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

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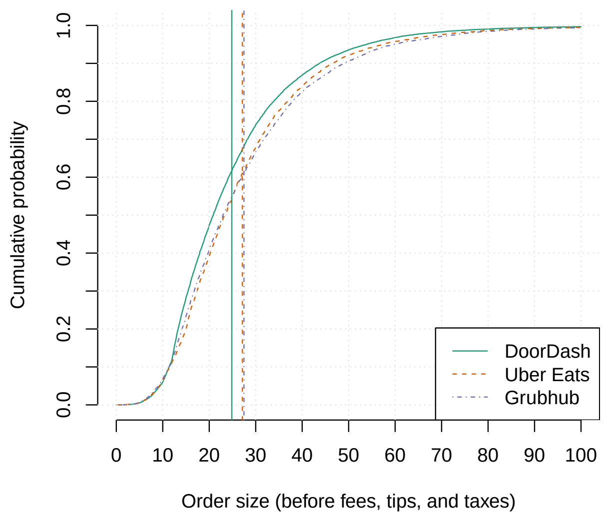
O.1 Additional description of data

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.

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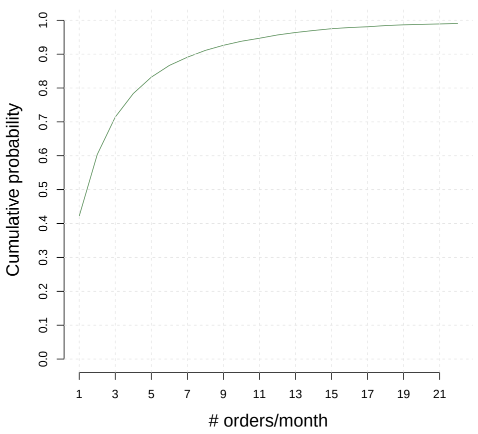
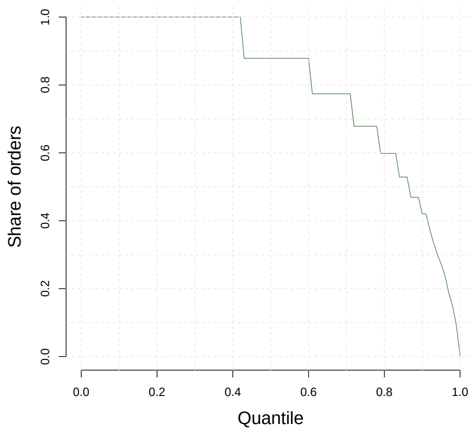
Figure O.2: Heterogeneity in monthly consumer order frequency, Q2 2021



(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?

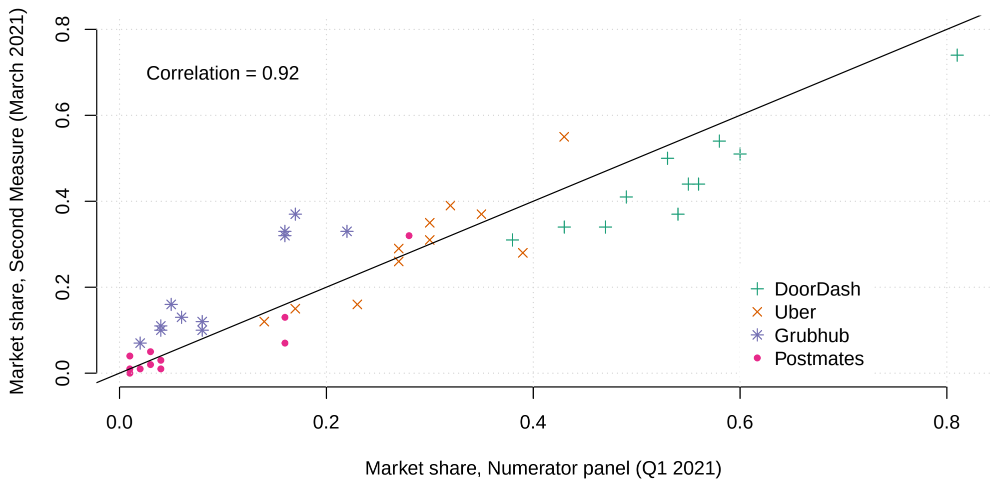
Regressor	Estimate	SE
Democrat vote share (2016 pres elxn)	0.40	0.01
Population within 5 miles (millions)	0.40	0.01
Age group share: under 20	-0.09	0.02
Age group share: 20s	-0.01	0.02
Age group share: 30s	0.00	0.03
Age group share: 40s	-0.02	0.03
Age group share: 50s	-0.02	0.03
Share with HS diploma	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).

O.2 Validation of transactions datasets

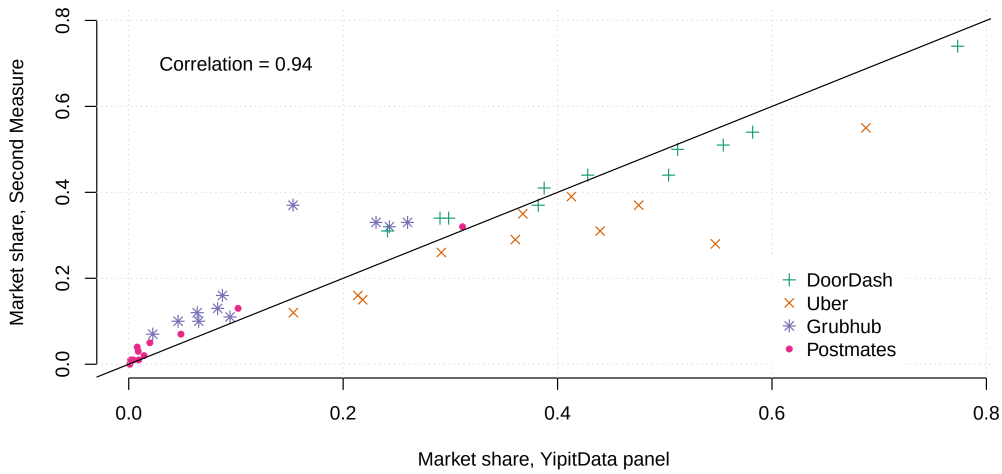
Figure O.3 compares market shares for April 2021 computed from the Numerator transactions panel to those reported by the market research firm Second Measure, which estimates platforms' market shares based on payment card records, for March 2021. Market shares are similar across these two data sources.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

Figure O.3: 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 6a. 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.4: 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.3 Delivery fee regressions

Table O.2: 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.3: Delivery fee regressions: CBSA/month fixed effects

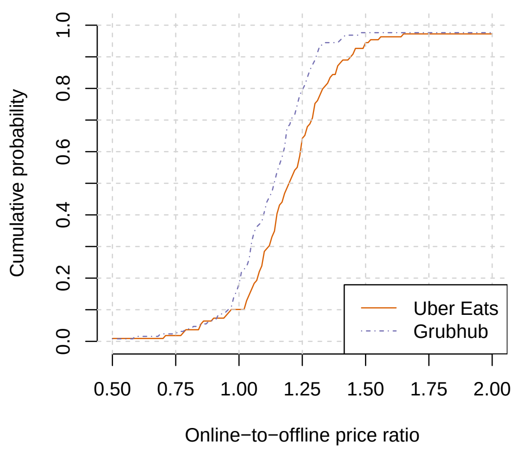
	DD	Uber	GH	PM
Distance	-0.32	0.02	0.505	0.61
	(0.03)	(0.06)	(0.002)	(0.08)
Distance 2	0.07	0.02	-0.011	-0.02
	(0.01)	(0.02)	(0.000)	(0.01)
Distance 3	-0.004	-0.002	0.000	0.000
	(0.001)	(0.002)	(0.000)	(0.000)
Distance x Population (millions)	0.28	0.08	0.240	-0.09
	(0.02)	(0.02)	(0.002)	(0.07)
Has Cap	-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.

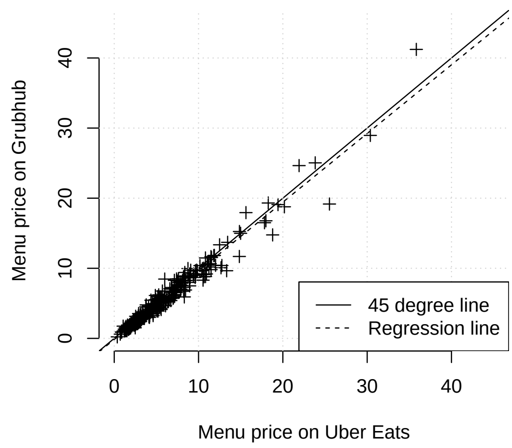
O.4 Additional analysis of restaurant prices

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.5 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.5b, 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.5: 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.5 Responses to commission caps

Table O.4: 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.5: 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 4 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.6: 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 4 applied to data from July 2020 to May 2021.

Table O.7: 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 4 with a treatment group composed of all ZIPs with any commission cap and a control group composed of all remaining ZIPs.

Table O.8: 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.8a reports results of the two-way fixed effects analyses described in the notes for Table 4 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.8b reports results of the two-way fixed effects analyses described in the notes for Table 4 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.9: 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)

Table O.10: 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 5. 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.11: Effects of commission caps on basket subtotals of platform orders

(a) Two-way fixed effects

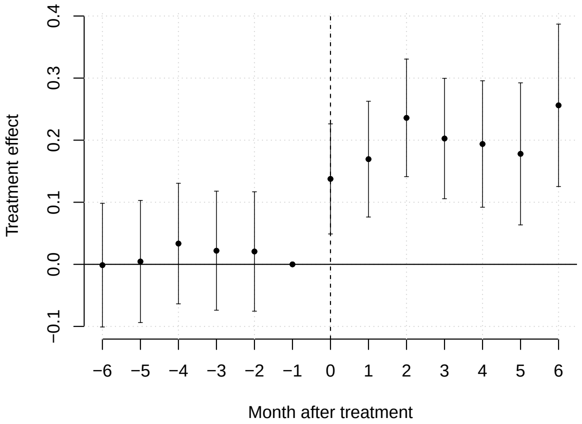
	DD	Uber	GH
Estimate	0.02	0.01	-0.00
SE	(0.01)	(0.01)	(0.01)

(b) Callaway and Sant'Anna (2021)

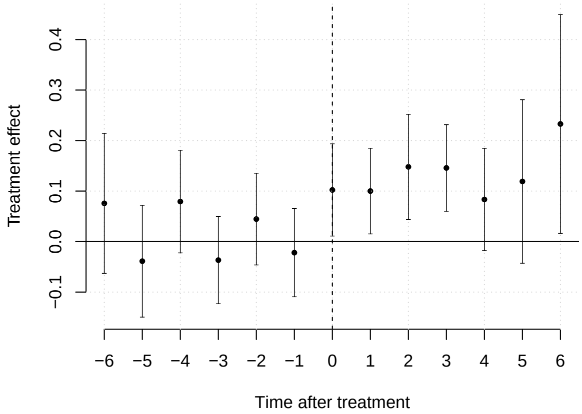
	DD	Uber	GH
Estimate	-0.03	0.03	0.01
SE	(0.02)	(0.02)	(0.06)

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.4 for details on the implementation of the Callaway and Sant'Anna (2021) estimator.

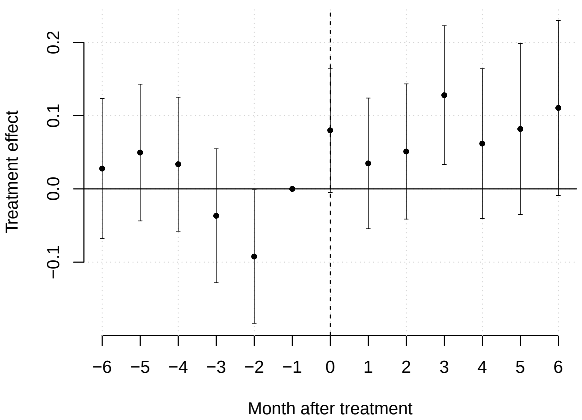
Figure O.6: Dynamic difference-in-differences estimates of commission caps' effects on platform fees



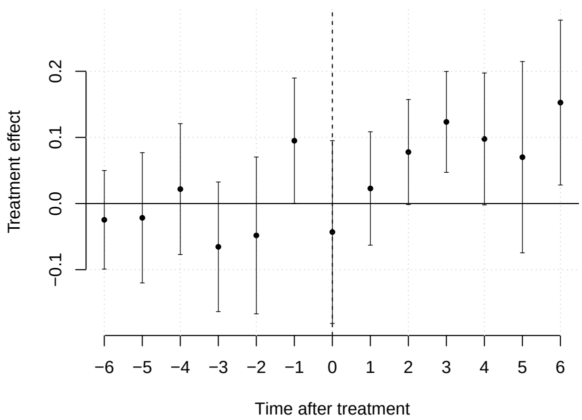
(a) DoorDash, TWFE



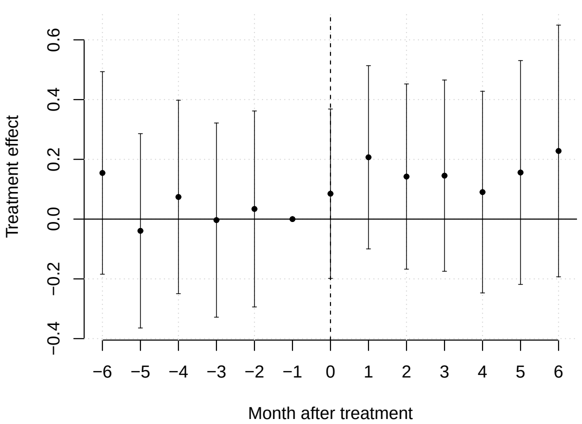
(b) DoorDash, Callaway and Sant'Anna (2021)



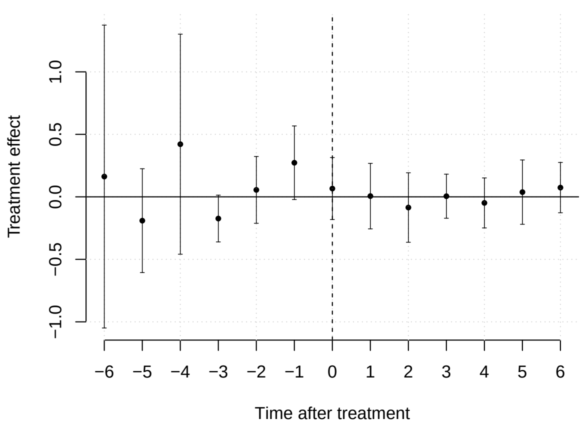
(c) Uber Eats, TWFE



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

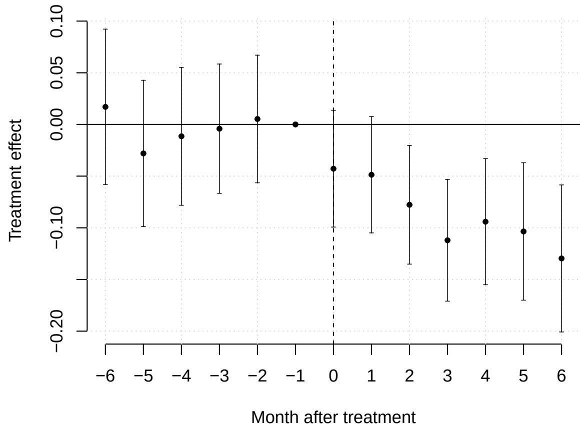


(e) Grubhub, TWFE

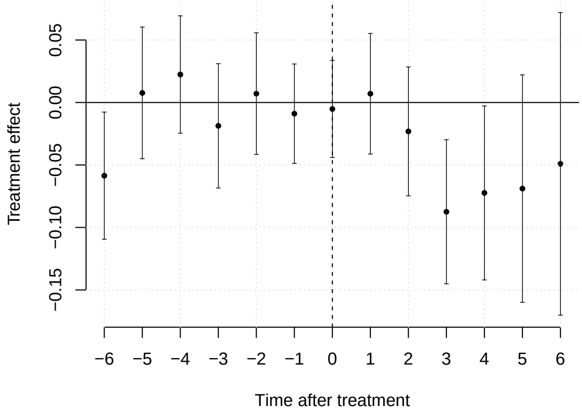


(f) Grubhub, Callaway and Sant'Anna (2021)

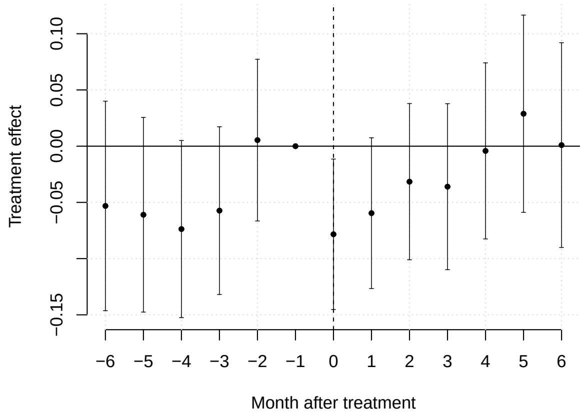
Figure O.7: Dynamic difference-in-differences estimates of commission caps' effects on platform orders



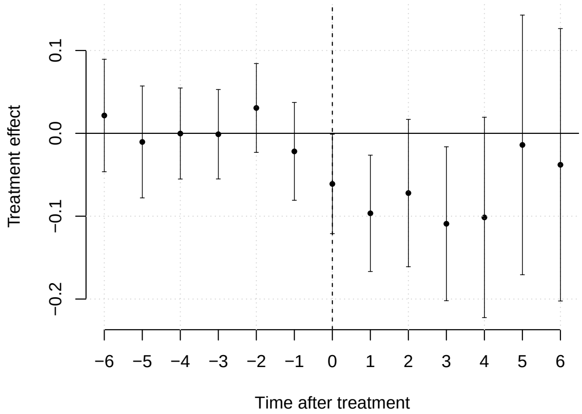
(a) DoorDash, TWFE



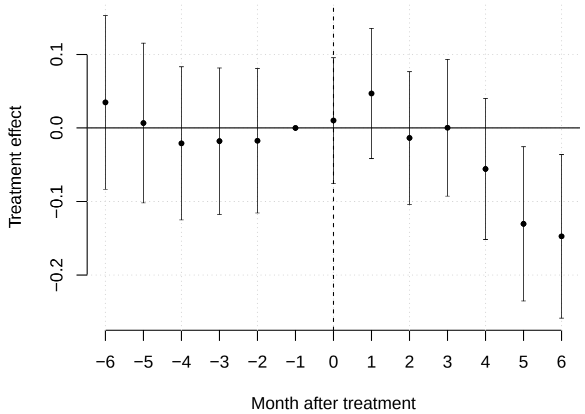
(b) DoorDash, Callaway and Sant'Anna (2021)



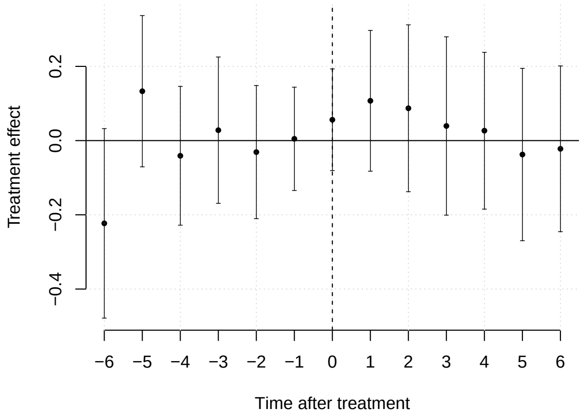
(c) Uber Eats, TWFE



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



(e) Grubhub, TWFE



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

O.6 Restaurant heterogeneity

Table O.12: 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}, $\beta_{\mathrm{NE}}^{\mathrm{chain}}$, and $\beta_{\mathrm{NE}}^{\text{non-chain}}$

$$\begin{aligned} \log \mathscr{s}_{fzt} &= \psi_{fz} + \psi_{ft} + \beta_{\mathrm{NE}} \log J_{fzt} + \varepsilon_{fzt} \\ \log \mathscr{s}_{fzt} &= \psi_{fz} + \psi_{ft} + \beta_{\mathrm{NE}}^{\mathrm{chain}} \log J_{fzt}^{\mathrm{chain}} + \beta_{\mathrm{NE}}^{\text{non-chain}} \log J_{fzt}^{\text{non-chain}} + \varepsilon_{fzt}, \end{aligned} \tag{1}$$

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 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.13: Restaurant-to-consumer network externalities (within-metro estimates)

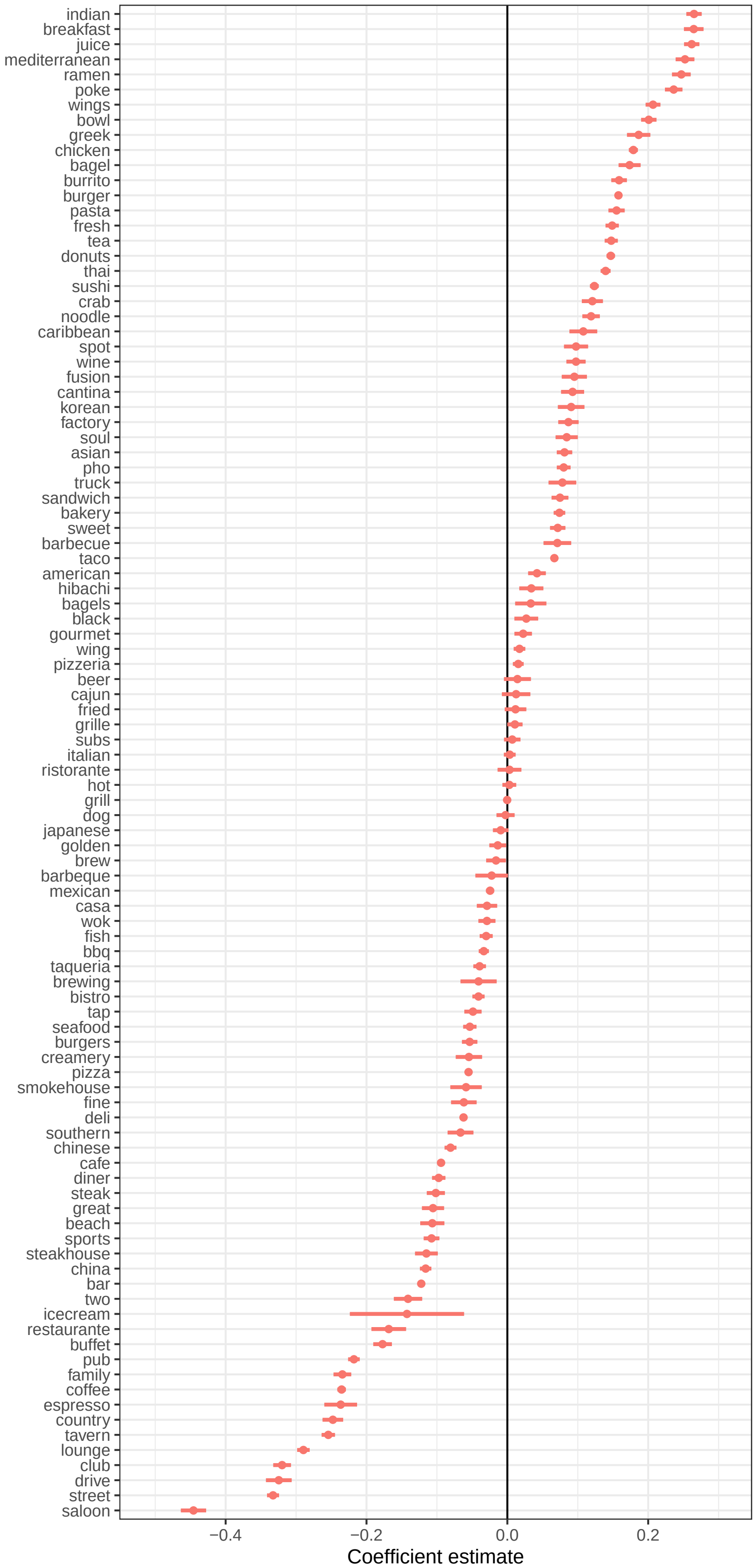
	Pooled	Separate
Log # restaurants	0.18	-
	(0.01)	-
Log # chain restaurants	-	0.12
	-	(0.03)
Log # non-chain restaurants	-	0.08
	-	(0.02)

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

$$\begin{aligned} \log \mathscr{s}_{fz} &= \psi_{fm} + \beta_{\mathrm{NE}} \log J_{fz} + \varepsilon_{fz} \\ \log \mathscr{s}_{fz} &= \psi_{fm} + \beta_{\mathrm{NE}}^{\mathrm{chain}} \log J_{fz}^{\mathrm{chain}} + \beta_{\mathrm{NE}}^{\text{non-chain}} \log J_{fz}^{\text{non-chain}} + \varepsilon_{fz}, \end{aligned} \tag{2}$$

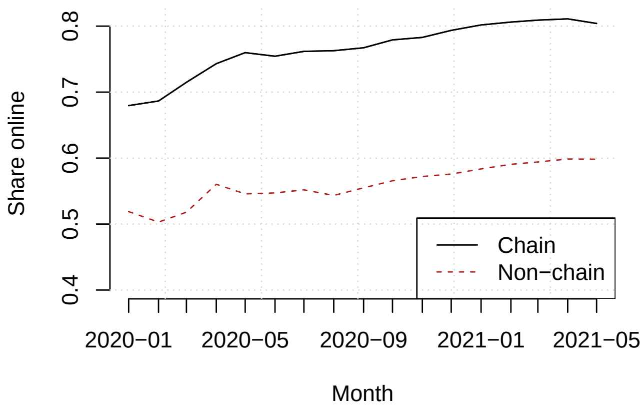
where $\mathscr{s}_{fz}$ are platform f's sales in ZIP z, J_{fz} is the number of restaurants on platform f within 5 miles of ZIP z, and ψ_{fm} is a fixed effect for platform f in the metropolitan area (CBSA) m of ZIP z. Additionally, J_{fz}^{chain} ($J_{fz}^{\text{non-chain}}$) is the number of chain (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.8: Heterogeneity in adoption probability by restaurant characteristics



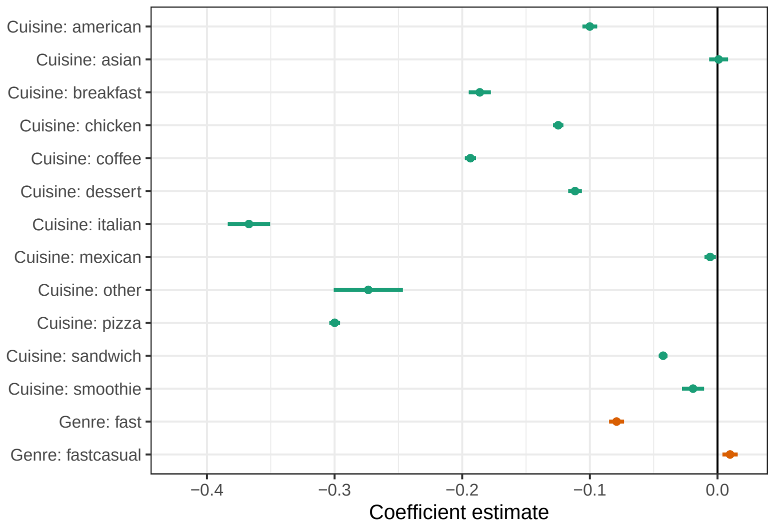
Note: this plot provides estimated coefficients and their 95% confidence intervals for a regression of an indicator for whether a restaurant joined at least one online platform on restaurant characteristics. The included characteristics are (i) an indicator for whether the restaurant belonged to a chain 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.9: 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.10: 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.14: 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.

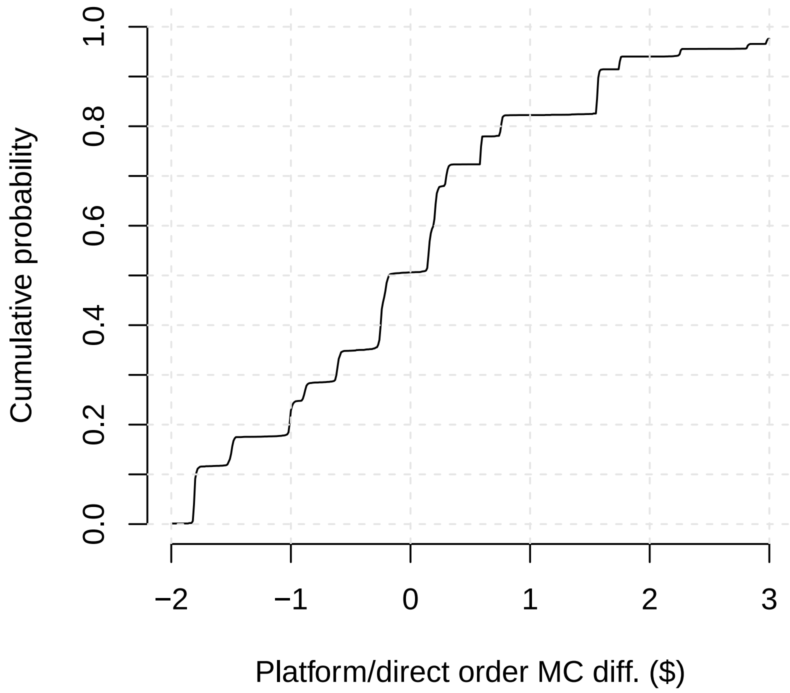
Table O.15: Platform adoption by restaurant type

	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 a within-type sample mean of the outcome variable. The "SE" column provides asymptotic standard errors.

O.7 Additional model estimates

Table O.16: Difference between platform and direct-order marginal costs



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

Table O.17: 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	ρ_m	All prices $\rho_{fz\mathcal{G}}$ for ZIPs in metro m
	p_m	All fees p_{fz} for ZIPs in metro m
	W_m	All waiting times W_{fz} for ZIPs in metro m
	$\mathcal{J}_m$	Locations & platform portfolios of restaurants in metro m
	w_m	Combined metro-level data: $\rho_m, p_m, W_m, \mathcal{J}_m$

O.8 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.17. 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 submarkets 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 portfolios 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 portfolio $\mathcal{G}$. Next, let w_m denote a sequence including all relevant metro-level observables. These include prices ρ_{jf} charged by restaurants j in ZIPs z in metro m, fees p_{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 portfolio charge the same prices. This assumption reflects my focus on symmetric pricing equilibria, and it motivates my use of the notation $\rho_{z\mathcal{G}} = \{\rho_{fz\mathcal{G}}\}_{f\in\mathcal{G}}$ to denote the prices of a restaurant in ZIP z that belongs to platform portfolio $\mathcal{G}$.

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 in what follows.

In my model, consumers simultaneously choose a restaurant and a platform. If the consumer orders from a particular restaurant j in ZIP z with platform portfolio $\mathcal{G}$, then the consumer will select the platform f that maximizes $\psi_{if} - \alpha_i \rho_{fz\mathcal{G}}$ 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

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

and

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

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

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

The parameter σ_ε controls the extent of smoothing. My justification for my smoothing procedure 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 market shares, which is computationally costly. 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 portfolio $\mathcal{G}$ conditional on their observed characteristics x_i, the characteristics of their market $w_{m(i)}$, and their unobserved tastes Ξ_i is

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

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 the product of γ and

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

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.9 Restaurant sales

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

$$S_{jf}(\mathcal{G}_j, w_m) = \sum_{z_i \in \mathcal{Z}(j)} M_z \int \Lambda(z_i, d_i, w_m, \Xi_i) \times \mu(f \mid \mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i) \times \frac{e^{V(\mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i)/\gamma}}{\sum_{\mathcal{G}} \sum_{z' \in \mathcal{Z}(z_i)} \sum_{k \in \mathcal{J}_{z'}(\mathcal{G})} e^{V(\mathcal{G}, z', z_i, d_i, w_m, \Xi_i)/\gamma}} dP_z(d_i, \Xi_i). \tag{3}$$

The quantity M_z in (3) is the number of potential orders in ZIP z (that is, the number in consumers in the ZIP times the number of potential orders per consumer T), and dP_z is the joint distribution of consumer demographics d_i and unobserved heterogeneity Ξ_i within z. Note that (3) 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 portfolio $\mathcal{G}_j$, and (iii) the consumer's probability of selecting a restaurant in z_j on platform portfolio $\mathcal{G}_j$. 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 platform portfolio $\mathcal{G}_j$ set the same prices,

$$S_{jf}(\mathcal{G}_j, w_m) = \sum_{z \in \mathcal{Z}(z_j)} M_z \int \Lambda(z_i, d_i, w_m, \Xi_i) \times \mu(f \mid \mathcal{G}_j, z_j, z_i, d_i, w_m, \Xi_i) \times \frac{\lambda(\mathcal{G}_j, z_j \mid z_i, d_i, w_m, \Xi_i)}{|\mathcal{J}_{z_j}(\mathcal{G}_j)|} dP_z(d_i, \Xi_i). \tag{4}$$

Restaurant j's sales across platforms are

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

O.10 Computation of equilibria

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

O.10.1 Iterative algorithm for platform adoption equilibria

I now turn my attention to the calculation of equilibria in restaurants' platform adoption game. Like the algorithm used to find platform pricing equilibria, my algorithm for finding platform adoption equilibria involves a learning rate parameter $\varkappa \in (0, 1]$ and a tolerance parameter $\delta > 0$; although I use the same notation for these parameters as in describing the platform pricing equilibrium algorithm, the values of these parameters need not be equal across algorithms. The algorithm for finding equilibria in restaurants' platform portfolio 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 portfolio $\mathcal{G}$ in the data.

2. Compute
$$\tilde{P}_z(\mathcal{G}) = \varkappa \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \Pi_z(\mathcal{G}', P_m, \omega_j)\right) + (1 - \varkappa) P_z(\mathcal{G})$$
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 (14) involves choice probabilities probability for each restaurant j. Given that restaurants are homogeneous within a ZIP in the specification of the model that I take to the data, restaurants within ZIP share probabilities of adopting platform portfolios. 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 portfolio choice game. Otherwise, set $P_m = \tilde{P}_m$ and return to step 2.

O.10.2 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 two algorithms expounded above, involves a learning rate $\varkappa_\rho \in (0, 1]$ and a tolerance $\delta_\rho > 0$ whose values may be selected independently of the parameter values chosen for these other two algorithms. 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 $\rho_m = \{\rho_{jf} : j, f \in \mathcal{G}_j\}$, where
$$\rho_{jf} = \frac{c_j}{1 - r_f} + \frac{\gamma}{\alpha}, \tag{5}$$
and z is taken to be the ZIP in which j is located.

2. Compute
$$\hat{\rho}_j = \frac{1}{1 - r} \odot \left(\Delta_\rho^{-1}(\rho_m) \tilde{S}_j(\rho_m) + c_j \right), \tag{6}$$
where Δ_ρ and $\tilde{S}_j$ are defined by (8), which follows the description of the algorithm. The vector $\hat{\rho}_j$ 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, c_j is a $|\mathcal{G}_j|$-vector with components c_{jf} for platforms $f \in \mathcal{G}_j$ Set $\tilde{\rho}_{jf} = \varkappa \hat{\rho}_{jf} + (1 - \varkappa)\rho_{jf}$.

3. Compute
$$d = \sqrt{\frac{1}{J_m} \sum_j \frac{1}{|\mathcal{G}_j|} \sum_{f \in \mathcal{G}_j} (\tilde{\rho}_{jf} - \rho_{jf})^2},$$
where J_m is the number of restaurants in market m. If $d < \delta$, terminate the algorithm and accept $\tilde{\rho}$ as an equilibrium in restaurants' prices. Otherwise, set $\rho_m = \tilde{\rho}_m$ and return to step 2.

The expressions (5) and (6) warrant some justification. I can manipulate restaurant j's first-order condition for optimal pricing to obtain
$$\rho_{jf} = \frac{c_j}{1 - r_f} + \frac{S_{jf}}{\left(-\frac{\partial S_{jf}}{\partial \rho_{jf}}\right)} + \frac{1}{1 - r_f} \sum_{g \neq f} [(1 - r_g)\rho_{jg} - mc_j] \frac{\frac{\partial S_{jg}}{\partial \rho_{jf}}}{-\frac{\partial S_{jf}}{\partial \rho_{jf}}}. \tag{7}$$

In matrix form,
$$\underbrace{\begin{bmatrix} (1 - r_{f_1}) S_{jf_1} \\ (1 - r_{f_2}) S_{jf_2} \\ \vdots \\ (1 - r_{f_k}) S_{jf_k} \end{bmatrix}}_{=\tilde{S}_j} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial \rho_{jf_1}} & \frac{\partial S_{jf_2}}{\partial \rho_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial \rho_{jf_1}} \\ \frac{\partial S_{jf_1}}{\partial \rho_{jf_2}} & \frac{\partial S_{jf_2}}{\partial \rho_{jf_d}} & \cdots & \frac{\partial S_{jf_k}}{\partial \rho_{jf_2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial \rho_{jf_k}} & \frac{\partial S_{jf_2}}{\partial \rho_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial \rho_{jf_k}} \end{bmatrix}}_{=\Delta_\rho} \underbrace{\begin{bmatrix} (1 - r_{f_1}) \rho_{jf_1} - c_{jf_1} \\ (1 - r_{f_2}) \rho_{jf_2} - c_{jf_2} \\ \vdots \\ (1 - r_{f_k}) \rho_{jf_k} - c_{jf_k} \end{bmatrix}}_{=b} = 0, \tag{8}$$
where $\mathcal{G}_j = \{f_1, \ldots, f_k\}$. This matrix formulation of restaurant j's first-order condition is the basis of (6). The derivatives appearing in the Δ_ρ matrix are straightforward to compute given the expression in (3). Indeed, the integrand in (3) 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.

I now justify the starting value (5) for prices in my iterative algorithm. Consider the case in which restaurant j belongs to a single platform with a commission rate r_f. The first-order condition (7) becomes

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

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

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

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

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

Therefore,

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

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

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

Therefore, the inverse semi-elasticity of demand is approximately

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

This fact, together with (9) and (10), suggest that (5) provides a reasonable initial guess for equilibrium prices ρ_{jf}.

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,

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

when

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

and $J_{z'\mathcal{G}} = |\mathcal{J}_{z'}(\mathcal{G})|$ is the number of restaurants in ZIP z' that belong to platform portfolio $\mathcal{G}$. The platform fee that enters ψ_{if} is that before ZIP z, i.e., the ZIP for which we are analyzing the platform's sales $\mathcal{s}_f$.

Note also that

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

Additionally,

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

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

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

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

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

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

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

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

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

Therefore,

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

Now note that the derivative of platform f's sales with respect to the price of platform g is

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

First,

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

Next, for $g\in\mathcal{G}$,

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

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

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

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

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

It follows that

$$\begin{aligned}
\frac{\partial \mathfrak{s}_f}{\partial p_g} &= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \left[\frac{\partial \mu_{ifz'\mathcal{G}}}{\partial p_g} \lambda_{iz'\mathcal{G}} + \frac{\partial \lambda_{iz'\mathcal{G}}}{\partial p_g} \mu_{ifz'\mathcal{G}} \right] dP(\Xi_i) \\
&= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \left[\frac{\alpha_i}{\sigma_\varepsilon} \mu_{f\mathcal{G}} \mu_{igz'\mathcal{G}} \lambda_{z'\mathcal{G}} - \frac{\alpha_i}{\gamma} \times \lambda_{iz'\mathcal{G}} \left(\mu_{igz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{z''\mathcal{G}'} \right) \mu_{ifz'\mathcal{G}} \right] dP(\Xi_i) \\
&= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \alpha_i \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} \left[\frac{\mu_{igz'\mathcal{G}}}{\sigma_\varepsilon} - \frac{1}{\gamma} \left(\mu_{igz'\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}' : g \in \mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{z''\mathcal{G}'} \right) \right] dP(\Xi_i).
\end{aligned}$$

Define

$$\begin{aligned}
\Lambda_{ff} &= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \frac{\alpha_i}{\sigma_\varepsilon} \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} dP(\Xi_i) \\
\tilde{\Gamma}_{fg} &= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \frac{\alpha_i}{\sigma_\varepsilon} \mu_{ifz'\mathcal{G}} \mu_{igz'\mathcal{G}} \lambda_{iz'\mathcal{G}} dP(\Xi_i) \\
Q_{fg} &= \sum_{z' \in \mathcal{Z}} \sum_{\mathcal{G}: f \in \mathcal{G}} \int \alpha_i \mu_{ifz'\mathcal{G}} \lambda_{iz'\mathcal{G}} \times \frac{1}{\gamma} \left(\mu_{g\mathcal{G}} - \sum_{z'' \in \mathcal{Z}} \sum_{\mathcal{G}'} \mu_{igz''\mathcal{G}'} \lambda_{iz''\mathcal{G}'} \right) dP(\Xi_i).
\end{aligned}$$

It is then apparent that

$$-\frac{\partial \mathfrak{s}_f}{\partial p_g} = \Lambda_{fg} - \tilde{\Gamma}_{fg} + Q_{fg}.$$

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

$$-\frac{\partial \mathfrak{s}}{\partial p} = \Lambda - \Gamma.$$

where $\mathfrak{s}$ is a vector including $\mathfrak{s}_f$ for each platform f and p is a vector including p_f for each platform f. The first-order condition is

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

where r is a vector containing each platform's commission rate, ρ 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 $\mathfrak{s}$ 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.[1] Let $\widetilde{mc} = mc - r \odot \rho$. Consider the equation

$$p = \widetilde{mc} + \Lambda^{-1} \left[\mathcal{H} \odot \Gamma\right] (p - \widetilde{mc}) + \Lambda^{-1} \mathcal{s}. \tag{11}$$

We can re-write it as

$$\Lambda(p - \widetilde{mc}) = \left[\mathcal{H} \odot \Gamma\right] (p - \widetilde{mc}) + \mathcal{s}$$

or

$$\left[\mathcal{H} \odot (\Lambda - \Gamma)\right] (p - \widetilde{mc}) = \mathcal{s}.$$

This is the same as

$$-\frac{\partial s}{\partial p}(p - \widetilde{mc}) = \mathcal{s},$$

which is the first-order condition. Now that I have shown that (11) is a necessary condition for equilibrium fees, I state my algorithm for finding an equilibrium in fees. The algorithm involves a tolerance parameter $\delta_c > 0$.

1. Set p_0 to an initial value.
2. Compute
$$p_1 = \widetilde{mc} + \Lambda(p_0)^{-1} \left[\mathcal{H} \odot \Gamma(p_0)\right] (p_0 - \widetilde{mc}) + \Lambda(p_0)^{-1} \mathcal{s}(p_0).$$
3. Compute $d = \|p_1 - p_0\|$. If $d < \delta_c$, terminate the algorithm and accept p_1. If $d \geq \delta_c$, set $p_0 \leftarrow p_1$.

I run this algorithm separately for each ZIP z.

O.10.3 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 ρ 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.10.4 Computing equilibria in restaurant platform adoption

Recall that probabilities of restaurants' platform portfolio choices constitute an equilibrium in the platform adoption stage game when they satisfy the following fixed point condi-

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

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

tion:

$$P_z(\mathcal{G}) = \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \Pi_z(\mathcal{G}', P_m, \omega_j)\right), \qquad \forall z, \mathcal{G}. \tag{12}$$

In practice, computing the right-hand side of (12) 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 portfolio $\mathcal{G}$ 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 (12) many times, and computing a pricing equilibrium involves finding many equilibria in platform adoption. I therefore use an approximation to compute the right-hand side of (12). Recall that

$$\Pi_j(\mathcal{G}, P_m, \omega_j) = \underbrace{\mathbb{E}_{\mathcal{J}_{m,-j}}\left[\sum_{f\in\mathcal{G}}[(1-r_{fz}))\rho^*_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}) - c_j]S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, \rho^*) \mid P_m\right]}_{:=\bar{\Pi}_j(\mathcal{G}, P_m)} - K_m(\mathcal{G}) + \omega_j(\mathcal{G}). \tag{13}$$

The expectation $\bar{\Pi}_j$ over $\mathcal{J}_{m,-j}$ is the part of (13) that is most difficult to compute. Computing the expectation exactly is prohibitive given that the number of possible configurations of rival restaurants across platform portfolios is immense under moderate counts of restaurants in a ZIP.[2] 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 computing the integrand of the expectation in (13) for each of these draws. One of the main challenges in computing the integrand is in computing the equilibrium restaurant prices ρ^*_{jf}. Because simulation is computationally expensive, I use an alternative approximation. In particular, I approximate the expectation in (12) 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 portfolio as computed in this fashion need not be integers. The expression (4) for sales made on platform f by a restaurant j located on platform portfolio $\mathcal{G}_j$, however, may be computed even when the number of restaurants $|\mathcal{J}_z(\mathcal{G})|$ on a platform portfolio $\mathcal{G}$ within range of ZIP z is not an integer. I use (4) to compute the S_{jf} term appearing in the integrand of the expectation in (13) in my approximation procedure. This integrand also features equilibrium restaurant

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

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

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

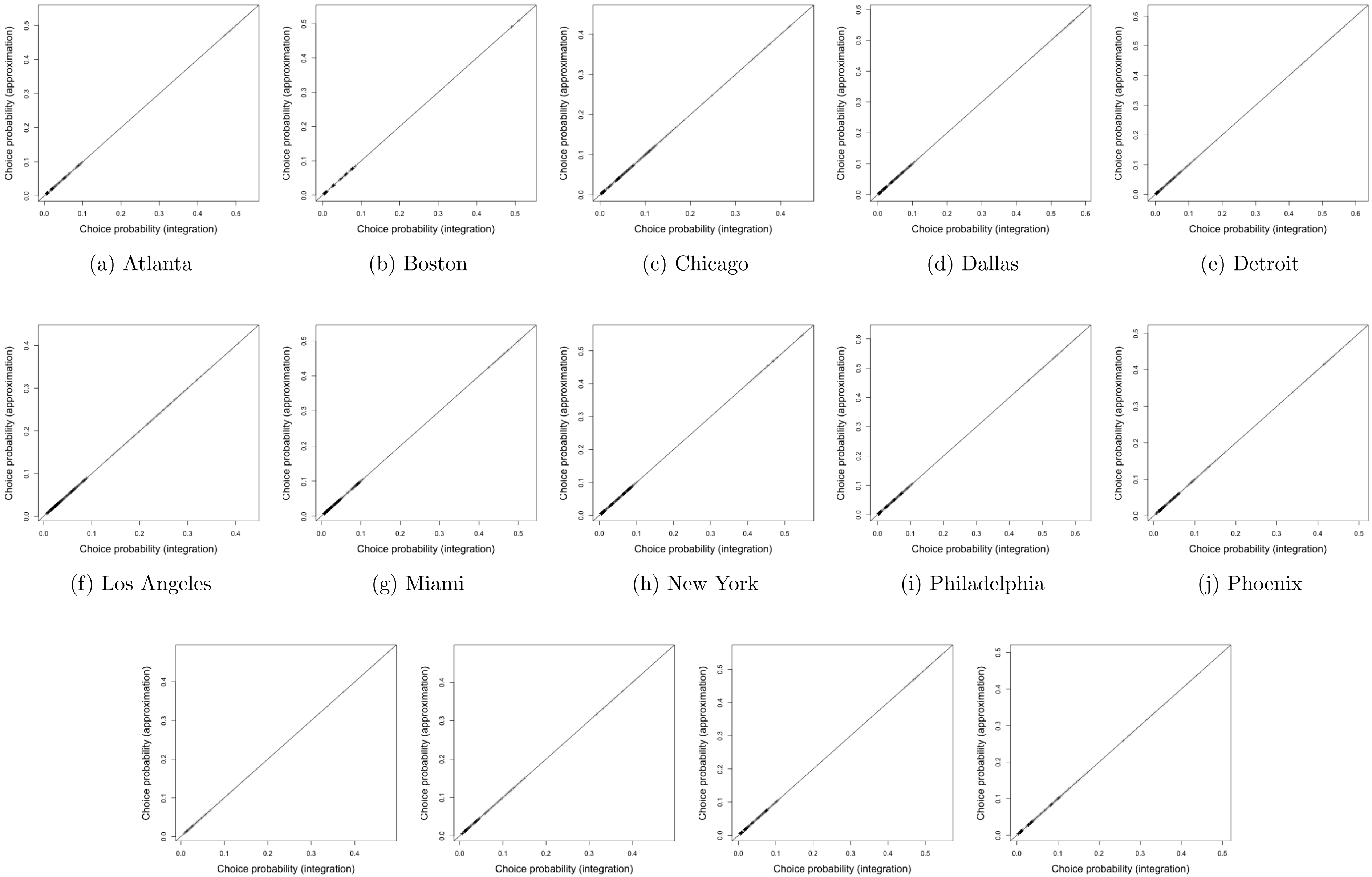
$$\binom{J+G-1}{G-1} = \binom{115}{15} > 2 \times 10^{18}.$$

prices ρ^*. I compute an equilibrium in restaurant prices following the algorithm detailed in Section O.10.2, with sales S_{jf} and derivatives of these sales computed as described earlier in this paragraph.

The approximation procedure that I use for computing the right-hand side of (12) 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.[3] Figure O.11 displays choice probabilities from equilibria in platform adoption under observed platform fees and commissions as computed (i) using the approximation described above and 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 portfolios 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.

[3]I run this regression at the ZIP/platform portfolio 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.11: Comparison of equilibrium choice probabilities from continuum approximation and integration approach



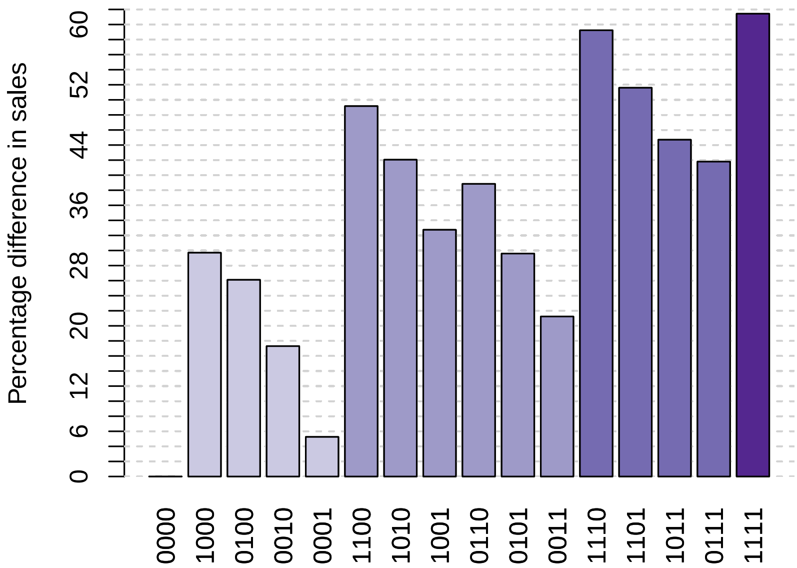
(a) Atlanta (b) Boston (c) Chicago (d) Dallas (e) Detroit

(f) Los Angeles (g) Miami (h) New York (i) Philadelphia (j) Phoenix

(k) Riverside (l) San Francisco (m) Seattle (n) Washington

O.11 Additional results

Figure O.12: Gains from platform adoption



Notes: This figure plots the average percentage difference in the sales of a restaurant that joins each platform portfolio relative to a restaurant in the same ZIP that joins no platform portfolio. 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.

Table O.18: Market-level welfare effects of eliminating delivery platforms (dollars per capita, annual)

Market	Change in Consumer surplus	Restaurant profits	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

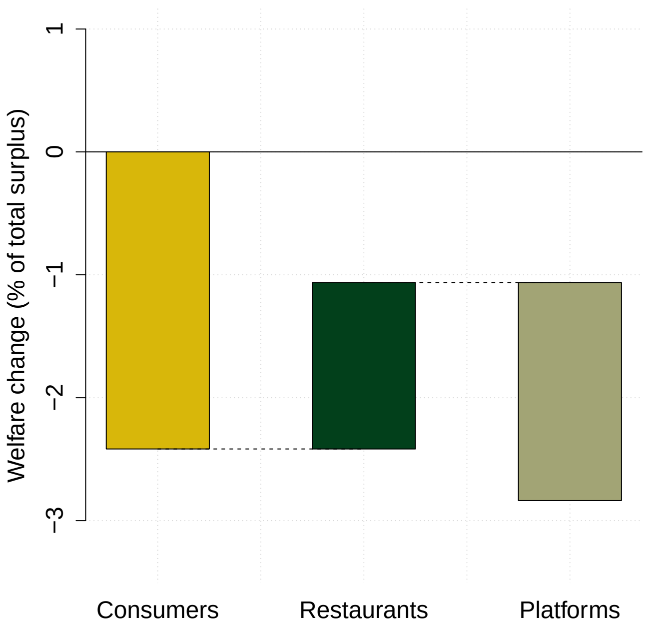
Notes: all welfare figures are transformed to annualized dollars per capita by dividing total welfare changes for April 2021 by markets' populations as estimated by the 2019 American Community Survey and multiplying these monthly per capita amounts by 12.

Table O.19: Market-level welfare effects of 15% commission cap (dollars per capita, annual)

Market	Change in Consumer welfare (fees only)	Consumer welfare (total)	Restaurant profits	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.13: Welfare effects of 15% commission cap relative to total surplus from platforms (zero platform fixed costs)



Notes: see the notes for Figure 9.

Bibliography

Callaway, Brantly, and Pedro H.C. Sant'Anna. 2021. "Difference-in-Differences with multiple time periods." *Journal of Econometrics* 225 (2): 200–230.

Conlon, Christopher, and Jeff Gortmaker. 2020. "Best practices for differentiated products demand estimation with PyBLP." *RAND Journal of Economics* 51 (4): 1109–1161.

MIT Election Data and Science Lab. 2018. "County Presidential Election Returns 2000-2020." 10.7910/DVN/VOQCHQ.

Morrow, W. Ross, and Steven J. Skerlos. 2010. "On the Existence of Bertrand-Nash Equilibrium Prices Under Logit Demand." 10.48550/ARXIV.1012.5832.

Sant'Anna, Pedro H.C., and Jun Zhao. 2020. "Doubly robust difference-in-differences estimators." *Journal of Econometrics* 219 (1): 101–122.