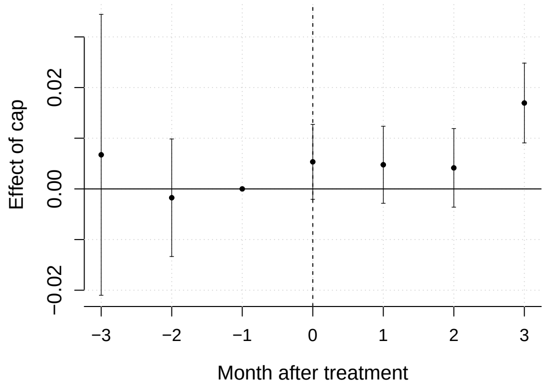
Figure O.17: Dynamic effects of commission caps on platform restaurant listing counts (disaggregated by platform)



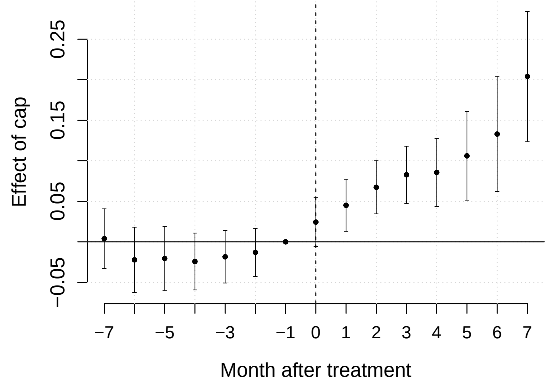
Notes: the plot provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents. The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2642 (total), 1056 (DoorDash), 668 (Uber Eats), 587 (Grubhub), and 332 (Postmates). 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.

Figure O.18: Dynamic effects of commission caps on platform restaurant listing counts (alternative estimators)

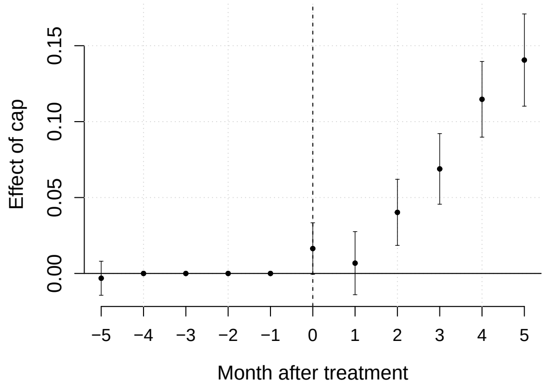
(a) TWFE



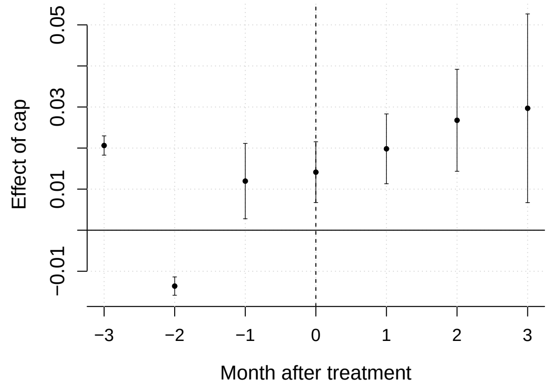
(b) IW



(c) IV



(d) Callaway and Sant'Anna (2021) (not yet)



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, scaled by the mean value of the dependent variable across ZIP3s in April 2020 (2642). The estimates derive from (O.18a) a two-way fixed effects estimator; (O.18b) the interaction-weighted estimator of Sun and Abraham (2021); (O.18c) the instrumental-variables-based estimator of Freyaldenhoven et al. (2019), which uses new COVID-19 cases per capita, stringency of local COVID-19 policy, and the interaction of new COVID-19 cases per capita and the Democratic vote share in the 2019 election as proxies for unobserved heterogeneity as well as three leads of the policy change as instruments; and (O.18d) 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.

O.8 Equilibrium uniqueness

Multiplicity of equilibria is a well-known concern in the two-sided markets literature. This problem arises when platform adoption is driven by network externalities: i.e., participation on each side is contingent on participation on the other. In the extreme case, a two-sided market may support both (i) a no-adoption equilibrium in which both buyers and sellers refrain from joining due to the lack of adoption on the other side and (ii) a full-adoption wherein each side's participation is driven by the high participation on the other. To address this coordination problem, Weyl (2010) introduced the concept of insulating tariffs, which are platform fees that condition on participation on the opposite side of the market and that ensure the platform can implement its preferred adoption level.

Although my model does not feature insulating tariffs, it does not suffer from the multiplicity concern raised above. This is because it does not feature a consumer adoption stage. Consumers are assumed to have access to all platforms at the time of ordering without having made any previous platform membership decision. Thus, restaurants deciding whether to join a platform face no uncertainty about the availability of consumers.

To illustrate the absence of multiplicity more concretely, I analyze a stylized version of the model. A monopolist platform sets a per-transaction fee c to consumers and a per-transaction commission r to restaurants. I assume for simplicity of exposition that restaurants do not set prices, and that the platform's commission charge is a fixed amount rather than a share of the price. I assume that sales on the platform equal $S(c, J)$, where J is the share of restaurants that have joined the platform. A restaurant joins the platform when its profits from doing so are non-negative. A restaurant's profits from joining the platform are

$$\Pi(J) = (b - r)\frac{S(c, J)}{J} - K,$$

where b is the restaurant's benefit from a platform sale, assumed to be fixed across restaurants, and K is the fixed cost of platform adoption. The fraction $S(c, J)/J$ reflects that restaurants belonging to the platform evenly share sales made on the platform. Assume now that $S(c, J)/J$ is a strictly decreasing function: this means that each restaurant's sales on the platform fall when more restaurants join the platform. This implies that $\Pi(J)$ is decreasing in J. Also assume for ease of exposition that $S(c, J)/J$ is continuous in J. There are three cases to analyze. First, suppose that $\Pi(0) < 0$. In this case, $\Pi(J) < 0$ for all $J \geq 0$. Hence, there is no level of platform adoption by restaurants at which restaurants are profitable, and consequently no restaurants join the platform. Now suppose that $\Pi(1) \geq 0$. Then, for any adoption level $J < 1$, it is profitable for another restaurant to join the platform as $\Pi(J) > \Pi(1) \geq 0$. This means that all restaurants join the platform. Last, by virtue of the fact that $S(c, J)/J$ is continuous in J, there is a case in which $\Pi(J^*) = 0$ for some $J^* \in (0, 1)$. In this case, a share J^* of restaurants join the platform. Indeed, if fewer restaurants join, it is profitable for those restaurants that did not join to adopt the platform. If more restaurants join, then the profits of restaurants using the platform would be negative. Both conclusions stem from the fact that Π is a decreasing function. Thus, in each case, there is a unique level of restaurant platform adoption. In addition, there is a unique level of sales associated with this unique level of restaurant platform adoption; it is given by the demand function $S(c, J)$.

Although this stylized model abstracts from features of the full model (e.g., price setting), it shares the same structure in key respects. In particular, it shows that removing consumer adoption frictions and incorporating business stealing eliminates the strategic uncertainty that typically generates multiplicity. As such, equilibrium uniqueness is a reasonable assumption in the full model.

O.9 Restaurant pricing model

I consider two distinct models of restaurant pricing. In the first, restaurant prices solve

$$p_j^* = \arg\max_{p_j} \sum_{f \in \mathcal{G}_j} \left[(1 - \vartheta r_f) p_{jf} - \kappa_{jf}\right] S_{jf}. \tag{12}$$

I call this the *incomplete response* model as the presence of $\vartheta < 1$ limits pricing responses to changes in commissions. The model does not structurally explain the source of limited pricing responses, which could owe to menu costs, a lack of sophistication in pricing, or costs in calculating optimal responses to commissions.

In the second model, restaurant prices solve

$$p_j^* = \arg\max_{p_j} \sum_{f \in \mathcal{G}_j} \left[(1 - r_f) p_{jf} - \kappa_{jf}\right] S_{jf} + \frac{\vartheta'}{2} \sum_{f \neq 0} (p_{jf} - p_{j0})^2 S_{jf} \tag{13}$$

I call this the *non-parity penalty* model, as it imposes a penalty for deviations from price parity (i.e., $p_{jf} = p_{j0}$). These penalties are proportional to the restaurant j's sales S_{jf} on platform f, as I hypothesize that the harms suffered by j from punishment by f and the brand image damage resulting from non-price parity on f are proportional to the amount of business that the restaurant does on f.

I estimate the pricing friction parameters ϑ from the incomplete response model and ϑ' from the non-parity penalty model by GMM. For the incomplete response model, I use the empirical analogue of the population moment condition described in the main text:

$$\mathbb{E}[\tilde{\kappa}_{jf}(\vartheta_0) Z_j] = 0, \qquad f \neq 0,$$

where $\tilde{\kappa}_{jf}(\vartheta)$ is the de-meaned marginal cost for restaurant j on platform f as recovered from first-order conditions for optimal pricing under the parameter ϑ. Similarly, I estimate ϑ' by minimizing a GMM objective function computed by (i) inverting first-order conditions for optimal pricing under the non-parity penalty model to obtain marginal costs $\kappa_{jf}(\vartheta')$, (ii) demeaning these on a platform-by-platform basis to obtain $\tilde{\kappa}_{jf}(\vartheta') = \kappa_{jf}(\vartheta') - \bar{\kappa}_{jf}(\vartheta')$, where $\bar{\kappa}_{jf}(\vartheta')$ is the mean of $\kappa_{jf}(\vartheta')$ over (j, f) pairs, and (iii) summing over restaurant/platform pairs interactions of $\tilde{\kappa}_{jf}(\vartheta')$ with an instrument Z_j equal to one if restaurant j was exposed to a commission cap and zero otherwise:

$$Q(\vartheta') = \sum_j \sum_{f \in \mathcal{G}_j, \neq 0} \tilde{\kappa}_{jf}(\vartheta') Z_j.$$

The estimator $\hat{\vartheta}'$ solves $Q(\hat{\vartheta}') = 0$. I obtain estimates $\hat{\vartheta} = 0.638$ and $\hat{\vartheta}' = 0.416$. The latter estimate implies that the cost to a restaurant of a \$2.00 difference between its price on platform f and its direct price is \$0.83 per order on platform f.

I use each pricing model to simulate effects of commission reductions on prices. Holding fixed consumer fees and restaurant platform adoption decisions as observed in the data, I compute equilibria in restaurant pricing when all platforms charge 30% commissions and when all platforms charge 15% commissions in each metro area under each of the two pricing models. In doing so, I use the estimates of ϑ and ϑ' reported above and the marginal costs estimated under these pricing friction parameter estimates. Table O.23 reports average price changes when commissions are reduced from 30% to 15%, weighting by sales under 30% commissions. Whereas the incomplete response model predicts a negligible average change in direct order prices, the non-parity penalty model predicts a 2.5% reduction in direct order prices. Both models predict significant average reductions in prices for platform orders, although the non-parity

Table O.23: Pricing effects of commission reduction under alternative pricing models (%)

Ordering channel	Model: Incomplete response	Non-parity penalty
Direct	0.08	-2.46
DoorDash	-9.06	-11.59
Uber Eats	-9.08	-12.18
Grubhub	-9.08	-12.15
Postmates	-9.26	-13.35

penalty model predicts larger (11–14%) reductions than the incomplete response model (9–10%). Given that I do not find evidence of price reductions for direct orders (see Table 16 in Appendix A), I use the incomplete response model in the article's counterfactual analysis.

O.10 Bootstrap procedure

The inference procedure uses a multi-stage bootstrap with both parametric and non-parametric components.

I begin by drawing $B = 100$ samples from the estimated asymptotic distribution of the consumer choice model parameters. To do so, I estimate the variance of the maximum likelihood estimator $\hat{\theta}^{\text{cons}}$ using the outer product of gradients, and draw Z^b from the resulting estimated distribution of $\sqrt{n}(\hat{\theta}^{\text{cons}} - \theta_0^{\text{cons}})$, where θ_0^{cons} is the true choice model parameter vector. Each draw defines $\hat{\theta}^{\text{cons},b} = \hat{\theta}^{\text{cons}} + n^{-1/2}Z^b$ as the bth bootstrapped estimator of θ^{cons}. All parameters other than metro/platform fixed effects are estimated on data from the three largest metro areas, so n refers to the number of consumer observations in these metros.

For the remaining metros, I estimate the sampling distribution of metro/platform fixed effects non-parametrically. For each metro and bootstrap draw b, I draw a bootstrap sample (i.e., with replacement and with the same size as the underlying sample) of consumers and re-estimate fixed effects setting the other choice model parameters equal to their values in $\hat{\theta}^{\text{cons},b}$. These bootstrapped fixed effect estimates are incorporated into $\hat{\theta}^{\text{cons},b}$ in what follows.

Given each draw $\hat{\theta}^{\text{cons},b}$, I estimate B bootstrapped estimators $\hat{\vartheta}^b$ of ϑ using the GMM procedure described in Section 5.2. This involves, for each $b \in \{1, \ldots, B\}$, (i) inverting restaurant pricing first-order conditions to obtain preliminary marginal costs $\hat{\kappa}(\vartheta; \hat{\theta}^{\text{cons},b})_{jf}$; (ii) constructing residualized versions $\tilde{\kappa}(\vartheta; \hat{\theta}^{\text{cons},b})_{jf}$; (iii) interacting these residualized marginal costs with the instrument Z_j; and (iv) averaging over a bootstrap subsample of restaurant/platform pairs (j, f). This yields the GMM objective function (with argument ϑ) minimized by the bth bootstrapped estimator $\hat{\vartheta}^b$.

Next, I estimate bootstrapped restaurant marginal costs $\hat{\kappa}^b$, under $\hat{\theta}^{\text{cons},b}$ and $\hat{\vartheta}^b$ for each $b \in \{1, \ldots, B\}$. For each b, I also take a bootstrap draw of restaurants within each ZIP/restaurant type pair. Let $\mathcal{J}^b$ denote the bth draw. I proceed to estimate the parameters of the platform adoption model at $\{\hat{\theta}^{\text{cons},b}, \mathcal{J}^b, \hat{\vartheta}^b, \hat{\kappa}^b\}$ for each b, obtaining estimates $\hat{\theta}^{\text{adopt},b}$ for each b. I last estimate the platform marginal costs mc_{fz} at $\{\hat{\theta}^b, \hat{mc}^b, \hat{\vartheta}^b, \hat{\theta}^{\text{adopt},b}\}$ for each b, yielding estimates $\hat{mc}^b_{fm}$.

The standard errors that I report are standard deviations of parameters (or transformations of parameters) across the b-superscripted bootstrap estimates. The 95% confidence interval of ϑ that I report is the range between the 2.5th percentile and 97.5th percentile of the B bootstrapped estimators $\hat{\vartheta}^b$ of ϑ.

O.11 Choice probabilities

This appendix provides expressions for choice probabilities in the consumer choice model. I begin by introducing some notation, which is summarized by Table O.24. Let x_i denote a sequence including all relevant consumer-level observables other than ordering outcomes. These observables include the consumer's demographic characteristics d_i and the consumer's ZIP of residence z_i. Additionally, let $\mathcal{Z}(z_i)$ denote the set of ZIPs within range of the consumer, and let $m(i)$ denote consumer i's metro of residence. Let $\Xi_i = (\zeta_i, \eta_i^\dagger, \tilde{\phi}_{i\tau})$.

I now develop notation for metro-level variables. Let $\mathcal{J}_m$ denote the geographical locations and platform subsets of all restaurants in metro m, let $\mathcal{J}_{\tau z}(\mathcal{G})$ denote the set of restaurants of type τ in ZIP z that are located on platform subset $\mathcal{G}$. Next, let w_m denote a sequence including all relevant metro-level observables. These include prices p_{jf} charged by restaurants j in ZIPs z in metro m, fees c_{fz} for ZIPs z in metro m, waiting times W_{fz} for ZIPs z in metro m, and $\mathcal{J}_m$. Throughout the section, I assume that restaurants belonging to the same type, ZIP, and platform subset charge the same prices. This assumption reflects my focus on symmetric pricing equilibria, and it motivates my use of the notation $p_{\tau z \mathcal{G}} = \{p_{f\tau z\mathcal{G}}\}_{f\in\mathcal{G}}$ to denote the prices of a type-τ restaurant in ZIP z that belongs to platform subset $\mathcal{G}$. Let θ denote the model parameters, which I often suppress in the notation.

Table O.24: Summary of notation

Level	Notation	Meaning
Consumer	d_i	Consumer i's demographics (age, marital status, income)
	z_i	Consumer i's ZIP
	x_i	Combined consumer-level data: z_i, d_i
	Ξ_i	Unobserved heterogeneity: $\zeta_i, \eta_i^\dagger$
Metro	p_m	All prices $p_{fz\mathcal{G}}$ for ZIPs in metro m
	c_m	All fees c_{fz} for ZIPs in metro m
	W_m	All waiting times W_{fz} for ZIPs in metro m
	$\mathcal{J}_m$	Locations & platform subsets of restaurants in metro m
	w_m	Combined metro-level data: $p_m, c_m, W_m, \mathcal{J}_m$

In my model, consumers simultaneously choose a restaurant and a platform. If the consumer orders from a restaurant j of type τ in ZIP z with platform subset $\mathcal{G}$, then the consumer will select the platform f that maximizes $\psi_{if} - \alpha_i p_{f\tau z\mathcal{G}}$ among platforms $f \in \mathcal{G}$. In practice, I smooth consumers' probabilities of selecting platforms for a particular restaurant when computing choice probabilities. This smoothing operation involves the functions

$$V(\mathcal{G}, \tau, z, x_i, w_{m(i)}, \Xi_i) = \sigma_\varepsilon \log\left(\sum_{f\in\mathcal{G}} e^{(\psi_{if} - \alpha_i p_{f\tau z\mathcal{G}})/\sigma_\varepsilon}\right)$$

and

$$\mu_i(f \mid \mathcal{G}, \tau, z, x_i, w_{m(i)}, \Xi_i) = \frac{e^{(\psi_{if} - \alpha_i p_{f\tau z\mathcal{G}})/\sigma_\varepsilon}}{\sum_{f'\in\mathcal{G}} e^{(\psi_{if'} - \alpha_i p_{f\tau z\mathcal{G}})/\sigma_\varepsilon}}.$$

Note that V provides a smoothed maximum of $\psi_{if} - \alpha_i p_{f\tau z\mathcal{G}}$ among platforms f to which a restaurant j of type τ on platform subset $\mathcal{G}$ in ZIP z belongs, whereas μ is a smoothed indicator for f maximizing

$\psi_{if} - \alpha_i p_{f\tau z\mathcal{G}}$ among these platforms. Indeed,

$$\lim_{\sigma_\varepsilon \downarrow 0} V(\mathcal{G}, \tau, z, x_i, \Xi_i) = \max_{f \in \mathcal{G}_j} [\psi_{if} - \alpha_i p_{f\tau z\mathcal{G}}]$$

$$\lim_{\sigma_\varepsilon \downarrow 0} \mu_i(f \mid \mathcal{G}, \tau, z, x_i, \Xi_i) = \mathbb{1}\left\{ f = \arg\max_{f' \in \mathcal{G}_j} \left[\psi_{if'} - \alpha_i p_{f'\tau z\mathcal{G}}\right] \right\}$$

The parameter σ_ε controls the extent of smoothing. I smooth because it facilitates the computation of derivatives of market shares. I compute these derivatives by integrating over analytical derivatives of smoothed consumer choice probabilities; without smoothing, I would need to numerically differentiate the integrals over indicators that define market shares, which is computationally difficult.

The consumer's probability of choosing a restaurant of type τ in ZIP $z \in \mathcal{Z}(z_i)$ with platform subset $\mathcal{G}$ conditional on their observed characteristics x_i, the characteristics of their market $w_{m(i)}$, and their unobserved tastes Ξ_i is

$$\begin{aligned} \lambda(\mathcal{G}, \tau, z \mid x_i, w_{m(i)}, \Xi_i) &= \Pr\left((\mathcal{G}, \tau, z) = \arg\max_{\mathcal{G}', \tau' z'} \left\{ \max_{j \in \mathcal{J}_{\tau', z'}(\mathcal{G}')} \left[V(\mathcal{G}, \tau, z, x_i, w_{m(i)}, \Xi_i) + \nu_{ijt} \right] \right\} \mid z_i, x_i, w_{m(i)}, \Xi_i \right) \\ &= \frac{|\mathcal{J}_{\tau z}(\mathcal{G})| e^{V(\mathcal{G}, \tau, z, x_i, w_{m(i)}, \Xi_i)}}{\sum_{\mathcal{G}', \tau'} \sum_{z' \in \mathcal{Z}(z_i)} |\mathcal{J}_{\tau' z'}(\mathcal{G}')| e^{V(\mathcal{G}', \tau, z', x_i, w_{m(i)}, \Xi_i)}}. \end{aligned}$$

For $z \notin \mathcal{Z}(z_i)$, we have $\lambda(\mathcal{G}, \tau, z \mid x_i, w_{m(i)}, \Xi_i) = 0$. That is, the consumer never orders from a restaurant outside of the five mile delivery radius.

I now provide an expression for a consumer's probability of ordering from any inside restaurant, i.e., from any restaurant $j \neq 0$. The inclusive value of inside restaurants is equal to

$$\bar{V}(x_i, w_{m(i)}, \Xi_i) = \eta_i + \log\left(\sum_{\mathcal{G}, \tau} \sum_{z \in \mathcal{Z}(z_i)} |\mathcal{J}_{\tau z}(\mathcal{G})| e^{V(\mathcal{G}, \tau, z, x_i, w_{m(i)}, \Xi_i)} \right).$$

Furthermore, consumer i's probability of choosing a restaurant $j \neq 0$ conditional on $(x_i, w_{m(i)}, \Xi_i)$ is

$$\Lambda(x_i, w_{m(i)}, \Xi_i) = \frac{e^{\bar{V}(x_i, w_{m(i)}, \Xi_i)}}{1 + e^{\bar{V}(x_i, w_{m(i)}, \Xi_i)}}$$

It follows that the probability with which the consumer places an order on platform f conditional on x_i, $w_{m(i)}$, and Ξ_i is

$$\ell(f \mid x_i, w_{m(i)}, \Xi_i; \theta) = \sum_{\mathcal{G}: f \in \mathcal{G}} \sum_{\tau} \sum_{z \in \mathcal{Z}} \lambda(\mathcal{G}, \tau, z | x_i, w_{m(i)}, \Xi_i) \mu(f \mid \mathcal{G}, \tau, z, x_i, w_{m(i)}, \Xi_i).$$

The probability that the consumer does not order from a restaurant conditional on $\{x_i, w_{m(i)}, \Xi_i\}$ is

$$\ell_0(x_i, w_{m(i)}, \Xi_i; \theta) = 1 - \Lambda(x_i, w_{m(i)}, \Xi_i).$$

O.12 Restaurant sales

The sales on platform f of a restaurant j of type τ_j in ZIP z_j that belongs to the platform subset $\mathcal{G}$ are

$$S_{jf}(\mathcal{G}_j, w_m) = \sum_{z_i \in \mathcal{Z}(j)} M_z \int \Lambda(z_i, d_i, w_m, \Xi_i) \times \mu(f \mid \mathcal{G}_j, \tau_j, z_j, z_i, d_i, w_m, \Xi_i) \times \frac{e^{V(\mathcal{G}_j, \tau_j, z_j, z_i, d_i, w_m, \Xi_i)}}{\sum_{\mathcal{G},\tau} \sum_{z' \in \mathcal{Z}(z_i)} \sum_{k \in \mathcal{J}_{\tau z'}(\mathcal{G})} e^{V(\mathcal{G}, \tau, z', z_i, d_i, w_m, \Xi_i)}} dP_z(d_i, \Xi_i). \tag{14}$$

The quantity M_z in (14) is the number of potential orders in ZIP z (that is, the number in consumers in the ZIP times the number T of potential orders per consumer), and dP_z is the joint distribution of consumer demographics d_i and unobserved heterogeneity Ξ_i within z. Note that (14) is the sum of restaurant j's sales on f across ZIPs z_i, and the sales within each ZIP z_i equal the product of (i) the consumer's probability of ordering from any restaurant Λ, (ii) the consumer's probability of ordering from f upon selecting a restaurant in z_j on platform subset $\mathcal{G}_j$, and (iii) the consumer's probability of selecting a restaurant in z_j on platform subset $\mathcal{G}_j$. Note also that $S_{jf}(\mathcal{G}_j, w_m)$ depends on restaurant j's prices through w_m, which includes all restaurant prices in metro m.

O.13 Computation of equilibria in platform adoption

I now turn to the determination of equilibria in restaurants' platform adoption game. This algorithm involves a learning rate parameter $r \in (0, 1]$ and a tolerance parameter $\delta > 0$. The algorithm for finding equilibria in restaurants' platform adoption choices in a market m is given by:

1. Set P_m to an initial sequence of choice probabilities. Except when checking for the non-uniqueness of equilibria, I set $P_m = \hat{P}_m$, where $\hat{P}_m = \{\hat{P}_{\tau z}(\mathcal{G})\}_{\tau,z,\mathcal{G}}$ and $\hat{P}_{\tau z}(\mathcal{G})$ is the share of restaurants of type τ in ZIP z that locate on platform subset $\mathcal{G}$ in the data.

2. Compute
$$\tilde{P}_{\tau z}(\mathcal{G}) = r \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_{\tau z}(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) + (1 - r) P_z(\mathcal{G})$$
for all z and $\mathcal{G}$, and collect these probabilities in $\tilde{P}_m = \{\tilde{P}_{\tau z}(\mathcal{G})\}_{\tau,z,\mathcal{G}}$. The fixed-point condition (9) involves probabilities for each restaurant j, but restaurants of the same type and ZIP have common probabilities of adopting platform subsets given that restaurants are homogeneous within a ZIP/type pair. There is thus is no loss in including only one probability for each type/ZIP pair. The constancy of Π_j among restaurants j sharing a ZIP/type z/τ rationalizes the use of the notation $\Pi_{\tau z}$ for restaurants within this ZIP/type cell.

3. Compute $D = \sqrt{\sum_{\tau,z,\mathcal{G}} (\tilde{P}_{\tau z}(\mathcal{G}) - P_{\tau z}(\mathcal{G}))^2}$. If $D < \delta$, terminate the algorithm and accept $\tilde{P}_z$ as an equilibrium in restaurants' platform subset choice game. Otherwise, set $P_m = \tilde{P}_m$ and return to step 2.

In practice, computing

$$\Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_{\tau z}(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) \tag{15}$$

is computationally burdensome because it involves integrating each restaurant's profits over the distribution of rival restaurants' choices for each platform subset $\mathcal{G}$ in the restaurant's choice set. Although the symmetry of restaurants within a type/ZIP pair makes it necessary only to compute these integrals for each type/ZIP pair rather than compute them separately for each restaurant, the computational burden is still large given that (i) there are many ZIPs in each market and (ii) computing equilibrium in platform adoption involves iterating on (15) many times. I therefore use an approximation to compute

(15). Recall that

$$\Pi_j(\mathcal{G}, P_m) = \underbrace{\mathbb{E}\left[\sum_{f\in\mathcal{G}}[(1-r_{fz}))p^*_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_j]S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*) \mid P_m\right]}_{:=\bar{\Pi}_j(\mathcal{G},P_m)} - K_{\tau(j)m}(\mathcal{G}). \tag{16}$$

The expectation $\bar{\Pi}_j$ over rival restaurants' platform adoption decisions $\mathcal{J}_{m,-j}$ is the part of (16) that is difficult to compute. Computing the expectation exactly is prohibitive given that the number of possible configurations of rival restaurants across platform subsets is immense under moderate counts of restaurants in a ZIP.[11] Simulation is a standard way to approximate expectations, but simulation is also somewhat computationally burdensome because it requires drawing multiple replicates of rival restaurant decisions $\mathcal{J}_{m,-j}$ for each $\mathcal{G}$ selected by the restaurant in question, and subsequently computing the integrand of the expectation in (16) for each of these draws. An alternative approximation of the expectation in (15) is the value of the integrand when the number of restaurants in z that select $\mathcal{G}$ is equal to the overall number of type τ restaurants in z times $P_{\tau z}(\mathcal{G})$. Note that the numbers of rival restaurants that choose each platform subset as computed in this fashion need not be integers. The expression (14) for sales made on platform f by a restaurant j located on platform subset $\mathcal{G}_j$, however, may be computed even when the number of type τ restaurants on a platform subset $\mathcal{G}$ in ZIP z is not an integer. I use (14) to compute the S_{jf} term appearing in the integrand of the expectation in (16) under this alternative approximation.

The alternative approximation of the right-hand side of (15) introduces little error. To evaluate the error, I compute expected restaurant profits for each platform subset in five randomly selected pairs of restaurant types and ZIPs (e.g., independent restaurants in ZIP 02138) in each metro using both the simulation approximation (with five simulation draws) and the alternative approximation. I then regress expected profits from the simulation approximation on those from the alternative approximation. The R^2 from the regression is 1.000 up to three decimal places, and the estimated slope coefficient is 1.001. The profits and equilibrium choice probabilities as computed with and without using the approximation procedure are so close because variability in the realized distribution of restaurants across platform subsets is small when, as is the case, the number of restaurants in the market is large. This limits the scope for the mean of profits evaluated at rival restaurants' decisions to diverge from profits evaluated at the mean of rival restaurants' decisions.

O.14 Cross-sectional variation in gaps between privately and socially optimal fees

Table O.25 reports results from regressions of (i) the gap between the privately and socially optimal consumer fees $c^{\mathrm{pr}}_{fm} - c^{\mathrm{so}}_{fm}$ for platform f in county m and (ii) the gap between the privately and socially optimal restaurant commissions $r^{\mathrm{pr}}_{fm} - r^{\mathrm{so}}_{fm}$ on platform f in county m on various platform/county characteristics relevant to distortions in platform fees. These characteristics, which are explained in detail in the table notes, are suggested by the illustrative model of Section 2, and vary between the two regressions.

[11] Consider a setting with J restaurants in a ZIP, each of which chooses between G platform subsets. The number of possible configurations of restaurant counts across platform subsets is

$$\binom{J+G-1}{G-1}.$$

When $J = 100$ and, as in my setting, $G = 16$,

$$\binom{J+G-1}{G-1} = \binom{115}{15} > 2 \times 10^{18}.$$

Consumer fees. The illustrative model suggested that consumer-side market power, which is inversely related to the absolute value of the semi-elasticity of a platform's sales with respect to its consumer fee, tends to make privately optimal consumer fees too high relative to the socially optimal consumer fees. Thus, I expect this semi-elasticity (as computed under the privately optimal fees) to be negatively related to the gap between privately and socially optimal consumer fees. I include it as a regressor in the regression with the consumer fee gap as the outcome.

The model also suggests that a higher rate of diversion from platform ordering to direct ordering, which I call offline business stealing, tends to make the gap between privately and socially optimal consumer fees smaller. Thus, I enter this diversion rate as a regressor and expect it to have a negative relationship to the gap between privately and socially optimal consumer fees.

Next, the illustrative model suggests that socially optimal consumer fees are lower when restaurants benefit more from platform sales as measured by their gross markups on platforms (i.e., price minus marginal cost without an adjustment for commissions). This suggests a larger gap between privately and socially optimal consumer fees when gross markups are larger. I thus expect a negative sign on the gross markup when included as a regressor.

Last, the illustrative model implies that the privately optimal consumer fee is lower when the platform earns more restaurant-side revenue from an additional sale. Restaurant-side revenue gains from an additional sales primarily depend on the privately optimal commission rate, which I include as a regressor. I expect the consumer fee gap to be smaller when the privately optimal commission rate is higher.

The results in Table O.25a corroborate the hypotheses proposed above. Furthermore, the included characteristics are powerful in explaining the consumer fee gap: the R^2 of the regression is 0.91. To assess the explanatory power of individual regressors, I compute the R^2 from a bivariate regression of the dependent variable on each regressor (call it R^2_k). For each regressor k, I also compute the R^2 from a regression of the dependent variable on all regressors except k (call it R^2_{-k}); these measures are inversely related to the explanatory power of regressor k. Consider the values of this latter measure R^2_{-k}, all regressors have at least some power in explaining the fee gap. With that said, the gross restaurant markup and especially the privately optimal commission have greater explanatory power than the cannibalization and semi-elasticity variables. This suggests that it is primarily variation in the network-externality-related distortions that drives cross-sectional variation in the magnitude of the total distortion in consumer fees.

Restaurant commissions. The regression described by Table O.25b characterizes drivers of the gap between the privately optimal commission rate r^{pr}_{fm} and the socially optimal commission rate r^{so}_{fm} across platform (f)/county (m) pairs. As with the consumer fee gap regression, I choose regressors based on optimality conditions for the profit-maximizing platform and social planner as derived in the context of the illustrative model of Section 2.

The first regressor that I specify is the absolute value of the semi-elasticity of the number of restaurants on platform f in county m with respect to f's commission rate in m, as evaluated under the privately optimal fees. The illustrative model suggests that platforms charge lower commissions when restaurant adoption is less elastic and hence the platform yields more restaurant-side market power. Therefore, I expect the gap between privately and socially optimal commission rates to have a negative relationship with this (negative) semi-elasticity.

In the illustrative model, the social planner sets the level of restaurant platform adoption so that the variety benefit that an additional restaurant provides to consumers equals the social cost from adding a restaurant to the platform. When the variety benefit is larger, the social planner sets a lower commission rate to attract more restaurants to the platform. Thus, I compute a variable measuring the variety benefits provided by additional restaurants that I expect to positively relate to the gap between privately and socially optimal commissions. This variable equals the increase in consumer welfare due to the additional restaurant platform adoption induced by a one percentage point reduction in commission as evaluated at the socially optimal consumer fees. In computing consumer welfare changes, I hold fixed platform fees and restaurant prices. To give the variable a similar scale across markets, I divide it by the number of orders placed on platform f under the socially optimal fees.

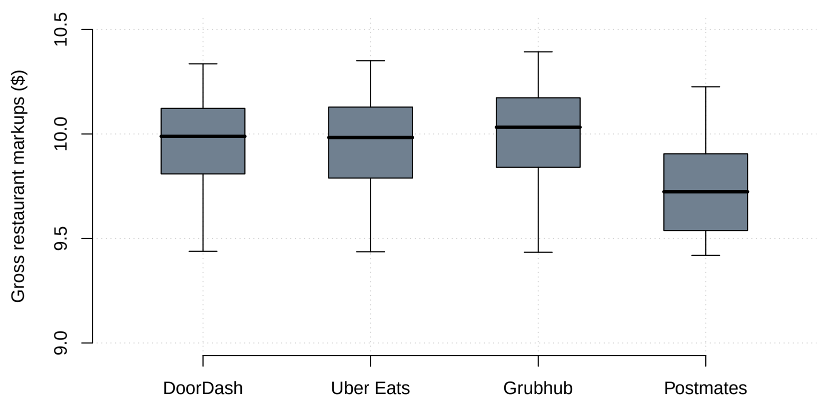
A key element of the cost of adding an additional restaurant to a platform is the restaurant's fixed cost of platform adoption. In markets with higher fixed costs of attracting restaurants to platforms, the socially optimal level of restaurant platform adoption is lower and hence the socially optimal commission rate is higher. Thus, I expect the fixed cost increase associated with attracting new restaurants to a platform to be negatively related to the gap between privately and socially optimal commissions. I measure the fixed costs of attracting restaurants to platform f as the increase in total fixed adoption costs associated with a one percentage point reduction in a platform f's commission rate as evaluated at the socially optimal fees, scaled by the number of orders placed on platform f under the socially optimal fees.

The benefit to a profit-maximizing platform of attracting an additional restaurant is the revenue it receives from the resulting additional orders. This revenue depends on the privately optimal consumer fee, which I include as a regressor. I expect the privately optimal commission rate to be lower when the privately optimal consumer fee is higher, as the gains from adding restaurants that boost sales are highest in this case. Thus, the privately optimal commission rate should negatively relate to the gap between the privately and socially optimal commission rates.

As shown by Table O.25b, the regression results from the align with the hypotheses proposed above. The "Fixed cost change" has the greatest explanatory power, followed by the "Privately optimal consumer fee" and "Variety change" variables.

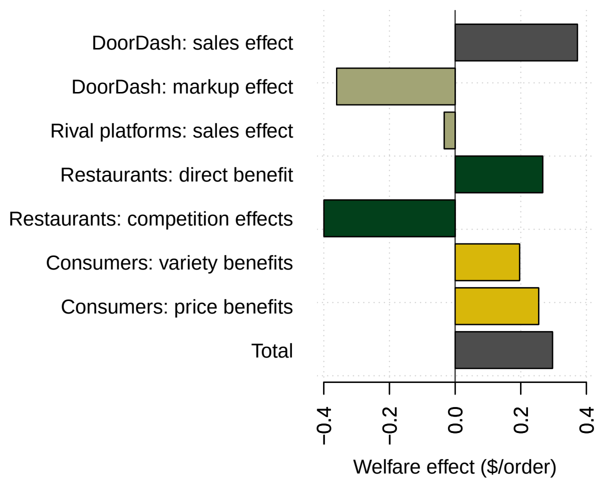
O.15 Additional results

Figure O.19: Heterogeneity in restaurant markups before commissions



Notes: this figure reports the 5th, 25th, 50th, 75th, and 95th percentiles of restaurant gross markups $p_{jf} - \kappa_{jf}$—which exclude platform commissions—for each platform, across restaurants belonging to each platform. The differences are computed at an equilibrium in which restaurant commissions are fixed at 30% and platform consumer fees maximize platform profits.

Figure O.20: Welfare effects of marginal commission adjustments



Notes: this figure provides welfare effects of a uniform one percentage point reduction in DoorDash's commission rate across counties. The effects are aggregated across counties and scaled by the number of platform orders under the privately optimal fees. The "DoorDash: sales effect" quantity is equal to the increase in DoorDash's profits owing to increased sales, holding fixed DoorDash's markups from the baseline equilibria. The "DoorDash: markup effect" quantity is equal to the reduction in DoorDash's profits owing to reduced commissions (and hence reduced markups), holding sales fixed at their levels in the baseline equilibria. The "Rival platforms: sales effect" quantity is equal to the reduction in rival platform profits. The "Restaurants: direct benefit" quantity is equal to the reduction in commission payments made by restaurants when their sales, platform adoption decisions, and prices are held fixed at their levels in the baseline equilibrium. The "Restaurants: competitive effects" quantity is equal to the overall impact of the commission reduction on platform profits, minus the "Restaurants: direct benefit" quantity defined above. The "Consumer: variety benefits" quantity is equal to the change in consumer welfare owing to the increased adoption of platforms by restaurants, holding restaurant prices fixed. The "Consumer: variety benefits" quantity is equal to the overall change in consumer welfare owing to commission reductions minus the "Consumer: variety benefits" quantity.

Table O.25: Cross-sectional variation in fee gaps

(a) Consumer fee gap $c^{\text{pr}}_{fm} - c^{\text{so}}_{fm}$ (\$)

Regressor (k)	Estimate	SE	R^2_k (only k)	R^2_{-k} (all but k)
Intercept	9.21	(0.28)		
Semi-elasticity	-13.06	(0.98)	0.32	0.88
Offline business stealing	-4.65	(0.39)	0.00	0.89
Gross restaurant markup	0.86	(0.02)	0.02	0.61
Privately optimal commission	-0.30	(0.01)	0.54	0.33
R^2	0.91			

(b) Restaurant commission gap $r^{\text{pr}}_{fm} - r^{\text{so}}_{fm}$ (%)

Regressor (k)	Estimate	SE	R^2_k (only k)	R^2_{-k} (all but k)
Intercept	23.08	(0.85)		
Semi-elasticity	-0.63	(0.31)	0.03	0.23
Variety change	13.55	(3.13)	0.05	0.21
Fixed cost change	-35.62	(3.78)	0.11	0.08
Privately optimal consumer fee	-1.03	(0.22)	0.05	0.20
R^2	0.24			

Notes: these tables provide results from regressions of the gaps between privately and socially optimal consumer fees and restaurant commissions on a panel of counties j and platforms f. First, I discuss the regressors in the regression whose results appear in Table O.25a. The "Offline business stealing" regressor is equal to share of consumers who begin ordering directly from a restaurant among those who stop ordering from platform f in county m upon an infinitesimal increase in platform f's consumer fee, holding fixed restaurant prices and restaurant platform adoption. This variable is evaluated under the socially optimal platform fees. The "Semi-elasticity" regressor is the absolute value of the semi-elasticity of orders on platform f with respect to platform f's consumer fee evaluated at the privately optimal fees, holding fixed restaurant prices and restaurant platform adoption at their levels under the privately optimal fees. This variable in inversely related to platform market power on the consumer side. The "Gross restaurant markup" regressor is equal to the sales-weighted average markup $p_{jf} - \kappa_{jf}$ earned by a restaurant j on platform f in county m before platform commissions. The "Privately optimal commission" regressor, r^{pr}_{fm}, is the platform f's commission rate in county m in a competitive equilibrium with profit-maximizing platforms.

I now turn to the regressors included in the regression with the gap between privately and socially optimal restaurant commissions as the dependent variable, whose results appear in Table O.25b. In this regression, the "Semi-elasticity" variable is the absolute value of the semi-elasticity of the number of restaurants adopting platform f in county m with respect to platform f's commission rate evaluated at the privately optimal fees. This variable is inversely related to platform market power on the restaurant side. The "Variety change" regressor is equal to the increase in consumer welfare from the change in restaurant platform adoption occurring when platform f reduces its commission in county m by one percentage point as evaluated at the socially optimal fees, holding fixed these fees and restaurant prices and divided by platform f's sales in m to ensure comparability of scale between observations. The "Fixed cost change" regressor is equal to the increase in the total fixed adoption costs incurred by restaurants due to a one percentage point reduction in commission, divided by platform f's sales in m to ensure comparability of scale between observations. The "Privately optimal consumer fee" regressor, c^{pr}_{fm}, is the platform f's consumer fee in county m in a competitive equilibrium with profit-maximizing platforms.

The R^2_k quantity reported by both Table O.25a and Table O.25b is the R^2 from a regression of the dependent variable on regressor k alone. It is a measure of k's power in explaining the dependent variable. The R^2_{-k} quantity is the R^2 from a regression of the dependent variable on all regressors in the full regression except regressor k. Lower values of R^2_{-k} indicate that k has greater power in explaining the dependent variable conditional on the other regressors.

Each platform/county pair is weighted by platform f's share of sales in j under the privately optimal fees. The sample size is $N = 104 \times 4 = 416$ (there are 104 counties and 4 platforms).

Table O.26: Heterogeneity in sales gains from platform adoption (%)

Metro	Mean	SD
Atlanta	20.09	3.74
Boston	38.05	9.41
Chicago	20.61	5.37
Dallas	25.18	5.21
Washington	35.25	1.20
Detroit	14.14	2.13
Los Angeles	19.78	2.30
Miami	31.87	6.71
New York	63.91	16.92
Philadelphia	35.81	1.55
Phoenix	22.03	10.97
Riverside	24.09	4.32
Seattle	54.03	8.99
San Francisco	35.75	3.67

Notes: this table reports in percentage terms, for each metro area, the mean relative difference in sales between a restaurant that has not joined any platform and a restaurant that has joined all four platforms. The difference is computed for each ZIP/type pair, where the two restaurant types are chains and independents. ZIP/type pairs are weighted by the number of restaurants that they contain. The table also reports, in the "SD" column, the standard deviation across ZIPs (again weighted by restaurant counts) of the percentage difference in sales between restaurants joining all platforms and restaurants joining no platforms. The differences are computed at an equilibrium in which restaurant commissions are fixed at 30% and platform consumer fees maximize platform profits.

Table O.27: Network elasticities of demand for the New York City metro

	Quantity response for...			
Platform	DD	Uber	GH	PM
DD	0.79	-0.19	-0.19	-0.20
Uber	-0.18	0.78	-0.18	-0.20
GH	-0.17	-0.18	0.89	-0.18
PM	-0.05	-0.05	-0.05	1.32

Notes: this table reports percentage sales responses to a percentage uniform increase in number of restaurants on each platform in the Chicago CBSA. Two challenges arise in defining these elasticities: (i) numbers of restaurants are subject to integer constraints, which complicates differentiation, and (ii) restaurants may multi-home, which requires a choice of how to add new restaurants to platform f. I address these challenges by defining network externalities as the percentage change in platforms' sales in a market m in response to the addition of one new chain restaurant and one new independent restaurant to each ZIP that belongs solely to platform f and to the offline platform. I scale the measure by multiplying by the number of restaurants that belong to f in m so that the elasticities are interpretable as percentage responses in sales to a percentage increase in the number of restaurants on platform f. Formally, the elasticity of f's sales with respect to the network on f' is

$$\epsilon^{J}_{m,ff'} = \left(\frac{\mathcal{s}'_{fm} - \mathcal{s}_{fm}}{\mathcal{s}_{fm}}\right) / \left(\frac{J'_{f'm} - J_{f'm}}{J_{f'm}}\right),$$

where $J_{f'm}$ and $J'_{f'm}$ are the number of restaurants on f' before and after the addition of one restaurant on f' to each ZIP, and $\mathcal{s}'_{fm}$ are f's sales after the addition of these new restaurants.

Table O.28: Between-platform diversion ratios for the New York metro

	Quantity response for...					
Platform	No purchase	Direct	DD	Uber	GH	PM
DD	0.24	0.57	-1.00	0.10	0.08	0.00
Uber	0.24	0.56	0.11	-1.00	0.08	0.00
GH	0.23	0.57	0.10	0.10	-1.00	0.00
PM	0.16	0.47	0.14	0.13	0.10	-1.00

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

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

where $c_{f'm}$ is a vector of the consumer fees charged by f' across all ZIPs within m; $\mathfrak{s}_{fm}$ 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.

Table O.29: Socially and privately optimal platform markups

Platform	Privately optimal		Socially optimal		Difference	
DD	3.64	(0.42)	-1.73	(0.99)	5.37	(1.10)
Uber	3.98	(0.40)	-1.11	(0.91)	5.08	(0.75)
GH	3.89	(0.50)	-1.09	(1.04)	4.99	(0.87)
PM	3.69	(1.00)	-1.10	(1.70)	4.80	(2.13)
Total	3.77	(0.48)	-1.50	(1.03)	5.27	(1.07)

Notes: this table displays the mean platform aggregate markups across counties. Each county is weighted by its sales on the indicated platform under the privately optimal fees. The "Total" row averages across platforms, using platforms' total sales under the privately optimal fees as weights. The markup is defined as the ratio of platform profits to the number of orders placed on the platform.

Table O.30: Effects of monopolization on DoorDash fees

Quantity	Privately optimal	Socially optimal
Consumer fee ($)	1.79	0.19
Restaurant commission (pp)	-6.98	-0.58

Notes: This table provides the effects of transitioning from the status quo market structure to one in which DoorDash is a monopolist on sales-weighted average consumer fees and restaurant commission rates. The weights are DoorDash's sales under the the status quo competitive regime.

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