# Online Appendix for "Price Controls in a Multi-Sided Market"*

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## Contents



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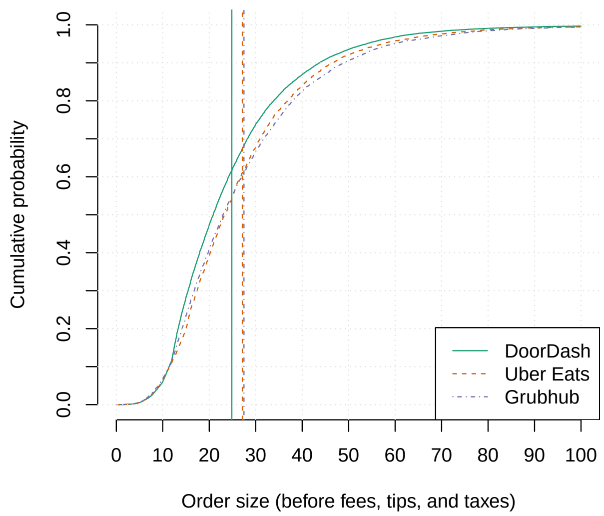
## O.1 Additional description of data

Table O.1: Observation counts for consumer panel by metro, Q2 2021

| CBSA | # consumers | # transactions |
|---|---|---|
| Atlanta-Sandy Springs-Roswell, GA | 4629 | 41775 |
| Boston-Cambridge-Newton, MA-NH | 1840 | 12399 |
| Chicago-Naperville-Elgin, IL-IN-WI | 6084 | 52415 |
| Dallas-Fort Worth-Arlington, TX | 4867 | 43101 |
| Detroit-Warren-Dearborn, MI | 2593 | 19074 |
| Los Angeles-Long Beach-Anaheim, CA | 7268 | 55500 |
| Miami-Fort Lauderdale-West Palm Beach, FL | 3860 | 30285 |
| New York-Newark-Jersey City, NY-NJ-PA | 10632 | 72803 |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 3904 | 26130 |
| Phoenix-Mesa-Scottsdale, AZ | 2827 | 22392 |
| Riverside-San Bernardino-Ontario, CA | 2779 | 20686 |
| San Francisco-Oakland-Hayward, CA | 1780 | 11074 |
| Seattle-Tacoma-Bellevue, WA | 1657 | 11225 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | 3488 | 28987 |
| Total | 58208 | 447846 |

Notes: this table reports the number of distinct panelists with at least one recorded restaurant order ("# consumers") and the total number of recorded restaurant orders ("# transactions") in the Numerator panel from April to June 2021.

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.

Table O.2: 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.3: Decomposition of delivery fee variation

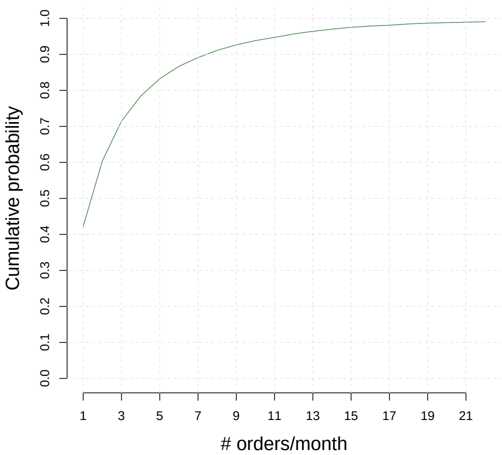
| Variance | DD | Uber | GH | PM |
|---|---|---|---|---|
| Across CBSAs | 0.36 | 0.67 | 0.51 | 1.86 |
| Across ZIPs within CBSA | 0.47 | 1.12 | 1.33 | 4.33 |
| Within ZIP | 1.89 | 5.87 | 5.72 | 2.96 |

Notes: this table reports the variance decomposition

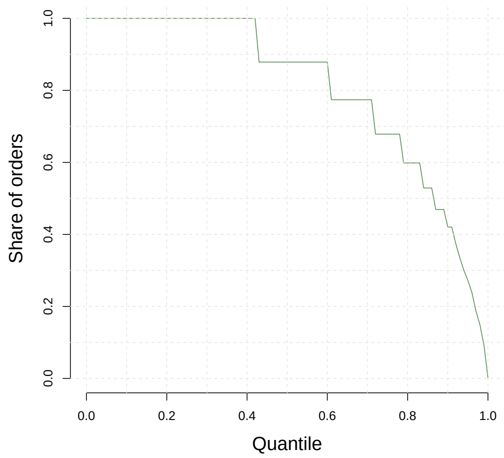
$$\mathrm{Var}(df_k) = \underbrace{\mathrm{Var}(\mathbb{E}[df_k|m])}_{\text{Across CBSAs}} + \underbrace{\mathbb{E}[\mathrm{Var}(\mathbb{E}[df_k|z]|m)]}_{\text{Across ZIPs within CBSA}} + \underbrace{\mathbb{E}[\mathrm{Var}(df_k|z)]}_{\text{Within ZIP}},$$

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.

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

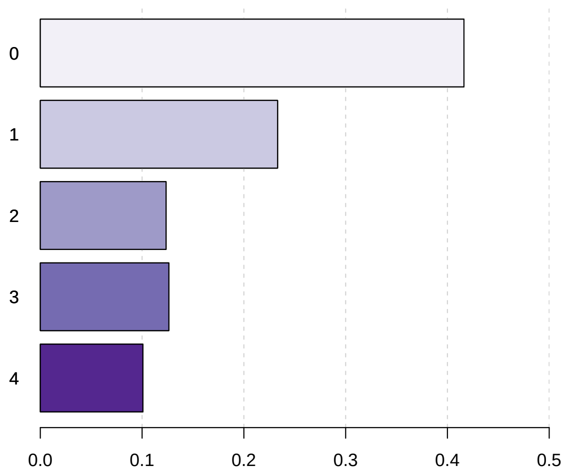
Notes: this figure describes the distribution of the monthly number of orders placed by consumers on the four major food delivery platforms. The figure describes consumer-month pairs in Q2 2021 the 14 metro areas on which I focus my analysis with at least one order on a major food delivery platform in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

Table O.4: Decomposition of average fees

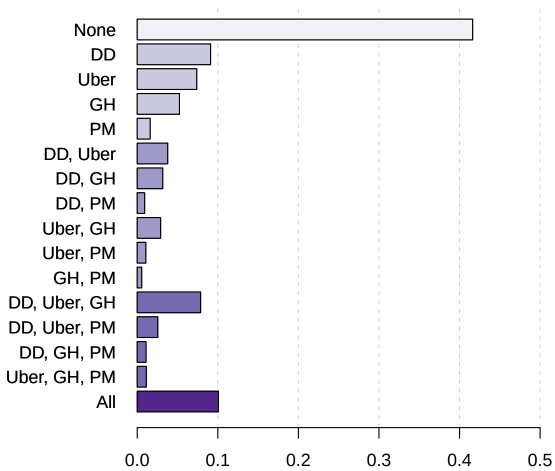
| Fee | DoorDash | Uber Eats | Grubhub | Postmates |
|---|---|---|---|---|
| Delivery | 1.87 | 1.58 | 2.91 | 3.43 |
| Service | 4.36 | 4.50 | 3.00 | 6.35 |
| Regulatory Response | 0.18 | 0.27 | 0.17 | 0.08 |

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



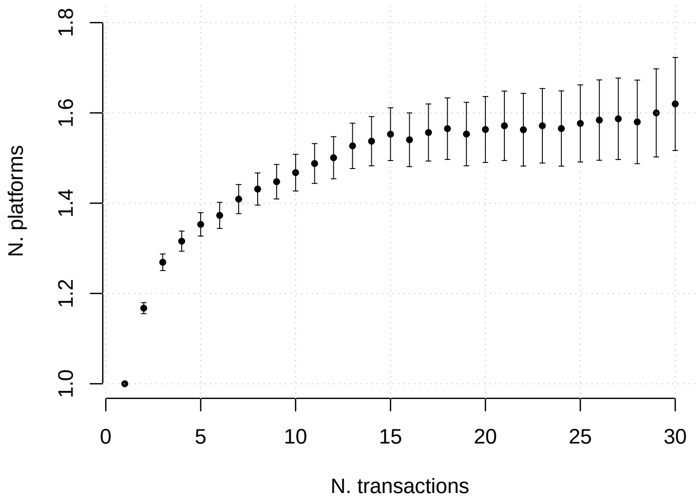
(a) Number of adopted platforms




(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 O.1 in April 2021. Deeper shades indicate sets that include more platforms.

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 $t^{\text{th}}$ 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.

Table O.5: Source of within-market fee variation

(a) Platform fixed effects

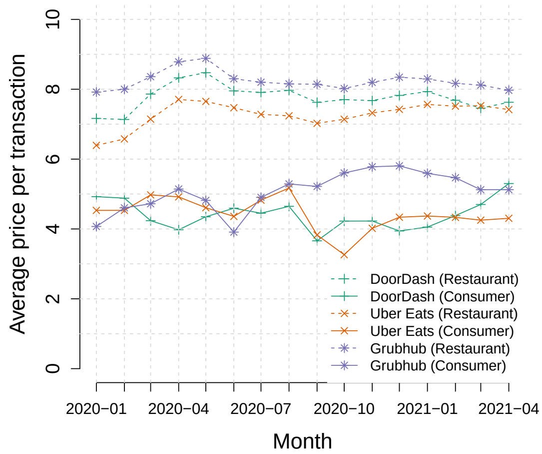
| Variable | Estimate | SE |
|---|---|---|
| Cap | 0.67 | 0.03 |
| Share age under 35 | -2.52 | 0.19 |
| Share married | -2.19 | 0.15 |
| Population density | -0.69 | 0.03 |

(b) Platform/CBSA fixed effects

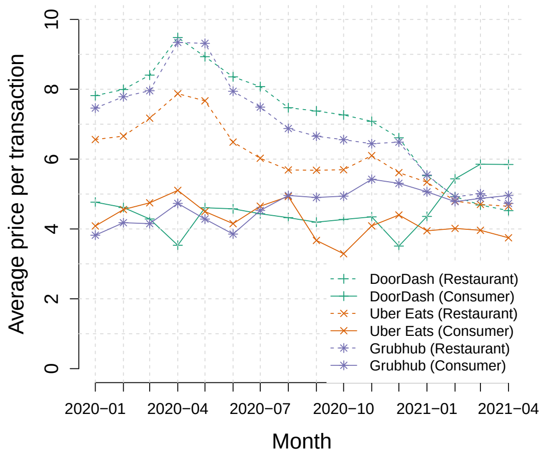
| Variable | Estimate | SE |
|---|---|---|
| Cap | 0.28 | 0.03 |
| Share age under 35 | -1.66 | 0.15 |
| Share married | -1.98 | 0.12 |
| Population density | -0.47 | 0.02 |

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.

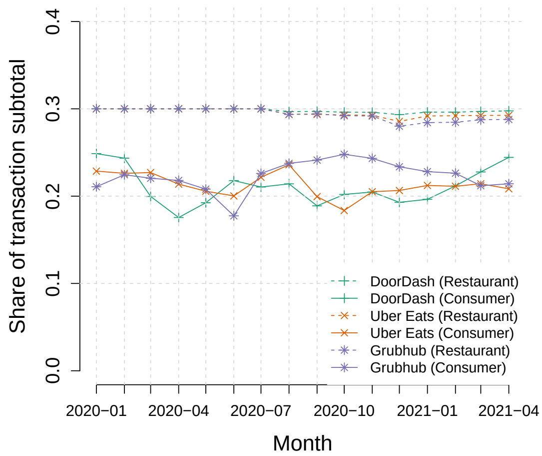
Figure O.5: Platforms' average fees and commissions in regions with and without a commission cap as of May 2021



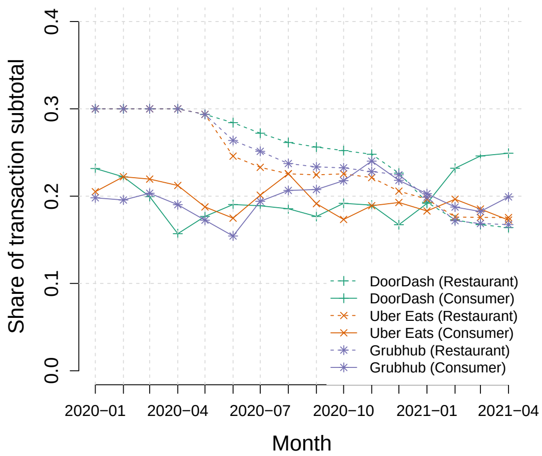

(a) Average prices per transaction: no cap




(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.

Table O.6: Multihoming in the food delivery industry, April 2021

(a) Consumers of delivery platforms

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

(b) Restaurants listed on delivery platforms

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

Notes: Table O.6a reports, for each pair of platforms $f$ and $f'$, the share of pairs of consecutive orders placed by the same consumer in April 2021 that include an order from $f'$ among those that contain an order from $f$. Table O.6b reports the share of restaurants on each major delivery platform that also belong to each other major delivery platform for April 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 Both consumers and restaurants multihome

I quantify multihoming in the food delivery industry by computing measures of consumer and restaurant multihoming. The measure of consumer multihoming for a pair of platforms $f$ and $f'$ equals the share of pairs of consecutive orders placed on any platform made by the same consumer that contain a purchase from $f$ among those that also contain a purchase from $f'$. To illustrate this measure, suppose that one consumer bought from DoorDash across two consecutive orders and a second consumer bought from DoorDash and then Uber Eats. Then, the multihoming measure for $f =$ Uber Eats and $f' =$ DoorDash among these two consumers would be one half.[1] I characterize restaurant multihoming by computing the share of restaurants listed on each platform that are also listed on each other platform. Table O.6 reports the results, which show that both consumers and restaurants multihome. Although consumers sometimes switch between platforms, they more often order from the same platform across consecutive orders. Online Appendix O.3 provides evidence that repeat ordering from platforms reflects persistent tastes for platforms rather than state dependence; this finding motivates my decision to include the former but not the latter in the model.

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

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

where $n_i$ is the number of orders that consumer $i$ placed on platforms and $s_{if}$ is the share of those orders that the consumer placed on platform $f$. Among consumers residing in the 14 markets on which my study focuses during the second quarter of 2021, $\bar{\text{HHI}}$ equals 0.86, which indicates a high degree of purity in consumers' platform-choice sequences. Additionally, Figure O.4 in the Online Appendix reports the average number of platforms from which a panelist has ordered after placing $t$ orders, for $t = 1, \ldots, 30$.

Modelling implication. The model flexibly allows for both consumer and restaurant multihoming.

### O.2.2 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 $\beta_{\text{NE}}$ of platform sales with respect to restaurant variety by OLS with the estimating equation

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

where $s_{fzt}$ 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 $\psi_{fz}$ and $\psi_{ft}$ are platform/ZIP and platform/month fixed effects, respectively. The unobservable $\varepsilon_{fzt}$ is assumed to be mean independent of $J_{fzt}$ conditional on the fixed effects $\psi_{fz}$ and $\psi_{ft}$. This assumption allows for restaurants to respond to time-invariant local demand disturbances, which are captured by $\psi_{fz}$, and to national time-varying demand disturbances, which are captured by $\psi_{ft}$. 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).

Table O.7: 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 $\beta_{\text{NE}}$ 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.

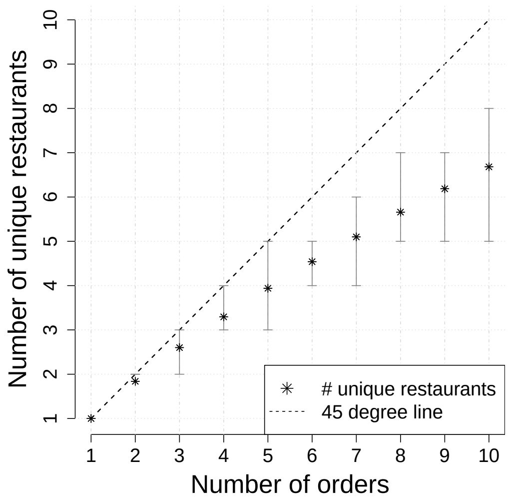
The first column of Table O.21 reports the estimate of $\beta_{\text{NE}}$, which suggests the empirical relevance of network externalities exerted by restaurants on consumers. The second column provides OLS estimates of $\beta^{\text{NE}}_{\text{chain}}$ and $\beta^{\text{NE}}_{\text{non-chain}}$ in

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

where $J^{\text{chain}}_{fzt}$ ($J^{\text{chain}}_{fzt}$) 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 consumer orders among that

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'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.

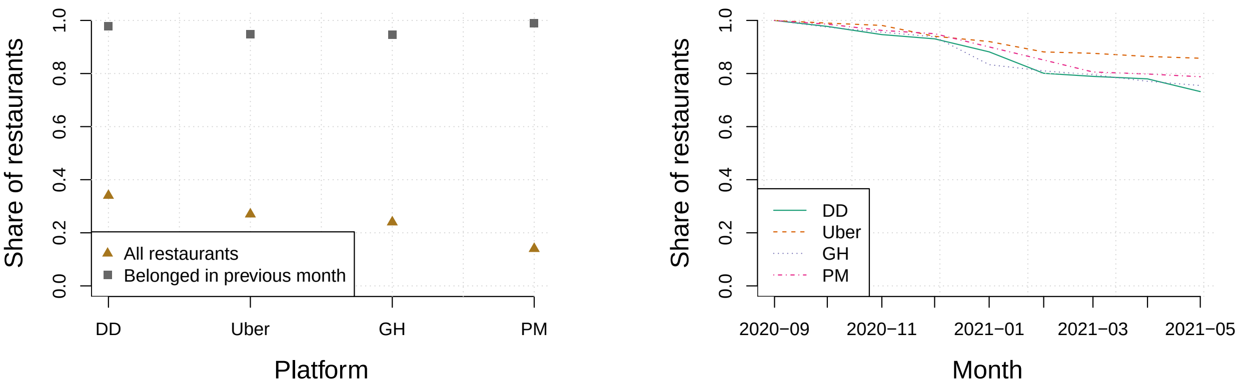
### O.2.3 Restaurants that join a platform tend to remain on the platform

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.

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.

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.2.4 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).

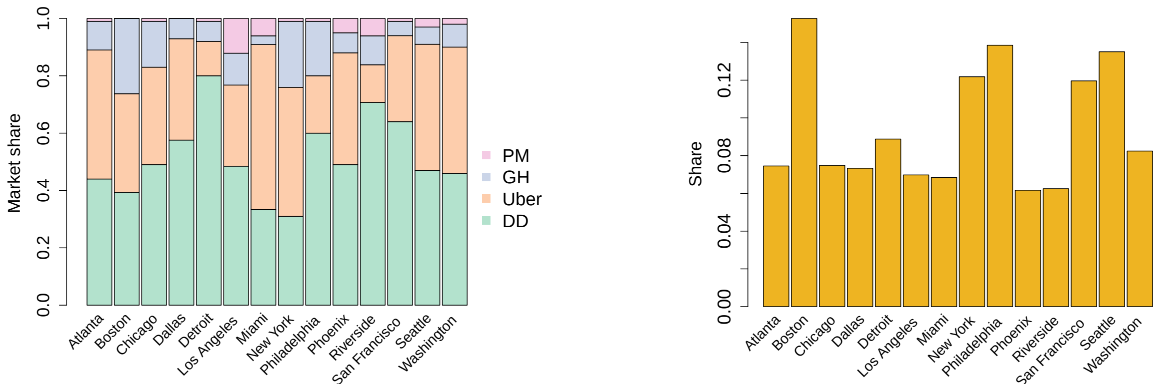
**Modelling implication.** Platform sales in my model depends on local consumer demographics, the local selection of restaurants on platforms, and local unobserved tastes for platforms.

### O.2.5 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.

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

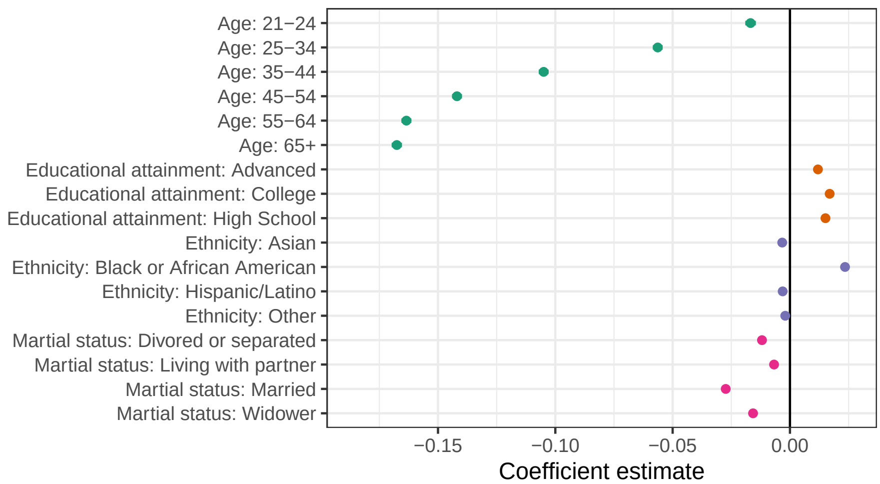
Figure O.8: Market shares, Q2 2021




(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.

Figure O.9: Demographics of food delivery users

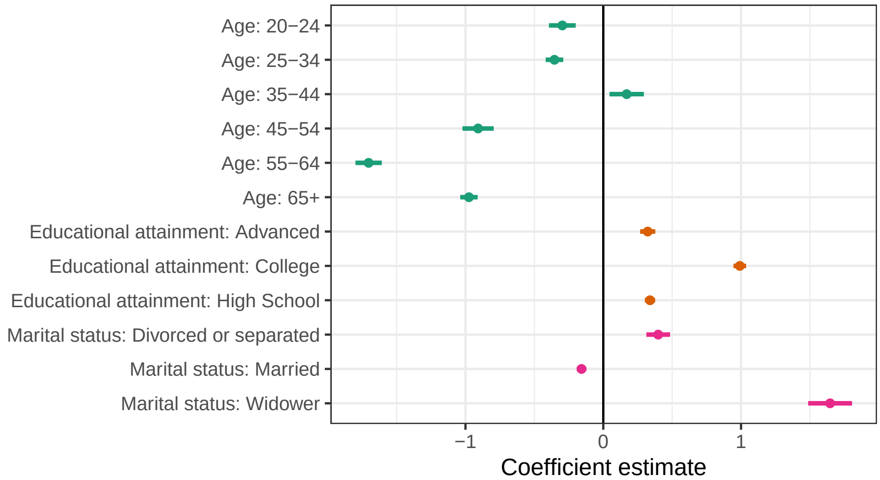



Notes: this figure displays estimated coefficients and 95% confidence intervals from a linear probability model regression of an indicator for a restaurant order being placed on one of the leading four food delivery platforms on month fixed effects and demographic variables using Numerator data from 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.

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.[2] 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.

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

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.

**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.8 presents the results of this analysis for choice sequences with a fixed number of purchases from a fixed number of platforms. Shuffling choice sequences has little effect on the average number of switches they contain; in fact, shuffling generates choice sequences with slightly *less* switching, whereas we would expect more switching in the shuffled sequences if state dependence 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.

Table O.8: Evaluation of state dependence

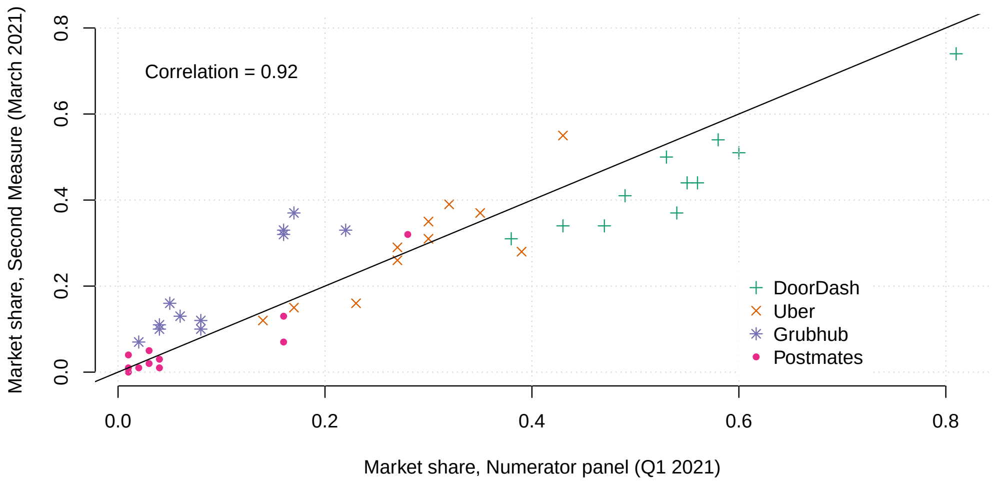
| # transactions ($\tau$) | # unique ($k$) | # switches Mean | 95% CI | | # switches (Shuffled data) | $N$ |
|---|---|---|---|---|---|---|
| 3 | 2 | 1.36 | 1.34 | 1.37 | 1.33 | 4708 |
| 4 | 2 | 1.71 | 1.69 | 1.72 | 1.65 | 4728 |
| 4 | 3 | 2.59 | 2.55 | 2.64 | 2.50 | 429 |

Notes: the "# switches" columns report the average number of switches between online platforms among consumers buying from $k$ unique platforms within $\tau$ 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 O.1 in Q2 2021.

## O.4 Validation of transactions datasets

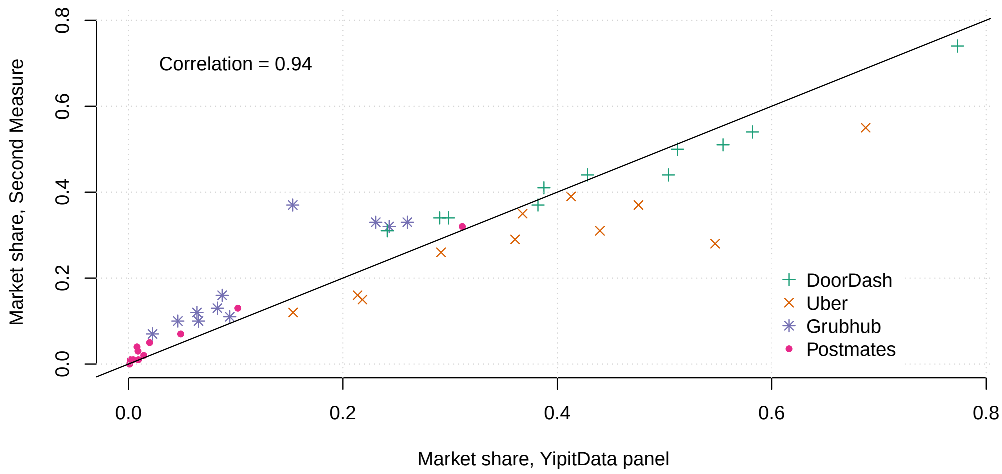
Figure O.11 compares market shares for April 2021 computed from the Numerator transactions panel to those reported by the market research firm Second Measure, which estimates platforms' market shares based on payment card records, for March 2021. Market shares are similar across these two data sources. 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.9: 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.10: 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 Difference-in-differences analysis of commission caps

### O.7.1 Technical appendix

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

I use additional datasets to supplement those above in conduct DiD analysis. These include: data on COVID-19 cases by county from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (Dong et al. 2020); the Oxford Covid-19 Government Response Tracker (OxCGRT) measure of the stringency of local COVID-19 policy (Hallas et al. 2020); and county-level data on the results of the 2020 US presidential election from MIT Election Data and Science Lab (2018). To obtain a ZIP3-level version of each county-level COVID-19 and election variable, I compute a population-weighted average of the variable across ZIPs within the ZIP3, assigning each ZIP the value of its encompassing county.

Multiple estimators appear in the literature on DiD research designs. The first is the standard two-way fixed effects (TWFE) estimator, which is an OLS estimator applied to linear equation with time fixed effects, panel unit fixed effects, and treatment indicators. Another is the interacted weighted (IW) estimator of Sun and Abraham (2021), which is an OLS estimator of a similar equation but including interactions of treatment indicators and cohort-membership indicators, wherein cohorts are defined by time of treatment. This estimator addresses problems facing TWFE in settings in which treatment effects differ between units that receive treatment at different times. Another estimator that addresses this problem is that of Callaway and Sant'Anna (2021). The version of the Callaway and Sant'Anna (2021) estimator that I compute generalizes that of doubly robust DiD estimator of Sant'Anna and Zhao (2020). I compute this estimator using both not-yet-treated units and never-treated units as the control group. Last, I compute the instrumental variables (IV) based estimator of Freyaldenhoven et al. (2019), which addresses endogeneity problems that give rise to pre-trends.

The TWFE, IW, and IV estimators permit the inclusion of time-varying covariates or "controls." These covariates may make the assumption of parallel trends that is generally required for the validity of DiD methods more plausible. I include as covariates (i) the OxCGRT stringency index, (ii) the number of new COVID-19 cases per capita, and (iii) the number of new COVID-19 cases per capita interacted with the Democrat vote share in the 2020 US presidential election. In addition, I use each of these variables as proxies for unobserved heterogeneity in computing the Freyaldenhoven et al. (2019) IV estimator. I do not use covariates in computing the Callaway and Sant'Anna (2021) estimator. Another way in which I use auxiliary variables in the analysis is in weighting. I weight geographical units by their populations in computing the TWFE, IW, and Callaway and Sant'Anna (2021) estimators. The implementation of the Freyaldenhoven et al. (2019) estimator that I used does not allow weights, and thus I instead emphasized larger geographies by dropping those below a certain population threshold from the analysis.

Several tables and figures in the article report overall effects as opposed to effects varying in time relative to the imposition of caps. The manner in which I compute these overall effects differs somewhat by estimator. The overall effects estimated by TWFE are estimates of the $\delta_f$ or $\delta$ parameter in whichever of equations (3) or (4) in the main text pertains to the table or figure in question. For the other estimators, I aggregate across dynamic effects to obtain overall effects. The estimands of Callaway and Sant'Anna (2021) are average treatment effects on the treated (ATTs) specific to treatment cohorts $g$ and calendar times $t$. I report a weighted average of cohort-time-specific ATTs across $(g, t)$ pairs such that cohort $g$ has been treated by $t$, with each cohort weighted by its size. For the IW estimator, I report a simple average of dynamic treatment effects at $\tau$ periods since treatment for $\tau = 1, \ldots, \bar{\tau}$, where $\bar{\tau}$ is the further period after treatment for which I estimate a dynamic treatment effect. I similarly compute a simple average of dynamic treatment effects for the IV estimator.

Suppressing the platform subscript, the TWFE, IW, and IV estimators with dynamic effects are based on the equation

$$y_{zt} = \psi_z + \phi_t + \sum_{\tau=-\bar{\tau}}^{\bar{\tau}} \delta_\tau x_{z,t-\tau} + \delta^+ \sum_{\tau>\bar{\tau}} x_{z,t-\tau} + \delta^- \sum_{\tau<-\bar{\tau}} x_{z,t-\tau} + w'_{zt}\beta + \epsilon_{zt}.$$

Here, $g(z)$ identifies the time of first treatment of ZIP $z$, and the $g(z)$ subscript of the $\delta$ parameters indicates that treatment effects may differ by treatment cohort as permitted by the IW estimator. The parameter $\tau$ in this equation governs the window of time surrounding treatment in which effects may vary. For the TWFE and IW estimator, I specify $\bar{\tau} = 7$. For the IV estimator, I specify $\bar{\tau} = 5$.

I compute standard errors for each estimator that I compute. For the standard TWFE estimator, the IW estimator, and the IV estimator, I compute classical asymptotic standard errors. For the Callaway and Sant'Anna (2021) estimator, I compute robust asymptotic standard errors.

### O.7.2 Effects on platform fees and sales

Table O.11: Fee responses to commission caps, alternative treatment and outcome variables

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

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

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

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

Table O.12: Fee responses to commission caps, July 2020 to May 2021

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

Notes: This table reports results of the DiD analyses of platform fees applied to data from July 2020 to May 2021. See the notes of Table 2 for additional details.

Table O.13: Fee responses to commission caps, alternative treatment/control groups

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

Notes: This table is an analogue of Table 2 with the exception that the treatment group in the underlying analysis includes ZIPs with any cap (including those above 15%) and the control group includes all remaining ZIPs. See the notes of Table 2 for additional details.

Table O.14: Responses of service fees and fixed fees to commission caps

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

Notes: the table reports TWFE estimates of the effects of commission caps on platforms' service fee rates and log fixed fees. I compute the service fee rate in a ZIP for a particular month by dividing the ZIP's average service fee amount in dollars by the average basket subtotal before fees, tips, and tax. I compute the average fixed fee by subtracting the average service fee from the average total fee. See the notes of Table 2 for additional details.

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

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

Notes: the table reports TWFE estimates of the effects of commission caps on platforms' service fee rates and log fixed fees. I compute the service fee rate in a ZIP for a particular month by dividing the ZIP's average service fee amount in dollars by the average basket subtotal before fees, tips, and tax. I compute the average fixed fee by subtracting the average service fee from the average total fee. See the notes of Table 2 for additional details.

Table O.16: Fee responses to commission caps, interactions with market share measures

(a) Interaction with market share in 2019

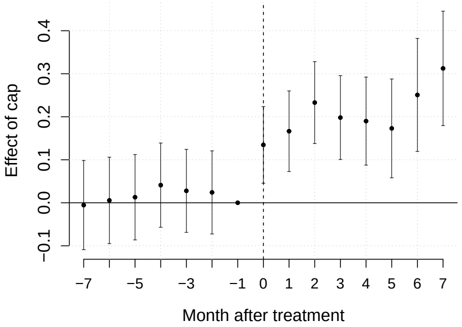
| | DD | Uber | GH |
|---|---|---|---|
| Treatment | 0.282 | 0.154 | 0.223 |
| | (0.054) | (0.066) | (0.116) |
| Treatment × market share | -0.213 | -0.213 | -0.373 |
| | (0.112) | (0.160) | (0.386) |

(b) Callaway and Sant'Anna (2021)

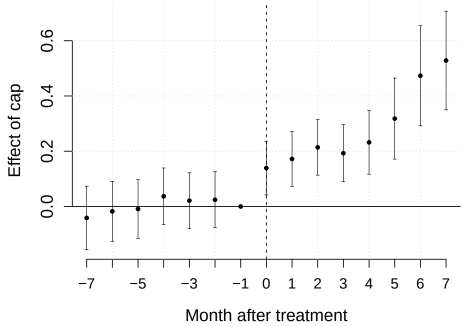
| | DD | Uber | GH |
|---|---|---|---|
| Treatment | 0.223 | 0.064 | 0.137 |
| | (0.026) | (0.025) | (0.064) |
| Treatment × HHI × market leader | -0.133 | 0.042 | -0.293 |
| | (0.062) | (0.105) | (0.462) |

Notes: this table provides TWFE results for specifications in which the treatment indicator ("Treatment") enters in an interaction with either (i) the platform's market share in 2019 in the ZIP's core-based statistical area (CBSA), or (ii) the Herfindahl–Hirschman index (HHI, a measure of market concentration) among leading food delivery platforms in the CBSA in 2019 interacted with an indicator for whether the platform was the leading platform in the CBSA in 2019. See the notes of Table 2 for additional details.

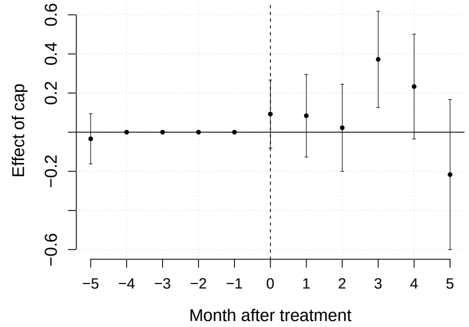
Figure O.14: Effects of commission caps on platforms' consumer fees



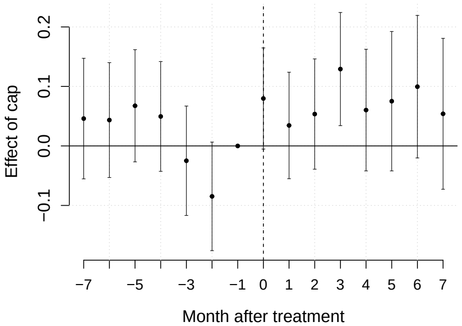

(a) DoorDash, TWFE



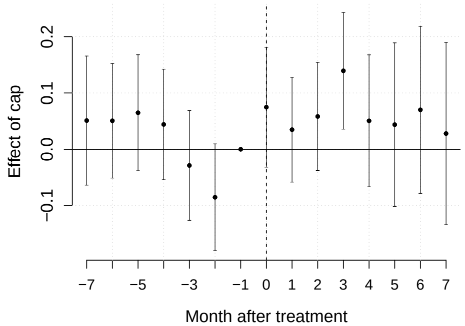

(b) DoorDash, IW



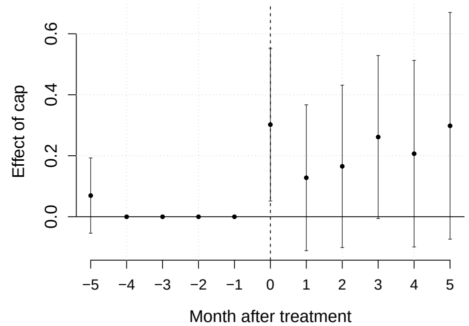

(c) DoorDash, IV



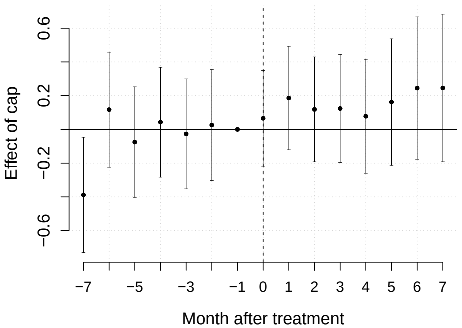

(d) Uber Eats, TWFE



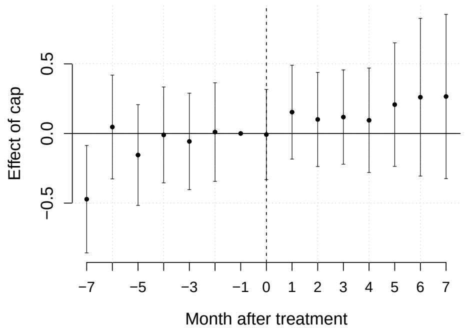

(e) Uber Eats, IW



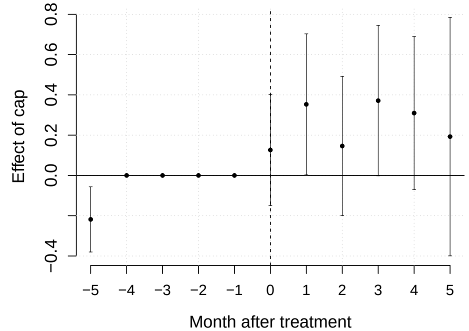

(f) Uber Eats, IV




(g) Grubhub, TWFE




(h) Grubhub, IW

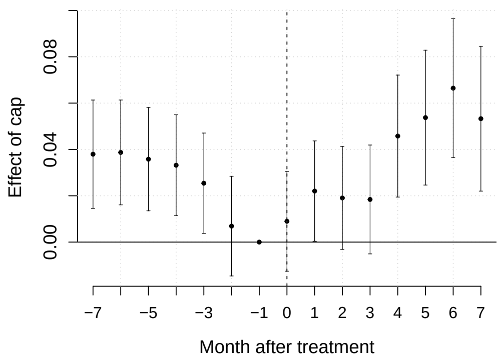



(i) Grubhub, IV

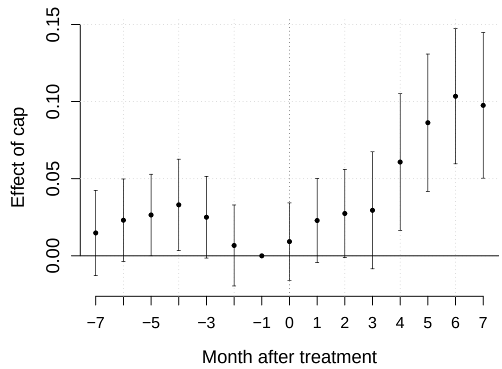
Notes: this figure plots estimates of dynamic effects of commission caps on platforms' consumer fees. These estimates were computed on the Edison ZIP/platform/month-level panel using three estimators described in the main text. The dots indicate point estimates and the bars around each point indicate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

Figure O.15: Dynamic effects of commission caps on direct-from-restaurant ordering (Numerator panel)

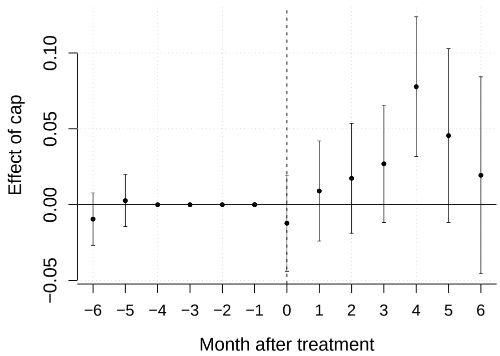
(a) TWFE



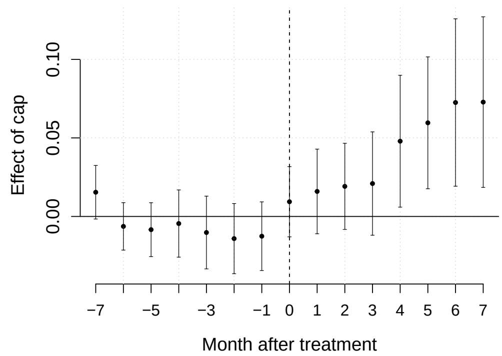

(b) IW, Sun and Abraham (2021)



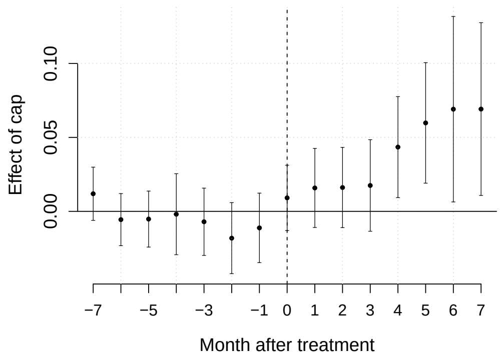

(c) IV, Freyaldenhoven et al. (2019)




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



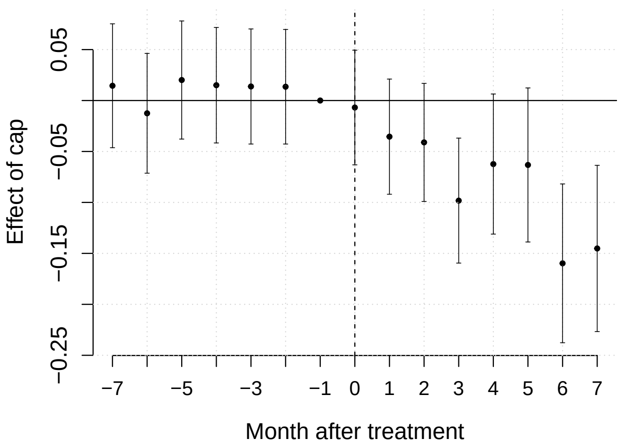

(e) Callaway and Sant'Anna (2021) (not yet)



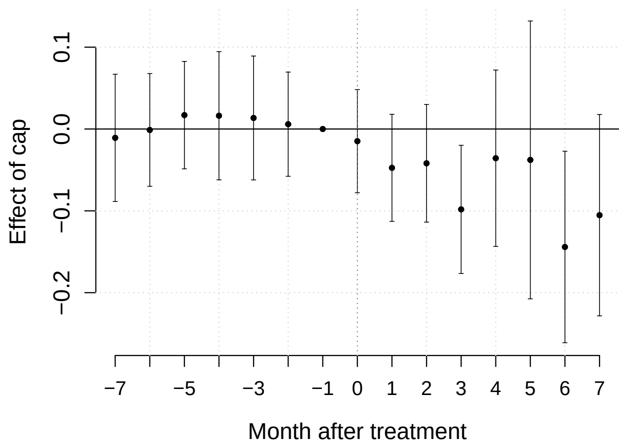

Notes: this figure includes plots of estimates of dynamically evolving effects of commission caps on the log of the total number direct-from-restaurant orders. Each unit in the analysis is a ZIP3, and each time period is a month. The figure includes estimates obtained from various estimators described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

Figure O.16: Dynamic effects of commission caps on platform ordering (Numerator panel)

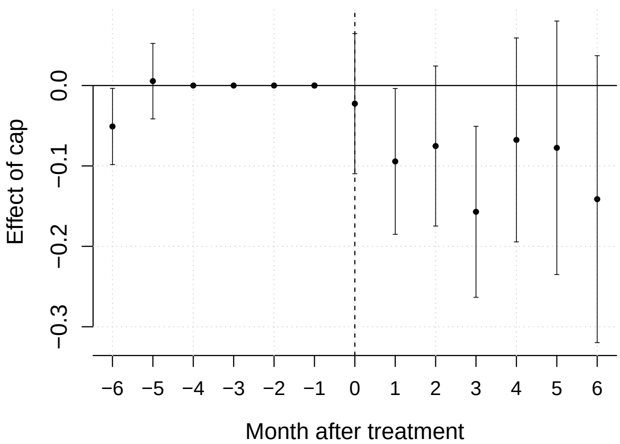
(a) TWFE



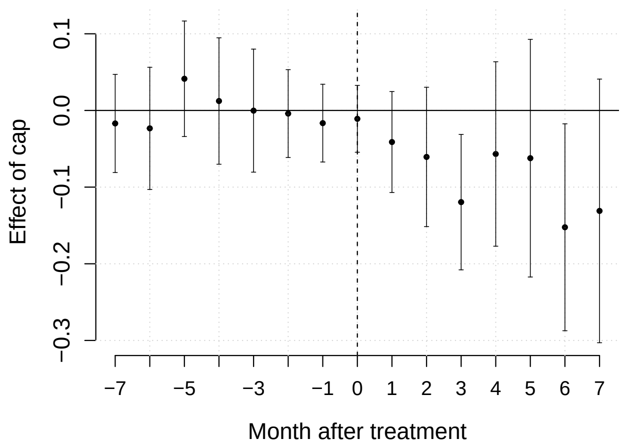

(b) IW, Sun and Abraham (2021)



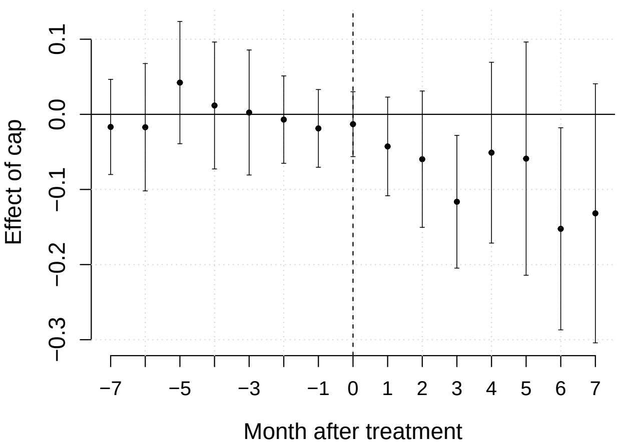

(c) IV, Freyaldenhoven et al. (2019)




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



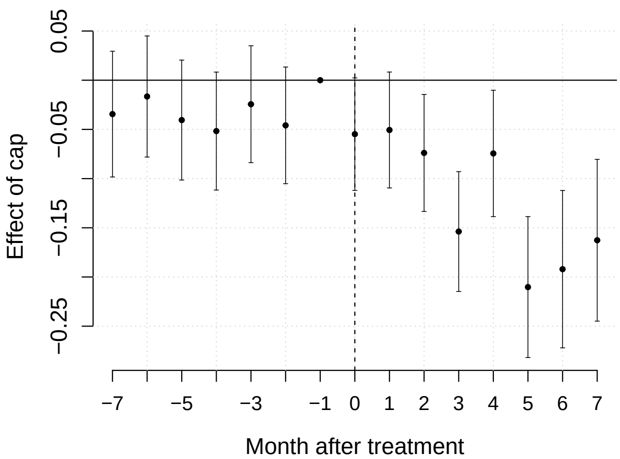

(e) Callaway and Sant'Anna (2021) (never)



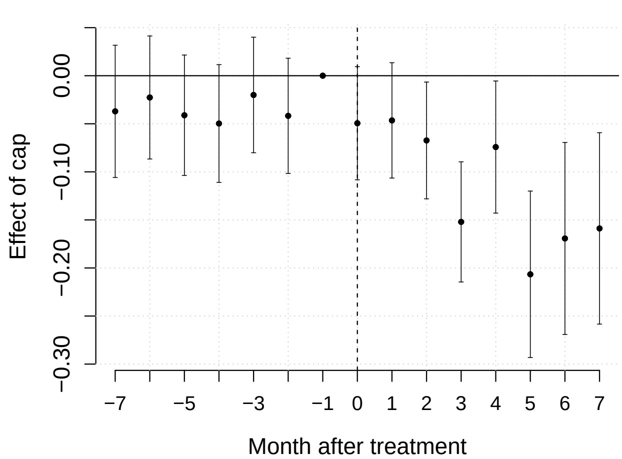

Notes: this figure includes plots of estimates of dynamic effects of commission caps on the log of the total number of restaurant orders placed on platforms. Each unit in the analysis is a ZIP3 and each time period is a month. The dots indicate point estimates and the bars around each point indicate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

Figure O.17: Dynamic effects of commission caps on platform ordering (Edison panel)

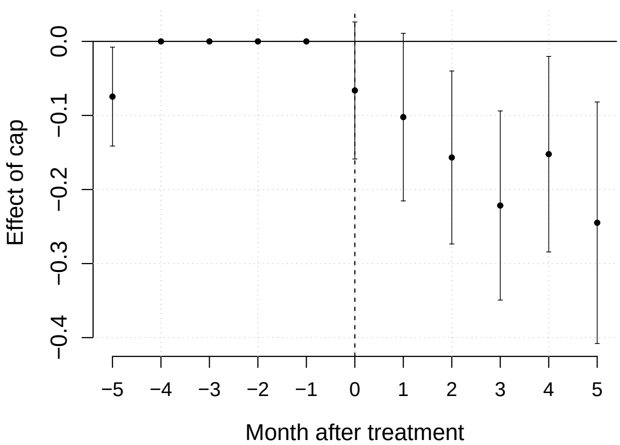
(a) TWFE



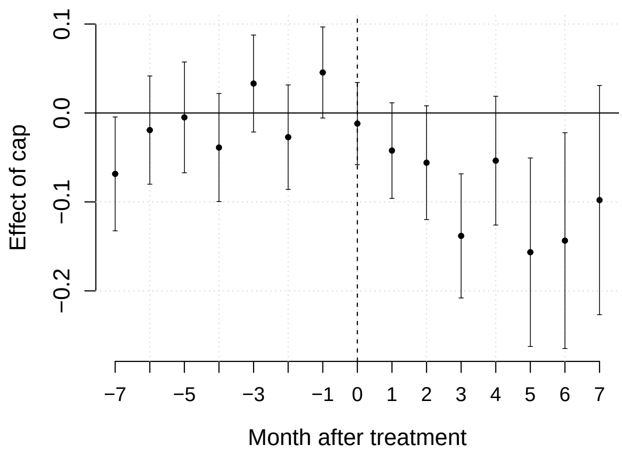

(b) IW, Sun and Abraham (2021)



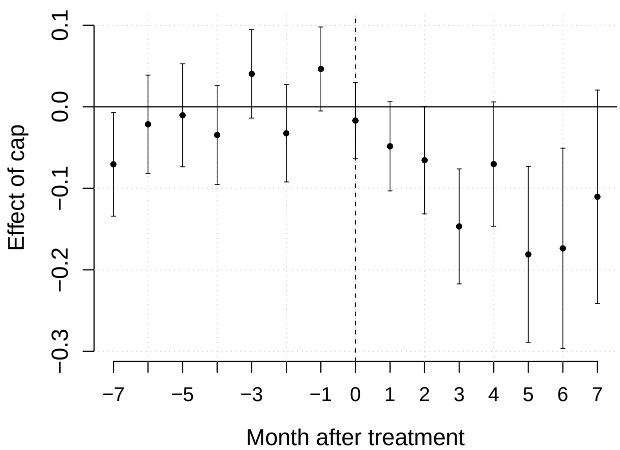

(c) IV, Freyaldenhoven et al. (2019)




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

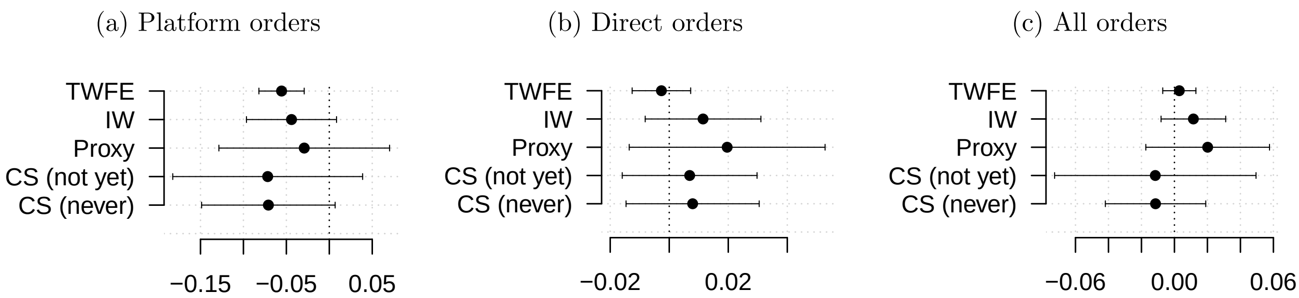



(e) Callaway and Sant'Anna (2021) (never)




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

Figure O.18: Effects of commission caps on restaurant sales (basket subtotals)




Notes: this figure reports difference-in-differences estimates of the effects of commission caps of 15% or less on the log of aggregate basket subtotals (i.e., order values before fees, tips, and taxes) placed (i) on delivery platforms, (ii) directly at restaurants, and (iii) across both channels. See the notes for Table 2 for an explanation of each estimator.

### O.7.3 Restaurant platform adoption

Table O.17: Effects of commission caps on restaurants' platform uptake, platform-specific estimates

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

Notes: "Diff-in-diff" reports OLS estimates of $\delta$ in (4) in which the outcomes are the shares of restaurants in the ZIP that belong to the food delivery platform indicated by the columns. In the regression, each ZIP is weighted by its total number of restaurants in January 2020. "Within-metro" reports estimates from cross-sectional regressions of the same outcomes on an indicator for an active commission cap of 15% or less, various COVID-19-related controls, and metro area fixed effects. In the regression, each ZIP is weighted by its number of restaurants. Asymptotic standard errors appear in parentheses.

Table O.18: Effects of commission caps on restaurants' platform uptake, continuous treatment

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

Notes: see the notes for Table 3. The treatment variable $x_{zt}$ used in the regressions whose results are displayed above is equal to the level of ZIP $z$'s commission cap in effect at time period $t$ if a commission cap was in effect and equal to 0.30 otherwise. The sample includes ZIPs with commission caps exceeding 15%.

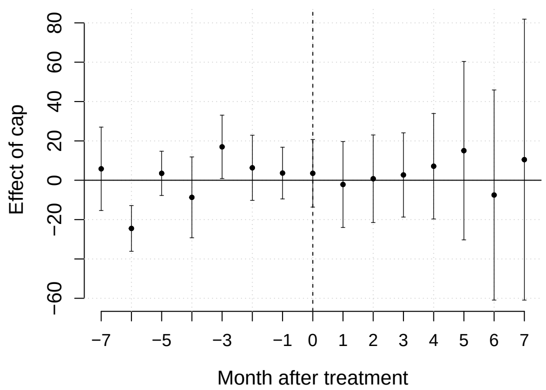
Table O.19: Effects of commission caps on platform restaurant listing counts (absolute listing counts)

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

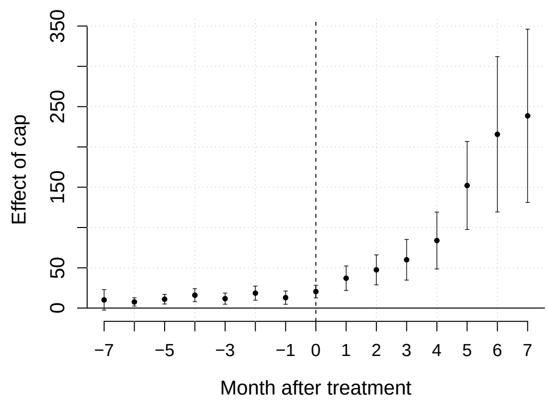
Notes: the table provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3). The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2757 (total), 1037 (DoorDash),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

Figure O.19: Dynamic effects of commission caps on platform restaurant listing counts (disaggregated by platform)

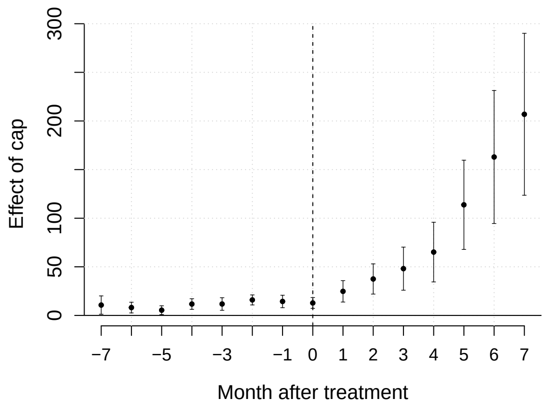
(a) DoorDash



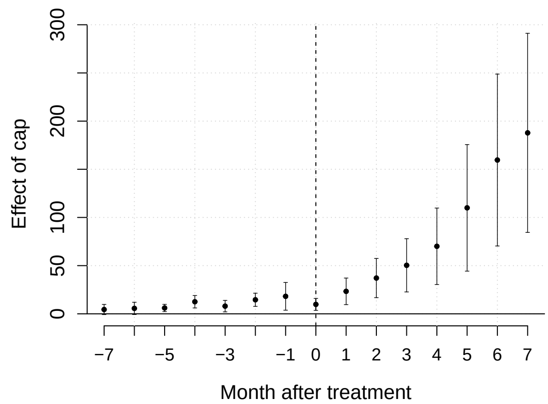

(b) Uber Eats




(c) Grubhub



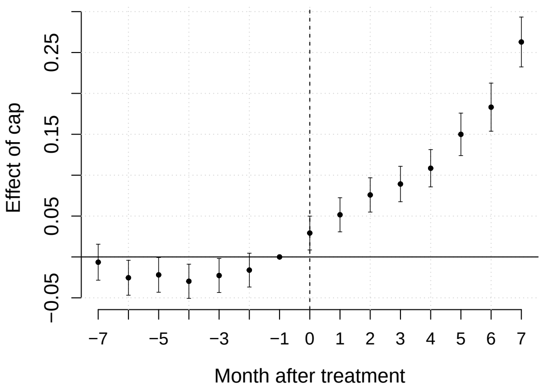

(d) Postmates



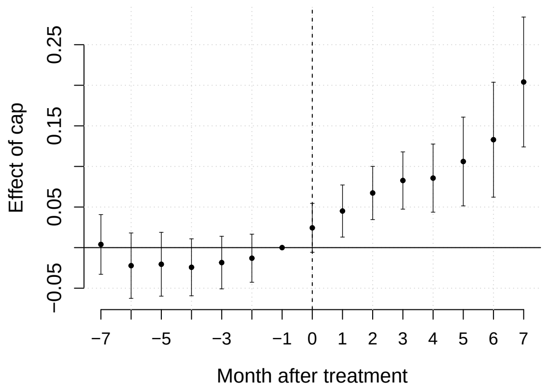

Notes: the plot provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents. The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2642 (total), 1056 (DoorDash), 668 (Uber Eats), 587 (Grubhub), and 332 (Postmates). The estimates derive from the Callaway and Sant'Anna (2021) estimator with never-treated units constituting the control group. The bars around each point provide 95% pointwise confidence intervals.

Figure O.20: Dynamic effects of commission caps on platform restaurant listing counts (alternative estimators)

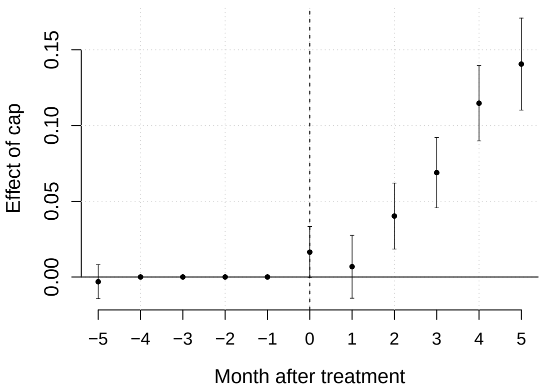
(a) TWFE



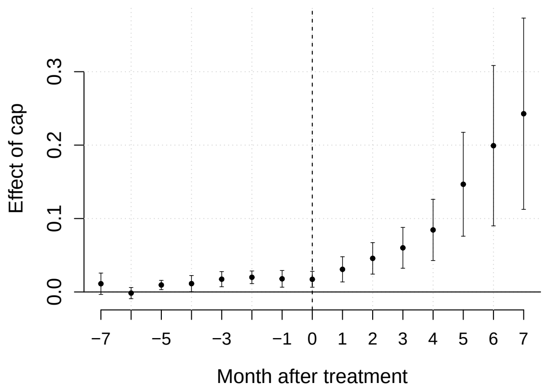

(b) IW




(c) IV




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




Notes: the plot provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents (the mean value of the dependent variable across ZIP3s in April 2020, weighting for population, was 2642). The estimates derive from (O.20a) a two-way fixed effects estimator; (O.20b) the interaction-weighted estimator of Sun and Abraham (2021); (O.20c) the instrumental-variables-based estimator of Freyaldenhoven et al. (2019), which uses new COVID-19 cases per capita, stringency of local COVID-19 policy, and the interaction of new COVID-19 cases per capita and the Democratic vote share in the 2019 election as proxies for unobserved heterogeneity as well as three leads of the policy change as instruments; and (O.20d) the Callaway and Sant'Anna (2021) estimator with never-treated units constituting the control group. The bars around each point provide 95% pointwise confidence intervals.

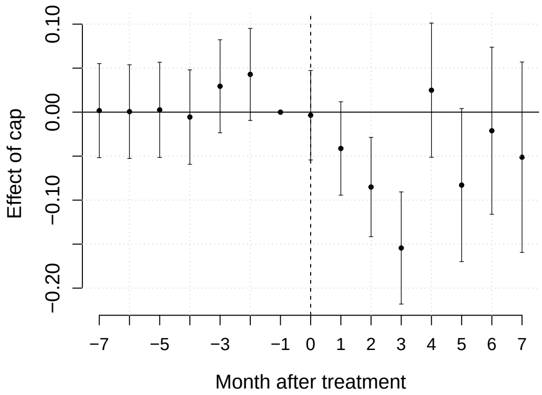
Table O.20: Effects of commission caps on platform restaurant listing counts (relative effects)

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

Notes: the table provides estimates of the effect of a 15% commission cap on the number of restaurant listings on food delivery platforms in a three-digit ZIP region (ZIP3) per million residents relative to the population-weighted mean value of this quantity in April 2020. The mean value of the dependent variable across ZIP3s in April 2020 (weighting for population) were 2642 (total), 1056 (DoorDash), 668 (Uber Eats), 587 (Grubhub), and 332 (Postmates). Each column provides results for a distinct estimator; see the notes for Table 2 for a description of these estimators. Asymptotic standard errors appear in parentheses.

### O.7.4 Restaurant prices

Figure O.21: Heterogeneity in adoption probability by restaurant characteristics




Notes: this figure plots estimates from a variant of (6) wherein effects of a commission cap vary with respect to time since the introduction of the commission cap.

## O.8 Restaurant heterogeneity

Table O.21: 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 $\beta_{\text{NE}}$, $\beta_{\text{NE}}^{\text{chain}}$, and $\beta_{\text{NE}}^{\text{non-chain}}$

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

where $\mathcal{s}_{fzt}$ are platform $f$'s sales in ZIP $z$ in month $t$, $J_{fzt}$ is the number of restaurants on platform $f$ within 5 miles of ZIP $z$ in month $t$, $\psi_{fz}$ is a platform/ZIP fixed effect, $\psi_{ft}$ is a platform/month fixed effect. Additionally, $J_{fzt}^{\text{chain}}$ ($J_{fzt}^{\text{non-chain}}$) 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.22: 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 $\beta_{\text{NE}}$, $\beta_{\text{NE}}^{\text{chain}}$, and $\beta_{\text{NE}}^{\text{non-chain}}$ in the equations

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

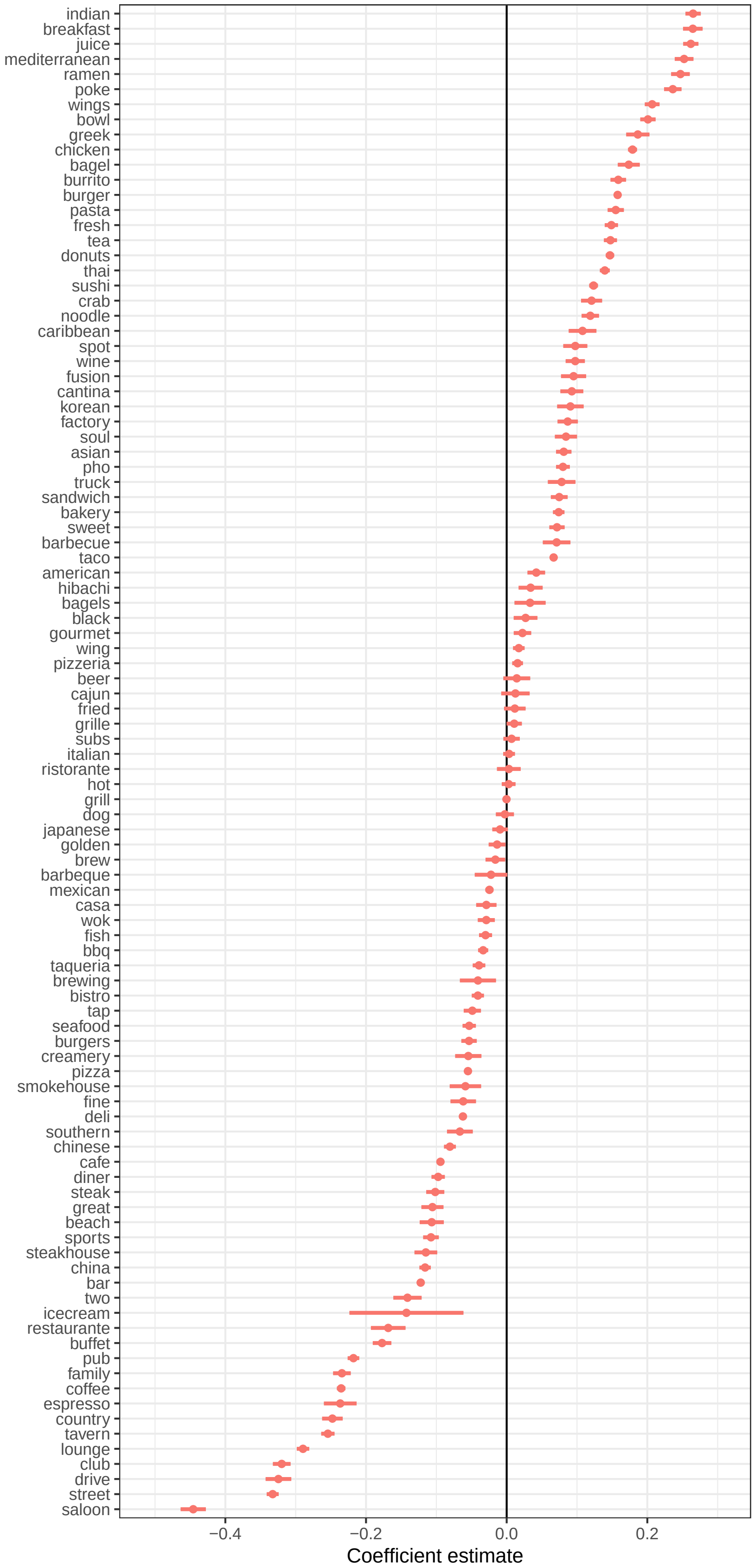
where $\mathcal{s}_{fz}$ are platform $f$'s sales in ZIP $z$, $J_{fz}$ is the number of restaurants on platform $f$ within 5 miles of ZIP $z$, and $\psi_{fm}$ is a fixed effect for platform $f$ in the metropolitan area (CBSA) $m$ of ZIP $z$. Additionally, $J_{fz}^{\text{chain}}$ ($J_{fz}^{\text{non-chain}}$) 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.

Table O.23: 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 |

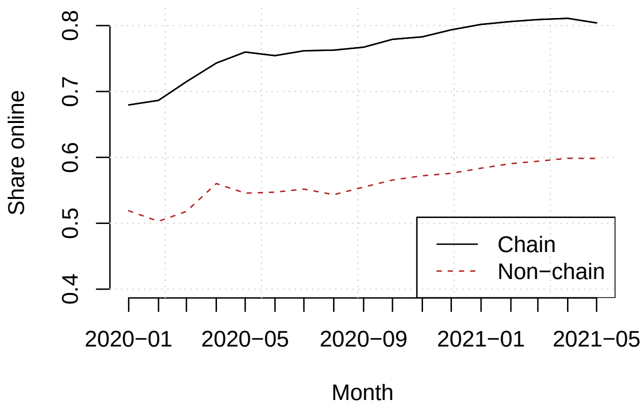
Notes: this table provides estimates from an ordinary least squares regression of the share of restaurants in a ZIP that join at least one food delivery platform (among DoorDash, Uber Eats, Grubhub, and Postmates) on (i) an indicator for a commission cap of 15% or lower being in effect, (ii) CBSA fixed 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.

Figure O.22: Heterogeneity in adoption probability by restaurant characteristics



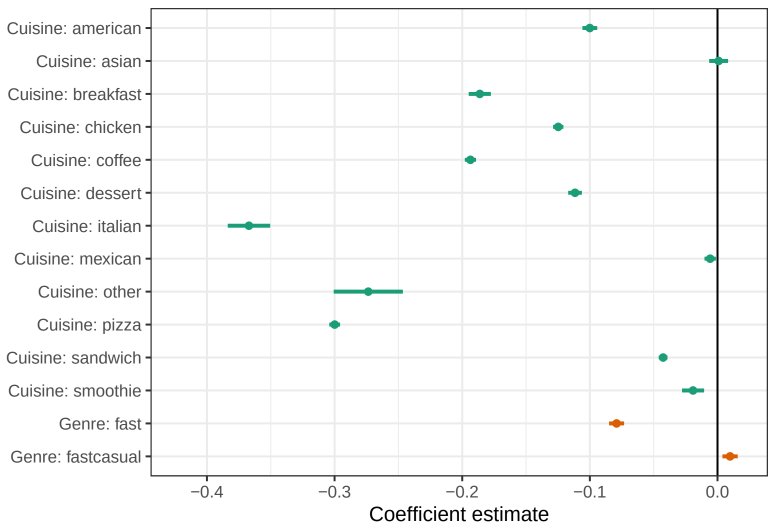

Note: this plot provides estimated coefficients and their 95% confidence intervals for a regression of an indicator for whether a restaurant joined at least one online platform on restaurant characteristics. The included characteristics are (i) an indicator for whether the restaurant belonged to a chain 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.23: 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.24: 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.

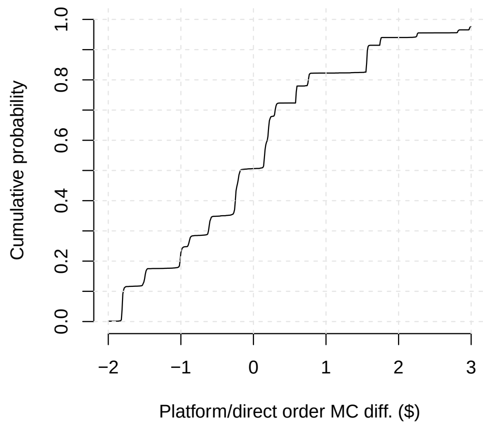
Table O.24: Platform adoption by restaurant type

| | 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.25: 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.25. 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 $\nu_{ijt}$ 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 $\theta$ denote the model parameters, which I often suppress in the notation.

Table O.25: 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: $z_i, d_i$ |
| | $\Xi_i$ | 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 $\mu$ is a smoothed indicator for $f$ maximizing $\psi_{if} - \alpha_i p_{fz\mathcal{G}}$

among these platforms. Indeed,

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

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

The parameter $\sigma_\varepsilon$ 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 $\sigma_\varepsilon$ 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 $\Xi_i$ 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 $\Xi_i$ 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

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

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 $\Xi_i$ 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 $\Lambda$, (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,

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

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 $f$.[3] 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

[3] The quantities $a_j$ and $b_j$ are defined by

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

structure.[4]

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 $(d_i, \Xi_i)$ orders from restaurant $j$. Note that

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

Therefore,

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

where the last approximation holds when $S_{ij} \approx 0$ almost surely across $i$; that is, for almost all $(d_i, \Xi_i)$, a consumer of type $(d_i, \Xi_i)$ 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

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

[4] 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).

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 $\Delta_p$ 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, $\kappa_j$ 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

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

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 $\Delta_p$ 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 $\Xi_i$ 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 $z$,

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

when

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

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,

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

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

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

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

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

Define

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

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 $\mathscr{s}$ is a vector including $\mathscr{s}_f$ for each platform $f$ and $c$ is a vector including the consumer fee $c_f$ for each platform $f$. The first-order condition is

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

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 $\mathscr{s}$ 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.[5] Let $\widetilde{mc} = mc - r \odot p$. Consider the equation

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

We can re-write it as

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

or

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

This is equivalent to

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

which is the first-order condition. Now that I have shown that (16) 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 $c_0$ to an initial value.
2. Compute
$$c_1 = \widetilde{mc} + \Lambda(c_0)^{-1}\left[\mathcal{H} \odot \Gamma(c_0)\right](c_0 - \widetilde{mc}) + \Lambda(c_0)^{-1}\mathscr{s}(c_0).$$
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 $\mathscr{r} \in (0, 1]$ and a tolerance parameter $\delta > 0$. The algorithm for finding equilibria in restaurants' platform adoption choices in a market $m$ is given by:

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

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

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
$$\tilde{P}_z(\mathcal{G}) = \varkappa \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\Pi_z(\mathcal{G}', P_m) + \omega_j(\mathcal{G}')\right]\right) + (1-\varkappa)P_z(\mathcal{G})$$
for all $z$ and $\mathcal{G}$, and collect these probabilities in $\tilde{P}_m = \{\tilde{P}_z(\mathcal{G})\}_{z,\mathcal{G}}$. Note that the fixed-point condition (10) 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.[6] 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

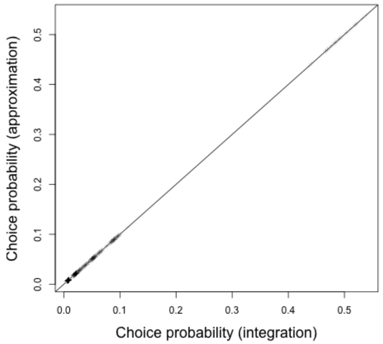
[6] Consider a ZIP with $J$ restaurants in a ZIP, each of which chooses between $G$ platform subsets. The number of possible configurations of restaurant counts across platform subsets is
$$\binom{J+G-1}{G-1}.$$
When $J = 100$ and $G = 16$ (as in my study),
$$\binom{J+G-1}{G-1} = \binom{115}{15} > 2 \times 10^{18}.$$

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.

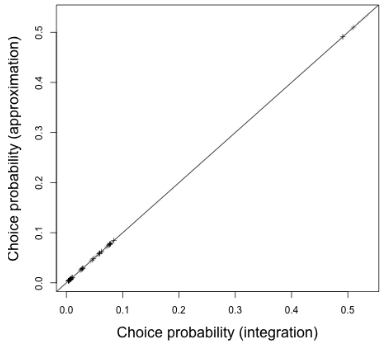
The approximation procedure that I use for computing the right-hand side of (17) in finding platform adoption equilibria has little approximation error. A regression of profits $\bar{\Pi}_j(\mathcal{G}, P_m)$ as computed using the approximation on those computing without using the approximation (and 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.[7] Figure O.26 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.

[7] 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 $\bar{\Pi}$.

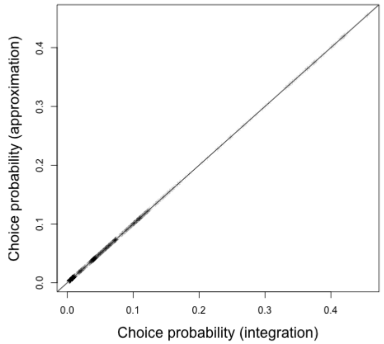
Figure O.26: Comparison of equilibrium choice probabilities from continuum approximation and integration approach



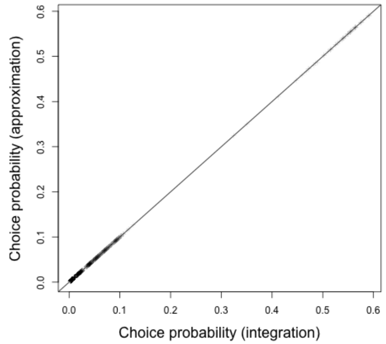

(a) Atlanta



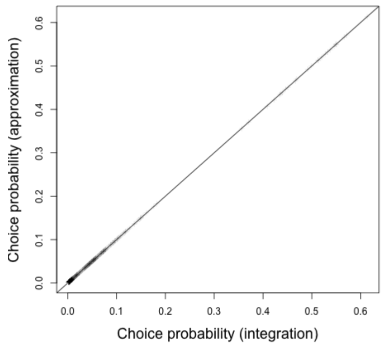

(b) Boston



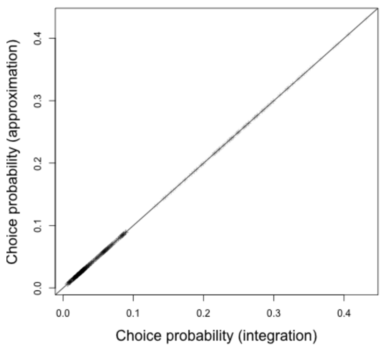

(c) Chicago



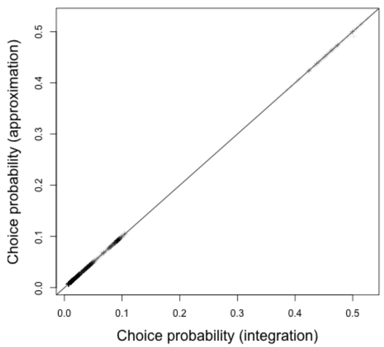

(d) Dallas



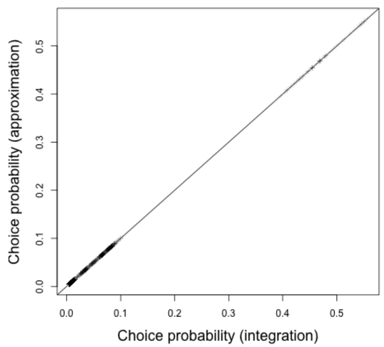

(e) Detroit



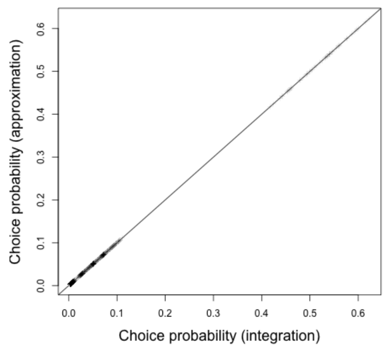

(f) Los Angeles




(g) Miami




(h) New York




(i) Philadelphia

## O.15 Additional results

Table O.26: 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.27: Network elasticities of demand for the Chicago metro

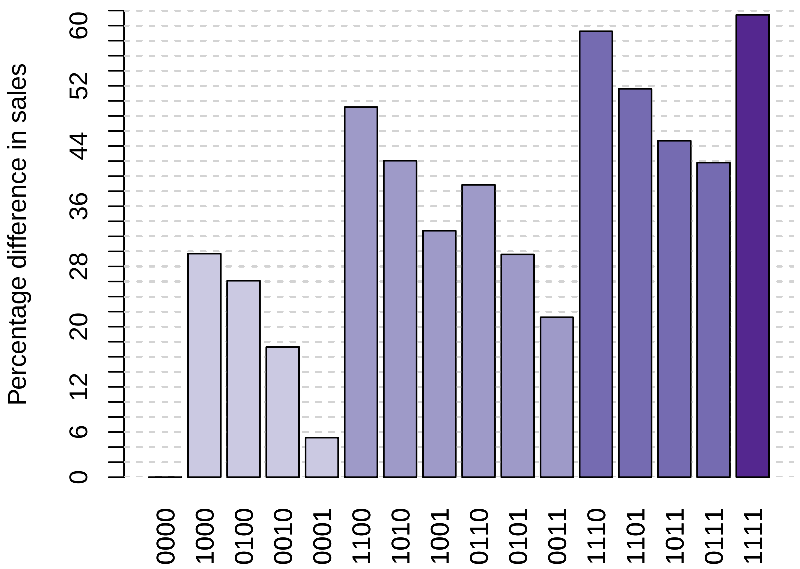
| | Quantity response for... | | | |
|---|---|---|---|---|
| Platform | DD | Uber | GH | PM |
| DD | 0.48 | -0.13 | -0.15 | -0.16 |
| Uber | -0.11 | 0.58 | -0.13 | -0.14 |
| GH | -0.07 | -0.08 | 0.74 | -0.09 |
| PM | -0.03 | -0.03 | -0.03 | 1.10 |

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

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

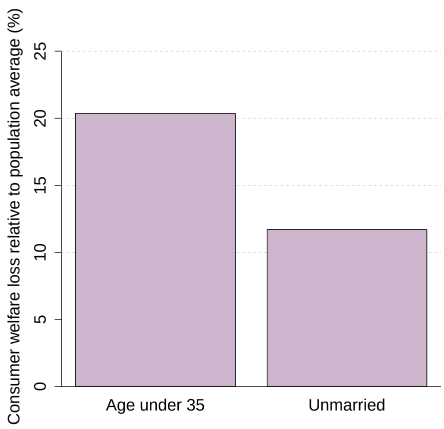
where $J_{f'm}$ and $J'_{f'm}$ are the number of restaurants on $f'$ before and after the addition of one restaurant on $f'$ to each ZIP, and $\mathscr{s}'_{fm}$ are $f$'s sales after the addition of these new restaurants.

Figure O.27: 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.28: 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.28: 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 |

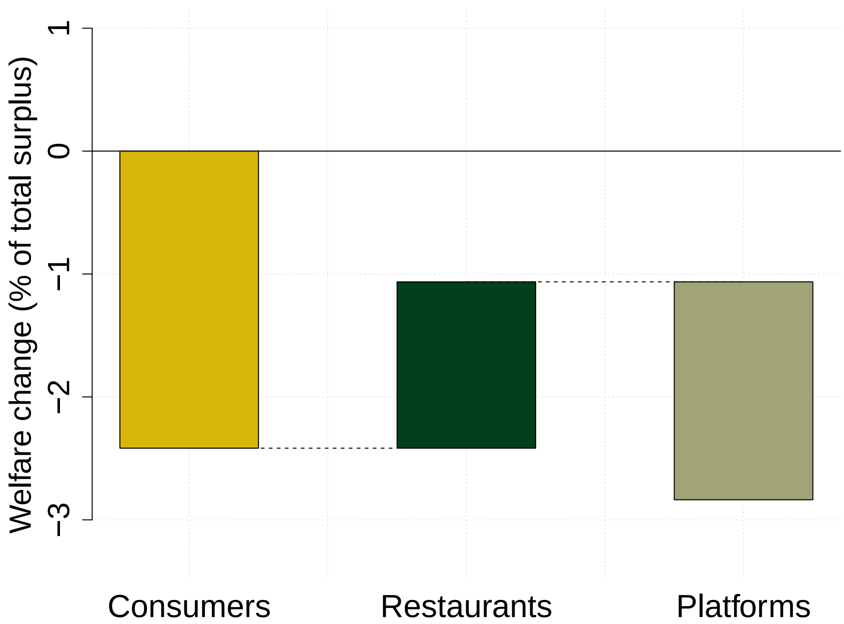
Notes: all welfare figures are transformed to annualized dollars per capita by dividing total welfare changes for April 2021 by markets' populations as estimated by the 2019 American Community Survey and multiplying these monthly per capita amounts by 12.

Table O.29: 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.29: Welfare effects of 15% commission cap relative to total surplus from platforms (zero platform fixed costs)




Notes: see the notes for Figure 8.

## 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.30 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.30: 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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