Online appendix for "Price controls in a multi-sided market"*

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Contents

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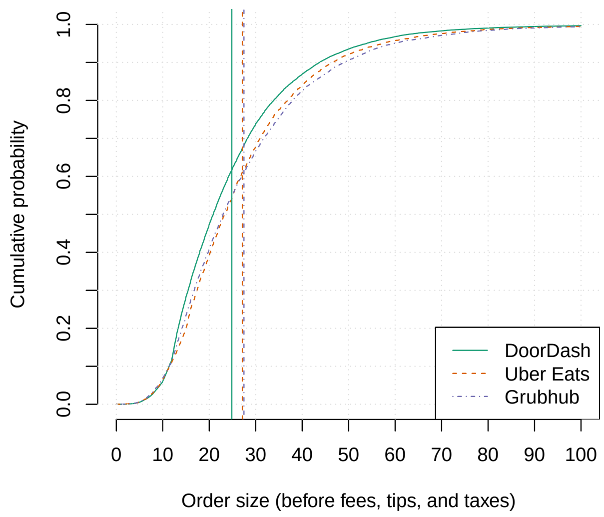
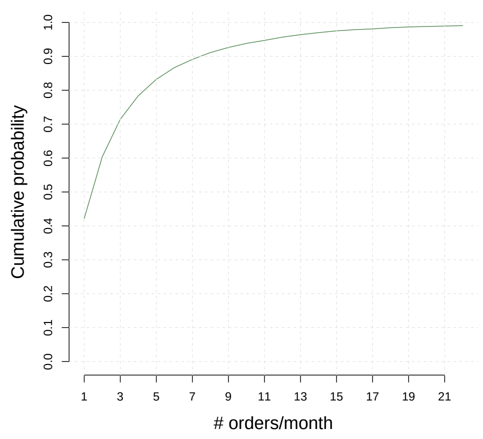
O.1 Additional description of data

Figure O.1: Distribution of order value before fees, tips, and taxes by platform, Q2 2021

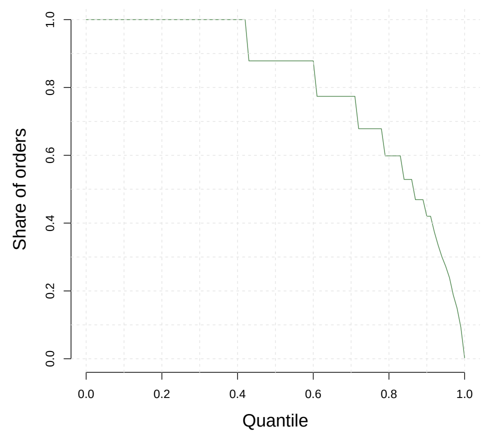


Notes: This figure plots the distribution function of order size before fees, tips, and taxes for each of the three largest food delivery platforms in the United States in Q2 2021 during this time period. The vertical lines indicate the mean order values on each platform. The orders used to construct the figure include all orders from these platforms in the Numerator transactions panel described in Section 2 in Q2 2021.

Figure O.2: Heterogeneity in monthly consumer order frequency, Q2 2021



(a) CDF of monthly order frequencies



(b) Share of orders accounted for by top $(1-x) \times 100\%$ of consumers

Notes: this figure describes the distribution of the monthly number of orders placed by consumers on the four major food delivery platforms. The figure describes consumer-month pairs in Q2 2021 the 14 metro areas on which I focus my analysis with at least one order on a major food delivery platform in the month in question.

Table O.1: Which places adopt commission caps?

Regressor	Estimate	SE
Democrat vote share (2016 pres elxn)	0.40	0.01
Population within 5 miles (millions)	0.40	0.01
Age group share: under 20	-0.09	0.02
Age group share: 20s	-0.01	0.02
Age group share: 30s	0.00	0.03
Age group share: 40s	-0.02	0.03
Age group share: 50s	-0.02	0.03
Share with HS diploma	0.03	0.02
Share with college degree	0.15	0.02
Share with advanced degree	0.33	0.03
R^2	0.20	
Mean dependent variable	0.11	

Notes: this table reports estimates from a ZIP-level linear regression of an indicator for a ZIP being subject to a commission cap by the end of June 2021 on various ZIP characteristics. These characteristics include: (i) the vote share of the Democratic candidate (Hillary Clinton) in the 2016 presidential election in the ZIP's county; (ii) the population within five miles of the ZIP in millions; (iii) the shares of the population in various age groups; and (iv) the shares of the population over 18 years of age in various educational attainment groups. The county-level elections data are provided by MIT Election Data and Science Lab (2018).

Table O.2: 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

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

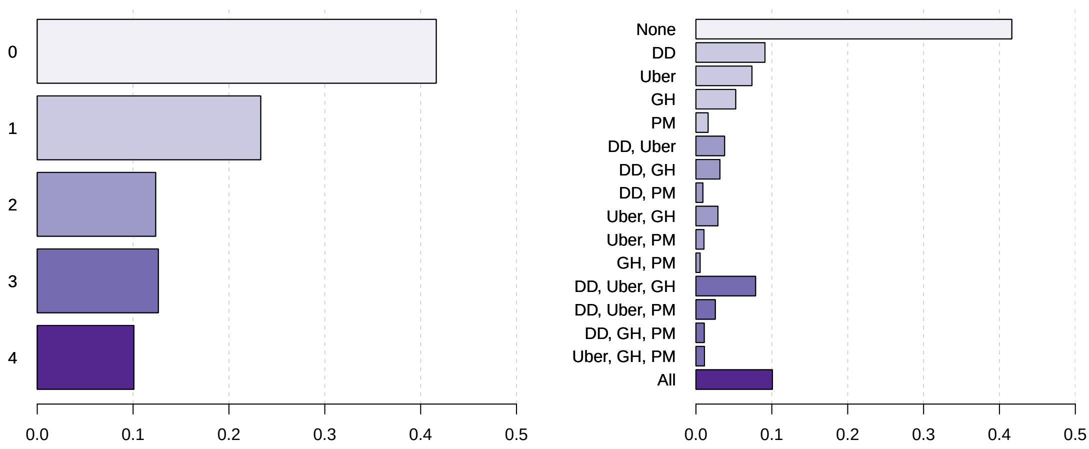
for delivery fee measurements df_k, CBSAs m, and ZIP codes z. The table uses all delivery measurements from ZIPs with at least two recorded delivery fees.

Table O.3: 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.3: 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 markets listed in Table 1 in April 2021. Deeper shades indicate sets that include more platforms.

Table O.4: Source of within-market fee variation

(a) Platform fixed effects

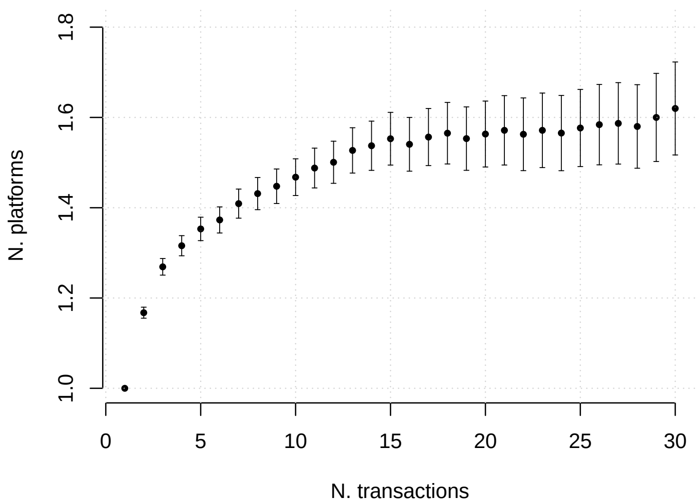
Variable	Estimate	SE
Cap	0.67	0.03
Share age under 35	-2.52	0.19
Share married	-2.19	0.15
Population density	-0.69	0.03

(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

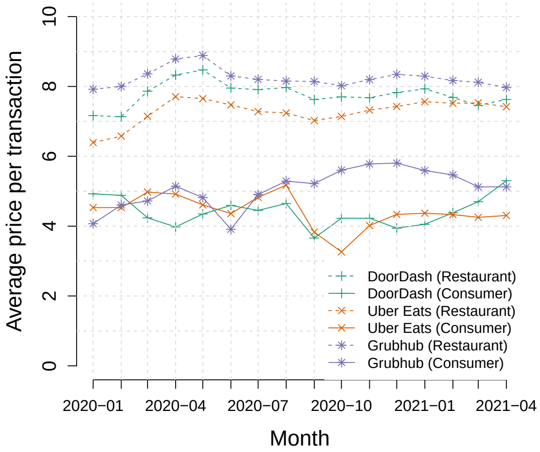
Notes: I assess the drivers of within-market variation in fees by regressing ZIP/platform-level fees on an indicator for the presence of a commission cap and demographic characteristics of the ZIP. I first run these regressions first including only platform fixed effects, and I then add fixed effects for platform/market pairs. This second regression is useful for understanding whether commission caps and demographic differences provide variation in fees within markets. Each of the $N = 17220$ observations used in the regression is a platform/ZIP pair. "Cap" indicate the presence of a 15% commission rate in the ZIP. "Share under 35" is the share of the population within five miles of the ZIP that is under 35 years of age. "Share married" is the share of the population within five miles of the ZIP that is married. "Population density" is the population (in millions) of the area within five miles of the ZIP. Panel (a) reports the results of a regression with platform indicators included as regressors whereas Panel (b) reports the results of a regression with indicators for platform/CBSA pairs as regressors.

Figure O.4: Average cumulative numbers of platforms used by consumers

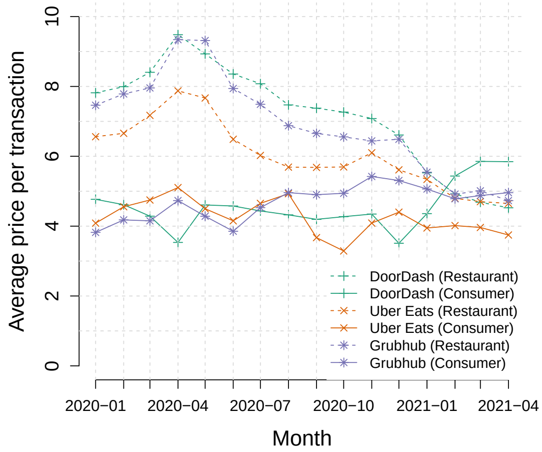


Notes: this figure displays, for $t = 1, \ldots, 30$, the average number of unique delivery platforms from which a consumer in the Numerator panel has placed an order through their first to t^{th} order from a food delivery platform. I use data from April to June 2021 for the 14 markets on which I focus my paper's analysis to produce this figure. The average for t is taken over all Numerator panelists in this data subset who made at least t orders from April to June 2021. The vertical bars provide 95% confidence intervals for the estimated means.

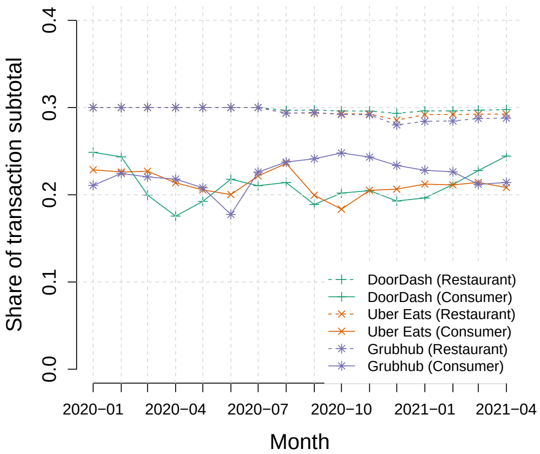
Figure O.5: Platforms' average fees and commissions in regions with and without a commission cap as of May 2021



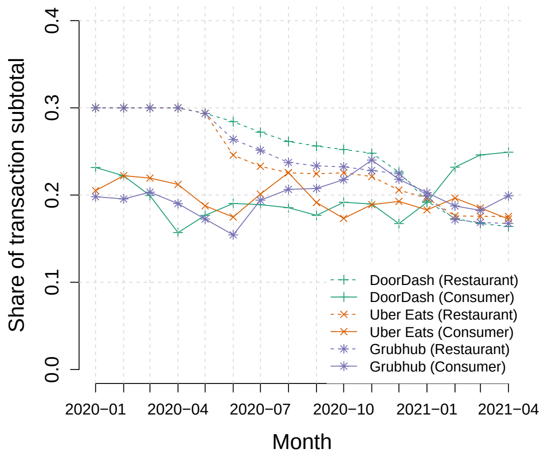
(a) Average prices per transaction: no cap



(b) Average prices per transaction: cap



(c) Average prices as shares of subtotal: no cap



(d) Average prices as shares of subtotal: 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 average consumer fees are obtained by averaging the ZIP-level estimate of the average consumer fee in the Edison data across ZIPs, using the number of orders placed in each ZIP as weights. The figure provides these average restaurant commissions and consumer fees for each month from January 2020 to April 2021 both (i) in absolute terms and (ii) as a share of the order subtotal. In addition, the figure plots average commissions and average consumer fees separately for regions with and without active commission caps in May 2021.

O.2 Additional empirical findings

Section 3 presents four empirical findings that inform my modelling decisions. The current section provides presents four additional empirical findings.

O.2.1 Consumers place more orders on platforms that attract new restaurants

Network externalities exerted by restaurants on consumers influence the effects of commission caps. To assess the relevance of such network externalities, I estimate the elasticity β_{NE} of platform sales with respect to restaurant variety by OLS with the estimating equation

$$\underbrace{\log \mathscr{s}_{fzt}}_{\text{Log sales}} t = \underbrace{\psi_{fz} + \psi_{ft}}_{\substack{\text{ZIP and month}\\ \text{fixed effects}}} + \underbrace{\beta_{\mathrm{NE}} \log J_{fzt}}_{\text{Network externalities}} + \varepsilon_{fzt}, \tag{1}$$

where $\mathscr{s}_{fzt}$ 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 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.

In addition to estimating (1), I estimate a model with metro area fixed effects on a cross section of ZIPs. Rather than relying on assumptions about adoption trends over time, this approach requires common unobserved shifters of demand and platform adoption to be constant within a metro. Online Appendix O.8 provides results from this approach, which are similar to those that I obtain for (1).

The first column of Table O.17 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 $\beta^{\mathrm{NE}}_{\text{chain}}$ and $\beta^{\mathrm{NE}}_{\text{non-chain}}$ in

$$\log \mathscr{s}_{fzt} = \psi_{fz} + \psi_{ft} + \beta^{\text{chain}}_{\mathrm{NE}} \log J^{\text{chain}}_{fzt} + \beta^{\text{non-chain}}_{\mathrm{NE}} \log J^{\text{non-chain}}_{fzt} + \varepsilon_{fzt}, \tag{2}$$

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.

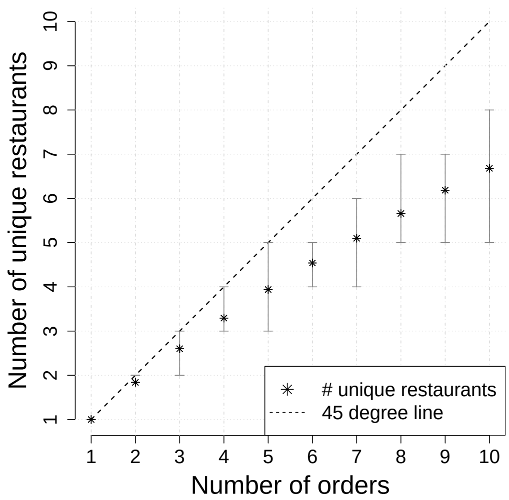
Consumers typically switch between restaurants across consecutive orders placed on food delivery platforms. Figure O.6 describes the number of unique restaurants from which a

Table O.5: Restaurant-to-consumer network externalities (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 (1). The second column provides estimates of $\beta^{\text{NE}}_{\text{chain}}$ and $\beta^{\text{NE}}_{\text{non-chain}}$ in (2). 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 located within a CBSA.

Figure O.6: Number of unique restaurants by number of platform orders



Notes: the figure displays, for $k = 1, \ldots, 10$, the average of the number of unique restaurants among a consumer's first k platform orders in the second quarter of 2021. The average is taken across consumers who placed at least 10 orders in this quarter. The bars around each point provide interquartile ranges of the number of unique restaurants from which consumers placed orders.

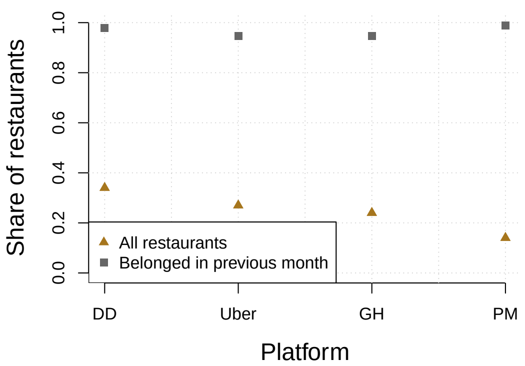
consumer orders among that consumer's first k orders placed on platforms in the second quarter of 2021. In particular, the figure provides the average and interquartile range of this variable for each $k = 1, \ldots, 10$ among consumers who placed at least 10 orders on platforms in the second quarter of 2021. The figure shows that consumers tend to order from several distinct restaurants—on average, over six of them—across ten consecutive orders. This pattern is consistent with consumer tastes for restaurants varying across ordering occasions. When consumer tastes for restaurants vary across time, a platform can increase its sales to a consumer by adding new restaurants to its network; this is because a wider network is more likely to include restaurants that the consumer happens to fancy at any particular moment in time. My model features this mechanism: it includes consumers whose order-specific tastes for restaurants give rise to a positive effect of a platform's number of member restaurants on the number of orders that consumers place on the platform.

Modelling implication. The number of restaurants available on the platform affects platforms' sales in my consumer choice model. There is not clear evidence of a difference in consumer responsiveness to chain and non-chain restaurants, and I do not distinguish between chain and non-chain restaurants in my model.

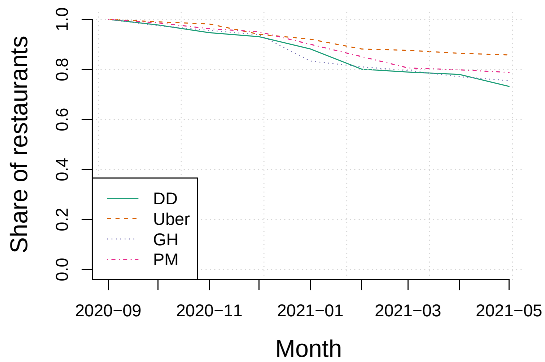
O.2.2 Restaurants that join a platform tend to remain on the platform

Figure O.7: Persistence of restaurants' platform memberships

(a) Platform membership in April 2021 among restaurants belonging to platforms in previous month



(b) Share of restaurants on each platform among restaurants on the platform in September 2020



Notes: Figure O.7a reports the share of restaurants on each platform in April 2021 among (i) all restaurants and (ii) among restaurants that belonging to the platform in the previous month, March 2021. Figure O.7b reports the share of restaurants on each platform in each month from September 2020 to May 2021 among all restaurants that belonged to the platform in September 2020.

Figure O.7a plots the share of restaurants on each major platform in April 2021 among restaurants on all platforms and among restaurants on the platform in March 2021. The figure shows that restaurants that were previously on the platform are more likely to belong to the platform than restaurants that were not on the platform. Figure O.7b plots the share of restaurants on each platform in each month from September 2020 to May 2021 among restaurants that belonged to the platform in September 2020. The figure shows that, even eight months on, a significant majority of restaurants on a platform are still listed on the platform. These figures suggest that restaurants may exhibit state dependence in their choice of platforms. Consequently, a platform may be able to boost its future profitability by enrolling new restaurants. Platforms may take the effects of their restaurant networks on future profitability into account when setting commissions.

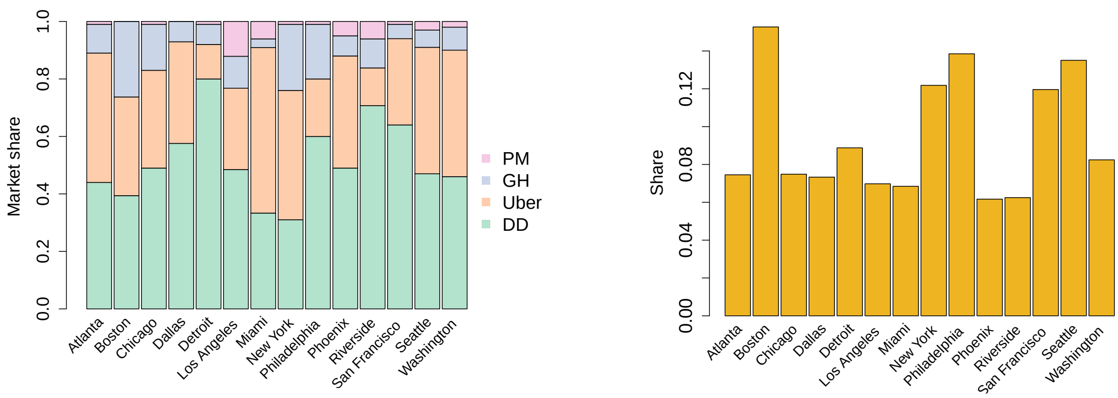
Modelling implication. My model of platform commission-setting accounts for platforms' dynamic pricing incentives by including the sizes of platforms' restaurant networks in platforms' objective functions.

O.2.3 Platform market shares vary across metropolitan areas

Figure O.8a plots each major platform's share of spending on food delivery platforms in Q2 2021 for 14 large US metropolitan areas. Additionally, Figure O.8a 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).

Modelling implication. Platform sales in my model depends on local consumer demographics, the local selection of restaurants on platforms, and local unobserved tastes for platforms.

Figure O.8: Market shares, Q2 2021



(a) Market shares among leading platforms

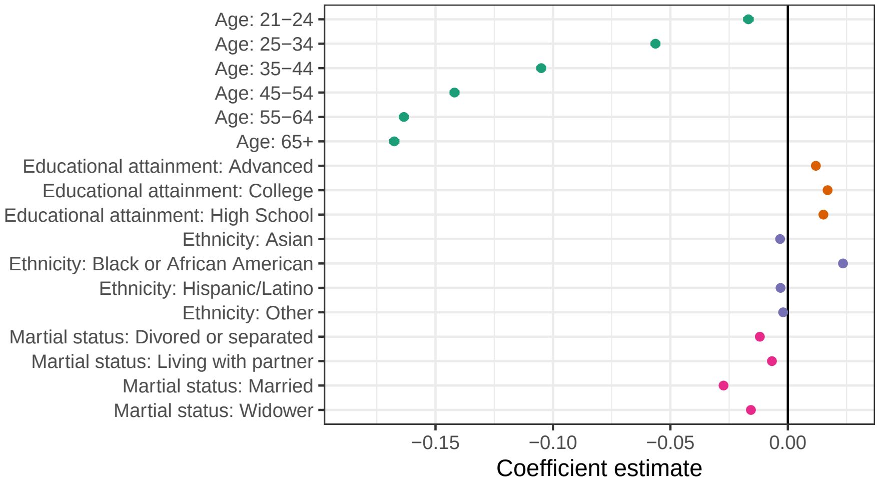
(b) Online platform shares of restaurant expenditure

Notes: Panel (a) reports CBSA-specific shares of expenditure on DoorDash, Uber Eats, Grubhub, and Postmates orders in the Numerator panel for Q2 2021. Panel (b) reports CBSA-specific shares of expenditure on the four leading delivery platforms out of all expenditure on restaurant orders in the Numerator panel for Q2 2021.

O.2.4 Younger consumers are more likely to use delivery platforms

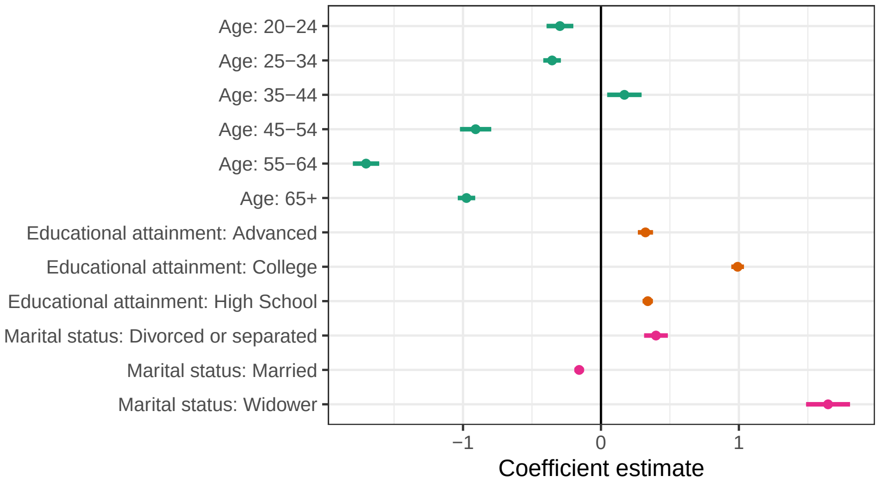
To determine which consumer characteristics explain usage of food delivery platforms, I regress an indicator for whether a restaurant order was placed on a delivery platform (rather than directly from a restaurant) on various consumer characteristics. These characteristics include indicator variables for age groups, educational attainment levels, racial/ethnic backgrounds, marital statuses, employment statuses, household sizes, income groups, and gender. Figure O.9 plots several of the coefficients from this regression. 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, the reference group for marital status in the regression.

Figure O.9: 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.10: Demographic correlates of restaurant platform adoption



Notes: this figure displays estimated coefficients and 95% confidence intervals for a ZIP-level regression with the share of restaurants listed on at least one of the major four food delivery platforms as the dependent variable in and various demographic characteristics of the area around the ZIP as regressors. These regressors include: the share of the population in the various age groups specified in the figure; the share of the population over 18 years of age with the various levels of educational attainment specified in the figure; and the share of the population over 15 years of age with the various levels of educational attainment specified in the figure. The regression also includes month and CBSA fixed effects. Additionally, each ZIP is weighted by the number of restaurants in the ZIP. I estimate the regression on data for April and May 2021.

If restaurants respond to changes in the profitability of joining delivery platforms, then an increase in tastes for platform ordering among restaurants' potential consumers should induce restaurants to join platforms. To assess this hypothesis, I regress the share of restaurants in a ZIP that belonged to at least one delivery platform in April 2021 on the share of the population within five miles of the ZIP that belongs to various age groups, educational attainment groups, and marital status groups.[1] Figure O.10 displays the results. Restaurants in areas with high population shares of younger people are more likely to join platforms than restaurants nearby many people over the age of 55: a share of people over 65 years of age that is 10 percentage points (p.p.) higher at the expense of people under 20 years of age is associated with a 9.7 p.p. lower share of restaurants that join online platforms. Additionally, the share of restaurants on platforms is lower in areas with more married people. In April 2021, over 40% of restaurants did not belong to any platform, and about 10% belong to all online platforms. Appendix Figure O.3 reports the distribution of restaurants across subsets of platforms.

Modelling implication. I include age and marital status as shifters of consumer tastes in my model. Additionally, I use the population of young consumers nearby a restaurant as a shifter of restaurants' platform adoption decisions in estimating my model.

O.3 State dependence versus persistent platform tastes

Consumers do not typically switch between platforms across 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 tastes for platforms. Persistent tastes for platforms introduce serial correlation into consumers' ordering choices even when previous orders have no effect on the consumer's contemporaneous order, holding all else equal. 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.6 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 was important. These results suggest that persistent tastes play a larger role than state dependence in explaining repeat purchasing. This observation informs my choice to include persistent heterogeneous tastes but not state dependence in my model.

[1] I use ZIP-level estimates from the 2019 American Community Survey to construct the regressors included in this regression.

Table O.6: Evaluation of state dependence

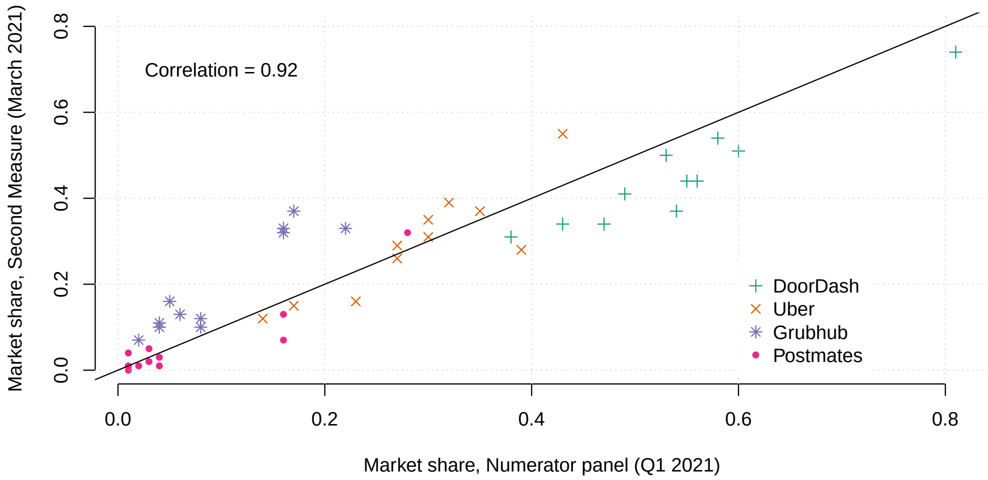
# transactions (τ)	# unique (k)	# switches Mean	95% CI		# switches (Shuffled data)	N
3	2	1.36	1.34	1.37	1.33	4708
4	2	1.71	1.69	1.72	1.65	4728
4	3	2.59	2.55	2.64	2.50	429

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 listed in Table 1 in Q2 2021.

O.4 Validation of transactions datasets

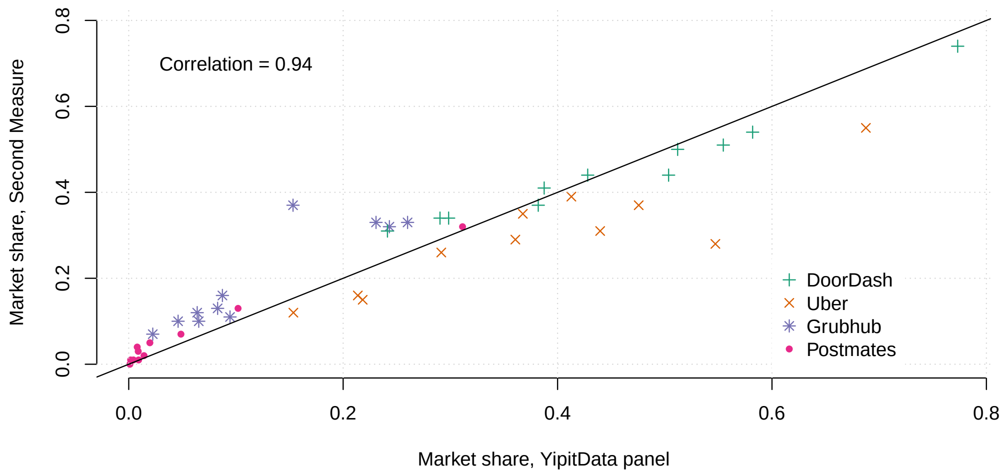
Figure O.11 compares market shares for April 2021 computed from the Numerator transactions panel to those reported by the market research firm Second Measure, which estimates platforms' market shares based on payment card records, for March 2021. Market shares are similar across these two data sources. 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.11: Market shares: validation of Numerator panel



Note: This plot compares market shares from my Numerator data on transactions from email receipts to market shares based on payment card transactions. The horizontal axis reports market shares for CBSA/platform pairs for the first quarter of 2021, which are also reported by Figure O.8a. The vertical axis reports market shares computed by Second Measure, a market research firm, using transactions data collected from a panel of consumers' payment card records. The Second Measure market shares are for March 2021, and 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.12: Market shares: validation of Edison panel



Note: This plot compares market shares from the transactions data provided by Edison, which is based on a panel of receipts, to market shares based on payment card transactions. The horizontal axis reports market shares for CBSA/platform pairs for March 2021 as implied by the Edison ZIP-level estimates of sales volumes (in dollars) on each delivery platform. The vertical axis reports market shares computed by Second Measure, a market research firm, using transactions data collected from a panel of consumers' payment card records. The Second Measure market shares are for March 2021, and 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.

O.5 Delivery fee regressions

Table O.7: Delivery fee regressions: CBSA/month fixed effects

	DD	Uber	GH	PM
Distance	-0.33	-0.01	0.510	0.57
	(0.04)	(0.06)	(0.002)	(0.08)
Distance 2	0.07	0.03	-0.011	-0.01
	(0.01)	(0.02)	(0.000)	(0.01)
Distance 3	-0.004	-0.002	0.000	-0.000
	(0.001)	(0.002)	(0.000)	(0.000)
Distance x Population (millions)	0.30	0.11	0.238	-0.15
	(0.02)	(0.02)	(0.002)	(0.06)
Has Cap	0.16	0.38	-0.33	0.08
	(0.03)	(0.04)	(0.01)	(0.18)
Population (millions)	-0.59	-0.49	-0.10	0.38
	(0.03)	(0.05)	(0.01)	(0.22)
Price Category: $$	-0.22	-0.12	0.42	0.26
	(0.03)	(0.03)	(0.01)	(0.17)
Price Category: $$$	0.06	-0.50	0.75	-0.47
	(0.07)	(0.14)	(0.01)	(0.21)
Price Category: $$$$	0.16	-1.28	1.53	-1.29
	(0.18)	(0.35)	(0.03)	(0.90)
Time of Day: Midday (11am-2pm)	-0.00	-0.10	-0.21	-0.48
	(0.03)	(0.06)	(0.01)	(0.20)
Time of Day: Afternoon (2pm-5pm)	0.10	-0.39	-0.23	-0.59
	(0.03)	(0.07)	(0.01)	(0.20)
Time of Day: Evening (5pm-9pm)	0.03	-0.05	-0.18	-0.25
	(0.03)	(0.07)	(0.01)	(0.20)
Time of Day: Night (9pm-12am)	0.03	-0.00	0.42	-0.45
	(0.03)	(0.08)	(0.01)	(0.21)
Time of Day: Late (12am-5am)	0.07	0.07	1.77	-0.25
	(0.03)	(0.10)	(0.02)	(0.24)
Day of Week: Tuesday	-0.00	0.01	0.03	-0.23
	(0.04)	(0.06)	(0.01)	(0.22)
Day of Week: Wednesday	-0.04	0.03	0.03	-0.30
	(0.04)	(0.07)	(0.01)	(0.21)
Day of Week: Thursday	0.02	0.11	-0.05	-0.71
	(0.04)	(0.07)	(0.01)	(0.21)
Day of Week: Friday	0.06	0.11	-0.02	-0.06
	(0.04)	(0.07)	(0.01)	(0.22)
Day of Week: Saturday	-0.03	0.02	0.02	-0.27
	(0.10)	(0.08)	(0.01)	(0.22)
Day of Week: Sunday	0.15	0.62	0.01	0.19
	(0.07)	(0.26)	(0.01)	(0.21)
Educational Attainment Share: High School	0.63	3.08	1.31	4.77
	(0.26)	(0.48)	(0.09)	(1.99)
Educational Attainment Share: University	0.81	2.72	1.06	4.27
	(0.21)	(0.38)	(0.08)	(1.67)
Share Married	-0.47	-4.53	-3.32	-4.79
	(0.21)	(0.37)	(0.08)	(1.38)
Share of Ages 20s	-2.09	-4.57	-5.21	-10.18
	(0.72)	(1.17)	(0.25)	(4.57)
Share of Ages 30s	-2.08	-1.88	1.29	-8.53
	(0.63)	(0.99)	(0.22)	(4.10)
Share of Ages 40s	-9.30	-9.26	-0.32	-27.73
	(1.31)	(2.20)	(0.44)	(8.66)
Share of Ages 50s	3.30	-11.32	-0.37	23.41
	(1.05)	(1.72)	(0.34)	(6.24)
Share of Ages 60+	-3.24	-0.70	0.59	-12.90
	(0.50)	(0.75)	(0.16)	(2.84)
R^2	0.19	0.22	0.53	0.39

Notes: "Distance 2" and "Distance 3" are, respectively, quadratic and cubic terms in delivery distance. "Population (millions)" is the population residing within 5 miles of the delivery address. "Has Cap" indicates whether a commission cap was in effect at the delivery address. The "Educational Attainment," "Share Married," and "Share of Ages" variables report the share of the population within 5 miles that belongs to the indicated subpopulations. All regressions include CBSA/month, cuisine, and restaurant chain fixed effects. Standard errors appear in parentheses under their corresponding estimates.

Table O.8: Delivery fee regressions: CBSA/month fixed effects

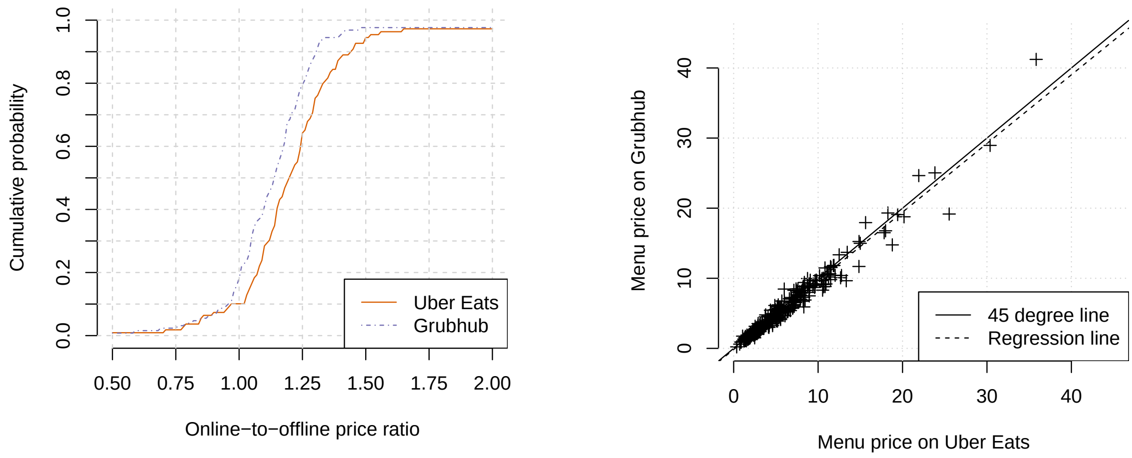
	DD	Uber	GH	PM
Distance	-0.32	0.02	0.505	0.61
	(0.03)	(0.06)	(0.002)	(0.08)
Distance 2	0.07	0.02	-0.011	-0.02
	(0.01)	(0.02)	(0.000)	(0.01)
Distance 3	-0.004	-0.002	0.000	0.000
	(0.001)	(0.002)	(0.000)	(0.000)
Distance x Population (millions)	0.28	0.08	0.240	-0.09
	(0.02)	(0.02)	(0.002)	(0.07)
Has Cap	-0.05	0.84	-0.24	-0.27
	(0.05)	(0.07)	(0.02)	(0.34)
Population (millions)	-0.30	-0.32	-0.20	-0.40
	(0.05)	(0.08)	(0.01)	(0.44)
Price Category: $$	-0.22	-0.13	0.42	0.23
	(0.03)	(0.03)	(0.01)	(0.17)
Price Category: $$$	0.03	-0.39	0.73	-0.53
	(0.07)	(0.13)	(0.01)	(0.22)
Price Category: $$$$	0.16	-0.92	1.51	-1.22
	(0.17)	(0.34)	(0.03)	(0.88)
Time of Day: Midday (11am-2pm)	0.00	0.06	-0.21	-0.46
	(0.03)	(0.06)	(0.01)	(0.21)
Time of Day: Afternoon (2pm-5pm)	0.07	-0.35	-0.24	-0.53
	(0.03)	(0.07)	(0.01)	(0.21)
Time of Day: Evening (5pm-9pm)	0.02	-0.11	-0.20	-0.18
	(0.03)	(0.07)	(0.01)	(0.21)
Time of Day: Night (9pm-12am)	0.01	-0.15	0.44	-0.30
	(0.03)	(0.08)	(0.01)	(0.21)
Time of Day: Late (12am-5am)	0.06	-0.04	1.79	0.10
	(0.03)	(0.10)	(0.02)	(0.25)
Day of Week: Tuesday	-0.06	-0.01	-0.01	-0.26
	(0.04)	(0.07)	(0.01)	(0.22)
Day of Week: Wednesday	-0.07	-0.06	0.03	-0.27
	(0.04)	(0.07)	(0.01)	(0.21)
Day of Week: Thursday	-0.03	-0.05	-0.04	-0.63
	(0.04)	(0.07)	(0.01)	(0.22)
Day of Week: Friday	0.00	0.03	-0.03	-0.05
	(0.04)	(0.07)	(0.01)	(0.23)
Day of Week: Saturday	-0.02	-0.12	0.02	-0.21
	(0.10)	(0.08)	(0.01)	(0.22)
Day of Week: Sunday	0.08	0.65	0.01	0.31
	(0.07)	(0.25)	(0.01)	(0.22)
Educational Attainment Share: High School	0.34	6.31	1.22	8.69
	(0.30)	(0.54)	(0.11)	(2.41)
Educational Attainment Share: University	0.59	5.69	1.44	7.36
	(0.24)	(0.45)	(0.08)	(1.99)
Share Married	0.33	-5.11	-2.59	-5.39
	(0.24)	(0.48)	(0.10)	(1.81)
Share of Ages 20s	-2.28	-9.08	-5.23	-15.07
	(0.80)	(1.40)	(0.28)	(5.51)
Share of Ages 30s	0.10	-0.49	-1.04	-7.18
	(0.75)	(1.35)	(0.26)	(5.68)
Share of Ages 40s	-7.74	-14.65	-5.41	-49.41
	(1.55)	(2.49)	(0.49)	(10.14)
Share of Ages 50s	1.91	-11.60	-3.17	12.67
	(1.19)	(1.85)	(0.37)	(7.02)
Share of Ages 60+	-1.85	-3.86	-1.51	-16.35
	(0.55)	(0.84)	(0.17)	(3.23)
R^2	0.23	0.29	0.55	0.46

Notes: "Distance 2" and "Distance 3" are, respectively, quadratic and cubic terms in delivery distance. "Population (millions)" is the population residing within 5 miles of the delivery address. "Has Cap" indicates whether a commission cap was in effect at the delivery address. The "Educational Attainment," "Share Married," and "Share of Ages" variables report the share of the population within 5 miles that belongs to the indicated subpopulations. All regressions include county/month, cuisine, and restaurant chain fixed effects. Standard errors appear in parentheses under their corresponding estimates.

O.6 Additional analysis of restaurant prices

For each of the 419 items with at least 10 sales in my data in the first six months of 2021, I compute the item's average price for direct-from-restaurant orders, on Uber Eats, and on Grubhub across transactions in my sample. Figure O.13 displays, for each of Uber Eats and Grubhub, the cumulative distribution function of the item's average price on the platform to its average price for direct-from-restaurant orders. This figure shows that prices are typically 10–30% higher on Uber Eats and Grubhub than they are for direct-from-restaurant orders. Under a 30% commission rate, a restaurant equalizes its revenue from a direct sale and a platform-intermediated sale by charging 43% more on platforms. Thus, pass-through of platforms' commissions into prices is substantial but incomplete. Figure O.13b, plots the prices at each of Uber Eats and Grubhub for each item, shows that restaurants typically charge the same price across platforms.

Figure O.13: Comparison of restaurant menu prices across channels and platforms, Jan.–Jun. 2021



(a) Distributions of platform-to-offline price ratios

(b) Prices on online platforms

Notes: this figure plots (i) the cumulative distribution function of the ratio of the price of a menu item on a food delivery platform (for each of Uber Eats and Grubhub) to its price for a direct-from-restaurant order and (ii) prices of menu items on Uber Eats to those on Grubhub.

O.7 Responses to commission caps

Table O.9: Responses of fees and orders to commission caps: Callaway and Sant'Anna (2021)

Platform	Fees	# orders
Total	-	-0.10
		(0.03)
DD	0.14	-0.05
	(0.05)	(0.03)
Uber	0.04	-0.05
	(0.04)	(0.05)
GH	0.10	-0.02
	(0.08)	(0.13)

Notes: this table provides results from difference-in-differences estimates of the effects of a commission cap of 15% or less on either (i) log average fees or (ii) the log of the number of orders. I produce the estimates using the doubly robust difference-in-differences estimator of Callaway and Sant'Anna (2021), which generalizes the estimator proposed by Sant'Anna and Zhao (2020). This estimator combines aspects of the outcome regression and inverse probability weighting methods commonly used in difference-in-differences regression. The reported figures are averages of estimates of the group-time average treatment effects on the treated (ATT), where groups are defined by treatment period and time refers to the calendar time of the effect; the reported measures are averages of group-time specific ATT estimates across group-time pairs that use group size as weights, i.e., θ_W^O as defined in Callaway and Sant'Anna (2021). Each estimator is computed on a ZIP/month level panel, and each observation is weighted by the ZIP's population. I use never-treated observations as the control group. In addition, I use the mean monthly new COVID-19 cases per capita in a ZIP from January 2020 to May 2021 as a ZIP-level control. I compute the estimator separately for each of DoorDash (DD), Uber Eats (Uber), and Grubhub (GH). I also run each analysis using total sales summed across platforms as the outcome variable; these results are provided by the "Total" rows. I lack detailed data on the breakdown of Postmates receipts across a large number of ZIPs, which explains why I do not provide estimates for Postmates. The table reports asymptotic standard errors in parentheses.

Table O.10: Responses of fees and orders to commission caps: continuous treatment

Platform	Fees	# orders
Total	-	0.41
		(0.07)
DD	-1.14	0.25
	(0.11)	(0.07)
Uber	-0.48	0.11
	(0.10)	(0.08)
GH	-1.19	-0.43
	(0.39)	(0.11)

Notes: This table reports results of the analyses described in the notes for Table 3 with the treatment indicator x_{zt} replaced 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.

The estimation sample includes ZIPs with commission caps greater than 0.15.

Table O.11: Responses of fees and orders to commission caps, July 2020 to May 2021

(a) Two-way fixed effects

Platform	Fees	# orders
Total	-	-0.01
		(0.01)
DD	0.17	-0.04
	(0.03)	(0.01)
Uber	0.13	-0.05
	(0.02)	(0.02)
GH	0.12	0.09
	(0.06)	(0.02)

(b) Callaway and Sant'Anna (2021)

Platform	Fees	# orders
Total	-	-0.08
		(0.03)
DD	0.11	-0.03
	(0.05)	(0.03)
Uber	0.14	-0.12
	(0.03)	(0.04)
GH	0.13	0.05
	(0.09)	(0.13)

Notes: This table reports results of the analyses described in the notes for Table 3 applied to data from July 2020 to May 2021.

Table O.12: Responses of fees and orders to commission caps, alternative treatment/control groups

(a) Two-way fixed effects

Platform	Fees	# orders
Total	-	-0.06
		(0.01)
DD	0.14	-0.03
	(0.02)	(0.01)
Uber	0.05	0.01
	(0.01)	(0.01)
GH	0.17	0.05
	(0.05)	(0.01)

(b) Callaway and Sant'Anna (2021)

Platform	Fees	# orders
Total	-	-0.05
		(0.02)
DD	0.13	-0.05
	(0.04)	(0.02)
Uber	-0.04	0.04
	(0.03)	(0.03)
GH	-0.05	0.06
	(0.10)	(0.07)

Notes: This table reports results of the analyses described in the notes for Table 3 with a treatment group composed of all ZIPs with any commission cap and a control group composed of all remaining ZIPs.

Table O.13: Responses of service fees and fixed fees to commission caps

(a) Service fee rate responses to caps

	DD	Uber	GH
Estimate	-0.04	0.06	-0.02
SE	(0.02)	(0.03)	(0.04)

(b) Fixed fee (log) responses to caps

	DD	Uber	GH
Estimate	0.09	0.19	0.05
SE	(0.03)	(0.03)	(0.07)

Notes: Table O.13a reports results of the two-way fixed effects analyses described in the notes for Table 3 but with the service fee rate as the dependent variable. 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. Table O.13b reports results of the two-way fixed effects analyses described in the notes for Table 3 but with the log of the average fixed fee as the dependent variable. I compute the average fixed fee by subtracting the average service fee from the average total fee.

Table O.14: Effects of commission caps on restaurants' platform adoption, platform-specific estimates

(a) Difference-in-differences estimates

Platform	Estimate
Total	0.099
	(0.006)
DD	0.013
	(0.003)
Uber	0.041
	(0.002)
GH	0.019
	(0.002)
PM	0.025
	(0.002)

(b) Within-metro estimates

Platform	Estimate
Total	0.207
	(0.011)
DD	0.024
	(0.004)
Uber	0.072
	(0.003)
GH	0.057
	(0.003)
PM	0.055
	(0.002)

Notes: this table reports estimates of the effects of commission caps on the share of restaurants joining each food delivery platform. I obtain these estimates using the procedures described in the notes for Table 4, but with the share of restaurants on each individual platform in the "Platform" column as the outcome variable.

Table O.15: Effects of commission caps on restaurants' platform adoption, continuous treatment

(a) Difference-in-differences estimates

Share online	# platforms joined
-0.058	-0.114
(0.011)	(0.024)

(b) Within-metro estimates

Share online	# platforms joined
-0.515	-1.541
(0.026)	(0.061)

Notes: see the notes for Table 4. 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.

Table O.16: Effects of commission caps on basket subtotals of platform orders

(a) Two-way fixed effects

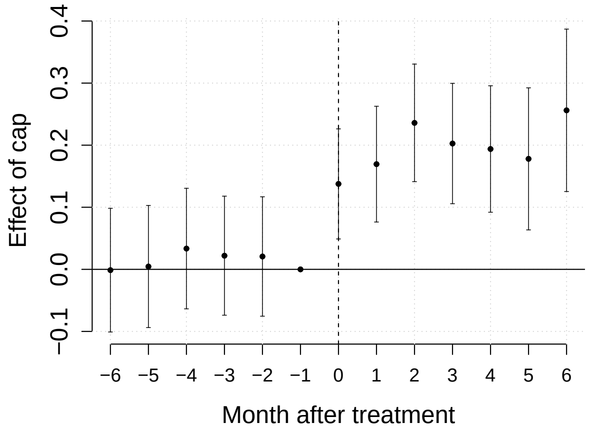
	DD	Uber	GH
Estimate	0.02	0.01	-0.00
SE	(0.01)	(0.01)	(0.01)

(b) Callaway and Sant'Anna (2021)

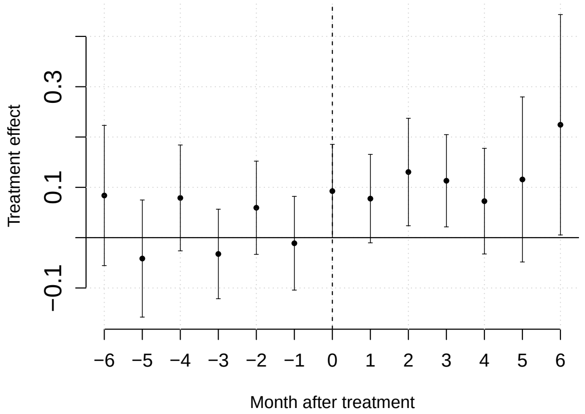
	DD	Uber	GH
Estimate	-0.03	0.03	0.01
SE	(0.02)	(0.02)	(0.06)

Notes: the table reports results for the difference-in-differences research design described in Section 3.1 of the main text, with the log of the average basket subtotal as the outcome variable. See the notes of Table O.9 for details on the implementation of the Callaway and Sant'Anna (2021) estimator.

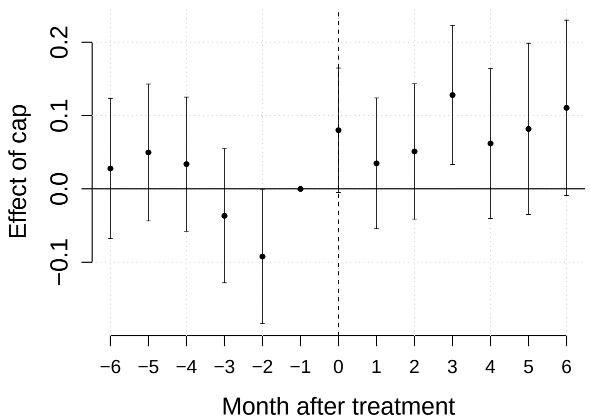
Figure O.14: Dynamic difference-in-differences estimates of commission caps' effects on platform fees



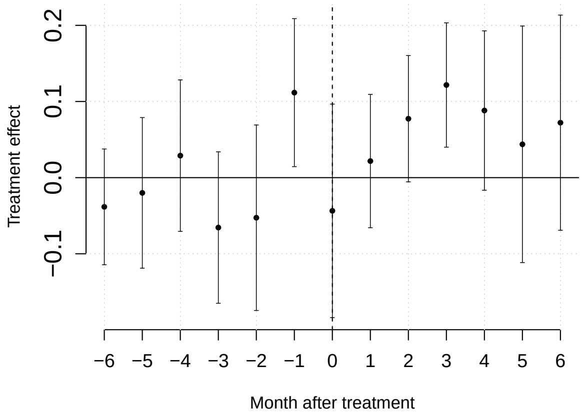
(a) DoorDash, TWFE



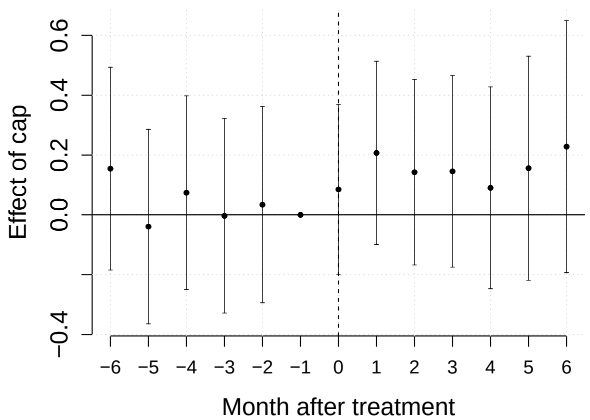
(b) DoorDash, Callaway and Sant'Anna (2021)



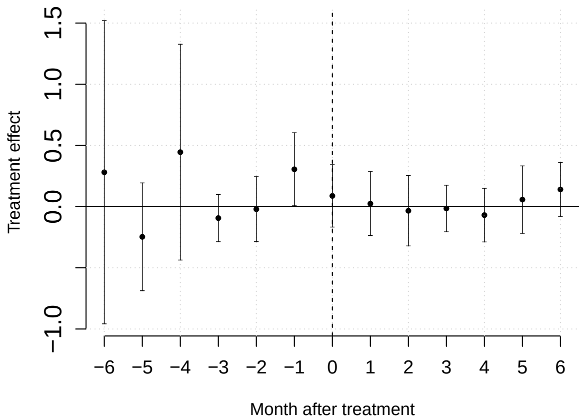
(c) Uber Eats, TWFE



(d) Uber Eats, Callaway and Sant'Anna (2021)

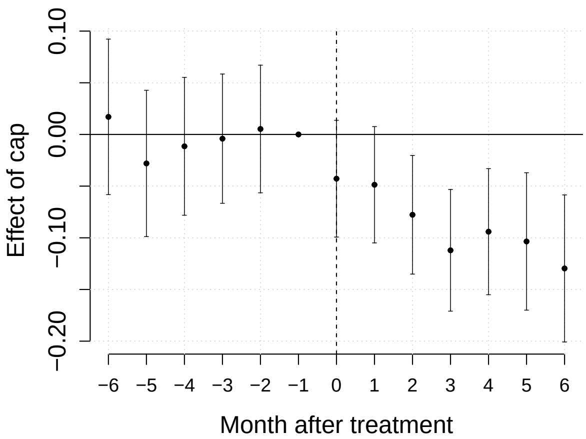


(e) Grubhub, TWFE

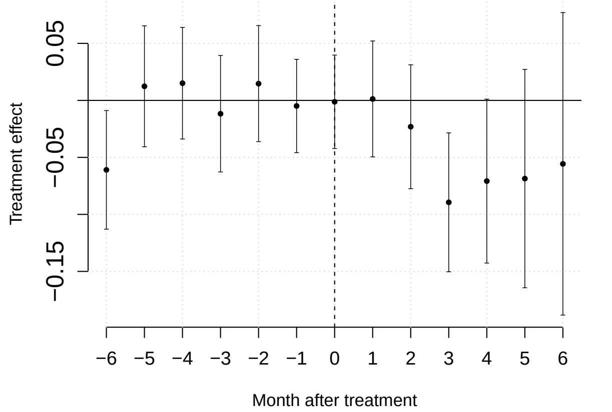


(f) Grubhub, Callaway and Sant'Anna (2021)

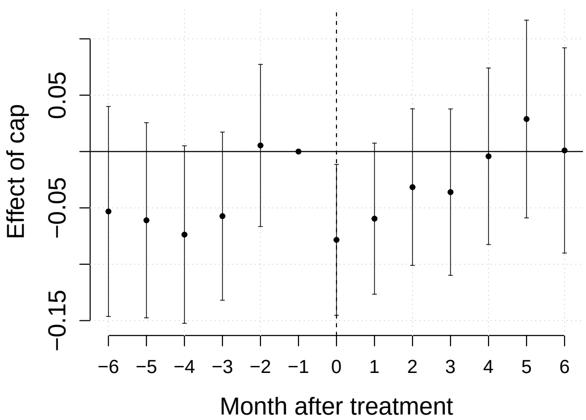
Figure O.15: Dynamic difference-in-differences estimates of commission caps' effects on platform orders



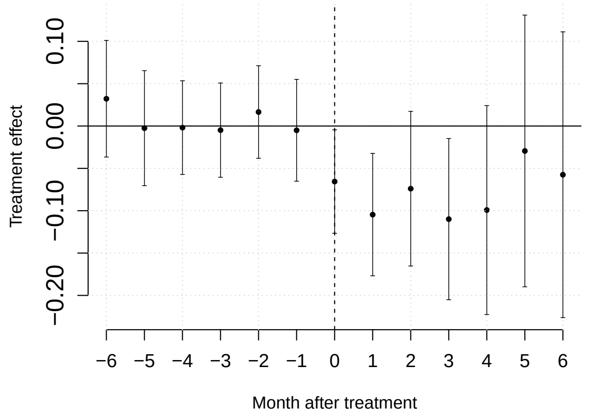
(a) DoorDash, TWFE



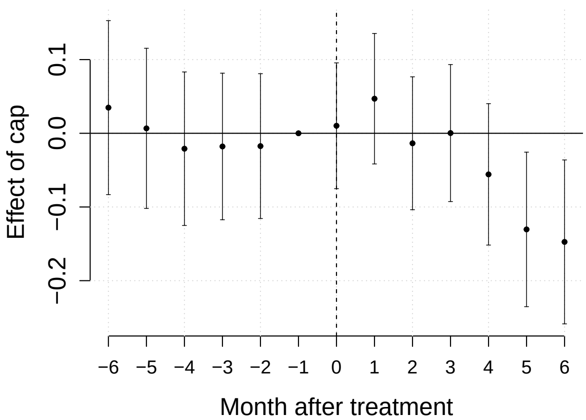
(b) DoorDash, Callaway and Sant'Anna (2021)



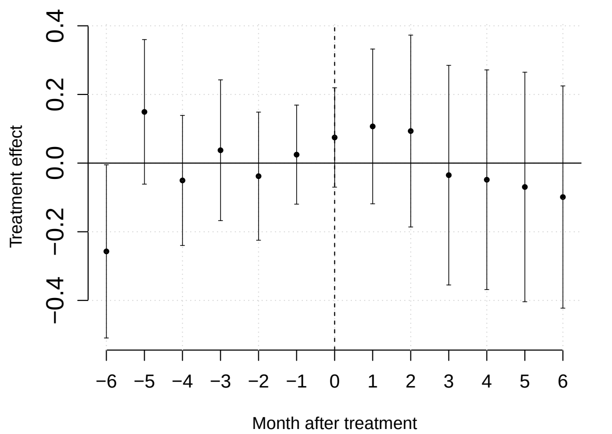
(c) Uber Eats, TWFE



(d) Uber Eats, Callaway and Sant'Anna (2021)



(e) Grubhub, TWFE



(f) Grubhub, Callaway and Sant'Anna (2021)

O.8 Restaurant heterogeneity

Table O.17: Restaurant-to-consumer network externalities (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 parameters β_{NE}, $\beta_{\text{NE}}^{\text{chain}}$, and $\beta_{\text{NE}}^{\text{non-chain}}$

$$\begin{aligned}\log \mathscr{s}_{fzt} &= \psi_{fz} + \psi_{ft} + \beta_{\text{NE}} \log J_{fzt} + \varepsilon_{fzt} \\ \log \mathscr{s}_{fzt} &= \psi_{fz} + \psi_{ft} + \beta_{\text{NE}}^{\text{chain}} \log J_{fzt}^{\text{chain}} + \beta_{\text{NE}}^{\text{non-chain}} \log J_{fzt}^{\text{non-chain}} + \varepsilon_{fzt},\end{aligned} \tag{3}$$

where $\mathscr{s}_{fzt}$ are platform f's sales in ZIP z in month t, J_{fzt} is the number of restaurants on platform f within 5 miles of ZIP z in month t, ψ_{fz} is a platform/ZIP fixed effect, ψ_{ft} is a platform/month fixed effect. Additionally, J_{fzt}^{chain} ($J_{fzt}^{\text{non-chain}}$) is the number of chain (non-chain) restaurants on platform f within 5 miles of ZIP z. 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 located within a CBSA.

Table O.18: Restaurant-to-consumer network externalities (within-metro estimates)

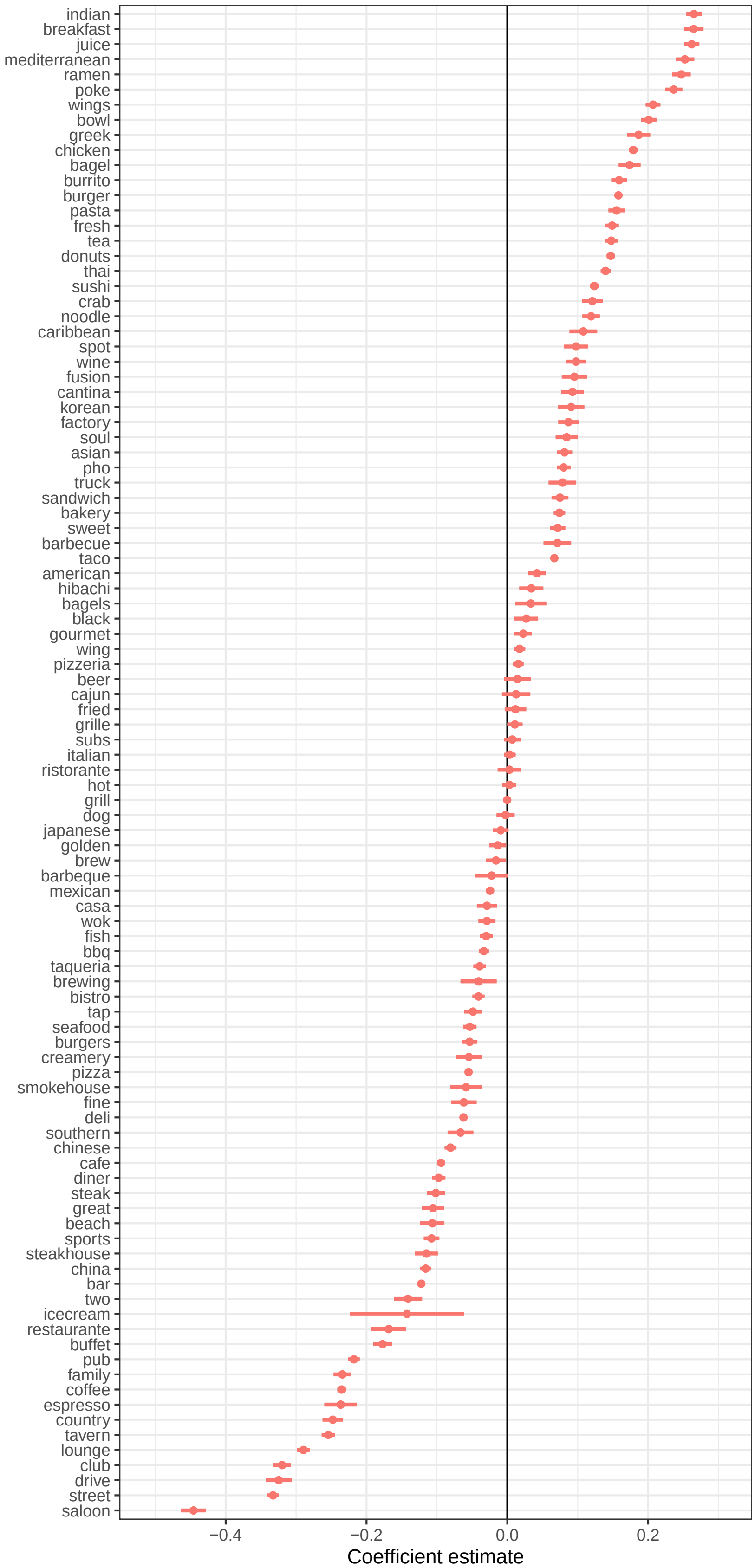
	Pooled	Separate
Log # restaurants	0.18	-
	(0.01)	-
Log # chain restaurants	-	0.12
	-	(0.03)
Log # non-chain restaurants	-	0.08
	-	(0.02)

Notes: this table reports OLS estimates of the parameters β_{NE}, $\beta_{\text{NE}}^{\text{chain}}$, and $\beta_{\text{NE}}^{\text{non-chain}}$ in the equations

$$\begin{aligned}\log \mathscr{s}_{fz} &= \psi_{fm} + \beta_{\text{NE}} \log J_{fz} + \varepsilon_{fz} \\ \log \mathscr{s}_{fz} &= \psi_{fm} + \beta_{\text{NE}}^{\text{chain}} \log J_{fz}^{\text{chain}} + \beta_{\text{NE}}^{\text{non-chain}} \log J_{fz}^{\text{non-chain}} + \varepsilon_{fz},\end{aligned} \tag{4}$$

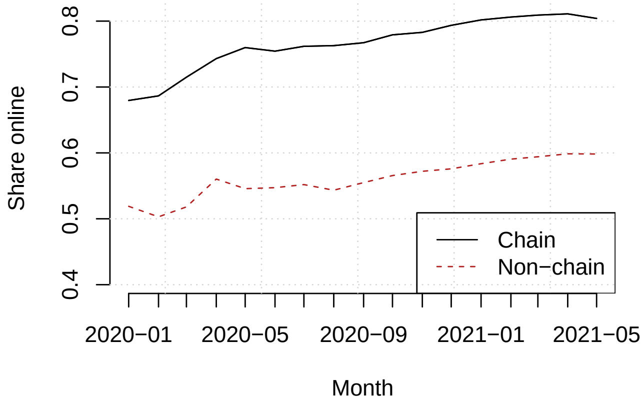
where $\mathscr{s}_{fz}$ are platform f's sales in ZIP z, J_{fz} is the number of restaurants on platform f within 5 miles of ZIP z, and ψ_{fm} is a fixed effect for platform f in the metropolitan area (CBSA) m of ZIP z. Additionally, J_{fz}^{chain} ($J_{fz}^{\text{non-chain}}$) is the number of chain (non-chain) restaurants on platform f within 5 miles of ZIP z. 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 ZIP-level data from May 2021. I include all ZIPs located within a CBSA.

Figure O.16: Heterogeneity in adoption probability by restaurant characteristics



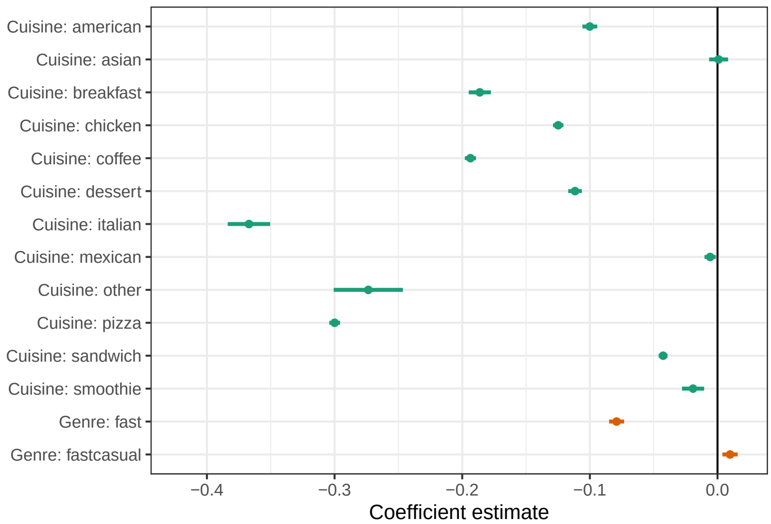
Note: this plot provides estimated coefficients and their 95% confidence intervals for a regression of an indicator for whether a restaurant joined at least one online platform on restaurant characteristics. The included characteristics are (i) an indicator for whether the restaurant belonged to a chain with at least 100 locations (omitted) and (ii) indicators for whether a word appeared in the name of the restaurant. I assembled the list of words included in the regression by collecting the 100 words appearing most frequently in restaurant names, excluding words that are uninformative about the cuisine or format of the restaurant (e.g., "the", "and", "inc", "restaurant"). I estimate the regression on the universe of US restaurants in May 2021.

Figure O.17: Platform adoption over time by restaurant type



Note: this plot displays the share of chain and non-chain restaurants that belong to at least one online platform for each month from January 2020 to May 2021.

Figure O.18: Heterogeneity in platform adoption among chain restaurants



Note: this plot displays estimated coefficients and 95% confidence intervals from a regression of an indicator for whether a chain restaurant belongs to at least one online platform in May 2021 on:

(i) Indicator variables for the restaurant's cuisine type (omitted category: hamburgers), and

(ii) Indicator variables for the restaurant's genre, which is either fast food, fast casual, or casual (omitted category).

The estimation sample includes restaurants belonging to chains with at least 100 locations across the United States in 2021.

Table O.19: Heterogeneity in restaurant responses to commission caps

	Overall	Chain	Non-chain
Estimate	0.064	0.040	0.084
SE	0.004	0.007	0.004

Notes: this table provides estimates from an ordinary least squares regression of the share of restaurants in a ZIP that join at least one food delivery platform (among DoorDash, Uber Eats, Grubhub, and Postmates) on (i) an indicator for a commission cap of 15% or lower being in effect, (ii) CBSA fixed effects, and (iii) the monthly number of new COVID-19 cases in the ZIP's county. The reported estimates are of the coefficient of the commission cap indicator. I estimate the regression on data for May 2021. The "Overall" column reports estimates for all restaurants, the "Chain" column reports estimates for restaurants belonging to chains with at least 100 locations in the US in 2021, and the "Non-chain" column reports estimates for all other restaurants. The "SE" row provides asymptotic standard errors.

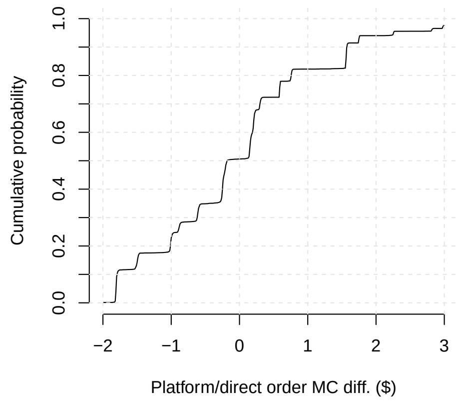
Table O.20: Platform adoption by restaurant type

	Estimate	SE
Top 10 chains	0.863	0.001
Top 11-50 chains	0.762	0.001
Other chains	0.749	0.001
Independent restaurants	0.598	0.000

Notes: this table reports estimates from an ordinary least squares regression of an indicator for whether a restaurant belongs to at least one online platform on indicators for restaurant type. The four types of restaurants considered are: (i) top 10 chains, which includes restaurants belonging to one of the top 10 chains in the United States by location count in 2021, (ii) top 11–50 chains, which includes restaurants belonging to one of the top 11–50 chains in the United States by location count in 2021, (iii) other chains, which includes all other restaurants belonging to a chain with at least 100 locations in the US in 2021, and (iv) independent restaurants, which includes all other restaurants. All restaurants in the United States in May 2021 are included in the estimation sample. No intercept is included in the regression; therefore, each estimate is the average of the outcome variable in my sample among restaurants of the indicated type. The "SE" column provides asymptotic standard errors.

O.9 Additional model estimates

Figure O.19: Difference between platform and direct-order marginal costs



Notes: this table reports the cumulative distribution function of the estimated difference $\kappa_z^{\text{platform}} - \kappa_z^{\text{direct}}$ across ZIPs.

O.10 Choice probabilities

This appendix provides expressions for choice probabilities that are omitted from the main text. I begin by introducing some notation, which is summarized by Table O.21. 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 $\Xi_i = (\zeta_i, \eta_i^\dagger)$.

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 $\mathcal{J}_z(\mathcal{G})$ denote the set of restaurants 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 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 $p_{z\mathcal{G}} = \{p_{fz\mathcal{G}}\}_{f\in\mathcal{G}}$ to denote the prices of a restaurant in ZIP z that belongs to platform subset $\mathcal{G}$.

I specify the ν_{ijt} as independent draws from a mean-zero type 1 extreme value distribution, which has the distribution function $F_{T1EV}(x) = \exp\{-\exp\{-(x+C)\}\}$, where $C \approx 0.5772$ is the Euler–Mascheroni constant. Let θ denote the model parameters, which I often suppress in the notation.

Table O.21: 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 in ZIP z with platform subset $\mathcal{G}$, then the consumer will select the platform f that maximizes $\psi_{if} - \alpha_i p_{fz\mathcal{G}}$ 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

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

and

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

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

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

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

The parameter σ_ε controls the extent of smoothing. My justification for smoothing is that 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. I suppress dependence on σ_ε throughout this section.

The consumer's probability of choosing a restaurant 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

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

For $z \notin \mathcal{Z}(z_i)$, we have $\lambda(\mathcal{G}, z \mid x_i, w_{m(i)}, \Xi_i) = 0$. 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

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

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

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

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.11 Restaurant sales

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

$$S_{jf}(\mathcal{G}_j, w_m) = \sum_{z_i \in \mathcal{Z}(j)} M_z \int \Lambda(z_i, d_i, w_m, \Xi_i) \times \mu(f \mid \mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i) \times \frac{e^{V(\mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i)}}{\sum_{\mathcal{G}} \sum_{z' \in \mathcal{Z}(z_i)} \sum_{k \in \mathcal{J}_{z'}(\mathcal{G})} e^{V(\mathcal{G}, z', z_i, d_i, w_m, \Xi_i)}} dP_z(d_i, \Xi_i). \tag{5}$$

The quantity M_z in (5) 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 (5) 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.

When all restaurants in the same ZIP z_j that belong to the same platforms $\mathcal{G}_j$ set the same prices,

$$S_{jf}(\mathcal{G}_j, w_m) = \sum_{z \in \mathcal{Z}(z_j)} M_z \int \Lambda(z_i, d_i, w_m, \Xi_i) \times \mu(f \mid \mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i) \times \frac{\lambda(\mathcal{G}_j, z_j \mid z_i, d_i, w_m, \Xi_i)}{|\mathcal{J}_{z_j}(\mathcal{G}_j)|} dP_z(d_i, \Xi_i). \tag{6}$$

Restaurant j's sales across platforms are

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

O.12 Restaurant pricing and commission pass-through

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

$$0 = (1 - r_f)S_{jf} + [(1 - r_f)p^*_{jf} - \kappa_{jf}]\frac{\partial S_{jf}}{\partial p_{jf}} + \sum_{g \neq f}[(1 - r_g)p^*_{jg} - \kappa_{jf}]\frac{\partial S_{jg}}{\partial p_{jf}}. \tag{7}$$

This yields a markup of

$$(1 - r_f)p^*_{jf} - \kappa_{jf} = a_j + b_j(1 - r_f), \tag{8}$$

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.[2] Equation (8) 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.[3]

I now provide an approximation of restaurants' markups. Consider the case in which restaurant j belongs to a single platform with a commission rate r_f. The first-order condition (14) becomes

$$p_{jf} = \frac{\kappa_j}{1 - r_f} + \frac{S_{jf}}{\left(-\frac{\partial S_{jf}}{\partial p_{jf}}\right)} \tag{9}$$

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 shorthand for $V(\mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i)$ and $dP(i)$ is shorthand 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,

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

[2]The quantities a_j and b_j are defined by

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

[3]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 (8).

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

$$\frac{\partial S_{jf}}{\partial p_{jf}} \approx -\alpha S_{jf}.$$

Therefore, the inverse semi-elasticity of demand is approximately

$$\frac{S_{jf}}{\left(-\frac{\partial S_{jf}}{\partial p_{jf}}\right)} \approx \frac{1}{\alpha}. \tag{10}$$

This fact, together with (9) and (10), suggest that

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

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

O.13 Estimation of the commission-setting model

Recall that a single-platform firm f in metro m sets its commission rate r_{fm} to maximize

$$\bar{\Lambda}_{fm}(r_m) + h_{fm} J_{fm}(r_m).$$

Manipulating the first-order condition for this problem yields

$$h_{fm} = -\left(\frac{\partial J_f}{\partial r_{fm}}\right)^{-1} \frac{\partial \bar{\Lambda}_{fm}}{\partial r_{fm}}. \tag{11}$$

I assume that Uber Eats and Postmates set their commissions to maximize their joint profits. Letting f denote Uber Eats and f' denote Postmates, the analogous expression to (11) for joint profit maximization between two platforms is

$$\begin{bmatrix} h_{fm} \\ h_{f'm} \end{bmatrix} = -\begin{bmatrix} \frac{\partial J_{fm}}{\partial r_{fm}} & \frac{\partial J_{f'm}}{\partial r_{fm}} \\ \frac{\partial J_{fm}}{\partial r_{f'm}} & \frac{\partial J_{f'm}}{\partial r_{f'm}} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial \bar{\Lambda}_f}{\partial r_{fm}} + \frac{\partial \bar{\Lambda}_{f'}}{\partial r_{fm}} \\ \frac{\partial \bar{\Lambda}_f}{\partial r_{f'm}} + \frac{\partial \bar{\Lambda}_{f'}}{\partial r_{f'm}} \end{bmatrix}.$$

I estimate the h_{fm} parameters using a plug-in estimator that I compute by substituting estimates obtained in the earlier steps of my estimation procedure into $\bar{\Lambda}_{fm}$ and J_{fm} in place of their associated true parameters.

O.14 Computation of equilibria

This appendix describes the algorithms that I use to compute equilibria of the various games constituting my model.

O.14.1 Iterative algorithm for equilibria in restaurant prices and platform fees

I now describe algorithm for computing equilibria in the stage of the model wherein restaurants set prices and platforms set consumer fees. This algorithm has two parts. The first part involves iterating on an expression derived from first-order conditions for the optimality of restaurants' prices whereas the second part involves iterating on an expression derived from first-order conditions for the optimality of platforms' consumer fees. The first part, like the algorithm expounded above, involves a learning rate $\varkappa_p \in (0, 1]$ and a tolerance $\delta_p > 0$ whose values may be selected independently of the parameter values chosen for the algorithm used to find an equilibrium in platform adoption. I use the convention $r_0 = 0$ (i.e., that the offline platform's commission rate is zero) throughout the analysis below.

Restaurant pricing. The first part of the algorithm proceeds as follows:

1. Set $p_m = \{p_{jf} : j, f \in \mathcal{G}_j\}$, where

$$p_{jf} = \frac{\kappa_j}{1 - r_f} + \frac{1}{\alpha}, \tag{12}$$

   and z is taken to be the ZIP in which j is located.

2. Compute

$$\hat{p}_j = \frac{1}{1 - r} \odot \left(\Delta_p^{-1}(p_m)\tilde{S}_j(p_m) + \kappa_j \right), \tag{13}$$

   where Δ_p and $\tilde{S}_j$ are defined by (15), which follows the description of the algorithm. The vector $\hat{p}_j$ is a vector with $|\mathcal{G}_j|$ components. I abuse notation by using $1/(1 - r)$ to denote a $|\mathcal{G}_j|$-vector with components $1/(1 - r_f)$ for platforms $f \in \mathcal{G}_j$. The $\odot$ operator denotes component-wise multiplication. Similarly, κ_j is a $|\mathcal{G}_j|$-vector with components c_{jf} for platforms $f \in \mathcal{G}_j$ Set $\tilde{p}_{jf} = \varkappa\hat{p}_{jf} + (1 - \varkappa)p_{jf}$.

3. Compute

$$d = \sqrt{\frac{1}{J_m} \sum_j \frac{1}{|\mathcal{G}_j|} \sum_{f \in \mathcal{G}_j} (\tilde{p}_{jf} - p_{jf})^2},$$

   where J_m is the number of restaurants in market m. If $d < \delta$, terminate the algorithm and accept $\tilde{p}$ as an equilibrium in restaurants' prices. Otherwise, set $p_m = \tilde{p}_m$ and return to step 2.

The expressions (12) and (13) warrant some justification. I can manipulate restaurant j's first-order condition for optimal pricing to obtain

$$p_{jf} = \frac{\kappa_j}{1 - r_f} + \frac{S_{jf}}{\left(-\frac{\partial S_{jf}}{\partial p_{jf}}\right)} + \frac{1}{1 - r_f} \sum_{g \neq f} [(1 - r_g)p_{jg} - \kappa_j] \frac{\frac{\partial S_{jg}}{\partial p_{jf}}}{-\frac{\partial S_{jf}}{\partial p_{jf}}}. \tag{14}$$

In matrix form,

$$\underbrace{\begin{bmatrix} (1 - r_{f_1})S_{jf_1} \\ (1 - r_{f_2})S_{jf_2} \\ \vdots \\ (1 - r_{f_k})S_{jf_k} \end{bmatrix}}_{=\tilde{S}_j} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial p_{jf_1}} & \frac{\partial S_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_1}} \\ \frac{\partial S_{jf_1}}{\partial p_{jf_2}} & \frac{\partial S_{jf_2}}{\partial p_{jf_d}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial p_{jf_k}} & \frac{\partial S_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{=\Delta_p} \underbrace{\begin{bmatrix} (1 - r_{f_1})p_{jf_1} - \kappa_{jf_1} \\ (1 - r_{f_2})p_{jf_2} - \kappa_{jf_2} \\ \vdots \\ (1 - r_{f_k})p_{jf_k} - \kappa_{jf_k} \end{bmatrix}}_{=b} = 0, \tag{15}$$

where $\mathcal{G}_j = \{f_1, \ldots, f_k\}$. This matrix formulation of restaurant j's first-order condition is the basis of (13). The derivatives appearing in the Δ_p matrix are straightforward to compute given the expression in (5). Indeed, the integrand in (5) has simple analytical derivatives. I compute the derivative of the integral in practice by taking the mean of analytical derivative of the integrand across simulation draws of Ξ_i and across the distribution of observables d_i in ZIP z.

The starting value (12) for prices in my iterative algorithm is justified by the approximation discussed in Appendix O.12.

Consumer fee setting. I now describe the part of the algorithm that involves iterating on an expression obtained from the first-order condition for platforms' consumer fees. This algorithm is based on the method of Morrow and Skerlos (2010) as articulated by by Conlon and Gortmaker (2020).

Note that, suppressing the z subscript and letting $\mathcal{Z}$ denote the set of ZIPs within range of z,

$$\mathscr{s}_f = \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} dP(d_i, \Xi_i),$$

when

$$\begin{aligned} \mu_{ifz'\mathcal{G}} &= \frac{e^{\tilde{\psi}_{ifz'\mathcal{G}}}}{\sum_{f' \in \mathcal{G}} e^{\tilde{\psi}_{if'z'\mathcal{G}}/\sigma_\varepsilon}} \\ \tilde{\lambda}_{iz'\mathcal{G}} &= \frac{J_{z'}(\mathcal{G}) e^{\tilde{V}_i(\mathcal{G}, z')}}{e^{-\eta_i} + \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}'} J_{z''}(\mathcal{G}) e^{\tilde{V}_i(\mathcal{G}', z'')}} \\ \tilde{\psi}_{iz'f\mathcal{G}} &= \psi_{if} - \alpha_i p_{fz'\mathcal{G}} \\ \tilde{V}_i(\mathcal{G}, z') &= \sigma_\varepsilon \log \left(\sum_{f \in \mathcal{G}} e^{\tilde{\psi}_{ifz'\mathcal{G}}/\sigma_\varepsilon} \right), \end{aligned}$$

and $J_{z'\mathcal{G}} = |\mathcal{J}_{z'}(\mathcal{G})|$ is the number of restaurants in ZIP z' that belong to platforms $\mathcal{G}$. Note also that

$$\frac{\partial \mathcal{s}_f}{\partial c_f} = \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \left[\frac{\partial \mu_{ifz'\mathcal{G}}}{\partial c_f} \lambda_{iz'\mathcal{G}} + \mu_{ifz'\mathcal{G}} \frac{\partial \lambda_{iz'\mathcal{G}}}{\partial c_f} \right] dP(d_i, \Xi_i).$$

Additionally,

$$\frac{\partial \mu_{ifz'\mathcal{G}}}{\partial c_f} = -\frac{\alpha_i}{\sigma_\varepsilon} \mu_{ifz'\mathcal{G}} (1 - \mu_{ifz'\mathcal{G}}).$$

The limit of this derivative as $\sigma_\varepsilon \downarrow 0$ is zero when $\tilde{\psi}_{ifz'\mathcal{G}} \neq \tilde{\psi}_{igz'\mathcal{G}}$ for any $f, g \in \mathcal{G}$ such that $g \neq f$. When $\tilde{\psi}_{ifz'\mathcal{G}} = \max_{g \neq f} \tilde{\psi}_{igz'\mathcal{G}}$, then the limit of the derivative is $-\infty$. The derivative of the numerator of $\lambda_{z'\mathcal{G}}$ is

$$\frac{\partial}{\partial c_f} \left[J_{z'\mathcal{G}} e^{\tilde{V}_i(\mathcal{G}, z')} \right] = J_{z'\mathcal{G}} \times -\alpha_i e^{\tilde{V}_i(\mathcal{G}, z')} \mu_{ifz'\mathcal{G}}$$

The derivative of the denominator of $\lambda_{z'\mathcal{G}}$ is

$$\frac{\partial}{\partial c_f} \left[e^{-\eta_i} + \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}'} J_{z''\mathcal{G}} e^{\tilde{V}_i(\mathcal{G}', z'')} \right] = -\alpha_i \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}': f \in \mathcal{G}'} J_{z''\mathcal{G}} e^{\tilde{V}_i(\mathcal{G}', z'')} \mu_{fz''\mathcal{G}'}.$$

Let D denote the denominator of $\lambda_{z'\mathcal{G}}$ and let

$$N_{z'G} = J_{z'\mathcal{G}} e^{\tilde{V}_i(\mathcal{G}, z')}.$$

denote the numerator of $\lambda_{z'\mathcal{G}}$. The overall derivative is

$$\begin{aligned}
\frac{\partial \lambda_{z'\mathcal{G}}}{\partial c_f} &= -\alpha_i \frac{J_{z'\mathcal{G}} e^{\tilde{V}_i(\mathcal{G}, z')} \mu_{fz'\mathcal{G}} D - N_{z'\mathcal{G}} \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}': f \in \mathcal{G}'} J_{z''\mathcal{G}'} e^{\tilde{V}_i(\mathcal{G}', z'')} \mu_{fz''\mathcal{G}'}}{D^2} \\
&= -\alpha_i \frac{\mu_{fz'\mathcal{G}} N_{z'\mathcal{G}} D - N_{z'\mathcal{G}} \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}': f \in \mathcal{G}'} \mu_{fz''\mathcal{G}'} N_{z''\mathcal{G}'}}{D^2} \\
&= -\alpha_i \times \frac{N_{z'\mathcal{G}}}{D} \left(\mu_{f\mathcal{G}} - \frac{\sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}': f \in \mathcal{G}'} \mu_{fz''\mathcal{G}'} N_{z''\mathcal{G}'}}{D} \right) \\
&= -\alpha_i \times \lambda_{z'\mathcal{G}} \left(\mu_{f\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}': f \in \mathcal{G}'} \mu_{fz''\mathcal{G}'} \lambda_{z''\mathcal{G}} \right).
\end{aligned}$$

Therefore,

$$\frac{\partial \mathcal{s}_f}{\partial c_f} = -\sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \alpha_i \mu_{fz'G} \lambda_{z'\mathcal{G}} \left[\frac{1 - \mu_{fz'\mathcal{G}}}{\sigma_\varepsilon} + \left(\mu_{fz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}'} \mu_{fz''\mathcal{G}'} \lambda_{z''\mathcal{G}'} \right) \right] dP(d_i, \Xi_i).$$

Now note that the derivative of platform f's sales with respect to the fee of platform $g \neq f$ is

$$\frac{\partial \mathcal{s}_f}{\partial c_g} = \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \left[\frac{\partial \mu_{ifz'\mathcal{G}}}{\partial c_g} \lambda_{iz'\mathcal{G}} + \mu_{ifz'\mathcal{G}} \frac{\partial \lambda_{iz'G}}{\partial c_g} \right] dP(d_i, \Xi_i).$$

First,

$$\frac{\partial \mu_{ifz'\mathcal{G}}}{\partial c_g} = \frac{\alpha_i}{\sigma_\varepsilon} \mu_{ifz'\mathcal{G}} \mu_{igz'\mathcal{G}}.$$

When $g \in \mathcal{G}$,

$$\begin{aligned}
\frac{\partial \lambda_{iz'\mathcal{G}}}{\partial c_g} &= -\alpha_i \frac{J_{z'\mathcal{G}} e^{\tilde{V}_i(\mathcal{G},z')} \mu_{igz'\mathcal{G}} D - N_{z'\mathcal{G}} \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} J_{z''\mathcal{G}} e^{\tilde{V}_i(\mathcal{G}',z'')} \mu_{igz''\mathcal{G}'}}{D^2} \\
&= -\alpha_i \frac{\mu_{igz'\mathcal{G}} N_{z'\mathcal{G}} D - N_{z'\mathcal{G}} \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} N_{z''\mathcal{G}'}}{D^2} \\
&= -\alpha_i \times \frac{N_{z'\mathcal{G}}}{D} \left(\mu_{igz'\mathcal{G}} - \frac{\sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}} N_{z''\mathcal{G}'}}{D} \right) \\
&= -\alpha_i \times \lambda_{iz'\mathcal{G}} \left(\mu_{igz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{iz''\mathcal{G}'} \right).
\end{aligned}$$

For $g \notin \mathcal{G}$,

$$\begin{aligned}
\frac{\partial \lambda_{iz'\mathcal{G}}}{\partial c_g} &= \alpha_i \frac{\lambda_{iz'\mathcal{G}} \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} N_{z''\mathcal{G}'}}{D} \\
&= \alpha_i \lambda_{iz'\mathcal{G}} \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{iz''\mathcal{G}'}.
\end{aligned}$$

Under the convention that $\mu_{igz'\mathcal{G}} = 0$ for $g \notin \mathcal{G}$,

$$\frac{\partial \lambda_{iz'\mathcal{G}}}{\partial c_g} = -\alpha_i \times \lambda_{iz'\mathcal{G}} \left(\mu_{igz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{iz''\mathcal{G}'} \right).$$

It follows that

$$\begin{aligned}
\frac{\partial s_f}{\partial c_g} &= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G} : f \in \mathcal{G}} \int \left[\frac{\partial \mu_{ifz'\mathcal{G}}}{\partial c_g} \lambda_{iz'\mathcal{G}} + \frac{\partial \lambda_{iz'\mathcal{G}}}{\partial c_g} \mu_{ifz'\mathcal{G}} \right] dP(d_i, \Xi_i) \\
&= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G} : f \in \mathcal{G}} \int \left[\frac{\alpha_i}{\sigma_\varepsilon} \mu_{f\mathcal{G}} \mu_{igz'\mathcal{G}} \lambda_{z'\mathcal{G}} - \alpha_i \times \lambda_{iz'\mathcal{G}} \left(\mu_{igz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{z''\mathcal{G}'} \right) \mu_{ifz'\mathcal{G}} \right] dP(d_i, \Xi_i) \\
&= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G} : f \in \mathcal{G}} \int \alpha_i \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} \left[\frac{\mu_{igz'\mathcal{G}}}{\sigma_\varepsilon} - \left(\mu_{igz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{z''\mathcal{G}'} \right) \right] dP(d_i, \Xi_i).
\end{aligned}$$

Define

$$\Lambda_{ff} = \sum_{z'\in\mathcal{Z}} \sum_{\mathcal{G}: f\in\mathcal{G}} \int \frac{\alpha_i}{\sigma_\varepsilon} \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} dP(d_i, \Xi_i)$$

$$\tilde{\Gamma}_{fg} = \sum_{z'\in\mathcal{Z}} \sum_{\mathcal{G}: f\in\mathcal{G}} \int \frac{\alpha_i}{\sigma_\varepsilon} \mu_{ifz'\mathcal{G}} \mu_{igz'\mathcal{G}} \lambda_{iz'\mathcal{G}} dP(d_i, \Xi_i)$$

$$Q_{fg} = \sum_{z'\in\mathcal{Z}} \sum_{\mathcal{G}: f\in\mathcal{G}} \int \alpha_i \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} \times \left(\mu_{g\mathcal{G}} - \sum_{z''\in\mathcal{Z}} \sum_{\mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{iz''\mathcal{G}'} \right) dP(d_i, \Xi_i).$$

It is then apparent that

$$-\frac{\partial \jmath_f}{\partial c_g} = \Lambda_{fg} - \tilde{\Gamma}_{fg} + Q_{fg}.$$

Let $\Gamma_{fg} = \tilde{\Gamma}_{fg} - Q_{fg}$. Then,

$$-\frac{\partial \jmath}{\partial c} = \Lambda - \Gamma.$$

where $\jmath$ is a vector including $\jmath_f$ for each platform f and c is a vector including the consumer fee c_f for each platform f. The first-order condition is

$$\left(\mathcal{H} \odot \frac{\partial \jmath}{\partial c} \right) (c + r \odot p - mc) + \jmath = 0,$$

where r is a vector containing each platform's commission rate, p is a vector including the average restaurant price in ZIP z on each platform f, and mc is a vector containing each platform f's marginal cost mc_f in ZIP z. The vector $\jmath$ similarly contains each platform f's sales in z. The $\odot$ operator denotes entry/component-wise multiplication. Letting F denote the number of online platforms, $\mathcal{H}$ is a matrix of dimension $F \times F$; its (f, f') entry indicates whether f and f' have the same owner.[4] Let $\widetilde{mc} = mc - r \odot p$. Consider the equation

$$c = \widetilde{mc} + \Lambda^{-1} [\mathcal{H} \odot \Gamma] (c - \widetilde{mc}) + \Lambda^{-1} \jmath. \tag{16}$$

We can re-write it as

$$\Lambda(c - \widetilde{mc}) = [\mathcal{H} \odot \Gamma] (c - \widetilde{mc}) + \jmath$$

or

$$[\mathcal{H} \odot (\Lambda - \Gamma)] (c - \widetilde{mc}) = \jmath.$$

This is equivalent to

$$-\frac{\partial s}{\partial c}(c - \widetilde{mc}) = \jmath,$$

which is the first-order condition. Now that I have shown that (16) is a necessary condition

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

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

for equilibrium fees, I state my algorithm for finding an equilibrium in fees. The algorithm involves a tolerance parameter $\delta_c > 0$.

1. Set c_0 to an initial value.
2. Compute
$$c_1 = \widetilde{mc} + \Lambda(c_0)^{-1}\left[\mathcal{H} \odot \Gamma(c_0)\right](c_0 - \widetilde{mc}) + \Lambda(c_0)^{-1}\mathcal{s}(c_0).$$
3. Compute $D = \|c_1 - c_0\|$. If $D < \delta_c$, terminate the algorithm and accept c_1. If $D \geq \delta_c$, set $c_0 \leftarrow c_1$.

I run this algorithm separately for each ZIP z.

Combining the parts Last, I describe how I combine the two parts of the algorithm outlined above. I begin by finding a tentative equilibrium in restaurant prices p using the first part of the algorithm. I execute the consumer-fee part of the algorithm under the restaurant prices selected by the first part of the algorithm. This yields initial consumer fees. I then run the two parts of the algorithm in order repeatedly until the convergence conditions of the algorithms are simultaneously satisfied.

O.14.2 Iterative algorithm for platform adoption equilibria

I now turn my attention to the calculation of equilibria in restaurants' platform adoption game. This algorithm involves a learning rate parameter $\mathcal{r} \in (0, 1]$ 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 $\hat{P}_m = \{\hat{P}_z(\mathcal{G})\}_{z,\mathcal{G}}$ and $\hat{P}_z(\mathcal{G})$ is the share of restaurants in ZIP z that locate on platform subset $\mathcal{G}$ in the data.
2. Compute
$$\tilde{P}_z(\mathcal{G}) = \mathcal{r} \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_z(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) + (1 - \mathcal{r})P_z(\mathcal{G})$$
for all z and $\mathcal{G}$, and collect these probabilities in $\tilde{P}_m = \{\tilde{P}_z(\mathcal{G})\}_{z,\mathcal{G}}$. Note that the fixed-point condition (9) involves choice probabilities probability for each restaurant j. Given that restaurants are homogeneous within a ZIP in the model, restaurants within a ZIP have common probabilities of adopting platform subsets. There is therefore is no loss in including only one probability for each ZIP.
3. Compute $D = \sqrt{\sum_z \sum_{\mathcal{G}} (\tilde{P}_z(\mathcal{G}) - P_z(\mathcal{G}))^2}$. 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

$$\Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_z(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) \tag{17}$$

is computationally burdensome for a given P_m because this computation 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 ZIP makes it necessary only to compute these integrals for each ZIP rather than compute them separately for each restaurant in each ZIP, 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 (17) many times. I therefore use an approximation to compute (17). Recall that

$$\Pi_j(\mathcal{G}, P_m) = \underbrace{\mathbb{E}\left[\sum_{f\in\mathcal{G}}[(1-r_{fz}))p^*_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_j]S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*) \mid P_m\right]}_{:=\bar{\Pi}_j(\mathcal{G}, P_m)} - K_m(\mathcal{G}). \tag{18}$$

The expectation $\bar{\Pi}_j$ over rival restaurants' platform adoption decisions $\mathcal{J}_{m,-j}$ is the part of (18) 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.[5] Simulation is a standard way to approximate expectations, but simulation is also computationally burdensome because it requires drawing many 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 (18) for each of these draws. One of the main challenges in computing the integrand is in computing the equilibrium restaurant prices and platform fees. Because simulation is computationally expensive, I use an alternative approximation. In particular, I approximate the expectation in (17) as the value of the integrand when the number of restaurants in z that select $\mathcal{G}$ is equal to the overall number of restaurants in z times $P_z(\mathcal{G})$. Note that the numbers of rival restaurants that choose each platform subset as computed in this fashion need not be integers. The expression (6) 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 restaurants $|\mathcal{J}_z(\mathcal{G})|$ on a platform subset $\mathcal{G}$ within range of ZIP z is not an integer. I use (6) to compute the S_{jf} term appearing in the integrand of the expectation in (18) in my approximation procedure.

[5]Consider a ZIP 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

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

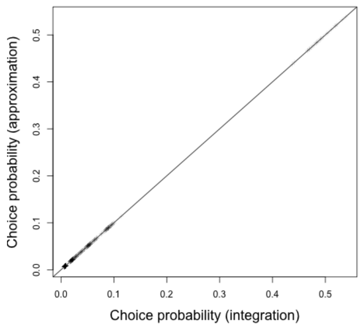
When $J = 100$ and $G = 16$ (as in my study),

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

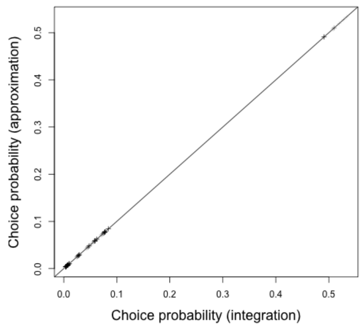
The approximation procedure that I use for computing the right-hand side of (17) in finding platform adoption equilibria has little approximation error. A regression of profits $\bar{\Pi}_j(\mathcal{G}, P_m)$ as computed using the approximation on those computing without using the approximation (and instead using simulation with 50 draws of $\mathcal{J}_{m,-j}$ from P_m) yields a coefficient of 1.003 and an R^2 of 0.997 to three decimal places.[6] Figure O.20 displays choice probabilities from equilibria in platform adoption under observed platform fees and commissions as computed (i) using the approximation described above and (ii) without using this approximation ("integration") for each market subregion that I study in my counterfactual analyses. 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 the number of restaurants in the market is large (as in my data). 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.

[6] I run this regression at the ZIP/platform-subset level, and I set P_m to the choice probabilities that I estimate in the CCP step of my estimation of the parameters governing restaurants' fixed costs of platform adoption. In addition, I use observed platform fees and commissions to compute $\bar{\Pi}$.

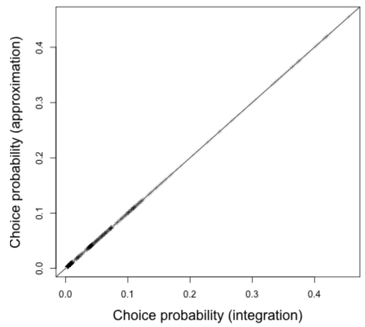
Figure O.20: Comparison of equilibrium choice probabilities from continuum approximation and integration approach



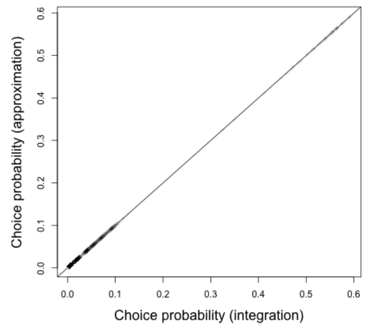
(a) Atlanta



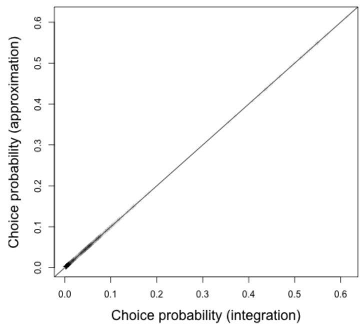
(b) Boston



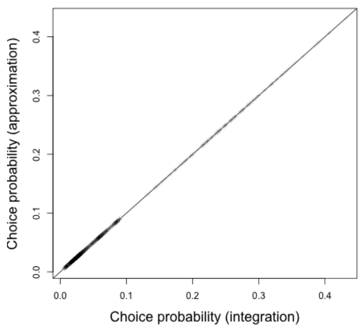
(c) Chicago



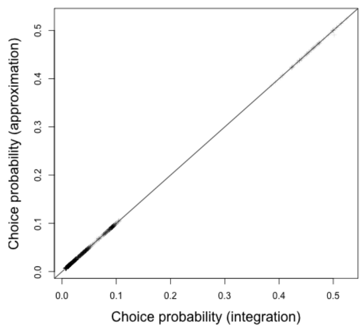
(d) Dallas



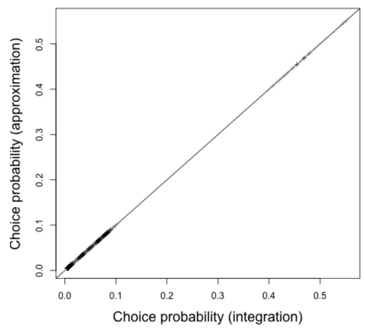
(e) Detroit



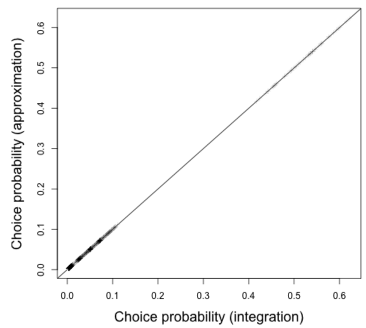
(f) Los Angeles



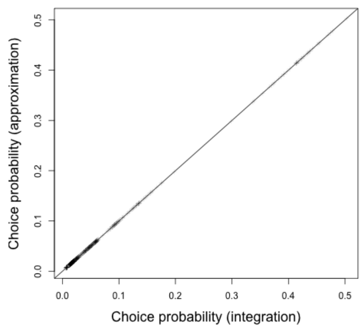
(g) Miami



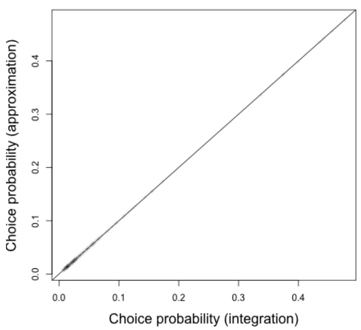
(h) New York



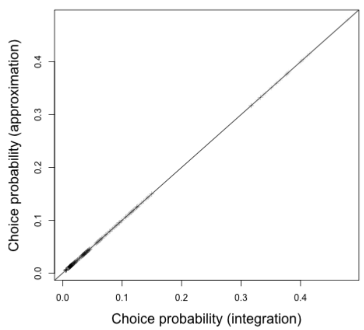
(i) Philadelphia



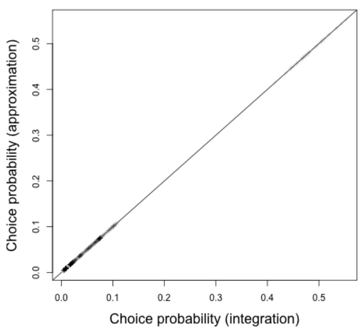
(j) Phoenix



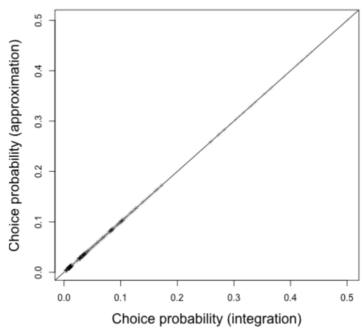
(k) Riverside



(l) San Francisco



(m) Seattle



(n) Washington

O.15 Additional results

Table O.22: Price elasticities of demand for the Chicago metro

	Quantity response for...			
Platform	DD	Uber	GH	PM
DD	-0.99	0.23	0.29	0.39
Uber	0.14	-0.96	0.20	0.28
GH	0.07	0.08	-1.26	0.13
PM	0.03	0.03	0.04	-3.05

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

$$\epsilon^c_{m,ff'} = \frac{\bar{c}_{f'm}}{\mathscr{s}_{fm}} \frac{\partial \mathscr{s}_{fm}(c_{f'm} + h)}{\partial h}\bigg|_{h=0},$$

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; $\mathscr{s}_{fm}$ are platform f's sales in m; and I have suppressed the dependence of $\mathscr{s}_{fm}$ 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.23: Network elasticities of demand for the Chicago metro

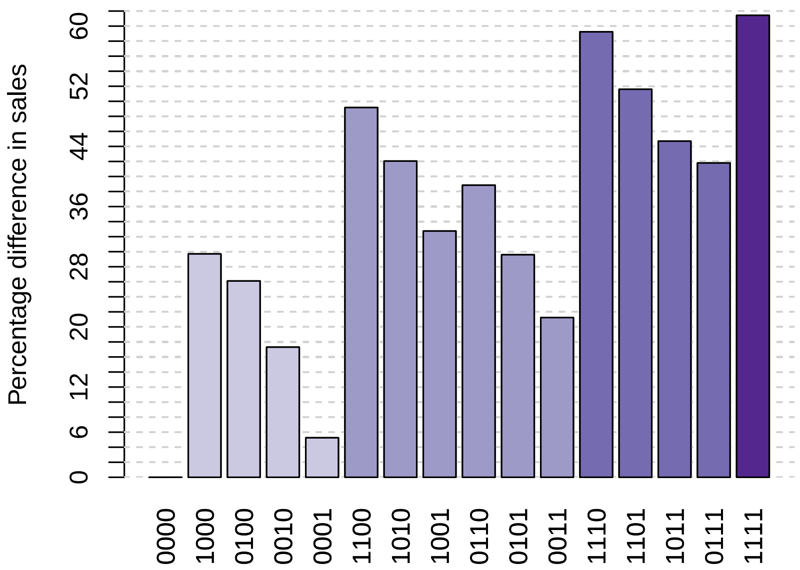
	Quantity response for...			
Platform	DD	Uber	GH	PM
DD	0.48	-0.13	-0.15	-0.16
Uber	-0.11	0.58	-0.13	-0.14
GH	-0.07	-0.08	0.74	-0.09
PM	-0.03	-0.03	-0.03	1.10

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 me to specify the nature in which I 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 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

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

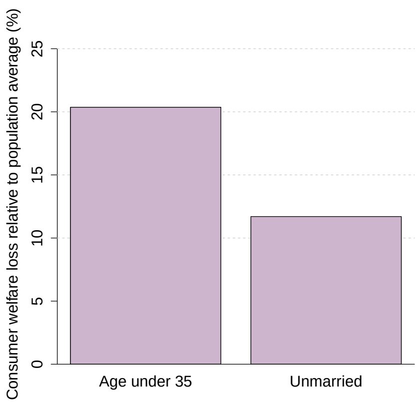
where $J_{f'm}$ and $J'_{f'm}$ are the number of restaurants on f' before and after the addition of one restaurant on f' to each ZIP, and $\mathscr{s}'_{fm}$ are f's sales after the addition of these new restaurants.

Figure O.21: Gains from platform adoption



Notes: This figure plots the average percentage difference in the sales of a restaurant that joins each platform subset relative to a restaurant in the same ZIP that joins no platform subset. The average is taken over ZIPs, with each ZIP being weighted by the number of restaurants that it contains. All ZIPs in the 14 markets studied in my primary empirical analysis are included, and the estimates are produced using my preferred estimates. Each four-digit string of ones and zeros indicates a platform set a 1 (0) in the first position indicates the presence (resp., absence) of DoorDash in the platform set. Similarly, a 1 in the second position indicates the presence of Uber Eats; a 1 in the third position indicates the presence of Grubhub; and a 1 in the fourth and final position indicates the presence of Postmates. Deeper shades indicate sets that include more platforms.

Figure O.22: Heterogeneity in consumer losses from commission caps



Notes: this table reports ratios of the mean welfare loss among consumers in various demographic groups from a 15% commission cap over the overall mean welfare loss from a 15% commission cap. The mean is taken over consumers across the 14 markets that I analyze.

Table O.24: Market-level welfare effects of eliminating delivery platforms (dollars per capita, annual)

Market	Change in Consumer surplus	Change in Restaurant profits	Change in Platform variable profits	Total welfare Lower	Total welfare Upper
Atlanta	-54.37	17.86	-47.73	-84.25	-36.52
Boston	-42.50	18.48	-38.58	-62.60	-24.02
Chicago	-74.95	20.09	-64.58	-119.45	-54.86
Dallas	-52.94	20.81	-46.48	-78.60	-32.13
Detroit	-29.80	8.20	-29.12	-50.72	-21.60
Los Angeles	-77.69	6.60	-66.53	-137.62	-71.10
Miami	-53.49	14.39	-46.66	-85.77	-39.10
New York	-97.23	34.62	-82.91	-145.51	-62.61
Philadelphia	-68.37	29.48	-57.45	-96.34	-38.90
Phoenix	-40.26	7.00	-34.52	-67.78	-33.26
Riverside	-42.59	6.52	-35.62	-71.69	-36.07
San Francisco	-103.04	18.86	-94.26	-178.44	-84.17
Seattle	-48.98	14.89	-40.35	-74.45	-34.09
Washington	-101.49	29.13	-91.52	-163.88	-72.36

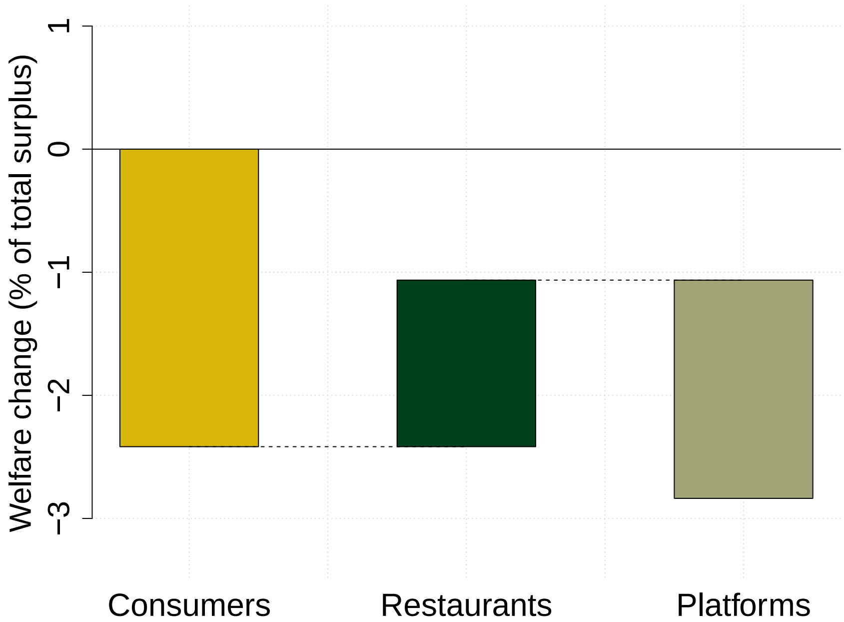
Notes: all welfare figures are transformed to annualized dollars per capita by dividing total welfare changes for April 2021 by markets' populations as estimated by the 2019 American Community Survey and multiplying these monthly per capita amounts by 12.

Table O.25: Market-level welfare effects of 15% commission cap (dollars per capita, annual)

Market	Change in Consumer welfare (fees only)	Change in Consumer welfare (total)	Change in Restaurant profits	Change in Platform profits	Total welfare
Atlanta	-3.78	-2.60	0.86	-1.89	-3.63
Boston	-2.61	-1.63	0.03	-1.31	-2.91
Chicago	-4.45	-2.55	1.92	-1.84	-2.47
Dallas	-3.71	-2.15	0.40	-1.52	-3.27
Detroit	-2.04	-1.11	0.48	-0.87	-1.51
Los Angeles	-4.84	-3.20	3.17	-2.45	-2.48
Miami	-3.85	-2.62	0.98	-1.91	-3.55
New York	-5.97	-3.58	0.79	-2.62	-5.41
Philadelphia	-4.50	-2.33	0.51	-1.46	-3.29
Phoenix	-2.68	-1.86	1.24	-1.33	-1.94
Riverside	-3.09	-1.98	1.48	-1.39	-1.90
San Francisco	-5.90	-3.71	3.03	-2.87	-3.54
Seattle	-3.02	-2.05	0.61	-1.50	-2.94
Washington	-5.65	-2.94	2.55	-2.31	-2.70

Notes: all welfare and profit figures are transformed to annualized dollars per capita by dividing total welfare changes for April 2021 by markets' populations as estimated by the 2019 American Community Survey and multiplying these monthly per capita amounts by 12. The "(fee only)" column gives the change in dollarized expected utility relative to the baseline equilibrium from increasing prices to their levels in an equilibrium under the commission cap while holding restaurants' platform adoption probabilities fixed at their values in the baseline equilibrium. The "(Total)" column provides the dollarized difference in expected utility between equilibria under commission caps and baseline equilibria.

Figure O.23: Welfare effects of 15% commission cap relative to total surplus from platforms (zero platform fixed costs)



Notes: see the notes for Figure 5.

O.16 Multihoming and restaurant profitability

Restaurants are free to multihome across food delivery platforms. This freedom may reduce restaurant profits in two ways. First, platforms have a greater competitive pressure to lower commission rates when the restaurants that the low commissions attract are exclusive to the platform. Second, a prohibition on multihoming would directly reduce restaurant membership on delivery platforms and thereby weaken restaurants' competitive pressures to join platforms, which entails fixed adoption costs and commission charges. To assess the impact of multihoming, I compare the baseline equilibrium with one in which restaurants cannot accept orders on more than one platform. Table O.26 summarizes this comparison for Los Angeles. A ban on multihoming slightly reduces equilibrium platform commissions, and dramatically reduces restaurant uptake of platforms. Not only do restaurants join fewer platforms, but fewer restaurants join any platform whatsoever. This is because the multihoming prohibition's direct effect of removing multihoming restaurants from platforms reduces restaurants' competitive pressures to join platforms. That is, the prohibition's effects are amplified by the strategic complementarity of platform membership. Restaurant profits increase when multihoming is banned, although total welfare experiences a much larger decline.

Table O.26: Effects of multihoming prohibition

Outcome	Effect
Avg. consumer fee (\$)	0.61
Avg. commission rate (p.p.)	-1.39
Avg. platforms adopted (%)	-76.15
Shr. adopting a platform (p.p.)	-27.36
Platform orders (%)	-43.95
Restaurant profits (\$ p.c.)	5.22
Platform profits (\$ p.c.)	-28.51
Consumer welfare (\$ p.c.)	-18.46
Total welfare (\$ p.c.)	-41.75

Notes: welfare changes are reported in dollars per resident of the all changes in dollars per market resident over the age of 18 on an annual basis, which I denote by "\$ p.c." The table evaluates a multihoming prohibition in Los Angeles.

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