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

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Contents

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O.1 Why do platforms charge fixed consumer fees?

Platforms could charge either fixed fees that do not depend on the dollar amount of purchases or fees that are proportional to these dollar amounts. Each sort of fee has its advantages and disadvantages. The primary benefits of a proportional fee is that it makes platform fees increasing in merchant prices, which encourages merchants to reduce their prices. From the platform's perspective, this raises sales and thus platform revenue. This argument is developed by Shy and Wang (2011), who argue that proportional fees reduce double marginalization in the context of payment card networks when merchants have market power. 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, is more distortionary than a fixed fee when it comes to driving consumer choices of which items from merchants' menus to order under the assumption that 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 socially optimal price structure involves restaurants pricing at marginal cost and platforms charging a fixed fee equal to the cost of facilitating a delivery; i.e., both the merchant and the platform price at marginal cost. The fact that a fixed fee is reflective of cost relates to the argument of Wang and Wright (2017) that a fee structure including a fixed component in addition to a proportional elements is optimal when platforms have fixed costs of facilitating transactions. 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, as the platform fee for ordering these items would be lower despite the fact that the cost to the platform is the same as that for delivering more expensive menu items. This leaves less social surplus available for the platform to capture through its prices. The argument above, which relates to substitution between merchants' offerings with heterogeneous costs, is relevant in the food delivery industry but is not directly related to the arguments of Shy and Wang (2011) or Wang and Wright (2017). 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., a structure in which 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:

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

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

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

The restaurant's profits are

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

Here, $\bar{p}_j(q) = p_j(q)(1+q)$. The restaurant's optimal prices satisfy the following first-order condition:

$$\begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \kappa_1 \\ \kappa_2 \end{bmatrix} - \frac{1}{1+q} \begin{bmatrix} \frac{\partial S_1}{\partial p_1} & \frac{\partial S_2}{\partial p_1} \\ \frac{\partial S_1}{\partial p_2} & \frac{\partial S_2}{\partial p_2} \end{bmatrix}^{-1} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix}. \tag{2}$$

A comparison of (1) and (2) 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, and thus puts 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 $(\kappa_1, \kappa_2) = c(10, 30)$ whereas the second, which I call homogeneous costs, has $(\kappa_1, \kappa_2) = c(20, 20)$. 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 under each of the two cost structures (these do not sum to one given the presence of an outside option). 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.1 and O.2 contain results from the numerical exercise. First consider sales of each good under the heterogeneous cost structure, which are reported by Table O.1a. We see 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 for which they have generally have lower valuations. Under the homogeneous cost structure, this problem does not arise as platform fees do not vary between the two goods; see Table O.1b. As shown by Table O.2, 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. However, upon equalizing costs in the homogeneous cost structure, the proportional fee structure outperforms the fixed fee structure given that it depresses 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 in the model for three principal reasons. First, 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. Second, platforms charge proportional

Table O.1: Sales by good under fixed and proportional platform fees

(a) Heterogeneous costs

Regime	Sales Good 1	Sales Good 2	Ratio 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 Good 1	Sales Good 2	Ratio 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.2: Welfare under fixed and proportional platform fees

(a) Heterogeneous costs

Regime	Consumer surplus	Profits Rest	Profits Plat	Total welfare
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 Rest	Profits Plat	Total welfare
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

fees to merchants, leaving the consumer side as the only place to incorporate potentially important fixed fees in the model. Last, it was platform fixed fees that responded to commission regulation in practice, and thus modelling fixed fee responses is a way to match the empirical reality.

O.2 Why are platform fees non-neutral?

In the context of multi-sided markets, neutrality refers to the property that, conditional on the total fee level that the platform earns from a transaction, the division of a platform's fees across distinct sides of the market is irrelevant for real economic outcomes (Rochet and Tirole 2006). In this appendix, I illustrate that neutrality applies to a basic model in which a platform charges a fee to consumers and a commission charge to restaurant, both of which are proportional to the restaurant's price. Suppose that a restaurant makes sales to consumers both directly and through a platform; let p_0 denote the restaurant's price for direct sales and let p_1 denote the price for platform sales. The restaurant's problem of maximizing profits through price setting is

$$\max_{p_0,p_1} [(1-r)p_1 - \kappa_1]\, S_1(p_0, p_1(1+c)) + (p_0 - \kappa_0)S_0(p_0, p_1(1+c)).$$

Here, c is the consumer fee rate; r is the commission rate; S_0 is the volume of sales made directly to consumers; S_1 is the volume of sales made on the platform; and κ_0 and κ_1 are the marginal costs for direct and platform orders, respectively. Letting $\theta = (1+c)/(1-r)$ and $x = p_1(1+c)$, it is straightforward to show that the first-order condition for the optimality of p_1 can be written as

$$[x - \kappa_1\theta]\, \frac{\partial S_1}{\partial p_1}\,(p_0, x)) + (p_0 - \kappa_0)\frac{\partial S_0}{\partial p_1}\,(p_0, x) \times \theta + S_0\,(p_0, x) = 0.$$

Assuming that this equation uniquely determines x, we see that x is pinned down by θ and p_0. In other words, this equation implicitly defines $x(\theta, p_0)$, i.e., the fee-inclusive consumer platform price as a function of the fee level and the offline price. Next, we show that the offline price in turn is pinned down by the fee level. Indeed, we can write the first-order condition for p_0 as

$$[(1-r)p_1 - \kappa_1] \frac{\partial S_1}{\partial p_0} \left(p_0, x(\theta, p_0)\right) + (p_0 - \kappa_0) \frac{\partial S_0}{\partial p_0} \left(p_0, x(\theta, p_0)\right) + S_0 \left(p_0, x(\theta, p_0)\right) = 0.$$

Given that $(1-r)p_1 = \theta^{-1} x(\theta, p_0)$ by the definition of x and θ, the first-order condition for p_0 can be written as

$$\left[\frac{x(\theta, p_0)}{\theta} - \kappa_1\right] \frac{\partial S_1}{\partial p_0} \left(p_0, x(\theta, p_0)\right) + (p_0 - \kappa_0) \frac{\partial S_0}{\partial p_0} \left(p_0, x(\theta, p_0)\right) + S_0 \left(p_0, x(\theta, p_0)\right) = 0.$$

Note that neither c nor r appears in this equation. Thus, p_0 only depends on θ, not c or r individually. It is also straightforward to see that, as above, platform revenue depends only on θ, and not on c or r individually. This means that, conditioning on the fee level θ, the levels of c and r individually do not affect restaurant sales or revenue.

Two changes to the model that lead to non-neutrality are (i) pricing frictions and (ii) fixed consumer fees. By pricing frictions, I refer to any factor that inhibits the restaurant from setting p_0 and p_1 to maximize the restaurant's total profits. A leading example of a pricing friction is the no-surcharge rule in payment card markets, a rule that payment card networks have historically enforced that requires merchants to not charge a higher price to consumers paying with payment cards than to those paying with cash. Merchants may also avoid charging prices p_1 on a platform far in excess of their off-platform prices p_0 due to a perception among consumers that such price gaps are unfair or due to a platform's threat to reduce merchant visibility within the platform if the merchant significantly marks up prices on the platform. A model with the following pricing problem incorporates the presence of pricing frictions of the sort described above:

$$\max_{p_0, p_1} \left[(1-r)p_1 - \kappa_1\right] S_1(p_0, p_1(1+c)) + (p_0 - \kappa_0) S_0(p_0, p_1(1+c)) - \frac{\phi}{2}(p_1 - p_0)^2. \tag{3}$$

The no-surcharge rule (when perfectly and harshly enforced) corresponds to the case of $\phi = \infty$. Throughout the main text, I refer to the sort of pricing friction introduced by the $(\phi/2)(p_1 - p_0)^2$ term as a non-parity penalty.

A diverse body of literature suggests the relevance of non-parity penalties for pricing in the food delivery industry. Fassnacht and Unterhuber (2016) study consumer sentiment toward price gaps between a seller's online and offline retail channels, and find that consumers perceive higher online prices as unfair and that higher online prices predispose consumers to spread negative word-of-mouth about the retailer. Choi and Mattila (2009) reach a similar conclusion. Additionally, the unwillingness to restaurant managers to charge platform prices far in excess of direct-to-consumer prices relates to the uniformity of retailers' prices across geography as studied by DellaVigna and Gentzkow (2019). The authors of this study attribute the failure of retailers to price differentially across geography to managerial inertia and brand image concerns; these phenomena could also explain why restaurant managers enact smaller gaps between prices on platforms and those for first-party orders than strict profit-maximization would imply.

In addition to pricing frictions, fixed consumer fees may induce non-neutrality. I argued in Online Appendix O.1 that fixed fees outperform proportional fees when merchants sell goods with highly heterogeneous costs. When a platform charges a fixed fee on the consumer side and a proportional commission on the restaurant side, the platform's fees will be non-neutral. Consider for illustrative purposes the case of a restaurant that makes its sales exclusively through a platform. This restaurant's pricing problem is

$$\max_{p} \left[(1-r)p - \kappa\right] S(p + c).$$

The first-order condition can be written as

$$p = \frac{\kappa}{1-r} - \frac{S(p+c)}{S'(p+c)}.$$

For clarity of exposition, I assume that the inverse semi-elasticity $-S(p+c)/S'(p+c)$ takes on a constant value b (e.g., as occurs with exponential demand $S(p) = \alpha e^{-\beta p}$). Under this assumption, platform revenue is

$$R = pr + c = r\left(\frac{\kappa}{1-r} + b\right) + c.$$

If the fee-inclusive price $p + c$ paid by consumers under a constant level of platform revenue R depends on c and r individually, then the fee structure will be non-neutral. This is indeed the case here: when $c = R - pr$,

$$p + c = \frac{\kappa}{1-r} + b + \left(R - r\left(\frac{\kappa}{1-r} + b\right)\right) = \kappa + (1-r)b + R,$$

for $r \in [0, 1)$. Given that the fee inclusive prices depend on r conditional on platform revenue R, the fee structure is non-neutral.

O.3 Consumer fee indices

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

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

where DF_{fz} is a measure of platform f's delivery fees in ZIP z, SF_{fz} is a measure of platform f's service fee in z's municipality, and RR_{fz} is the regulatory response fee charged by f in z. Given that delivery fees vary across orders placed within the same municipality at the same time, I defined DF_{fz} as a hedonic price index. This index, formally defined in Online Appendix O.3.1, 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.5 for a decomposition of fee indices into their components.

Table O.3 provides observation counts and sample means for the platform pricing datasets for Q2 2021.

O.3.1 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:

$$DF_{fz} = \mathbb{E}[df_{kfz} | x_k = \bar{x}, f, z], \tag{4}$$

Table O.3: Description of platform pricing data, Q2 2021

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

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

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 (4) 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

$$df_{kfz} = x_k'\beta_f + w_z'\mu_f + \phi x_k^{\text{dist}} w_z^{\text{dens}} + \epsilon_{kfz}, \tag{5}$$

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; 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.[1] 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 (5) 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.[2] 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.4 Additional description of data

[1] 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.

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

Table O.4: Decomposition of delivery fee variation

Variance	DD	Uber	GH	PM
Across CBSAs	0.36	0.67	0.51	1.86
Across ZIPs within CBSA	0.47	1.12	1.33	4.33
Within ZIP	1.89	5.87	5.72	2.96

Notes: this table reports the variance decomposition

$$\mathrm{Var}(df_k) = \underbrace{\mathrm{Var}(\mathbb{E}[df_k|m])}_{\text{Across CBSAs}} + \underbrace{\mathbb{E}[\mathrm{Var}(\mathbb{E}[df_k|z]|m)]}_{\text{Across ZIPs within CBSA}} + \underbrace{\mathbb{E}[\mathrm{Var}(df_k|z)]}_{\text{Within ZIP}},$$

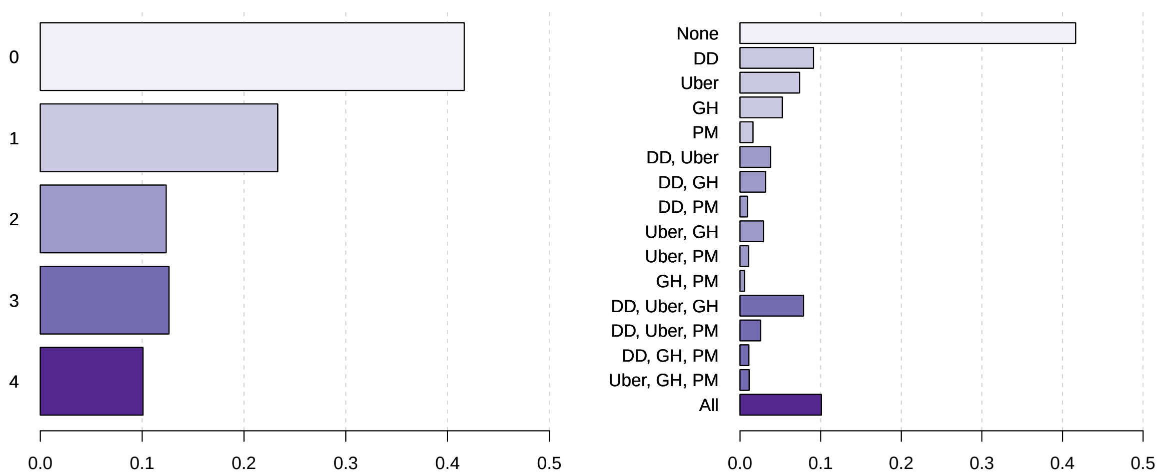
for delivery fee measurements df_k, CBSAs m, and ZIP codes z. The table uses all delivery measurements from ZIPs with at least two recorded delivery fees.

Table O.5: 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.

Figure O.1: Distribution of restaurants across platform sets, April 2021

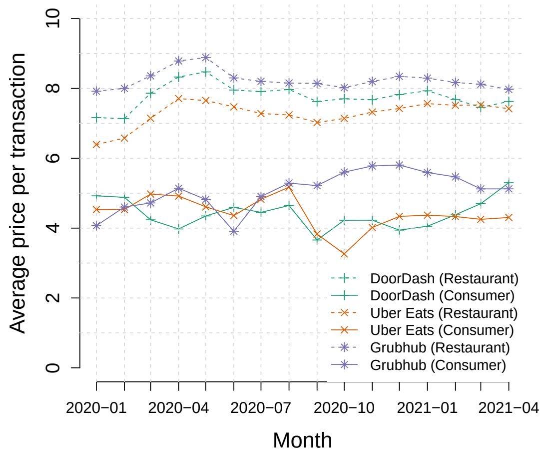


(a) Number of adopted platforms

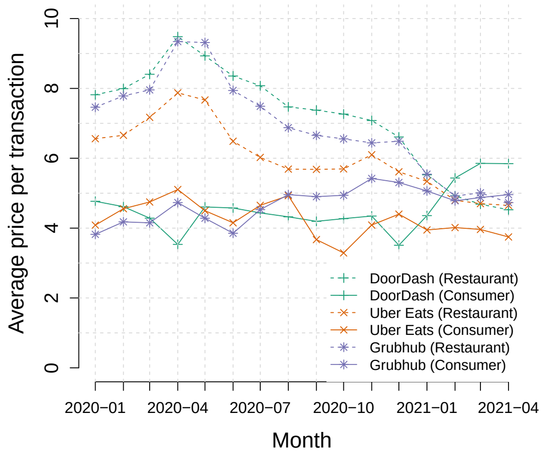
(b) Identities of adopted platforms

Notes: this figure plots the distribution of restaurants across sets of portfolios (e.g., joining no online platform, joining only DoorDash, joining Uber Eats and Grubhub) in the 14 metros on which the article focuses in April 2021. Deeper shades indicate sets that include more platforms.

Figure O.2: Platforms' average fees and commissions in regions with and without a commission cap as of 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.

Table O.6: Source of within-market fee variation

(a) Platform fixed effects

Variable	Estimate	SE
Cap	0.67	0.03
Share age under 35	-2.52	0.19
Share married	-2.19	0.15
Population density	-0.69	0.03

(b) Platform/CBSA fixed effects

Variable	Estimate	SE
Cap	0.28	0.03
Share age under 35	-1.66	0.15
Share married	-1.98	0.12
Population density	-0.47	0.02

Notes: I assess the drivers of within-market fee variation by regressing ZIP/platform-level fees on an indicator for the presence of a commission cap and demographic ZIP characteristics. I run these regressions with (i) platform fixed effects and (ii) platform/market fixed effects. Each of the $N = 17220$ observations is a platform/ZIP pair. "Cap" indicate the presence of a $\leq 15\%$ commission cap. "Share under 35" is the share of the population within five miles that is under 35 years of age. "Share married" is the share of the population within five miles that is married. "Population density" is the population (in millions) of the area within five miles.

O.5 State dependence versus persistent platform tastes

O.5.1 Both consumers and restaurants multihome

I quantify multihoming in the food delivery industry by computing measures of consumer and restaurant multihoming. The measure of consumer multihoming 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'. To illustrate this 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 multihoming measure for $f =$ Uber Eats and $f' =$ DoorDash among these two consumers would be one half.[3] I characterize restaurant multihoming by computing the share of restaurants listed on each platform that are also listed on each other platform. Table O.7 reports the results, which show that both consumers and restaurants multihome.

Although consumers sometimes switch between platforms, they more often order from the same platform across consecutive orders. Explanations for repeated ordering include state dependence—that is, an effect of the consumer's ordering history on the consumer's contemporaneous ordering decision—and persistent taste heterogeneity. To assess the relevance of state dependence, I compare the numbers of switches between platforms that consumers make in consecutive platform-intermediated orders with and without shuffling each consumer's sequence of orders. Persistent tastes do not induce serial dependence in a consumer's sequence of choices (conditional on the consumer) whereas state dependence does introduce serial dependence. Thus, similarity of dynamics between the original and shuffled choice sequences would suggest a low degree of state dependence. Table O.8 presents the results of this analysis for choice sequences with a fixed number of purchases from a fixed number of platforms. Shuffling choice sequences has little effect on the average number of switches they contain; in fact, shuffling generates choice sequences with slightly less switching, whereas we would expect more switching in the shuffled sequences if state dependence were important. These results suggest that persistent tastes explain repeat purchasing.

O.5.2 Consumers place more orders on platforms that attract new restaurants

I assess the elasticity β_{NE} of platform sales with respect to restaurant variety by estimating via OLS

$$\underbrace{\log \mathcal{s}_{fzt}}_{\text{Log sales}} t = \underbrace{\psi_{fz} + \psi_{ft}}_{\substack{\text{ZIP and month}\\ \text{fixed effects}}} + \underbrace{\beta_{\mathrm{NE}} \log J_{fzt}}_{\text{Network externalities}} + \varepsilon_{fzt}, \tag{6}$$

where $\mathcal{s}_{fzt}$ are platform f's sales in ZIP z in month t, J_{fzt} is the number of restaurants on platform f within five miles of ZIP z in month t, and ψ_{fz} and ψ_{ft} are platform/ZIP and platform/month fixed effects, respectively. The unobservable ε_{fzt} is assumed to be mean independent of J_{fzt} conditional on the fixed effects ψ_{fz} and ψ_{ft}. This assumption allows for restaurants to respond to time-invariant local demand disturbances, which are captured by ψ_{fz}, and to national time-varying demand disturbances, which are captured by ψ_{ft}. The assumption does not, however, allow for restaurants' platform adoption to respond to local monthly demand deviations. This may be a valid restriction when frictions in the platform

[3] Another measure of consumer multihoming is the average Herfindahl–Hirschman index of a consumer's shares of orders made across platforms:

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

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, $\bar{\mathrm{HHI}}$ equals 0.86, which indicates a high degree of purity in consumers' platform-choice sequences. Additionally, Figure **??** reports the average number of platforms from which a panelist has ordered after placing t orders, for $t = 1, \ldots, 30$.

Table O.7: Multihoming 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.7a 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.7b reports the share of restaurants on each major delivery platform that also belong to each other major delivery platform for April 2021.

Table O.8: Evaluation of state dependence

# transactions (τ)	# unique (k)	# switches Mean	95% CI		# switches (Shuffled data)	N
3	2	1.36	1.34	1.37	1.33	4708
4	2	1.71	1.69	1.72	1.65	4728
4	3	2.59	2.55	2.64	2.50	429

Notes: the "# switches" columns report the average number of switches between online platforms among consumers buying from k unique platforms within τ orders from online platforms. The "# switches (Shuffled data)" column report average numbers of switches as defined above as when each consumer's purchasing sequence is randomly shuffled. I conducted the analysis on Numerator data from the 14 markets on which the article's analysis focuses.

adoption process prevent restaurants from suddenly joining platforms. This research design follows that of Natan (2022), who discusses the underlying identifying assumptions in greater detail.

Table O.9: Sales and restaurant listing counts (difference-in-differences estimates)

	Pooled	Separate
Log # restaurants	0.12	-
	(0.02)	-
Log # chain restaurants	-	0.09
	-	(0.02)
Log # non-chain restaurants	-	0.08
	-	(0.02)

Notes: this table reports ordinary least squares estimates of the parameter β_{NE} in (6). The second column provides estimates of $\beta^{\text{NE}}_{\text{chain}}$ and $\beta^{\text{NE}}_{\text{non-chain}}$ in (7). Chain restaurants are those that belong to a chain that had at least 100 locations across the US in 2021. I estimate the model on a panel of ZIPs from April 2020 to May 2021. I include all ZIPs within a CBSA.

The first column of Table O.9 reports the estimate of β_{NE}, which suggests the empirical relevance of network externalities exerted by restaurants on consumers. The second column provides OLS estimates of $\beta^{\text{NE}}_{\text{chain}}$ and $\beta^{\text{NE}}_{\text{non-chain}}$ in

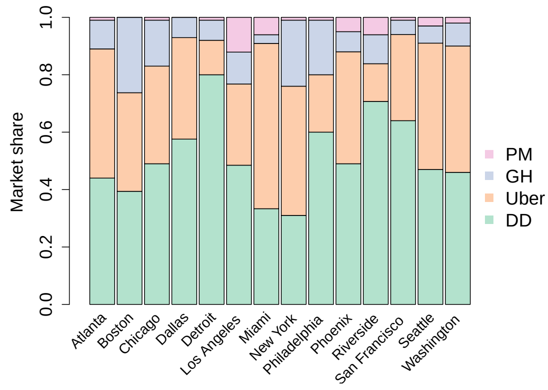
$$\log s_{fzt} = \psi_{fz} + \psi_{ft} + \beta^{\text{chain}}_{\text{NE}} \log J^{\text{chain}}_{fzt} + \beta^{\text{non-chain}}_{\text{NE}} \log J^{\text{non-chain}}_{fzt} + \varepsilon_{fzt}, \tag{7}$$

where J^{chain}_{fzt} (J^{chain}_{fzt}) is the number of chain (non-chain) restaurants on platform f within 5 miles of ZIP z in month t. Chain restaurants are those that belong to a chain that had at least 100 locations across the US in 2021. Consumer responses to these two sorts of restaurants are similar in magnitude.

O.5.3 Platform market shares vary across metropolitan areas

Figure O.3 plots each major platform's share of spending on food delivery platforms in Q2 2021 for 14 large US metropolitan areas. Additionally, Figure O.3 plots the share of restaurant orders placed on a food delivery platform rather than directly from a restaurant in the same time period for the same metros. Both platforms' market shares and the relative significance of platforms vary across metros; this variation could owe to cross-metro differences in demographics, in restaurant membership of platforms, local tastes for food delivery platforms unexplained by demographics or platform adoption by restaurants (e.g., local taste differences explained by platform advertising).

Figure O.3: Market shares, Q2 2021



Notes: the figure displays reports CBSA-specific shares of expenditure on DoorDash, Uber Eats, Grubhub, and Postmates orders in the Numerator panel for Q2 2021.

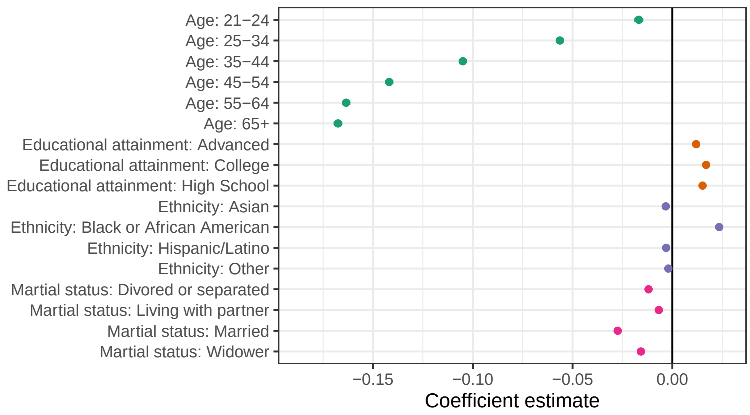
O.5.4 Young and unmarried consumers are more likely to use delivery platforms

To determine which consumer characteristics explain usage of food delivery platforms, I regress an indicator for whether a restaurant order was placed on a delivery platform (rather than directly from a restaurant) on various consumer characteristics. These characteristics include indicators for age groups, educational attainment levels, racial/ethnic backgrounds, marital statuses, employment statuses, household sizes, income groups, and gender. Figure O.4 plots several of the estimated coefficients. Younger consumers are much likelier to order from food delivery platforms than older consumers. Additionally, married consumers are less likely to use platforms than single consumers.

O.6 Validation of transactions datasets

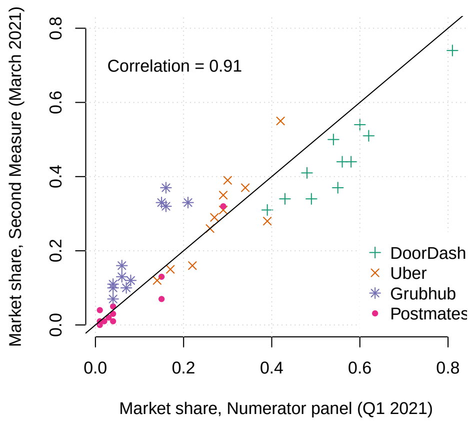
Figure O.5 compares market shares for April 2021 computed from the Numerator transactions panel to those reported by the market research firm Second Measure, which estimates platforms' market shares based on payment card records, for March 2021. Market shares are similar across these two data sources. 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.

Figure O.4: Demographics of food delivery users



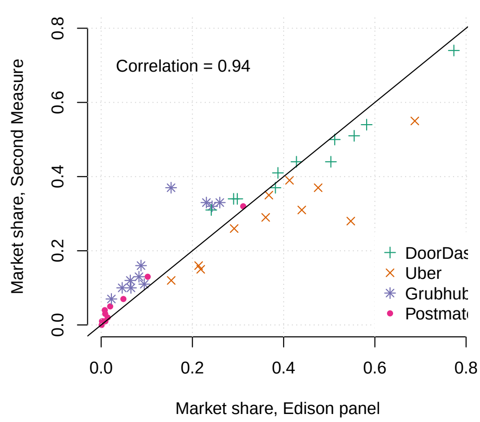
Notes: this figure displays estimated coefficients and 95% confidence intervals from a linear probability model regression of an indicator for a restaurant order being placed on one of the leading four food delivery platforms on month fixed effects and demographic variables using Numerator data from 2021. Note that 5.5% of orders are placed on delivery platforms in the estimation sample. The following regressors were included in the regression, although their coefficients are omitted from the plot: gender indicator, employment status indicators, household size indicators, income group indicators. The sample size is 8,188,362.

Figure O.5: 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.6: 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.5.

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

O.7.1 Technical appendix

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 produce estimators of overall order volumes at the ZIP3/month level. To produce these estimates, 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.

I use additional datasets to supplement those above in conduct DiD analysis. These include: 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); the Oxford Covid-19 Government Response Tracker (OxCGRT) measure of the stringency of local COVID-19 policy (Hallas et al. 2020); and county-level data on the results of the 2020 US presidential election from MIT Election Data and Science Lab (2018). 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.

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. Another is the interacted weighted (IW) estimator of Sun and Abraham (2021), which is an OLS estimator of a similar equation but including interactions of treatment indicators and cohort-membership indicators, wherein cohorts are defined by time of treatment. This estimator addresses problems facing TWFE in settings in which treatment effects differ between units that receive treatment at different times. Another estimator that addresses this problem 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. Last, I compute the instrumental variables (IV) based estimator of Freyaldenhoven et al. (2019), which addresses endogeneity problems that give rise to pre-trends.

The TWFE, IW, and IV estimators permit the inclusion of time-varying covariates or "controls." These covariates may make the assumption of parallel trends that is generally required for the validity of DiD methods more plausible. I include as covariates (i) the OxCGRT stringency index (Hallas et al. 2020), (ii) the number of new COVID-19 cases per capita, and (iii) the number of new COVID-19 cases per capita interacted with the Democrat vote share in the 2020 US presidential election. 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.

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 (**??**) or (8) 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 Effects on platform fees and sales

Table O.10: 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. Asymptotic standard errors appear in parentheses.

Table O.11: Fee responses to commission caps, exclude 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.12: 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.13: Fee responses to commission caps, 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)

Notes: This table reports results of the DiD analyses of platform fees applied to data from July 2020 to May 2021. See the notes of Table O.10 for additional details.

Table O.14: 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)

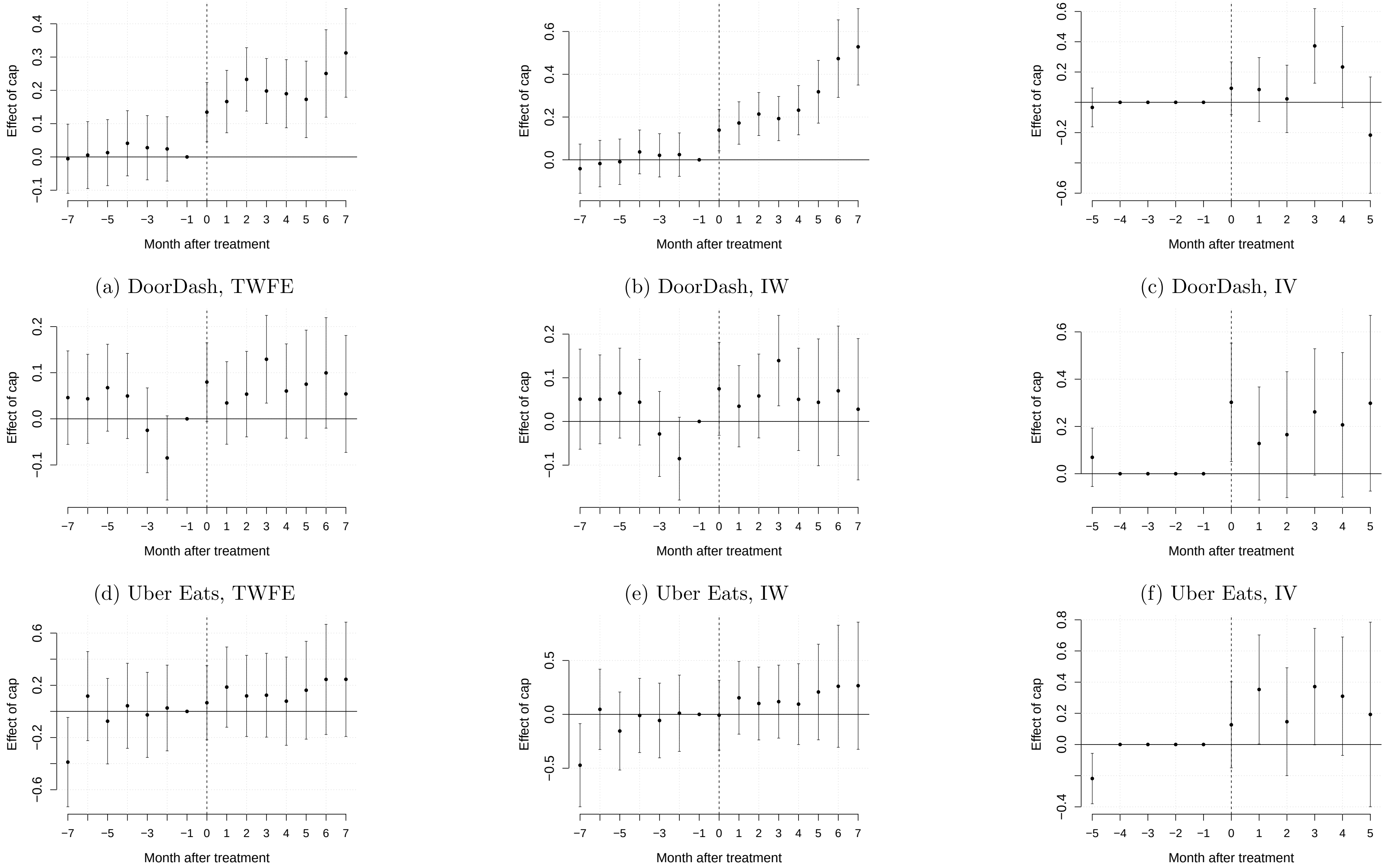
Notes: This table is an analogue of Table O.10 with the exception that the treatment group in the underlying analysis includes ZIPs with any cap (including those above 15%) and the control group includes all remaining ZIPs. See the notes of Table O.10 for additional details.

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.10 for additional details.

Figure O.7: Effects of commission caps on platforms' 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

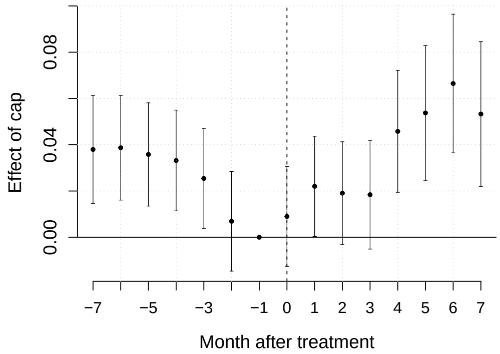
(h) Grubhub, IW

(i) Grubhub, IV

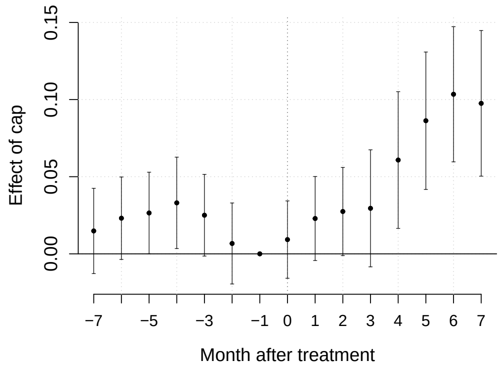
Notes: this figure plots estimates of dynamic effects of commission caps on platforms' consumer fees. These estimates were computed on the Edison ZIP/platform/month-level panel using three estimators described in the main text. The dots indicate point estimates and the bars around each point indicate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

Figure O.8: Dynamic effects of commission caps on direct-from-restaurant ordering (Numerator panel)

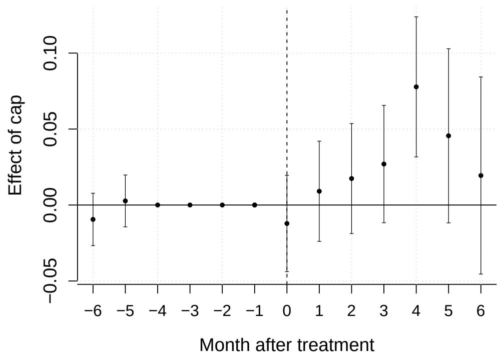
(a) TWFE



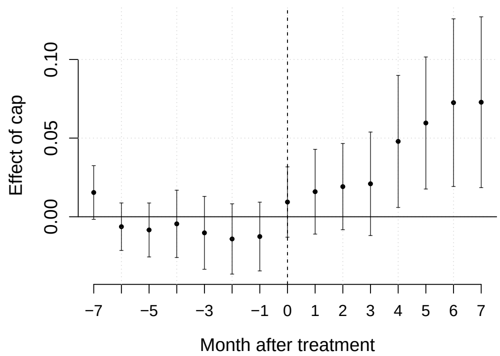
(b) IW, Sun and Abraham (2021)



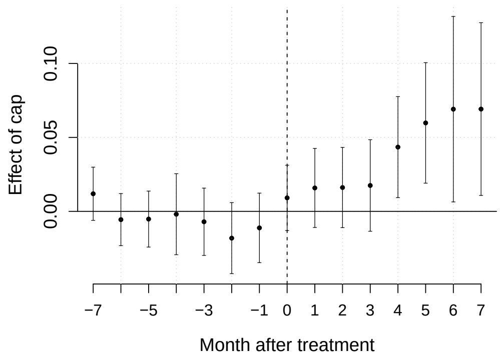
(c) IV, Freyaldenhoven et al. (2019)



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



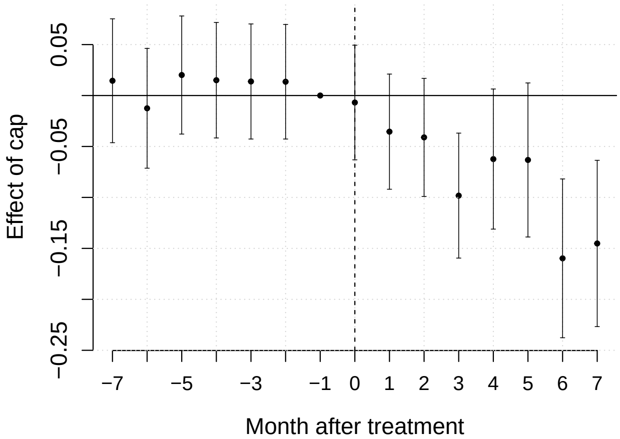
(e) Callaway and Sant'Anna (2021) (not yet)



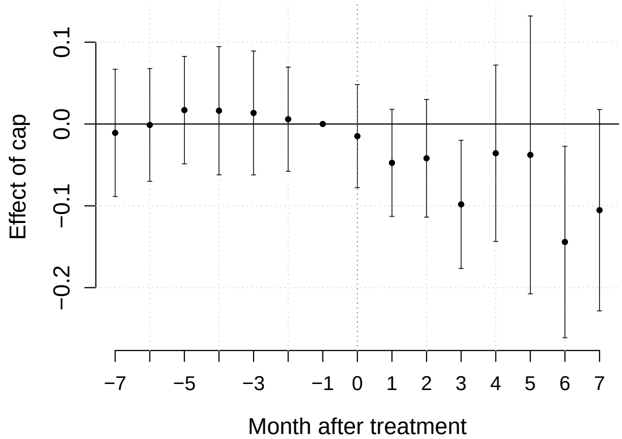
Notes: this figure includes plots of estimates of dynamically evolving effects of commission caps on the log of the total number direct-from-restaurant orders. Each unit in the analysis is a ZIP3, and each time period is a month. The figure includes estimates obtained from various estimators described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

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

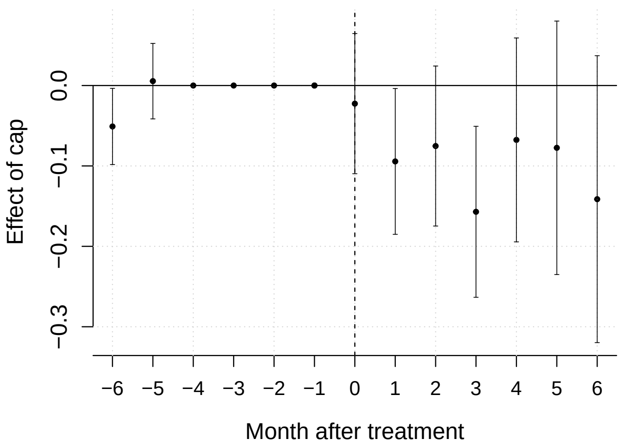
(a) TWFE



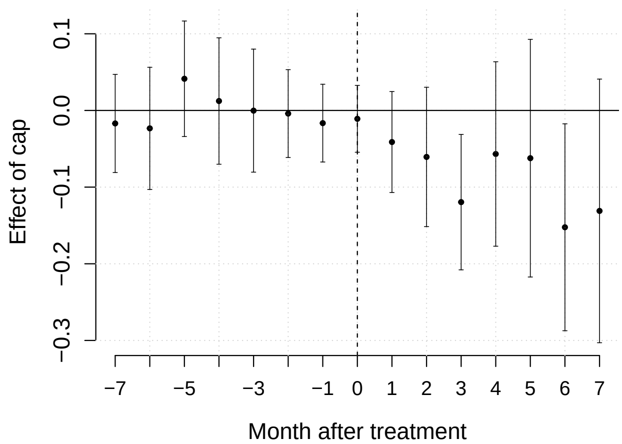
(b) IW, Sun and Abraham (2021)



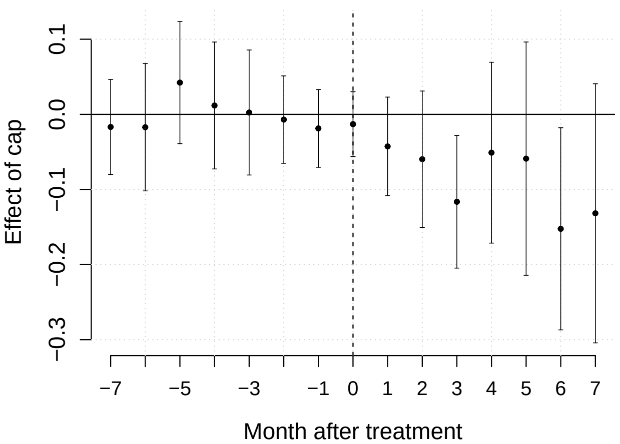
(c) IV, Freyaldenhoven et al. (2019)



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



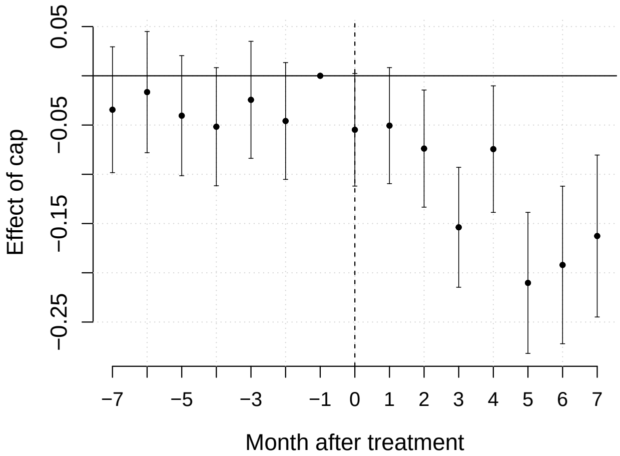
(e) Callaway and Sant'Anna (2021) (never)



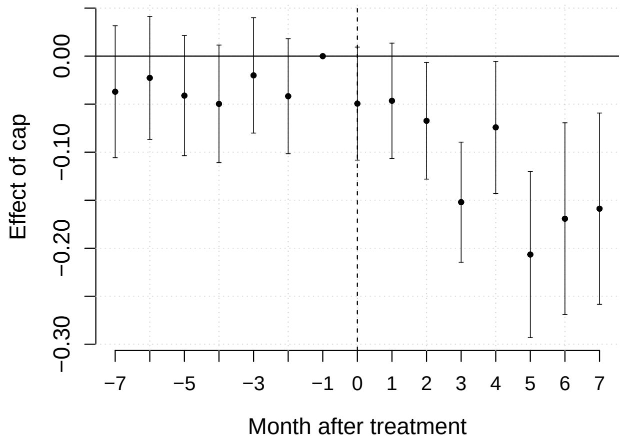
Notes: this figure includes plots of estimates of dynamic effects of commission caps on the log of the total number of restaurant orders placed on platforms. Each unit in the analysis is a ZIP3 and each time period is a month. The dots indicate point estimates and the bars around each point indicate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

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

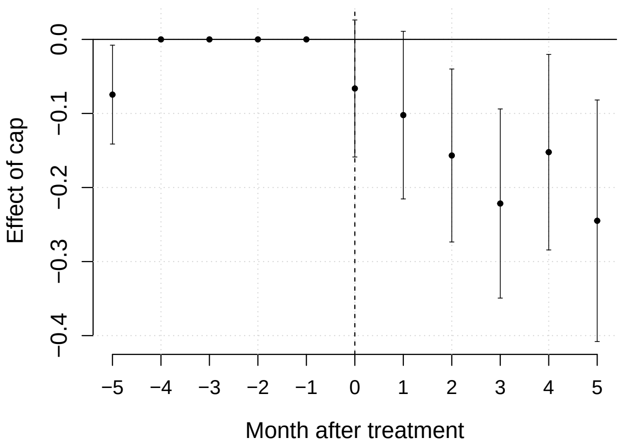
(a) TWFE



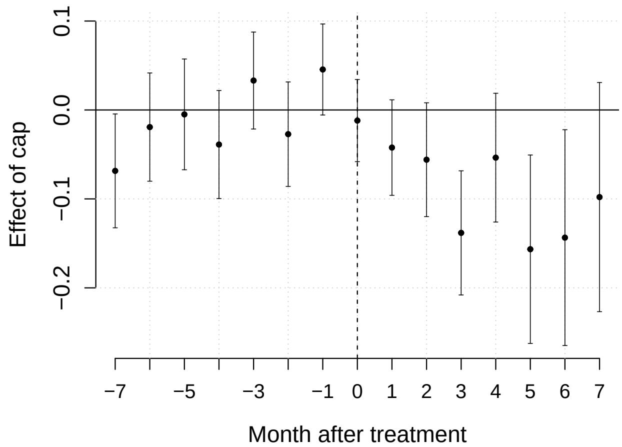
(b) IW, Sun and Abraham (2021)



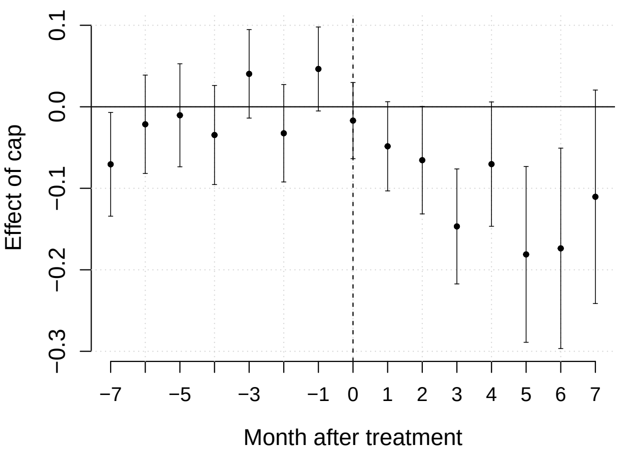
(c) IV, Freyaldenhoven et al. (2019)



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



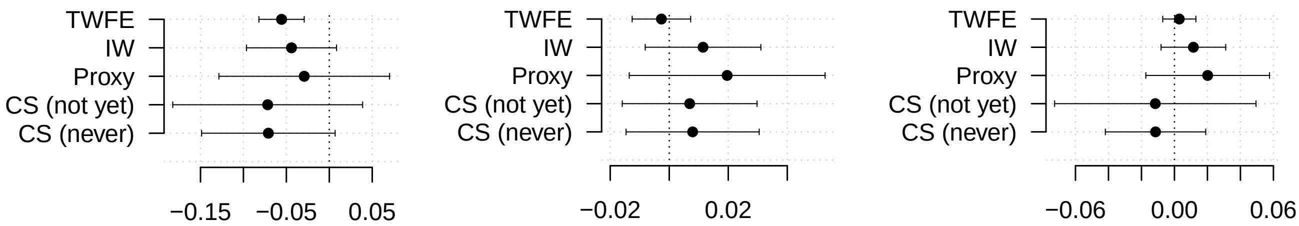
(e) Callaway and Sant'Anna (2021) (never)



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.11: Effects of commission caps on restaurant sales (basket subtotals)

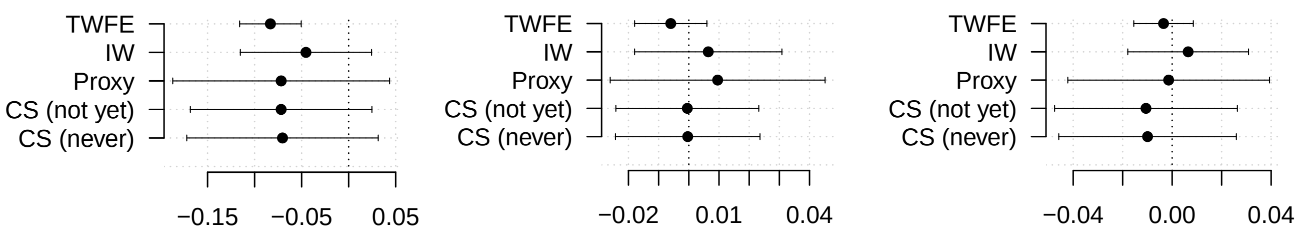
(a) Platform orders (b) Direct orders (c) All orders



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.10 for an explanation of each estimator.

Figure O.12: 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.11 but on a sample that excludes areas that ever had a commission cap that exempted chain restaurants.

O.7.3 Restaurant platform adoption

Although my data record all restaurants on delivery platforms at a monthly frequency, the data on all US restaurants—including those that do not belong to a platform—are at an annual frequency. I therefore estimate TWFE regressions at an annual level with platform adoption measures as outcomes. The time periods here are January 2020 (t_0) and January 2021 (t_1). The estimating equation is

$$y_{zt} = \underbrace{\psi_z + \phi_t}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\delta x_{zt}}_{\text{Treatment}} + \underbrace{\mathbb{1}\{t = t_1\} w'_{zt}\beta}_{\text{Controls}} + \varepsilon_{zt}, \tag{8}$$

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.16: 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 (8) 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.16a reports estimates from a sample that includes all areas that either had no commission cap or a cap of 15% or under, Table O.16b 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.16 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.16 provides the results for May 2021. The results are similar to those from the DiD approach. Table O.17 provides estimates of platform-specific uptake effects. These estimates suggest a positive effect of caps on restaurants' probabilities of joining each platform. Table O.18 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.17: 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 (8) 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.18: 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.16. 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.19: 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.20: 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)

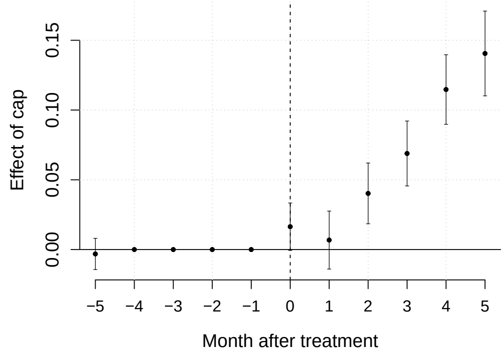
Notes: the table provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents relative to the population-weighted mean value of this quantity in April 2020. The mean value of the dependent 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.10 for a description of these estimators. Asymptotic standard errors appear in parentheses.

Table O.21: Effects of commission caps on platform restaurant listing counts (relative effects), exclude 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.20 but with areas that ever had commission caps that exempted chains excluded from the estimation sample.

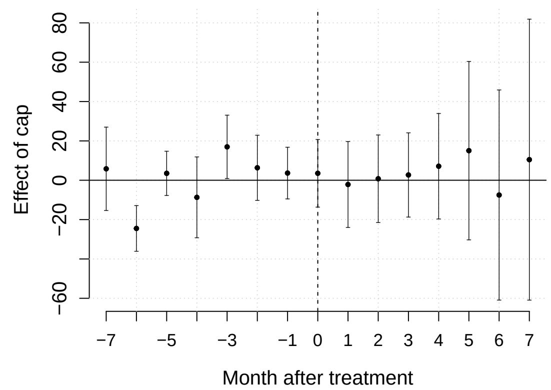
Figure O.13: Dynamic effects of commission caps on restaurants' platform adoption (Freyaldenhoven et al. 2019 proxy estimator)



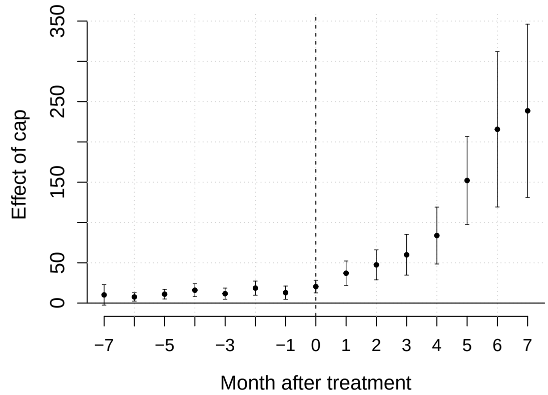
Notes: the plot provides estimates of the effects of commission caps on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents relative to the population-weighted mean number of listings in April 2020 (which was 2642). The bars around each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

Figure O.14: Dynamic effects of commission caps on platform restaurant listing counts (disaggregated by platform)

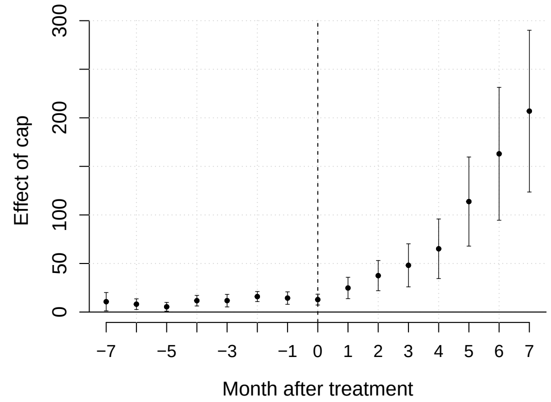
(a) DoorDash



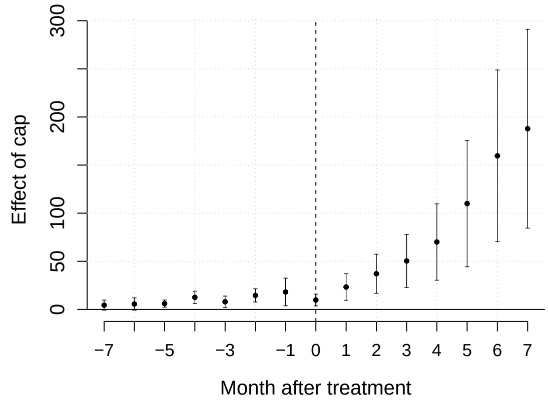
(b) Uber Eats



(c) Grubhub



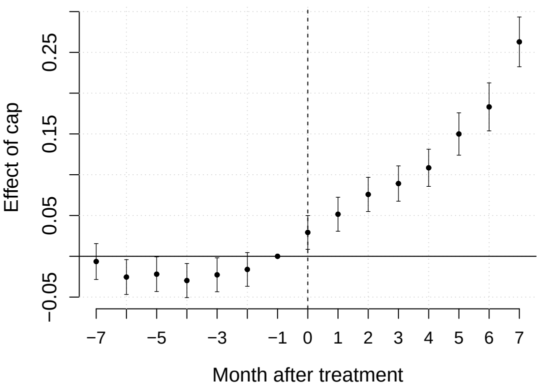
(d) Postmates



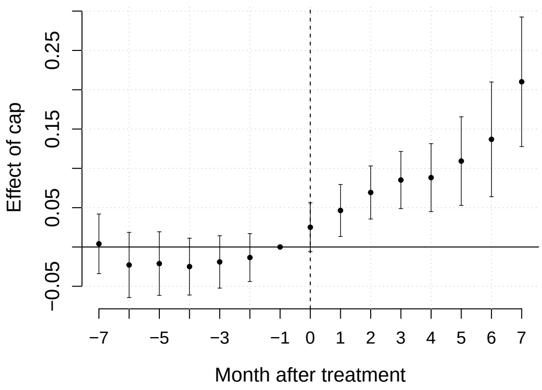
Notes: the plot provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents. The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2642 (total), 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.15: Dynamic effects of commission caps on platform restaurant listing counts (alternative estimators)

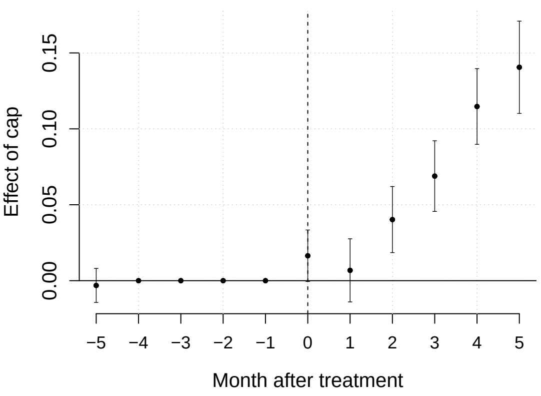
(a) TWFE



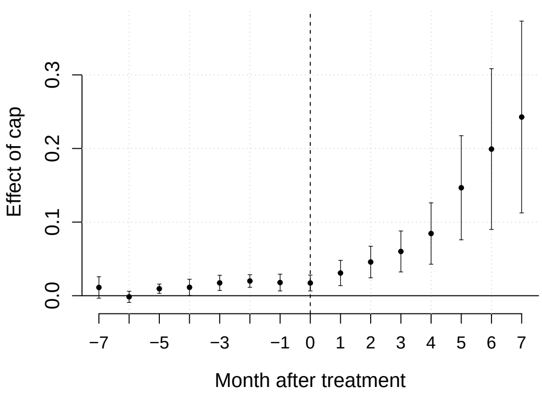
(b) IW



(c) IV



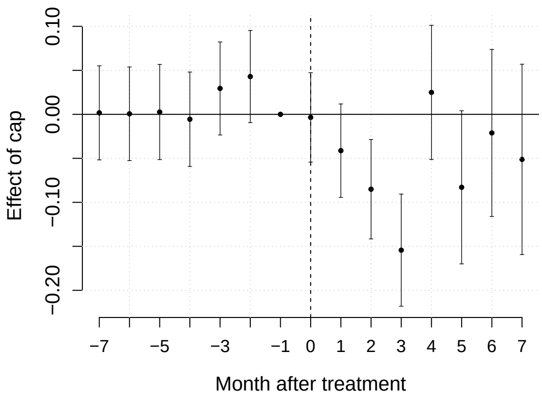
(d) Callaway and Sant'Anna (2021) (not yet)



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 (the mean value of the dependent variable across ZIP3s in April 2020, weighting for population, was 2642). The estimates derive from (O.15a) a two-way fixed effects estimator; (O.15b) the interaction-weighted estimator of Sun and Abraham (2021); (O.15c) 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.15d) 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.7.4 Restaurant prices

Figure O.16: Response of restaurant prices to commission caps



Notes: this figure plots estimates from a variant of (??) wherein effects of a commission cap vary with respect to time since the introduction of the commission cap.

O.8 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.22. 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.22: 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.9 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

$$\begin{aligned} S_{jf}(\mathcal{G}_j, w_m) = \sum_{z_i \in \mathcal{Z}(j)} M_z \int \Lambda(z_i, d_i, w_m, \Xi_i) \times \mu(f \mid \mathcal{G}_j, \tau_j, z_j, z_i, d_i, w_m, \Xi_i) \times \\ \frac{e^{V(\mathcal{G}_j, \tau_j, z_j, z_i, d_i, w_m, \Xi_i)}}{\sum_{\mathcal{G}, \tau} \sum_{z' \in \mathcal{Z}(z_i)} \sum_{k \in \mathcal{J}_{\tau z'}(\mathcal{G})} e^{V(\mathcal{G}, \tau, z', z_i, d_i, w_m, \Xi_i)}} dP_z(d_i, \Xi_i). \end{aligned} \tag{9}$$

The quantity M_z in (9) 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 (9) 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.10 Restaurant pricing and commission pass-through

Restaurants in the model adjust their markups as commission rates change rather than perfectly passing through commissions. To understand why, note that the first-order condition in the restaurant's pricing problem is

$$0 = (1 - r_f) S_{jf} + [(1 - r_f) p^*_{jf} - \kappa_{jf}] \frac{\partial S_{jf}}{\partial p_{jf}} + \sum_{g \neq f} [(1 - r_g) p^*_{jg} - \kappa_{jf}] \frac{\partial S_{jg}}{\partial p_{jf}}. \tag{10}$$

This yields a markup of

$$(1 - r_f) p^*_{jf} - \kappa_{jf} = a_j + b_j (1 - r_f), \tag{11}$$

where a_j measures the effect of changes in p_{jf} on j's sales on other platforms, and b_j is the inverse semi-elasticity of restaurant j's sales on platform f with respect to its price at f.[4] Equation (11) governs how restaurants adjust their markups in response to commission rates r_f. This markup adjustment implies imperfect pass-through of commissions to prices and therefore the non-neutrality of the price structure.[5]

I now provide an approximation of restaurants' markups. Consider the case in which restaurant j belongs

[4] The quantities a_j and b_j are defined by

$$a_j = \left(\frac{\partial S_{jf}}{\partial p_{jf}} \right)^{-1} \sum_{g \neq f} [(1 - r_g) p^*_{jg} - \kappa_{jf}] \frac{\partial S_{jg}}{\partial p_{jf}}, \qquad b_j = \left(\frac{\partial S_{jf}}{\partial p_{jf}} \right)^{-1} S_{jf}.$$

[5] The markup adjustment generally depends on responses of a_j and b_j to r_f, but these objects' responses do not completely counteract the direct effect of r_f on the markup as suggested by (11).

to a single platform with a commission rate r_f. The first-order condition becomes

$$p_{jf} = \frac{\kappa_j}{1 - r_f} + \frac{S_{jf}}{\left(-\frac{\partial S_{jf}}{\partial p_{jf}}\right)} \tag{12}$$

in this case. Abstracting from spatial heterogeneity and setting the market size to one for simplicity, we can write the sales S_{jf} of the restaurant as

$$S_{jf} = \int \underbrace{\frac{e^{V_{ij}}}{1 + \sum_k e^{V_{ik}}}}_{:=S_{ij}} dP(i),$$

where V_{ij} is short for $V(\mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i)$ and $dP(i)$ is short for $dP_z(d_i, \Xi_i)$. The quantity S_{ij} is the conditional probability with which a consumer of type (d_i, Ξ_i) orders from restaurant j. Note that

$$\frac{\partial S_{ij}}{\partial p_{jf}} = -\alpha_i S_{ij}(1 - S_{ij}).$$

Therefore,

$$\frac{\partial S_{jf}}{\partial p_{jf}} = \int -\alpha_i S_{ij}(1 - S_{ij}) dP(i) \approx -\int \alpha_i S_{ij} dP(i),$$

where the last approximation holds when $S_{ij} \approx 0$ almost surely across i; that is, for almost all (d_i, Ξ_i), a consumer of type (d_i, Ξ_i) has a probability of ordering from restaurant j that is close to zero. This approximation holds when the number of restaurants is large. When $\alpha_i = \alpha$ for all i, we have it that the inverse semi-elasticity of demand is approximately

$$\frac{S_{jf}}{\left(-\frac{\partial S_{jf}}{\partial p_{jf}}\right)} \approx \frac{1}{\alpha}. \tag{13}$$

This fact, together with (12) and (13), suggest that

$$p_{jf} = \frac{\kappa_j}{1 - r_f} + \frac{1}{\alpha},$$

provides a reasonable initial guess for equilibrium prices p_{jf}.

O.11 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 $\varkappa \in (0, 1]$ 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
$$\tilde{P}_{\tau z}(\mathcal{G}) = \varkappa \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_{\tau z}(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) + (1 - \varkappa) P_z(\mathcal{G})$$
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 type/ZIP pair. There is thus is no loss in including only one probability for each type/ZIP pair.

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

$$\Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_{\tau z}(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) \tag{14}$$

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 (14) many times. I therefore use an approximation to compute (14). Recall that

$$\Pi_j(\mathcal{G}, P_m) = \underbrace{\mathbb{E}\left[\sum_{f\in\mathcal{G}}[(1 - r_{fz}))p^*_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_j]S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*) \mid P_m\right]}_{:=\bar{\Pi}_j(\mathcal{G},P_m)} - K_{\tau(j)m}(\mathcal{G}). \tag{15}$$

The expectation $\bar{\Pi}_j$ over rival restaurants' platform adoption decisions $\mathcal{J}_{m,-j}$ is the part of (15) 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.[6] 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 (15) for each of these draws. An alternative approximation of the expectation in (14) 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 (9) 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 (9) to compute the S_{jf} term appearing in the integrand of the expectation in (15) under this alternative approximation.

The alternative approximation of the right-hand side of (14) 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.

[6]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, $G = 16$,

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

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.12 Additional results

Table O.23: Price elasticities of demand for the New York metro

	Quantity response for...				
Platform	Direct	DD	Uber	GH	PM
DD	0.05	-2.08	0.25	0.24	0.47
Uber	0.05	0.24	-1.82	0.23	0.43
GH	0.06	0.29	0.29	-2.11	0.51
PM	0.01	0.04	0.03	0.03	-5.91

Notes: this table reports percentage sales responses to a percentage uniform increase in platform fees in the Chicago CBSA. Formally, I compute

$$\epsilon^{c}_{m,ff'} = \frac{\bar{c}_{f'm}}{s_{fm}} \left. \frac{\partial s_{fm}(c_{f'm} + h)}{\partial h} \right|_{h=0},$$

where $c_{f'm}$ is a vector of the consumer prices charged by f' in m; $\bar{c}_{fm}$ is f's average consumer fee across ZIPs in m; s_{fm} are platform f's sales in m; and I have suppressed the dependence of s_{fm} on all variables except the consumer prices charged by platform f'. These elasticities are standard price elasticities in the case in which there is a single ZIP in the market m.

Table O.24: Network elasticities of demand for the New York metro

	Quantity response for...			
Platform	DD	Uber	GH	PM
DD	0.55	-0.10	-0.10	-0.12
Uber	-0.10	0.57	-0.10	-0.12
GH	-0.10	-0.11	0.58	-0.12
PM	-0.02	-0.02	-0.02	0.97

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 multihome, 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

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

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 s'_{fm} are f's sales after the addition of these new restaurants.

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Table O.25: Aggregate effects of 15% commission caps (chain commissions of 25% in baseline)

Outcome	Effect
Share of restaurants online (pct)	5.72
Number of restaurant listings (pct)	6.73
Average consumer fee (dollars)	4.48
Average price on platforms (dollars)	-3.41
Platform-intermediated sales (pct)	-10.28

Notes: this table reports estimated effects of 15% commission caps on outcomes aggregated across metros when chain restaurants face a commission rate of 25% in the baseline equilibria.

Table O.26: Welfare effects of 15% commission cap under alternative restaurant responses ($, per capita, annual)

Outcome	Effect
Consumer surplus	-11.40
Restaurant profit (chain)	-1.60
Restaurant profit (indep.)	5.24
Platform profit	-2.97

Notes: this table reports effects of 15% commission caps on welfare outcomes aggregated across metros when chain restaurants' commissions in the baseline equilibria are 25%. The figures are reported on an annual dollar basis, divided by the combined population of the metros in question.

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