Price controls in a multi-sided market*

Michael Sullivan

Department of Economics, Yale University

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Abstract

This paper evaluates caps on the commissions that food delivery platforms (e.g., DoorDash) charge to restaurants. Commission caps benefit restaurants that partner with platforms, all else equal. This may entice restaurants to join platforms, thereby benefitting consumers who value variety in platforms' restaurant listings. A reduction in platform commissions may also lead restaurants to lower their prices, further benefitting consumers. But commission caps may lead platforms to raise their consumer fees, thereby reducing consumer ordering on platforms and consequently platforms' value to restaurants. The net effects of caps on restaurant and consumer welfare are thus uncertain. To estimate caps' effects, I assemble data on consumer restaurant orders, restaurants' platform adoption, and platform fees. An initial analysis of the data suggests that caps raise platforms' consumer fees, reduce consumer ordering on platforms, and lead restaurants to join platforms. To analyze these effects and their welfare implications, I develop a model of platform pricing, restaurant pricing, platform adoption by restaurants, and consumer ordering. Counterfactual simulations using the estimated model imply that commission caps bolster restaurant profits, but they do so at the expense of consumers and platforms. I estimate a total welfare reduction of caps equal to 6.2% of participant surplus from platforms.

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1 Introduction

The effects of policies on platform markets generally depend on equilibrium responses of all market participants connected by the affected platforms. This paper provides an empirical evaluation of a particular class of policies targeting a platform market: commission caps in the food delivery industry. Many US cities have capped the commissions that food delivery platforms (e.g., DoorDash and Uber Eats) charge to restaurants. Commission caps have effects on the welfare of restaurants and consumers that depend on countervailing responses of these two groups of market participants. These responses, which reflect the multi-sided nature of the food delivery industry, complicate the analysis of commission caps relative to that of price controls in standard one-sided markets. Caps may entice restaurants to join platforms, which would benefit consumers who value the breadth of platforms' restaurant networks. Restaurants may also reduce their prices in response to a reduction in commissions. But commission caps may lead platforms to raise the fees that they charge to consumers. This would harm consumers. It would also reduce consumer ordering on platforms and consequently the value of platform membership to restaurants. The net effects of caps on restaurant and consumer welfare are thus uncertain.

This paper empirically assesses the net effects of commission caps on consumer welfare, restaurant profits, platform profits, and total welfare. To this end, I assemble data characterizing the US food delivery industry. These data include a panel of consumers' restaurant orders placed on platforms, from restaurants on their premises, and on restaurants' websites or apps. This panel provides consumer locations at the ZIP-code level as well as item-level prices. I supplement this panel with monthly data on estimated platform sales and average platform fees charged to consumers at the ZIP-code level, as well as the universe of restaurants listed on each major delivery platform. Last, I personally collect data on platform order characteristics from the websites of leading food delivery platforms. These characteristics include fees, estimated waiting times, delivery addresses, and restaurant identifiers for hundreds of thousands of potential deliveries across 14 large US metropolitan areas.

As a first pass, I compute difference-in-differences estimates of caps' effects. Estimates exploiting the staggered rollout of caps across municipalities suggest that caps raised fees by 9–22% across platforms, reduced the number of orders placed on platforms by 6%, and induced a 4.0 percentage-point increase in the share of restaurants that join at least one platform; for context, about half of restaurants belonged to a platform in January 2020. These estimates suggest that commission caps harm consumers by prompting platform fee hikes, but that these harms are mitigated by an increase in the selection of restaurants available on platforms. The fact that platform sales fall suggests that the harms to consumers from fee increases exceed consumers' benefits from increased restaurant variety on platforms.

I subsequently develop a model of the food delivery industry with which to quantify commission caps' welfare effects, to assess mechanisms contributing to these effects, and to evaluate alternative policies intended to bolster restaurant profitability. In the model, platforms first set commission rates. Next, restaurants choose which platforms to join to optimize profits in a discrete game of incomplete information. After joining platforms, restaurants set profit-maximizing prices that may differ between direct-from-restaurant orders and orders placed on platforms. Platforms set fees charged to consumers in each ZIP code at the same time as restaurant set their prices. They do so to maximize their profits given constant marginal costs for fulfilling orders. Finally, each consumer chooses whether to order a restaurant meal, from which nearby restaurant to order, and whether to use a platform in ordering. Consumers' choices depend on platform fees, restaurant prices, and the number of nearby restaurants on each platform. This model captures network externalities affecting both sides of the platform market. In particular, consumers are more likely to choose a platform with a wide variety of restaurants: when a new restaurant joins a platform, consumers with strong tastes for the restaurant become more likely to order from the platform. Additionally, restaurants earn higher profits from joining a platform that is more popular among consumers (all else equal) because their incremental sales are higher from joining such a platform. Heterogeneity in consumer tastes for platforms influences how consumers substitute between platforms and the alternative of ordering directly from a restaurant. Consumers who are highly polarized in their tastes for platform ordering, for example, are unlikely to substitute between ordering from a platform and ordering directly from a restaurant.

The estimation procedure has multiple steps. The first step is maximum likelihood estimation of the consumer choice model. In the next step, I estimate platforms' and restaurants' marginal costs from their respective first-order conditions for optimal pricing. The subsequent step is estimation of the model of platform adoption by restaurants using a generalized method of moments (GMM) estimator. This GMM estimator selects parameters controlling the average fixed costs of platform adoption to match market-specific choice frequencies. In addition, the estimator selects the parameters governing restaurants' substitution patterns between subsets of platforms to match empirical covariances between measures of platform uptake by restaurants and a shifter of the profitability of platform adoption.

The main parameters of interest in the consumer choice model are those that govern consumer price sensitivity, network externalities, and patterns of consumer substitution. The endogeneity of platforms' fees and restaurant networks—both of which depend on local unobserved tastes for platforms—poses a challenge for the estimation of price sensitivity and network externalities. I address the endogeneity of prices and restaurant networks using platform/metro-area fixed effects; consequently, I rely on variation in fees and restaurant locations within a metro area to estimate price sensitivity and network externalities. This variation owes in part to variation in commission cap policies across municipalities within metro areas. My approach for estimating substitution patterns exploits the panel structure of the estimation sample, which characterizes how consumers switch between alternatives across orders.

I use the estimated model to compare equilibria with and without a 15% commission caps in various large metro areas. Counterfactual simulations imply that commission caps raise restaurant profits, reduce consumer welfare, and reduce platform profits. The sum of caps' effects on these components of total welfare is negative. The increase in restaurant profits across metro areas is 3.0% of the sum of participant surplus (i.e., the effect of platforms' availability on the sum of consumer welfare and restaurant profits, which is positive). The total welfare loss is 6.2% of participant surplus. Consumer welfare falls by 5.3% of participant surplus; this welfare loss exceeds the platform profit losses from a cap of 3.9% of participant surplus. Although consumers pay more for food delivery orders under commission caps, they benefit from the increased selection of restaurants available on platforms. Failing to account for the expansion in the variety of restaurants available on delivery platforms owing to a commission cap would lead the researcher to overstate the cap's harms to consumers by 70%. The fact that restaurants compete away many of their direct gains from the commission cap in ways that benefit consumers—i.e., by joining more platforms and possibly reducing their prices—mitigates the harms of the cap to consumers. Even after accounting for restaurants' platform adoption and price responses, however, harms to consumers from a cap exceed harms to platforms and benefits to restaurants.

One distributional rationale for a cap is that caps transfer surplus from platforms to local restaurants; this rationale is well founded in that caps boost restaurant profits at the expense of platform profits, but it does not acknowledge that consumers in large part pay for caps' benefits to restaurants. Alternative policies may obtain the increases in restaurant profits from a cap without caps' negative effects on total welfare. One such policy is a tax on platforms' commission revenues whose proceeds are remitted to restaurants: under an appropriately selected tax rate, this policy achieves the increase in restaurant profitability associated with a commission cap without a reduction in total welfare. Although a tax induces platforms to reduce commissions and raise consumer fees, these responses are small for a tax that is designed to provide as large a benefit to restaurants as a 15% cap. The small scale of responses to the tax mean that it does little to undermine consumer welfare and platform participation.

In addition to evaluating commission caps, I evaluate a common premise for commission caps: that platforms reduce restaurant profits. Such a reduction is possible given costs of joining platforms and commission charges, but platforms may also benefit restaurants by raising the number of orders from restaurants. Counterfactual simulation of a restaurant industry without platforms suggests that roughly half of restaurant orders placed on platforms would not be placed if platforms were eliminated. Additionally, platforms provide significant value to consumers; eliminating them reduces consumer welfare by almost $70 annually per capita on average across metro areas. Restaurant profits, however, increase by over $18 per capita a year on average across markets when platforms are abolished. These results explain the paradoxical coincidence of restaurants' voluntary platform membership with complaints that platforms reduce restaurant profitability: competitive pressures lead restaurants to join platforms even though restaurants would be collectively better off under industry-wide collusion not to join platforms.

1.1 Related literature

My paper makes several contributions to the empirical platforms literature.[1] First, it provides an empirical analysis of decentralized pricing between platforms' end users (i.e., consumers and restaurants) in a platform competition model. Pricing on food delivery platforms is decentralized in that sellers—not platforms—set the prices of menu items.[2] The pricing model most similar

[1] This literature often calls these markets two-sided markets or platform markets. I use these terms interchangeably. For overviews of the theory of multi-sided markets, see Rochet and Tirole (2006), Rysman (2009), and Jullien et al. (2021).

[2] The most popular US ride-hailing platforms (Uber and Lyft) use centralized pricing. See Chen et al. (2019), Rosaia (2020), Buchholz et al. (2020), Cook et al. (2021), Cohen et al. (2016), Ming et al. (2020) for analysis of ride-hailing platforms with centralized pricing, and Gaineddenova (2022) for analysis of a ride-hailing platform with decentralized pricing.

to my own is that of Robles-Garcia (2022). Robles-Garcia (2022) studies mortgage brokerage in the United Kingdom using a model with three pricing dimensions: brokers' fees to households, brokers' commissions to lenders, and lenders' interest rates. A difference between our settings is that UK mortgage lenders charge the same rates for brokered and non-brokered mortgages whereas restaurants typically charge higher prices on platforms. Other papers that empirically analyze a platform's prices charged to two sides of a market include Argentesi and Filistrucchi (2007), Ho and Lee (2017), and Jin and Rysman (2015).

I also provides a novel approach for modelling network externalities relative to existing empirical studies of platform. Numerous papers estimate network externalities using quasi-experimental research designs (e.g., Farronato et al. 2020 and Cao et al. 2021). In the literature that estimates network externalities in structural models, Lee (2013)'s modelling approach is closest to my own. Rather than directly specify demand for platforms by one side of a market as a function of the other side's platform usage—e.g., Rysman (2004), Kaiser and Wright 2006, Fan 2013, Ivaldi and Zhang 2020, and Sokullu 2016—Lee (2013) explicitly models the dependence of buyers' preferences and of sellers' profits on sellers' and buyers' platform participation, respectively. I proceed similarly. A novelty of my model is that seller-to-buyer network externalities stem from heterogeneous tastes for restaurants: a consumer is more likely to order from a platform that offers a broad variety of restaurants covering whatever the consumer is in the mood to order.

A recent literature assesses the welfare and distributional implications of digital platforms; see, for example, Castillo (2022), Calder-Wang (2022), Schaefer and Tran (2020), and Farronato and Fradkin (2022). I contribute to this literature by estimating effects of commission caps and of food delivery platforms on the distribution of surplus between restaurants and consumers belonging to different groups (i.e., different age groups and martial statuses).

There is extensive research on price controls,[3] but limited research on their application in multi-sided markets other than payment card markets. See Schmalensee and Evans (2005) for an overview of payment card interchange fee regulation, and Rysman 2007, Carbó-Valverde et al. 2016, and Huynh et al. 2022 for empirical studies of payment cards as platforms. Evans et al. (2015), Manuszak and Wozniak (2017), Kay et al. (2018), and Wang (2012) study caps on debit card interchange fees in the United States whereas Chang et al. (2005) study interchange fee regulation in Australia. Carbó-Valverde et al. (2016) studies reductions in interchange fees in Spain. Unlike these papers, I develop and estimate a model to study the welfare effects of price controls. Li et al. (2020) similarly develop a model to study welfare effects of caps on interchange fees; their approach differs from mine in that they calibrate a model of a monopolist platform.

Economic research on food-delivery commission caps is, to the best of my knowledge, limited to Li and Wang (2021). Li and Wang (2021) study the effects of caps on restaurant sales and delivery fees using a difference-in-differences research design. I complement their work by additionally estimating welfare effects of commission caps, and by conducting difference-in-differences analysis of platforms' sales, platform fees in addition to delivery fees, and platform adoption by restaurants.[4]

[3]See, for example, Chapelle et al. (2019) for an analysis of rent controls in Paris and Diamond et al. (2019) for an analysis of rent controls in San Francisco; Giberson (2011) for a discussion of price gouging laws in the United States; and Ghosh and Whalley (2004) for an analysis of price controls on rice in Vietnam.

[4]Food delivery platforms added new consumer fees in response to commission caps. In Chicago, for example, DoorDash added a "Chicago Fee" to consumers' bills for delivery orders after that city introduced a commission cap

There is little other economic research on the food delivery industry; other papers include Chen et al. (2022), Lu et al. (2021), and Feldman et al. (2022). Reshef (2020) also studies network externalities on a food ordering platform (Yelp).[5] My paper also relates to work on pass-through of restaurants' costs. Allegretto and Reich (2018) find that restaurants pass through almost all of their cost increases from minimum wage laws into menu prices. Additionally, Cawley et al. (2018) find that restaurants in Boulder, Colorado passed through about 70% of a tax on sugar-sweetened drinks into prices.

1.2 Roadmap

The remainder of my paper proceeds as follows. Section 2 provides background on the US food delivery industry and introduces my data. Section 3 presents empirical facts that I glean from my data and that inform my modelling choices. Section 4 develops the model. Section 5 outlines my estimation procedure. Section 6 reports the results of this estimation procedure. Section 7 describes my counterfactual analyses and presents their results.

2 Data and background

2.1 Industry background

The largest food delivery platforms in the United States are DoorDash, Uber Eats, Grubhub, and Postmates. Uber completed its acquisition of Postmates in December 2020, but did not immediately integrate Postmates into Uber Eats following this acquisition. These platforms have remained the largest US delivery platforms from the beginning of 2020 on through 2021; no new food delivery platforms of national significance emerged during this time period. Food delivery platforms facilitate deliveries of meals from restaurants to consumers, and they earn their revenue from payments collected from both consumers and restaurants. In the remainder of this paper, I refer to the prices that platforms charge to consumers as "fees," the prices that platforms charge to restaurants as "commissions," and the prices that restaurants charge to consumers for menu items simply as "prices." The following schematic equations summarize these prices:

$$\text{Consumer Bill} = p + c$$
$$\text{Restaurant Revenue} = (1 - r)p$$
$$\text{Platform Revenue} = rp + c,$$

where p is the price charged by the restaurant for the menu items purchased by the consumer, c is the fee, and r is the commission. Commission caps constrain platforms to choose $r \leq \bar{r}$. Average basket subtotals before fees, tips, and taxes were \$25 at DoorDash and \$28 at Uber Eats and Grubhub in Q2 2021. As shown by Online Appendix Figure O.1, order sizes exhibit moderate

policy.

[5] Additional papers analyzing Yelp include Luca and Reshef (2021) and Luca (2016), which study consumer reviews.

variation within platforms but are similarly distributed across platforms. About half of all orders are between \$15 and \$35 before fees, tips, and taxes.

Throughout this paper, I assume that the commission rates for all leading platforms were 30% in areas without active commission caps. Both Uber Eats and Grubhub charged 30% commissions in 2021. DoorDash's full-service membership tier featured a commission rate of 30% in April 2021.[6] Postmates did not publicly disclose its commission rates. I cannot rule out the possibility of restaurants negotiating commissions rates below those publicly advertised, but I do not analyze such negotiation because I do not observe contracts between restaurants and platforms.

Each platform charges consumers various fees that together constitute the overall consumer fee c. The principal fee is the delivery fee, which varies across restaurants, time, delivery distances, and delivery addresses. Delivery fees do not, however, depend on which items the consumer orders from a particular restaurant. Other fees include service fees and regulatory response fees that vary across municipalities but are typically constant within a municipality for an extended period of time. An example of a service fee is that charged by Uber Eats in my sample period, which amounted to 15% of an order's subtotal, but could not fall below \$2.50 or exceed \$4.50. An example of a regulatory response fee is the "Chicago Fee" of \$2.50 per order that DoorDash introduced in Chicago when that city enacted its commission cap of 15%. Platforms' service fees are often proportional to an order's value, but the other fees do not depend on the order value. In addition, platforms have responded to commission caps by adjusting their fixed fees rather than their service fees. These observations motivate my choice to treat platform consumer fees as fixed amounts rather than *ad valorem* rates throughout this paper.

Restaurants that adopt food delivery platforms control their menus and prices on these platforms. These prices need not equal prices charged by the restaurant for orders placed directly from the restaurant. Additionally, restaurants typically make an active choice to be listed on platforms rather than be listed by a platform without consent.[7] It is common for restaurant locations belonging to the same chain to nonetheless belong to different sets of online platforms.

Several other features of the food delivery industry warrant mention. Although I focus on consumers and restaurants, delivery orders also involve couriers. Couriers can deliver for multiple platforms simultaneously. I do not explicitly model couriers in this paper; instead, I specify that platforms incur constant marginal costs to deliver meals to consumers that capture platforms' compensation of drivers. These costs remain fixed as the number of delivery orders varies. My assumption of constant marginal costs is justified by the assumption that food delivery platforms are price takers in local labour markets. Additionally, some platforms offer subscription plans that allow users to pay fixed fees to reduce per-transaction delivery fees, although these plans do not reduce regulatory response fees. Data on subscriptions is lacking and subscription plans do not waive the regulatory response fees introduced in response to the commission caps that this paper studies. I therefore ignore subscription plans for the remainder of my paper. Food delivery

[6] Restaurants belonging to the other tiers, which had commission rates of 15% and 25%, received limited marketing services and smaller delivery areas.

[7] Some food delivery platforms list restaurants without their consent. When the consumer places an order from this restaurant, a courier for the delivery platform places the order at the restaurant on the consumer's behalf and then delivers the order to the consumer. This practice has decreased in popularity in recent years, and has been outlawed in several jurisdictions including California and Seattle. See Mayya and Li (2021) for a study of the practice of platforms listing restaurants without their consent.

platforms direct consumers toward restaurants using recommendation and search algorithms.[8] I abstract away from these algorithms in this paper.

Many local governments introduced commission caps after the beginning of the US COVID-19 pandemic. Figure 1 displays the share of the US population residing in a jurisdiction subject to a commission cap. This figure shows that the introduction of caps was staggered over time. Over 70 local governments had enacted commission caps by June 2021, at which point about 60 million people lived in jurisdictions with caps. Most caps limited commissions to 15%, although some limited commissions to other levels between 10% and 20%. The first commission caps were introduced as emergency measures in response to the initial US outbreak of COVID-19, which led governments to prohibit in-premises dining at restaurants. Restaurants subsequently shifted from dine-in services to take-out and delivery services. These emergency measures had either fixed expiration dates or expiry conditions.[9] As the COVID-19 pandemic progressed and debate about platforms' pricing practices garnered public attention, several jurisdictions made their commission caps permanent: San Francisco made its cap permanent in July 2021, New York City in August 2021, and Minneapolis in December 2021. The leading food delivery platforms have brought legal action against San Francisco and New York City in response to their permanent caps. To understand the effects of the caps on platforms' price structures, note that the average basket subtotal in 2021 was below but not far from $30 for each major delivery platform. A commission cap limiting a platform's commission rate from 30% to 15% would reduce the platform's revenue from a $30 order by $4.50 absent a change in the platform's fees charged to consumers. For context, platforms' average fees collected from consumers were generally between $4.00 and $6.00 from January 2020 to April 2021 (see Appendix Figure 17).

Figure 2 reports monthly average spending on food delivery platform orders in 2020–2021, indexed to January 2020. Usage of online food delivery platforms increased threefold between January and May 2020 as the US COVID-19 outbreak began.[10] Spending on delivery platform orders remained elevated relative to pre-pandemic levels even as in-premises dining re-opened in the summer of 2020 and governments relaxed public health measures throughout 2021.

Appendix Figure 17 reports the average fee paid by consumers and commissions charged to restaurants per transaction on each platform for each month from January 2020 to April 2021 in regions that had a commission cap in place as of May 1, 2021 and in those that did not. This figure illustrates that price structures skewed toward restaurant commissions before the initial US COVID-19 outbreak and throughout the pandemic in regions that did not implement commission caps. The disparity in charges paid by consumers and restaurants, however, contracted through 2020–2021 due to the introduction of commission caps.

2.2 Data

Transactions data. My study uses several sources of data characterizing the food delivery industry. First, I use a consumer panel provided by the data provider Numerator covering 2019–2021.

[8]See Huang (2021) for analysis food delivery platforms' search algorithms.

[9]Massachusetts's legislation introducing a state-wide cap, for example, specified that this cap would expire upon the end of the state's state of emergency declared in response to the COVID-19 pandemic.

[10]See Oblander and McCarthy (2021) for analysis of the effects of the COVID-19 pandemic on consumer ordering.

Figure 1: Share of US population in jurisdictions with commission caps

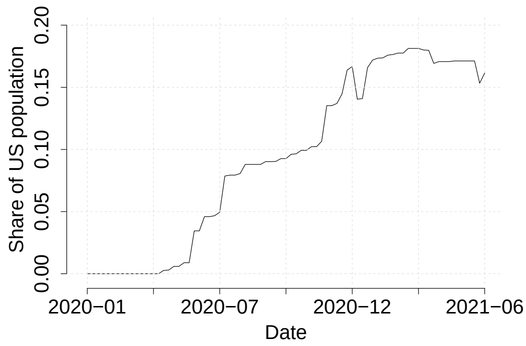
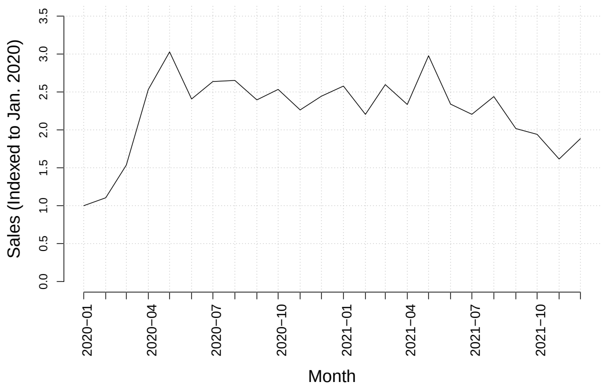


Figure 2: Food delivery platform spending, 2020–2021

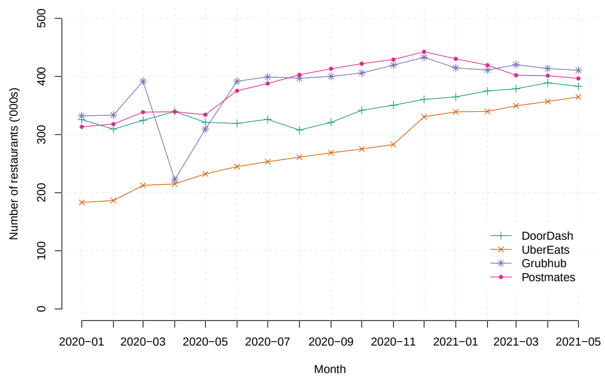


Notes: this plot reports indexed average monthly spending on orders placed on DoorDash, Uber Eats, Grubhub, and Postmates in the Numerator panel described in Section 2.2.

Panelists report their purchases to Numerator through a mobile application that integrates with email applications to collect and parse email receipts. Panelists also submit photographs of offline receipts to the mobile application. My study uses the records in this dataset that originate from restaurant purchases, whether they are placed on food delivery platforms or directly from restaurants. The orders placed directly from restaurants include orders placed at a brick-and-mortar restaurant locations, online orders for pick-ups, and delivery orders. At the panelist level, these data report ZIP code of residence and various demographic variables. At the level of a transaction, they report basket subtotal and total, the time of the transaction, the delivery platform on which the order was placed (if any), and often the restaurant from which the order was placed. These data also describe each item purchased in a given transaction, including an item identifier and item prices. The demographic composition of Numerator's core panel is close to that of the United States adult population as measured with census data. In addition, market shares computed from these data are similar to those computed from an external dataset of payment card transactions; see Appendix E for more information regarding this comparison.

The market definition that I use throughout this paper is a Core-Based Statistical Area (CBSA). CBSAs are defined by the U.S. Census Bureau as collections of counties comprising metropolitan areas, and I often call CBSAs "metros." Although the Numerator data include restaurant orders from across the United States, I focus on the markets listed by Table 1 because these are the markets for which I have detailed fee data. Table 1 reports the number of unique consumers in the

Figure 3: Restaurant membership by platform



Notes: this figure shows the number of restaurants that belong to each major food delivery platform in each month from January 2020 to May 2021.

consumer panel recording at least one restaurant order in Q2 2021 in the markets that I study in my primary analysis. The table also reports the number of restaurant transactions in the consumer panel for each metro in Q2 2021.

Table 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.

I supplement the Numerator data with platform/ZIP/month-level estimates of order volumes and average fees. Edison, a data provider, provides these estimates for each month from January 2020 to May 2021.[11] These estimates are based on a large panel of email receipts with information on delivery orders.[12] This dataset also includes data on average basket subtotals (i.e., the dollar value of food ordered excluding platform fees and taxes), average delivery fees, average service fees, average taxes, and average tips for each ZIP/month pair. I use these estimates to scale predicted orders in the Numerator panel to the market level. Estimates of nationwide spending on restaurants, which I obtain from scaling up the Numerator panel using the Edison data, are

[11] I use ZIP rather than ZCTA as shorthand for "ZIP code tabulation area" in this paper.
[12] The panel includes 2,516,994 orders for an average of about 148,000 orders a month.

very similar to estimates of food purchased away from home in the Consumer Expenditure Survey (CEX). The Edison sales estimates also imply DoorDash revenues that are close to those reported in the company's earnings reports, and market shares that are close to those estimated using an external panel of payment cards.[13]

Platform adoption I obtain data characterizing restaurants' platform adoption decisions from the data provider YipitData. These data provide a comprehensive record of restaurants in the United States that were listed on each of DoorDash, Uber Eats, Grubhub, and Postmates in each month from January 2020 to May 2021. Figure 3 displays the total number of restaurants listed on each of these platforms for each month in the data.[14] The data provided by YipitData include only restaurants that have joined at least one online platform. I construct a dataset on offline-only restaurants from the Data Axle (formerly Infogroup) dataset of business locations, which reports a comprehensive listing of United States business locations for 2021. In 2021, 28% of restaurant locations belonged to a chain with at least 100 locations, and 24% belonged to a chain with at least 500 locations. Note that I estimate my consumer choice model on data from April 2021 to June 2021 (i.e., Q2 2021). Because I do not have data on restaurant platform adoption decisions in June 2021, I use the May 2021 platform adoption data for both May 2021 and June 2021.

Platform pricing I collect data on platform fees in 2021. As explained in Section 2.1, these fees have three main components: delivery fees, service fees, and regulatory response fees. My procedure for collecting these data involves drawing from the set of restaurants in a ZIP and inquiring about terms of a delivery to an address in the ZIP. The address is obtained by reverse geocoding the geographical coordinates of the ZIP's centroid into a street address. Other variables that I record while collecting data on these fees include the time of delivery, the delivery address, the restaurant's address, restaurant characteristics, and the estimated waiting time. I repeat this procedure across many points in time for ZIPS in the 14 large metropolitan areas in the United States enumerated in Table 1. I followed an analogous procedure to collect data on service fees and regulatory response fees; this procedure involves entering delivery addresses near the centroid of ZIPs in the markets listed by Table 1, randomly choosing a restaurant from the landing page displayed after entering the delivery address, and inquiring about terms of a delivery from the restaurant to the chosen

[13] The Edison transactions dataset's ZIP code/platform/month-level estimates of expenditures at DoorDash, Uber Eats, Grubhub, and Postmates sum to $33.6 billion for 2020. These platforms account for 11.2% of all restaurant spending by Numerator panelists who linked their mobile email applications with Numerator's data-collection application. These estimates together imply restaurant spending of $2296 per consumer unit (CU) as defined by the CEX; the CEX reports 131 million CUs, which is a household definition, in the US in 2020. The CEX estimate of food spending away from home per CU in 2020 was $2375. Average restaurant spending among Numerator panelists falls below the CEX estimate. These panelists' household restaurant expenditures (defined as the product of individual restaurant expenditure and household size) averaged $1346 in 2020; failure of panelists to upload all receipts could account for this discrepancy. Note that the Edison transactions dataset also accurate estimates of DoorDash's revenue that accord with DoorDash's earning reports. Summing the product of sales and average fees (i.e., the sums of average delivery and service fees) across ZIP codes and months in each of Q4 2020 and Q1 2021, I obtain estimates of $935 million and $1.2 billion for DoorDash's revenue in these quarters. DoorDash's earnings reports claim revenues of $970 million and $1.1 billion for Q4 2020 and Q1 2021, respectively. See Figure O.4 in Online Appendix O.2 for a comparison of the Edison transactions data with an external payment card panel.

[14] The data report whether a restaurant is listed without having an agreement with the platform or whether it is partnered with the platform. For each platform, I plot only restaurants that are partnered with the platform. In addition, I consider only restaurants that are partnered with a platform as having adopted that platform in my empirical analysis.

Table 2: Description of platform pricing data, Q2 2021

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

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

Table 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.

delivery address. Table 2 provides observation counts and sample means for the platform pricing datasets for Q2 2021. Section 2.3 describes how I address my lack of data on Grubhub's service and regulatory response fees.

Delivery fees vary across metros and across ZIPs within a given metro. They vary to an even greater extent within ZIPs. Table 3 reports a variance decomposition of delivery fees for the three largest platforms that documents this fact.

I supplement the data described above with five-year American Community Survey (ACS) estimates of demographics at the ZIP code tabulation area level from 2014–2019. I use these data to study the dependence of platforms' fees on local demographics and the effect of local demographics on restaurants' platform adoption decisions. Additionally, I manually construct a dataset of commission caps that indicates the jurisdiction enacting each cap as well as the start date and end date of the cap. I conducted a search of online news articles to construct this dataset. This search identified 72 distinct commission caps on March 28, 2021, the same date that NBC News reported that it had discovered 68 commission caps across the United States. To characterize places that adopt commission caps, I regress an indicator for a commission cap on local characteristics; the results, which appear in Online Appendix Table O.1, reveal that places with a higher Democratic vote share in the 2016 presidential election, with a higher population density, and with a more educated population are more likely to enact commission caps.

2.3 Fee indices

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

$$c_{fz} = DF_{fz} + SF_{fz} + RR_{fz}, \tag{1}$$

where DF_{fz} is a measure of platform f's delivery fees in ZIP z, SF_{fz} is a measure of platform f's service fee in z's municipality, and RR_{fz} is the regulatory response fee charged by f in z. The remainder of this section describes the construction of these three terms.

The delivery fee measure DF_{fz} is the expected delivery fee charged by platform f in ZIP z conditional on a set of fixed order characteristics:

$$DF_{fz} = \mathbb{E}[df_{kfz} | x_k = \bar{x}, f, z], \tag{2}$$

where df_{kfz} is the delivery fee charged on order k on platform f in ZIP z, x_k are observable characteristics of order k, and $\bar{x}$ is a vector of order characteristics that is fixed across platforms f and ZIPs z. Variation in DF_{fz} reflects systematic differences in delivery fees across platforms and regions for an order with the same x_k characteristics.[15] It is important to include a rich set of order characteristics in x_k so that the fee indices do not reflect differences in the selection of restaurants across platforms and regions. In practice, the observable characteristics that I include in x_k are time of day and day of week, a cubic in the delivery distance, and indicator variables for various restaurant cuisines and restaurant chain indicators. I estimate (2) using a k-fold cross-validated Lasso (with $k = 10$), which is a penalized regression estimator intended to prevent overfitting in the presence of high-dimensional regressors. The high-dimensional regressors in my setting include a rich set of controls for geography. Appendix A discusses my procedure for estimating (2) in detail.

Note that my delivery fees data include expected waiting times as reported by platforms. I compute waiting time indices W_{fz} in the same manner as the delivery fee indices $\widehat{DF}_{fz}$ after substituting platforms' waiting times for the delivery fees df_{kfz} in the expressions above.

The service and regulatory response fee measures SF_{fz} and RR_{fz} are straightforwardly defined. I define SF_{fz} as platform f's median service fee in ZIP z's municipality. Service fees are generally proportional to their corresponding order's subtotal; I use a subtotal of \$30 to compute service fees in practice, given that average subtotals are close to \$30 in my data. Recall that my fee data does not include service fees for Grubhub. This omission is not critical given that Grubhub did not enact regulatory response fees aside from a fee of \$1 per order in California.[16] It does, however, limit my information on Grubhub's service fees. I use the Edison transactions data to overcome

[15] In practice, delivery fees vary widely within CBSAs. Tables O.2 and O.3 report estimates from regressions of delivery fees df_{kfz} on region fixed effects, a cubic in the delivery distance, and a wide range of order characteristics and geographical characteristics. The regions are either CBSAs or counties. The results show that there remains a high level of unexplained variation in delivery fees within a CBSA or county: the R^2 values from the regressions are generally low. These results also indicate meaningful variation in average fees across places within a CBSA: several delivery address characteristics correlate with delivery fees within a region, and replacing CBSA fixed effects with county fixed effects significant increases the explanatory power of the regressions.

[16] This fee was introduced in response to legislation mandating that platforms provide certain benefits to couriers.

this limitation. These data include the average service fee, average order value before taxes and fees, and estimated sales at the level of a ZIP/platform. The median and the sales-weighted mean of ZIPs' ratios of average service fees to average order value before taxes and fees are both 0.10. I therefore use 10% as Grubhub's service fee in computing SF_{fz}.[17] Regulatory response fees apply to entire municipalities, so I compute RR_{fz} by identifying all regulatory response fees in my data and then taking the sum of such fees charged by platform f in ZIP z's municipality.

3 Eight empirical facts

In this section, I present facts characterizing the food delivery industry that inform my modelling decisions.

3.1 Commission caps raise platforms' consumer fees and lower platform order volumes

I estimate effects of commission caps on platforms' consumer fees and platform order volumes using two-way fixed effects (TWFE) regressions. The estimating equation for platform f is

$$y_{fzt} = \underbrace{\psi_{fz} + \phi_{ft}}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\beta_{fx} x_{zt}}_{\text{Treatment}} + \underbrace{\beta_{fC} C_{zt}}_{\text{COVID control}} + \epsilon_{fzt}, \tag{3}$$

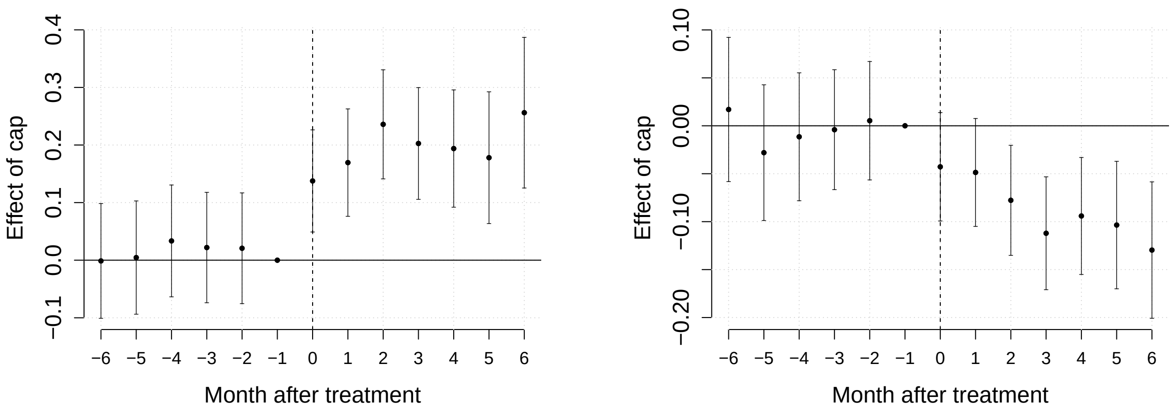
where y_{fzt} is an outcome variable for platform f in ZIP z for month t, ψ_{fz} are platform/ZIP fixed effects, ϕ_{ft} are platform/month fixed effects, x_{zt} is a measure of ZIP z's commission cap policy during t, C_{zt} is the number of new COVID-19 cases in ZIP z's county as a fraction of the county's population in month z, and ϵ_{zft} is an unobservable assumed to be mean independent of x_{zt}. Last, the β_{fx} parameters measure responses of the outcome variable to commission caps. The outcome y_{fzt} is either the log of platform f's average fee in ZIP z in month t or the log of platform f's number of orders in z during t.[18] I control for the number of COVID-19 cases in (3) because the severity of COVID-19 may affect both changes in these outcomes and a jurisdiction's decision to enact a commission cap. The treatment variable x_{zt} is an indicator for z having a commission cap of 15% or lower. I estimate the effects of commission caps of 15% or lower because 15% has been the most popular level of caps in the United States, and I focus on analysis of these caps. I exclude ZIPs where caps greater than 15% took effect from my TWFE analysis. Online Appendix O.5 provides results for an alternative specification in which the treatment group contains ZIPs with any commission cap and the control group contains all remaining US ZIPs. These results are similar to those for my baseline specification. The primary identifying assumption underlying my TWFE approach is that, conditional on trends in the local severity of COVID-19, the outcome

[17] I explored using separate Grubhub service fee rates for different geographical regions, but the ratio of average service fee to average order value in the Edison transactions data exhibits little systematic variation across geography.

[18] My panel of platform/ZIP/month-level sales and fee estimates includes variables reporting average order values including fees, tips and taxes; average order values excluding fees, tips, and taxes (i.e., average basket subtotals); average tips; and average taxes. I obtain my measure of average fees by subtracting the last three of these variables from the first. I conduct difference-in-differences analysis to assess the effect of commission caps on basket subtotals; see Table O.11 in the Online Appendix. The estimated effects are generally statistically insignificant, and they vary in sign. This suggests that there is no strong, systematic effect of caps on basket subtotals. This in turn suggests that the positive effects of caps on platforms' consumer fees reported in this section do not reflect increases in fees that are proportional to basket subtotals on account of a rise in subtotals.

Figure 4: Effects of commission caps on DoorDash fees and order volumes

(a) Effects on log fees (b) Effects on log number of orders



Notes: this figure reports estimates of commission caps' effects on DoorDash's log average fees and log order volumes from a variant of 3 wherein the effect β_{fx} varies by the month relative to the implementation of a commission cap. I estimate these effects by OLS.

variable in places that enacted commission caps would have followed the same trend as in places that never enacted commission caps if commission caps counterfactually had not been imposed in the former places.

Recent research in econometrics—e.g., de Chaisemartin and D'Haultfœuille (2020)—highlights problems affecting TWFE estimators in settings with heterogeneous treatment effects and staggered treatment. To check the robustness of my findings, I additionally estimate fee and order responses to commission caps using the estimator of Callaway and Sant'Anna (2021), who develop estimators for average treatment effects on the treated that are robust to heterogeneous treatment effects. The Callaway and Sant'Anna (2021) estimator yields similar estimates to those from my TWFE estimator; see Tables O.4 in Online Appendix O.5

Table 4: Responses to commission caps (fees and order volumes)

	Outcome	
Platform	Log fees	Log # orders
Total	-	-0.06
		(0.01)
DD	0.20	-0.06
	(0.02)	(0.01)
Uber	0.09	-0.05
	(0.02)	(0.01)
GH	0.12	0.07
	(0.06)	(0.02)

Notes: this table reports estimates of the effects β_{fz} in (3) of a commission cap of 15% or less on either (i) log average fees or (ii) the log of the number of orders. Each estimator is computed on a ZIP/month level panel, and each ZIP is weighted by its population. I compute each estimator separately for each of DoorDash (DD), Uber Eats (Uber), and Grubhub (GH). I also run each analysis using total sales summed across platforms as the outcome variable; these results are provided by the "Total" rows. I do not include results for Postmates because I lack data on Postmates fees across the sample period.

Table 4 provides estimated effects of commission caps on the log of platform fees and on the log of the number of orders for each of DoorDash (DD), Uber Eats (Uber), and Grubhub (GH). I also estimate the effects of commission cap on the total number of sales on these platforms; the "Total" row provides these estimates. Commission caps raised average fees by 0.9–0.20 log points across platforms, which amounts to 9–22% increases in fees. DoorDash's estimated fee increase represents about one-third of the average revenue that DoorDash loses on an order from the introduction of a 15% commission cap. Commission caps reduce the number of orders on the two largest platforms, DoorDash and Uber Eats, by about 5% and 7%, respectively; caps, however, raise orders on Grubhub. The fact that commission caps had substantial positive effects on fees while having relatively small—and possibly positive—effects on sales could owe to the fact that commission caps attracted restaurants to join platforms, as I discuss in a subsequent paragraph.

Figure provides event-study estimates of a comission cap's effects at various points in time before and after the introduction of the cap. I estimated these effects by OLS applied to a variant of 3 wherein the effect β_{fx} varies by time until the imposition of a commission cap.[19] The figure provides these estimates for DoorDash, the largest delivery platform. There is not evidence of pre-trends in DoorDash's fees or order volumes in places that introduced commission caps. Additionally, Figure suggests that platforms responded to commission caps with fee hikes almost immediately. Online Appendix O.5 provides additional event study plots from TWFE regressions and the Callaway and Sant'Anna (2021)/Sant'Anna and Zhao (2020) estimator. These plots similarly show a lack of fee and sales pre-trends in ZIPs that introduced commission caps.

Online Appendix O.5 provides results for a continuous treatment variable x_{zt} defined to be equal to the level of the commission cap in place in ZIP z in month t, or to 0.30 if no cap is in effect. This appendix also reports results from analyses that exclude observations for months before July 2020. These results are intended to assuage concerns that acute disruptions from the onset of the COVID-19 pandemic affect my results. By July 2020, prohibitions on on-premises dining had been lifted in every US state. The results of the post-July 2020 analyses are similar to those reported by Table 4. Table O.8 in the Online Appendix provides estimates of the effects of commission caps on (i) service fees proportional to basket subtotals and (ii) fixed fees, including delivery fees and regulatory response fees. These estimates constitute evidence that commission caps raised fixed fees but not service fee rates. Last, Table O.11 in the Online Appendix reports estimates of (3) with the log the average basket subtotal before fees, tips, and taxes as the outcome variable. I do not find a significant effect of commission caps on basket subtotals.

Modelling implication. Platforms' consumer fees are endogenously determined in my model, and they may respond to commission caps.

[19] In particular, this variant is

$$y_{fzt} = \psi_{fz} + \phi_{ft} + \sum_{\tau=-\bar{\tau}}^{\bar{\tau}} \beta_{fx\tau} x_{z,t-\tau} + \beta_{fx}^{+} \sum_{\tau>\bar{\tau}} x_{z,t-\tau} + \beta_{fx}^{-} \sum_{\tau<-\bar{\tau}} x_{z,t-\tau} + \beta_{fc} C_{zt} + \epsilon_{fzt},$$

The treatment variable $x_{z,t-\tau}$ equals one if and only if a commission cap was first imposed in ZIP z in month $t-\tau$. Figure 3.1 plots estimates of the $\beta_{fx\tau}$ coefficients, with the horizontal axis providing values of τ. The β_{fx}^{+} and β_{fx}^{-} parameters are effects of a commission cap introduced over $\bar{\tau}$ months in the past and over $\bar{\tau}$ months in the future, respectively. I set $\bar{\tau} = 10$ in practice.

3.2 Commission caps induce restaurant uptake of platforms

Commission caps may also affect restaurants' platform membership decisions. I use a difference-in-differences approach mirroring that in Section 3.1 to estimate restaurants' platform adoption responses to commission caps. Although my data include the universe of restaurants on delivery platforms at a monthly frequency, my data on all US restaurants—including those that do not belong to a platform—are recorded at an annual frequency. I therefore estimate TWFE regressions at an annual level with platform adoption measures as outcomes. The estimating equation is

$$y_{zt} = \underbrace{\psi_z + \phi_t}_{\substack{\text{ZIP and month} \\ \text{fixed effects}}} + \underbrace{\beta_x x_{zt}}_{\text{Treatment}} + \underbrace{\beta_C' C_{zt}}_{\text{COVID control}} + \varepsilon_{zt}, \tag{4}$$

where ψ_z are ZIP fixed effects, ϕ_t are time-period fixed effects, and x_{zt} is an indicator for whether a commission cap of 15% or lower is active in ZIP z during time period t. Additionally, the vector C_{zt} includes both (i) the number of new COVID-19 cases per capita in ZIP z's county in time period t and (ii) the cumulative number of COVID-19 cases per capita in ZIP z's county by time period t. The two time periods are January 2020 and January 2021. The sample includes (i) treated ZIPs where commission caps of 15% or lower were imposed between January and June 2020 and (ii) control-group ZIPs that did not have commission caps by the second period. The two outcomes y_{zt} are (i) the share of restaurants belonging to at least one platform and (ii) the average number of platforms that a restaurant in the ZIP joins. The identifying assumption required for the consistent estimation of β_x is that ZIPs in places with caps would have experienced the same trends in platform adoption as ZIPs in places without caps if the former places counterfactually never had caps. Online Appendix O.5 provides results for platform-specific adoption shares as outcome variables and for a continuous treatment variable.

Table 5: Effects of commission caps on restaurants' platform adoption

(a) Difference-in-differences estimates

Share online	# platforms joined
0.040	0.099
(0.003)	(0.006)

(b) Within-metro estimates

Share online	# platforms joined
0.070	0.207
(0.004)	(0.011)

Notes: Table 5a reports OLS estimates of β_x in (4). The two time periods on which I estimate (4) are January 2020 and January 2021. The outcome y_{zt} is the share of restaurants in the ZIP that belong to at least one platform. The sample includes ZIPs that either belonged to (i) a municipality wherein a municipality came into effect between the beginning of January 2020 and the end of June 2020 (treated group) or (ii) a municipality in which a cap was not imposed by the end of May 2021 (control group). Each ZIP is weighted by its average number of restaurants across the two time periods.

Table 5b table reports results from ZIP-level regressions of the share of restaurants in a ZIP that have adopted at least one online platform in May 2021 on an indicator for whether a commission cap applied in the ZIP. It also reports results for an analogous regression wherein the average number of platforms joined by a restaurant in the ZIP is the outcome variable. Each ZIP is weighted by its number of restaurants. The tables report standard errors in parentheses.

Table 5a provides ordinary least squares estimates of β_x in (4). These results suggest that commission caps lead to a 4.0 percentage-point increase in the share of restaurants belonging to at least one delivery platform and an increase of 0.099 in the average number of delivery platforms to which a restaurant belongs.

To assess the robustness of my difference-in-differences estimates, I also estimate the effects of commission caps on platform adoption using cross-sectional variation between municipalities within a metro area that differ in their commission cap policies. The underlying identification assumption is that the unobservable propensity for restaurants to join platforms does not differ within a metro area between places with and without commission caps. I estimate effects of commission caps using within-metro variation by regressing the share of restaurants in a ZIP belonging to at least one platform on metro fixed effects and on an indicator for a cap of 15% or less being effect. Table 5b provides the results of this regression for May 2021. The results suggest that commission caps induce a 7.0 percentage-point increase in the share of restaurants that belong to at least one platform. These effects are somewhat similar to those that I estimate using a difference-in-differences approach as reported in Table 5a.

Modelling implication. Platform adoption by restaurants is endogenous and depends on commission rates in my model.

3.3 Consumers place more orders on platforms that attract new restaurants

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

$$\underbrace{\log \mathscr{s}_{fzt}}_{\text{Log sales}} t = \underbrace{\psi_{fz} + \psi_{ft}}_{\substack{\text{ZIP and month}\\ \text{fixed effects}}} + \underbrace{\beta_{\mathrm{NE}} \log J_{fzt}}_{\text{Network externalities}} + \varepsilon_{fzt}, \tag{5}$$

where $\mathscr{s}_{fzt}$ are platform f's sales in ZIP z in month t, J_{fzt} is the number of restaurants on platform f within five miles of ZIP z in month t, and ψ_{fz} and ψ_{ft} are platform/ZIP and platform/month fixed effects, respectively. The unobservable ε_{fzt} is assumed to be mean independent of J_{fzt} conditional on the fixed effects ψ_{fz} and ψ_{ft}. This assumption allows for restaurants to respond to time-invariant local demand disturbances, which are captured by ψ_{fz}, and to national time-varying demand disturbances, which are captured by ψ_{ft}. The assumption does not, however, allow for restaurants' platform adoption to respond to local monthly demand deviations. This may be a valid restriction when frictions in the platform adoption process prevent restaurants from suddenly joining platforms. This research design follows that of Natan (2021), who discusses the underlying identifying assumptions in greater detail.

In addition to estimating (5), 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.6 provides results from this approach, which are similar to those that I obtain for (5).

Table 6: Restaurant-to-consumer network externalities (difference-in-differences estimates)

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

Notes: this table reports ordinary least squares estimates of the parameter β_{NE} in (5). The second column provides estimates of $\beta^{\text{NE}}_{\text{chain}}$ and $\beta^{\text{NE}}_{\text{non-chain}}$ in (6). 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 6 reports the estimate of β_{NE}, which suggests the empirical relevance of network externalities exerted by restaurants on consumers. The second column provides OLS estimates of $\beta^{\text{NE}}_{\text{chain}}$ and $\beta^{\text{NE}}_{\text{non-chain}}$ in

$$\log s_{fzt} = \psi_{fz} + \psi_{ft} + \beta^{\text{chain}}_{\text{NE}} \log J^{\text{chain}}_{fzt} + \beta^{\text{non-chain}}_{\text{NE}} \log J^{\text{non-chain}}_{fzt} + \varepsilon_{fzt}, \tag{6}$$

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

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.

3.4 Both consumers and restaurants multihome

I assess the extent of multihoming in the food delivery industry by computing measures of consumer and restaurant multihoming. I define a measure of consumer multihoming for each pair of platforms f and f' that equals the share of pairs of consecutive orders placed on a platform made by the same consumer that contain a purchase from f among those that also contain a purchase from f'. To illustrate this multihoming measure, suppose that I observed one consumer buy from DoorDash across two consecutive orders and that I observed a second consumer purchase 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.[20] I characterize restaurant multihoming by computing the

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

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

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 16 in the appendix reports the average number of platforms from which a panelist

Table 7: 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 7a reports, for each pair of platforms f and f', the share of pairs of consecutive orders placed by the same consumer in April 2021 that include an order from f' among those that contain an order from f. Table 7b reports the share of restaurants on each major delivery platform that also belong to each other major delivery platform for April 2021.

share of restaurants listed on each platform that are also listed on each other platform. Table 7 reports the results, which show that both consumers and restaurants multihome.

Although consumers sometimes switch between platforms, it is more common for consumers to order from the same platform across consecutive orders. Explanations for repeated ordering from a platform 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. Appendix Table 24 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.

has ordered after placing t orders, for $t = 1, \ldots, 30$.

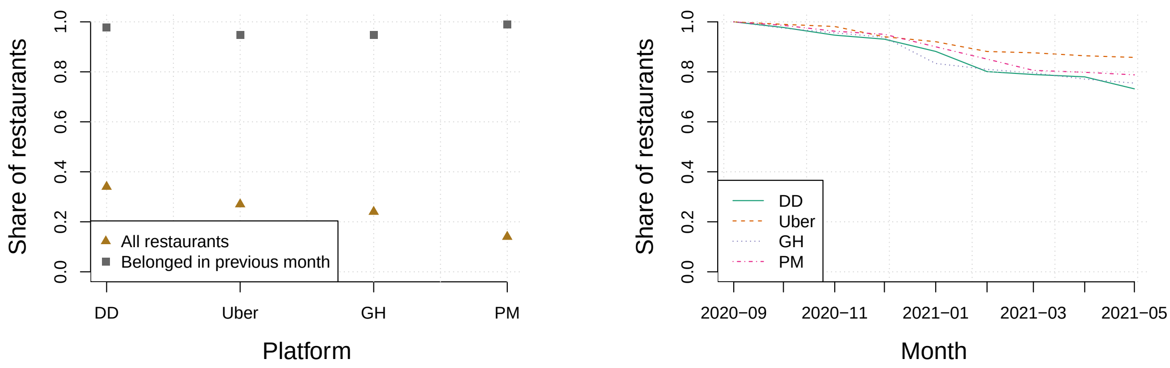
Modelling implication. My model allows for both consumer and restaurant multihoming. Additionally, repeat ordering from a platform arises in my model due to unobserved taste heterogeneity rather than state dependence.

3.5 Restaurants that join a platform tend to remain on the platform

Figure 5: 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 5a 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 5b reports the share of restaurants on each platform in each month from September 2020 to May 2021 among all restaurants that belonged to the platform in September 2020.

Figure 5a 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 5b plots the share of restaurants on each platform in each month from September 2020 to May 2021 among restaurants that belonged to the platform in September 2020. The figure shows that, even eight months on, a significant majority of restaurants on a platform are still listed on the platform. These figures suggest that restaurants may exhibit state dependence in their choice of platforms. Consequently, a platform may be able to boost its future profitability by enrolling new restaurants. Platforms may take the effects of their restaurant networks on future profitability into account when setting commissions.

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

3.6 Restaurants charge higher prices for platform-intermediated orders than for direct orders

Each leading delivery platform allows restaurants to post prices on the platform that differ from the restaurant's prices for direct orders and from the restaurant's prices on other platforms. I use my

Table 8: Markups of restaurant prices on food delivery platforms

Platform	Common markup	Platform-specific markups
Online	0.24	-
	(0.01)	-
DD	-	0.28
	-	(0.09)
Uber	-	0.27
	-	(0.01)
GH	-	0.23
	-	(0.01)

Notes: this table reports estimates of the ϑ_f parameters in (7). I estimate the equation via an ordinary least squares regression of log menu prices on platform indicator variables after transforming both variables by the within transformation (i.e., by subtracting off their within-item ι mean values across transactions) to purge the fixed effects φ_ι from (7). The estimation sample includes item-level transactions in Q2 2021. Classical asymptotic standard errors appear in parentheses.

item-level transactions data to estimate the average markups of restaurant menu items on delivery platforms relative to their direct-from-restaurant prices. This procedure involves estimating

$$\underbrace{\log p_{\iota ft}}_{\text{Log price}} = \underbrace{\varphi_\iota}_{\text{Item fixed effect}} + \underbrace{\vartheta_f}_{\text{Mean markup}} + \varepsilon_{\iota ft}, \tag{7}$$

where ι is a menu item, f is a platform, and t is a transaction. Additionally, $p_{\iota ft}$ is an observed menu price, φ_ι are menu-item fixed effects, and $\varepsilon_{\iota ft}$ captures both measurement error and item-level deviations from the mean log markup ϑ_f of prices on platform f. I assume that $\mathbb{E}[\varepsilon_{\iota ft}|\iota, f] = 0$, which requires that measurement error in $\log p_{\iota ft}$ is uncorrelated with platform f conditional on a menu item. I normalize $\vartheta_0 = 0$ for the platform $f = 0$ that represents direct-from-restaurant ordering. To understand why I interpret ϑ_f as a mean log markup of prices on platform f, note that

$$\mathbb{E}[\log(p_{\iota ft}/p_{\iota 0t}) \mid \iota, f] = \vartheta_f.$$

I estimate (7) by OLS on data from Q2 2021. Table 8 reports estimates of ϑ_f when (i) $\vartheta_f = \vartheta$ for a constant ϑ across all platforms f and (ii) when ϑ_f varies across platforms. This table implies that prices on online platforms are about 27% higher than those for direct orders on average, and that this markup does not vary considerably across platforms. Online Appendix O.4 additionally reports distributions of the markups of platform prices, and compares menu items' prices across platforms. This appendix shows that markups are concentrated between 0% and 50%, and that price variation among platforms is small.

To obtain the menu price measures that I use in estimating my model, I estimate mean differences in menu items' prices across platforms and restaurant locations using a Lasso regression with item fixed effects. The regression equation differs from (7) in that it allows markups of restaurants' prices on platforms to vary across markets and restaurant locations belonging to different subsets of platforms. Appendix B provides the details of this procedure. The price measures I obtain systematically vary between the direct and platform-intermediated ordering channels, but not between platforms. Additionally, I do not find evidence of differences in restaurant prices on platforms between areas with and without commission caps using my item fixed-effects approach. One explanation for this finding is that the menu items purchased across platforms and restaurant locations in my data are mostly sold by large chain restaurants. Chains may practice uniform or zone pricing; that is, they may not condition their prices on local demand and cost conditions, including the presence of a local commission cap.[21] Uniform and zone pricing could significantly limit price responses to a commission cap given that 56% of orders placed on the four leading food delivery platforms were from chains with at least 100 locations, and 48% were from chains with at least 500 locations in the first half of 2021. Using manually collected data on restaurant prices that includes prices at independent restaurants, I find that the relative markups of restaurant prices on platforms (i.e., prices on platforms divided by direct-from-restaurant prices) are about seven percentage points lower on average in places with commission caps.[22] Commission caps of 15% cut commission rates in half, but a seven percentage point reduction in restaurant prices markups on platforms is far less than one-half of the markups reported by Table 8. If markups of restaurants' prices on platforms mostly result from pass-through of commissions, this suggests that restaurant prices do not fully respond to commission caps. In fact, my model predicts that commission caps reduce the markups of prices on platforms relative to direct-order prices by over one-half. Motivated by the fact that caps have a limited effect on restaurant prices in practice, I evaluate commission caps with and without restaurant price responses in my model-based analysis.

Modelling implication. I model restaurant price-setting for both direct orders and platform-intermediated orders. This pricing model allows for incomplete pass-through of commissions.

3.7 Platform market shares vary across metropolitan areas

Figure 6a plots each major platform's share of spending on food delivery platforms in Q2 2021 for 14 large US metropolitan areas. Additionally, Figure 6a 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.

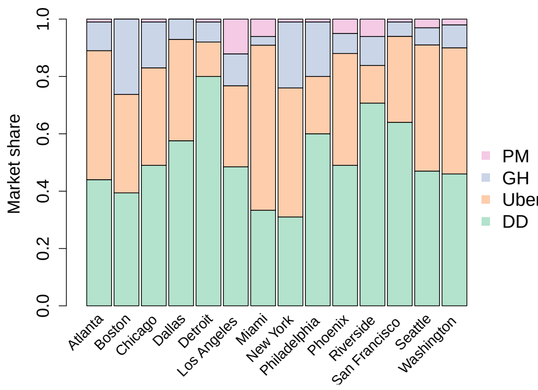
3.8 Younger consumers are more likely to use delivery platforms

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,

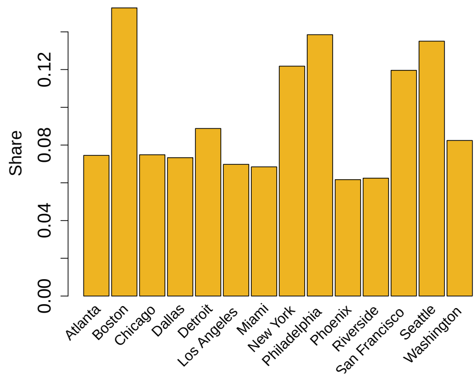
[21] See DellaVigna and Gentzkow (2019) and Adams and Williams (2019) for evidence of uniform and zone pricing in retail.

[22] See Appendix B for details of this analysis.

Figure 6: Market shares, Q2 2021



(a) Market shares among leading platforms

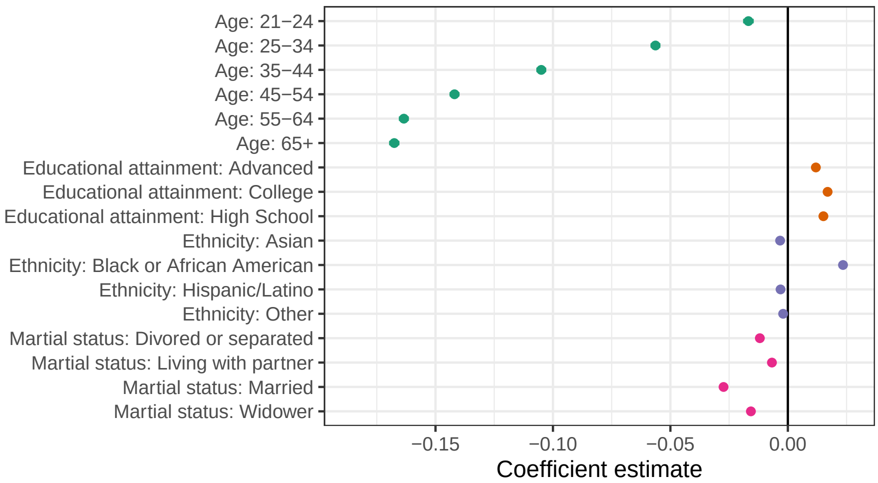


(b) Online platform shares of restaurant expenditure

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.

employment statuses, household sizes, income groups, and gender. Figure 7 plots several of the coefficients from this regression. Younger consumers are much likelier to order from food delivery platforms than older consumers. Additionally, married consumers are less likely to use platforms than single consumers, the reference group for marital status in the regression.

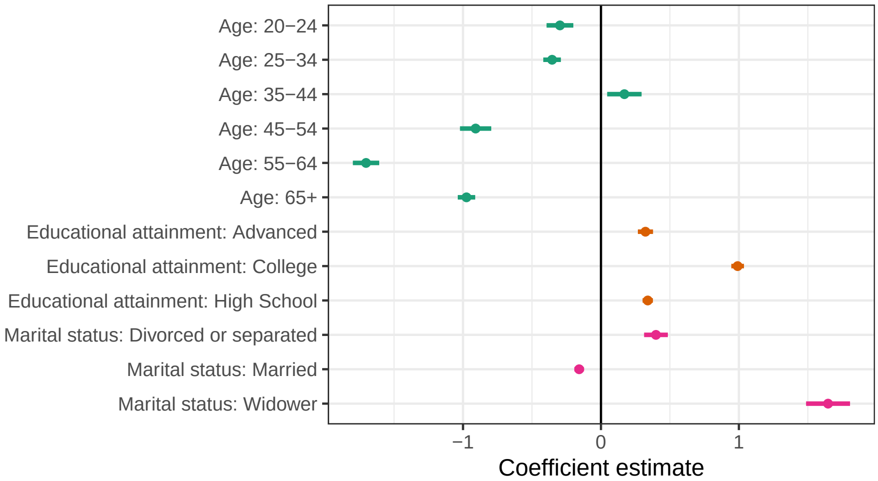
Figure 7: Demographics of food delivery users



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.

If restaurants respond to changes in the profitability of joining delivery platforms, then an increase in tastes for platform ordering among restaurants' potential consumers should induce restaurants to join platforms. To assess this hypothesis, I regress the share of restaurants in a ZIP that belonged to at least one delivery platform in April 2021 on the share of the population within five miles of the ZIP that belongs to various age groups, educational attainment groups, and marital

Figure 8: 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.

status groups.[23] Figure 8 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 15 reports the distribution of restaurants across subsets of platforms.

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

4 Model

4.1 Summary of model

To analyze the welfare effects of commission caps and the economic forces shaping these effects, I develop a model of the food delivery industry. This model features consumers who place orders from nearby restaurants through platforms. An order involves the sale of a representative menu item from a restaurant to a consumer. The platforms include online platforms as well as the direct platform $f = 0$, which represents the consumer's alternative of ordering directly from a restaurant.

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

Each restaurant j charges a price p_{jf} to a consumer who places an order from the restaurant on platform f. Each consumer and each restaurant belongs to a metro m, each of which is further partitioned into ZIPs z. Each ZIP contains a fixed number of consumers and a fixed number of restaurants.

Formally, I develop a sequential game to which I equip a perfect Bayesian equilibrium solution concept. Competition in each metro area is a separate game. Each game's players are platforms and restaurants. Platforms are characterized by market-specific marginal costs, and their strategic variables are consumer fees and restaurant commission rates. Platforms in the model do not charge either side of the market fixed fees for access to the platform. Restaurants differ in their geographical locations and in disturbances affecting their platform adoption decisions. Their strategic variables are platform adoption and prices.

The game has four stages. In the first stage, platforms choose their commission rates. When a consumer orders from a restaurant j on a platform f, the platform collects a flat fee c_{fz} from the consumer and a commission of $p_{jf}r_{fz}$ from the restaurant, where p_{jf} is restaurant j's price on platform f and r_{fz} is platform f's commission rate for ZIP z. The first stage of the model features simultaneous commission setting by platforms, whose commission rates constitute a Nash equilibrium. I capture dynamic incentives in commission setting by including the size of a platform's restaurant network—which affects a platform's future profitability—in the platform's objective function. Restaurants subsequently choose which platforms to join in response to these commission rates. Upon joining platforms, restaurants choose prices to charge for direct orders and for orders from each platform. These prices also depend on platform commissions; in general, restaurants partially pass through their commission charges to consumers by setting higher prices on platforms. Platforms set their consumer fees concurrently as restaurants set prices. Last, consumers place orders. I specify that platforms set commissions before restaurants join platforms because leading food delivery platforms advertise commission rates to restaurants considering platform membership. Platforms' contracts with restaurants do not prevent them from changing their fees after restaurants have joined platforms — this underlies my decision to specify that platforms set consumer fees after restaurants join platforms. Leading platforms, for example, often immediately add new fees after municipalities adopt commission caps. Restaurants are also free to adjust their prices on platforms, which motivates my decision to include restaurant pricing in the final strategic stage of my model.

Although I capture many complex features of the food delivery industry with my model, I abstract away from other features. First, restaurants in the same ZIP do not systematically differ in their appeal to consumers or their costs of platform adoption. Reducing restaurant heterogeneity to some extent is necessary for tractability of the restaurant platform adoption and pricing games, although I plan on extending the model to feature multiple discrete types of restaurants (e.g., chain versus independent restaurants, downmarket versus upscale restaurants). This extension is conceptually straightforward. Another way in which I simplify reality with my model is by specifying that platforms' consumer fees do not depend on basket subtotals (i.e., the dollar value of food ordered before fees and taxes). In reality, platforms charge delivery fees and regulatory response fees that do not depend on the subtotal in addition to service fees that do depend on the basket subtotal. Given that I study commission caps, and that platforms adjusted their fees in response to caps by introducing fixed regulatory response fees, I specify consumer fees as fixed, i.e., independent of the basket subtotal.[24] Last, my model is static whereas platforms may face dynamic pricing incentives in reality. Nonetheless, I capture platforms' dynamic incentives in setting commissions in a reduced-form way as described in the preceding paragraph.

The remainder of this section details the stages summarized above in backwards order.

4.2 Consumer choice

Consumer i contemplates ordering a restaurant meal at T occasions each month. In each occasion $t \in \{1, \ldots, T\}$, the consumer chooses whether to order a meal from a restaurant or to otherwise prepare a meal. When consumer i orders from a restaurant, the consumer chooses both a restaurant j and a food delivery platform $f \in \mathcal{F}$ from which to place the order. For notational convenience, I represent the alternative not to order from a restaurant as the *outside restaurant* $j = 0$. Let $\mathcal{G}_j \subseteq \mathcal{F}$ denote the set of platforms on which restaurant $j \neq 0$ is listed; I call the set $\mathcal{G}_j$ restaurant j's *platform portfolio.* The consumer chooses a restaurant/platform pair (j, f) among pairs for which (i) restaurant j is within five miles of consumer i's ZIP of residence and (ii) $f \in \mathcal{G}_j$ to maximize

$$v_{ijft} = \begin{cases} \psi_{if} - \alpha_i p_{jf} + \eta_i + \gamma \nu_{ijt}, & j \neq 0 \\ \gamma \nu_{i0t}, & j = 0, \end{cases}$$

where ψ_{if} is consumer i's taste for platform f, p_{jf} is restaurant j's price on platform f, η_i is a taste for dining at restaurants that is unobservable to the econometrician, and ν_{ijt} is consumer i's idiosyncratic taste for restaurant j in ordering occasion t. Consumer i's tastes ν_{ijt} are mutually independent across restaurants and ordering occasions, and they are also independent of all other random variables in the model. The relative magnitude of γ governs the importance of consumer i's tastes for restaurants relative to the consumer's tastes for platform-specific payoffs. As I explain in greater detail below, it also controls the extent of restaurant-to-consumer network externalities. Additionally, α_i is consumer i's price sensitivity, which I specify as

$$\alpha_i = \alpha + \alpha_{\text{LowInc}} \text{LowInc}_i,$$

where LowInc_i is an indicator for whether the consumer's household income is below \$40,000.

I specify consumer i's tastes ψ_{if} for platform f as

$$\psi_{if} = \delta_{fm} - \alpha_i c_{fz} - \tau W_{fz} + \lambda_f' d_i + \zeta_{if}.$$

for platforms $f \neq 0$. I normalize $\psi_{i0} = 0$ for all i. Here, δ_{fm} is a parameter governing the mean taste of consumers in market m for platform f; c_{fz} is platform f's fee to consumers in ZIP z; W_{fz} is platform f's waiting-time index in ZIP z; and d_i is a vector of consumer characteristics. The characteristics included in d_i are (i) an indicator for the consumer being younger than 35 years of age, and (ii) an indicator for the consumer being married. Additionally, ζ_{if} are consumer i's

[24] See Table O.8 in the Online Appendix for difference-in-differences evidence that platforms adjusted their fixed fees but not their proportional service fees in response to commission caps. Also note that the introduction of fixed "regulatory response fees" was an especially salient response of platforms to caps.

persistent idiosyncratic tastes for platform f. I specify ζ_{if} as

$$\zeta_{if} = \zeta_i^{\dagger} + \tilde{\zeta}_{if},$$

where $\zeta_i^{\dagger} \sim N(0, \sigma_{\zeta 1}^2)$ and $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta 2}^2)$ independently of all else. The $\zeta_i^{\dagger}$ unobservable governs consumer i's taste for the online ordering channel whereas $\tilde{\zeta}_{if}$ governs consumer i's particular taste for platform f. Note that the parameters $\sigma_{\zeta 1}$ and $\sigma_{\zeta 2}$ are random coefficients in the style of Berry et al. (1995) on channel and platform indicators. As noted above, the relative magnitude of γ governs the extent of network externalities. This point is especially clear when the ν_{ijt} are iid draws from a mean-zero type 1 extreme value distribution (as I assume in my empirical application) and the component $V_i(\mathcal{G}_j, p_j) := \max_{f \in \mathcal{G}_j}[\psi_{if} - \alpha_i p_{jf}]$ of consumer i's utility from restaurant j's platform portfolio does not depend on p_j. In this case,

$$\max_{j \neq 0} v_{ijt} = \max_{\mathcal{G} \in 2^{\mathcal{F}} : \{0\} \in \mathcal{G}} V_i(\mathcal{G}) + \eta_i + \gamma \log J_i(\mathcal{G}) + \gamma \tilde{\nu}_i(\mathcal{G}), \tag{8}$$

where $\nu_i(\mathcal{G})$ is a mean-zero type 1 extreme value random variable that is independently distributed across $\mathcal{G}$, and $J_i(\mathcal{G})$ is the number of restaurants available to i that belong to platform portfolio $\mathcal{G}$. Equation (8) re-expresses the consumer's choice of restaurant as a choice among types of restaurants, with each type defined by a platform portfolio $\mathcal{G}$. The contribution of the log number of restaurants on $\mathcal{G}$ to the consumer's payoff from choosing $\mathcal{G}$ relative to the contribution of the value from platforms $V_i(\mathcal{G})$ is determined by the ratio of γ to the parameters that control the magnitude of $V_i(\mathcal{G})$. To build intuition for the dependence of network externalities on γ, note that a platform cannot attract consumers by offering more restaurants when consumers like all restaurants equally, i.e., $\gamma = 0$. When γ is large, consumers are particular in their tastes for restaurants, and a platform can attract consumers who love a restaurant by enticing that restaurant to join the platform.

The model outlined above yields tractable choice probabilities even when $V_i(\mathcal{G}_j, p_j)$ depends on menu prices that vary across restaurants. This is because the consumer's choice of restaurant can generally be reformulated as a choice between platform portfolios and, since the sets of restaurants joining the various platform portfolios are disjoint, the consumer's tastes for each of these sets are mutually independent of each other as long as the ν_{ijt} unobservables are mutually independent of each other across j. Online Appendix O.8, which derives expressions for choice probabilities in the model, illustrates the tractability of my approach.

I specify consumer i's taste for restaurant meals η_i conditional on all market and consumer characteristics as

$$\eta_i = \mu_m^{\eta} + \lambda_{\eta}' d_i + \eta_i^{\dagger},$$

where μ_m^{η} governs average tastes for restaurant dining in market m, d_i are characteristics of consumer i, and $\eta_i^{\dagger}$ is consumer i's persistent unobserved taste for restaurant dining. I assume that the $\eta_i^{\dagger}$ random variable is independent of all other random elements in the model and to be distributed as $\eta_i^{\dagger} \sim N(0, \sigma_{\eta}^2)$. Consumers' basic propensities to order from restaurants become increasingly heterogeneous as σ_{η} is increased, which limits the substitutability of ordering and not ordering.

The parameters of my model are only identified in relation to each other, as changing the scale of consumer utilities does not affect consumer choice. The scale normalization that I use in estimating my model is $\gamma = 1$. My model's predictions do not depend on this normalization.

4.3 Restaurant pricing and platform fee setting

Each restaurant chooses the price of its menu item after all restaurants have joined platforms. Restaurants simultaneously set their prices across platforms to maximize their respective profits. Platforms concurrently set their consumer fees c_{fz} to maximize their profits. A caveat is that Uber Eats and Postmates, which are both owned by Uber, set their fees to maximize their joint profits. The solution concept of the combined restaurant pricing and platform fee-setting game is Nash equilibrium.

I first describe restaurant pricing. Let $p^*_{jf}(\mathcal{G}_j, \mathcal{J}_{m,-j})$ denote the equilibrium price set by restaurant j on platform f when $\mathcal{J}_m$ denotes the platform portfolio choices of all restaurants in metro m. The equilibrium prices solve

$$p^*_j = \arg\max_{p_j} \sum_{f \in \mathcal{G}_j} \left[(1 - r_f)p_{jf} - \kappa_{jf}\right] S_{jf}(\mathcal{J}_m, p_j, p^*_{-j}),$$

where κ_{jf} is restaurant j's marginal cost of fulfilling an order placed on platform f, p_{-j} are the prices of all restaurants in j's market excluding j, and S_{jf} are restaurant j's sales on platform f. These sales also depend on the platform's fees c_{fz}, which I suppress in the notation. Online Appendix O.8 provides an expression for sales S_{jf}, which is obtained by summing over j's sales on f in each ZIP within range of j. I restrict attention to equilibria in which all restaurants sharing a ZIP z and a platform portfolio $\mathcal{G}$ charge the same prices.

The multi-sided markets literature—e.g., Rochet and Tirole (2006)—recognizes that transfers between end-users of platforms can make the division of a platform's prices between sides of end-users irrelevant. This situation is commonly described as the neutrality of the price structure. In the food delivery setting, neutrality would arise if restaurants completely passed on platform commission charges to consumers through their prices. Restaurant price adjustments, however, do not imply neutrality in my setting. To understand why, note that the first-order condition in the restaurant's pricing problem is

$$0 = (1 - r_f)S_{jf} + [(1 - r_f)p^*_{jf} - \kappa_{jf}]\frac{\partial S_{jf}}{\partial p_{jf}} + \sum_{g \neq f}[(1 - r_g)p^*_{jg} - \kappa_{jf}]\frac{\partial S_{jg}}{\partial p_{jf}}. \tag{9}$$

This yields a markup of

$$(1 - r_f)p^*_{jf} - \kappa_{jf} = a_j + b_j(1 - r_f), \tag{10}$$

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.[25] Equation (10) governs how restaurants adjust their markups for sales on platforms f in response to platform f's

[25] The quantities a_j and b_j are defined by

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

commission rate r_f. This markup adjustment implies imperfect pass-through of commissions to prices and therefore the non-neutrality of the price structure.[26]

The optimal markup of a restaurant only on platform f that charges commission rate r_f is approximately γ/α in the simplified case in which all consumers share a price sensitivity $\alpha_i = \alpha$. This expression is intuitive in that a restaurant's market power is increasing in the extent of restaurant differentiation γ and decreasing in consumer price sensitivity α. Online Appendix O.10 establishes this approximation, and it provides additional analysis of optimal pricing.

I now consider platform fee setting. Each platform f's profits in a ZIP z depend on their constant marginal costs mc_{fz} of fulfilling deliveries in ZIP z. These costs include payments to drivers and costs of interfacing with consumers and restaurants. Platform marginal costs may vary across locations due to differences in going rates for delivery couriers across regions, which in turn reflect differences in local costs of labour, automobile insurance, and fuel. Interregional differences in the regulation of benefits owed to delivery drivers provide another source of cost variation. California's Proposition 22, for example, requires platforms to pay delivery drivers \$0.30 per mile driven to cover expenses related to their employment. I do not allow, however, platforms' marginal costs to depend on the number of orders placed on platforms. The assumption underlying this restriction is that platforms are price takers in local labour markets that determine the going wage rates for delivery couriers. A platform f's profits from sales in ZIP z are

$$\Lambda_{fz} = \underbrace{\mathcal{s}_{fz}(c_z, \mathcal{J}_m)}_{\text{Sales}} \times \left(\underbrace{c_{fz}}_{\substack{\text{Consumer}\\ \text{fee}}} + \underbrace{r_{fz}}_{\substack{\text{Restaurant}\\ \text{commission}}} \underbrace{\bar{p}^*_{fz}}_{\substack{\text{Average restaurant}\\ \text{price in } z \text{ on } f}} - \underbrace{mc_{fz}}_{\substack{\text{Marginal}\\ \text{cost}}} \right), \tag{11}$$

where $\mathcal{s}_{fz}$ are platform f's sales in ZIP z and $\mathcal{J}_m$ is the configuration of restaurants in metro m across platform portfolios. The quantity $\bar{p}^*_{fz}$ is the sales-weighted average price charged by a restaurant for a sale on f in ZIP z. DoorDash and Grubhub choose c_{fz} in each ZIP z to maximize Λ_{fz}, whereas Uber Eats and Postmates set their fees in ZIP z to maximize $\Lambda_{fz} + \Lambda_{f'z}$, where f denotes Uber Eats and f' denotes Postmates. In the stage-game equilibrium, each platform maximizes its relevant profit measure simultaneously, with this simultaneity extending to the optimality of restaurants' prices.

4.4 Restaurant choice of platform portfolio

Restaurants choose which platforms to join in a positioning game in the spirit of Seim (2006). In this model, restaurants simultaneously choose which platforms to join to maximize sums of their expected profits and idiosyncratic choice disturbances. These disturbances represent misperceptions of the profitability of platform adoption or managers' non-pecuniary motives for platform

[26]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 (10).

adoption. A restaurant j's expected profits from joining platform portfolio $\mathcal{G}$ are

$$\Pi_j(\mathcal{G}, P_m) = \underbrace{\mathbb{E}_{\mathcal{J}_{m,-j}}\left[\sum_{f\in\mathcal{G}}[(1-r_{fz}))p^*_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_{jf}]S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*) \mid P_m\right]}_{:=\bar{\Pi}_j(\mathcal{G},P_m)} - K_m(\mathcal{G}). \tag{12}$$

The expectation in (12) is taken over rivals' platform adoption decisions $\mathcal{J}_{m,-j}$, which are unknown to restaurant j at the time of its portfolio choice. The distribution of these decisions are determined by the probabilities $P_m = \{P_k(\mathcal{G}) : k, \mathcal{G}\}$ with which rival restaurants k choose each platform portfolio $\mathcal{G}$. Additionally, $K_m(\mathcal{G})$ is j's fixed cost of joining portfolio $\mathcal{G}$. This fixed cost applies to all restaurants in market m that join $\mathcal{G}$. I assume that restaurants correctly anticipate the prices p_{jf} and fees c_{fz} that obtain for any realized configuration $\mathcal{J}_m$ of restaurants across portfolios in the downstream pricing and fee-setting game.

Restaurant fixed costs $K_m(\mathcal{G})$ do not represent payments to platforms. Instead, they include fixed costs undertaken in contracting with delivery platforms; in maintaining the restaurant's listing and menu on the delivery platform; in interacting with delivery platforms regarding payments and customer service matters; in maintaining a logistical system for receiving and processing orders placed online; and in training staff to interface with delivery platforms. An alternative to modelling fixed costs that apply to platform portfolios $\mathcal{G}$ is to specify a fixed cost for each platform f and to obtain the cost of adopting each portfolio $\mathcal{G}$ by summing these platform-specific costs across all platforms $f \in \mathcal{G}$. I prefer my approach because it allows for economies of scale in platform adoption. The investments required to accept orders on one delivery platform—e.g., training staff to interface with platforms and setting up stations for delivery order pick-ups—may reduce the costs of joining additional delivery platforms.

Restaurant j's choice of platform portfolio maximizes the sum of its expected profits and a disturbance $\omega_j(\mathcal{G})$ that represents either (i) the restaurant's idiosyncratic misperceptions of the profitability of platform adoption or (ii) non-pecuniary motives for joining food delivery platforms:

$$\mathcal{G}_j = \arg\max_{\mathcal{G}:0\in\mathcal{G}} \left[\Pi_j(\mathcal{G}, P_m) + \omega_j(\mathcal{G})\right]. \tag{13}$$

The maximum in (13) is taken over all platform portfolios that involve joining the offline platform. This eliminates the possibility of restaurants choosing not to accept orders directly from consumers. To rule out the possibility of shifting all fixed costs by an identical amount without affecting choices, I normalize $K_m(\{0\})$ to zero. An equilibrium in the platform portfolio choice model is a sequence of probabilities $P^*_m = \{P^*_j(\mathcal{G}) : j, \mathcal{G}\}$ such that

$$P^*_j(\mathcal{G}) = \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \Pi_j(\mathcal{G}', P^*_m) + \omega_j(\mathcal{G}')\right) \tag{14}$$

for all restaurants j in market m and for all platform portfolios $\mathcal{G}$. Note that the right-hand side of (14) is the probability that restaurant j's best response to rivals' choice probabilities P^*_m is to join platform portfolio $\mathcal{G}$. Thus, an equilibrium is defined as a sequence of portfolio choice probabilities that arise when restaurants' best responses to each other's choice probabilities give rise to these choice probabilities. Note that condition (14) defines P^*_m as a fixed point. As long as the mapping from P_m^* to the right-hand side of (14) is continuous—as holds under my parametric assumptions—Brouwer's fixed point theorem ensures the existence of an equilibrium. Formally, the solution concept of the game is quantal response equilibrium (McKelvey and Palfrey 1995); in a quantal response equilibrium, restaurants' best responses to their rivals' platform adoption probabilities give rise to those adoption probabilities (i.e., adoption probabilities constitute a fixed point).

I specify restaurants' platform adoption disturbances as

$$\omega_j(\mathcal{G}) = \sum_{f \in \mathcal{G}} \sigma_{rc} \omega_{jf}^{rc} + \sigma_\omega \tilde{\omega}_j(\mathcal{G}), \tag{15}$$

where $\omega_j(\mathcal{G})$ are mean-zero type 1 extreme value random variables drawn independently across j and $\mathcal{G}$. Additionally, the ω_{jf}^{rc} are standard normal random variables drawn independently across restaurant j and platform f. The parameter σ_ω governs the variability of portfolio-specific idiosyncratic disturbances, whereas σ_{rc} governs the extent to which platform portfolios are differentially substitutable based on their constituent platforms. The specification in (15) makes the choice model a random coefficients logit model in the style of Berry et al. (1995). The random coefficients $\sigma_{rc}\omega_{jf}^{rc}$ in the model are on indicators $\mathbb{1}\{f \in \mathcal{G}\}$ for platform membership of a portfolio. In the absence of random coefficients, the probability that a restaurant diverts to a platform portfolio upon leaving its initial portfolio does not depend on the extent to which the new portfolio overlaps with the initial one. To illustrate, consider a model that does not feature random coefficients in which the expected profits net of the $K_m(\mathcal{G})$ fixed costs are equal across platform portfolios. Suppose that a restaurant in this setting initially belongs to DoorDash and Uber Eats before Uber Eats exits the restaurant's market. This restaurant would be as likely to switch to the portfolio containing only Grubhub as to the portfolio containing only DoorDash upon this exit. This is a strong restriction given that the restaurant's initial choice of DoorDash could reflect a favourable assessment of DoorDash; a model with random coefficients permits this possibility through the ω_{jf}^{rc} deviates that reflect restaurants' idiosyncratic assessments of platforms. Failing to capture differential substitution among portfolios based on their constituent platforms could bias the results of counterfactual analysis assessing fee caps. This possibility for bias owes in part to the role of random coefficients in making portfolios that contain one platform f better substitutes than the non-adoption portfolio $\mathcal{G} = \{0\}$ for multihoming portfolios containing f. Under higher values of σ_{rc}, increasing the profitability of platform adoption induces greater substitution from singlehoming to multihoming relative to substitution from the alternative of joining now platforms (i.e., $\mathcal{G} = \{0\}$) to multihoming. These patterns of substitution have different implications for consumer welfare.

Although the existence of an equilibrium in restaurants' platform adoption game is guaranteed, this equilibrium may not be unique. In practice, I am unable to find multiple equilibria at my estimated parameters.[27] See the appendix of Seim (2006) for a discussion of the uniqueness properties of

[27] In each metro area in my data, I compute equilibria using the algorithm outlined in Online Appendix O.10 from the following initial choice probabilities: (i) the ZIP-specific empirical frequencies of restaurants' platform portfolio choices, (ii) probability one of restaurants choosing not to join any platform, (iii) probability one of restaurants choosing to join all platforms, and (iv) the ZIP-specific empirical frequencies of restaurants' platform portfolio choices randomly shuffled between portfolios within each ZIP. I find the same equilibrium in each market using each of these initial choice probabilities.

equilibria in positioning games of the sort that I specify.

Note that my model may be interpreted as an incomplete information game wherein the $\omega_j(\mathcal{G})$ disturbances are fixed cost shocks privately known to j. This is the interpretation suggested by Seim (2006), who studies Bayesian-Nash equilibria of an incomplete information positioning game. A Bayesian-Nash equilibrium of the Seim (2006) incomplete information game is equivalent to a quantal response equilibrium of a normal form game with expected profits $\Pi_j(\mathcal{G}, P_m)$ as payoffs and without private fixed-cost shocks. I prefer the quantal response interpretation because it avoids an interpretation of the $\omega_j(\mathcal{G})$ disturbances as structural fixed-cost shocks that remain privately known in equilibrium. In conducting welfare analysis, I do not count the $\omega_j(\mathcal{G})$ toward restaurant profits.

I conclude this section by justifying my use of a Seim (2006) positioning game for restaurants' platform adoption. Equilibria in this game are easier to find than Nash equilibria in complete information games. Complete information entry games also suffer from problems related to multiplicity of Nash equilibria reflecting non-uniqueness in the identities of players that take particular actions. Given that an equilibrium in my setting is determined by a choice probability common to all restaurants of a particular type (as defined by ZIP z), I circumvent this problem of non-uniqueness in identities. One critique of positioning games in the spirit of Seim (2006) is that they give rise to *ex post* regret: after players have realized their actions, some players would generally like to change their actions in response to other players' actions. This is not a considerable problem in my setting because the large number of restaurants leaves little uncertainty in each restaurant's payoffs from joining a platform portfolio $\mathcal{G}_j$.[28]

4.5 Platform commission setting

The first stage of the model is platform commission setting. Taking as fixed other platforms' commission rates, each platform's commission rate maximizes a weighted sum of (i) the platform's expected profits and (ii) the expected size of the platform's network of restaurants. I include this second term in platforms' objective function to address the omission of dynamic pricing incentives from my measure of platform profits. If restaurants exhibit state dependence in the platforms with which they sign contracts to join (i.e., if they are more likely to belong to a platform to which they belonged historically), then a platform's future profitability increases when it induces a restaurant to join a platform. Rather than account for this effect in a fully structural manner, I take a reduced-form approach by specifying that platforms value the size of their networks in addition to their static profits in setting their commission rates. Model parameters h_{fm} govern the extent to which platforms value their restaurant networks. This approach has precedent. Castillo (2022) specifies a ride-hailing platform's objective function as a weighted sum of current platform profits, rider surplus, and driver surplus rather than explicitly modelling long-run platform profits. Gutiérrez (2022) similarly specifies Amazon's objective function as a weighted sum of Amazon's profits, consumer surplus, and seller surplus, including terms for consumer and seller surplus to

[28]Formally, for any sequence of choice probabilities $\{P_{J,m}\}_{J=1}^{\infty}$ indexed by the number of restaurants J, the difference between the share of restaurants joining each platform portfolio (as encoded in $\mathcal{J}_m$) and $P_z(\mathcal{G}_j)$ converges to zero almost surely due to the strong law of large numbers. This suggests that for a large number of restaurants, the integrand in the definition of $\bar{\Pi}_j$ is approximately constant across $\mathcal{J}_{m,-j}$ draws, thus leaving little scope for ex post regret.

capture unmodelled dynamic considerations. Additionally, Wang et al. (2022) propose a system for restaurant recommendation that has been adopted by Uber Eats. Their system balances the interests of restaurants, consumers, and couriers in making recommendations. The adoption of this system suggests that Uber Eats—and perhaps other platforms—value end users' interests in addition to their short-term profits in making strategic decisions.

The expected profits of platform f in metro m at the time of commission setting are

$$\bar{\Lambda}_{fm}(r_m) = \sum_{z \in \mathcal{Z}_m} \mathbb{E}_{\mathcal{J}_m} \left[\Lambda_{fz} \mid P_m^*(r_m) \right], \tag{16}$$

where Λ_{fz} are the ZIP-specific profits defined in (11) and $\mathcal{Z}_m$ is the set of all ZIPs in metro m. The r_m vector includes all platforms' commissions in metro m, and $P_m^*(r_m)$ are choice probabilities from an equilibrium in restaurants' platform adoption. The expectation is taken over the equilibrium distribution of restaurants' platform portfolio choices $\mathcal{J}_m$, which are governed by the $P_m^*(r_m)$ platform adoption probabilities. The problem of a single-platform firm f is then

$$\max_{r_{fm}} \left[\bar{\Lambda}_{fm}(r_m) + h_{fm} J_f(r_m) \right], \tag{17}$$

where $J_f(r_m)$ is the expected number of restaurants that adopt platform f in metro m and h_{fm} are model parameters. The problems of Uber Eats and Postmates, which are jointly owned, differ from (17) in that these platforms' objective functions are sums of $\bar{\Lambda}_{fm}(r_m) + h_{fm} J_f(r_m)$ over $f \in \{\text{Uber Eats}, \text{Postmates}\}$.

5 Estimation

5.1 Estimation of the consumer choice model

My estimation procedure features a step for each stage of my model. In the first step, I estimate the consumer choice model using a maximum likelihood estimator. This estimator maximizes the likelihood of consumers' observed sequences of platform choices conditional on observed covariates. Each consumer $i \in \{1, \ldots, n\}$ in my data places $T_i \leq T$ orders from restaurants, with T_i varying across i. Recall that T is the maximum number of ordering occasions in my model. In practice, I treat each panelist/month pair in my data as a separate consumer, and I set T to the 99th percentile of the number of monthly orders placed by a panelist in Q2 2021. This quantity is $T = 20$. I include consumers who place at least one restaurant order in Q2 2021 in my estimation sample, but I exclude consumers who place over T orders in a month.

My estimator's objective function is

$$\text{Ł}(\theta, Y_n, X_n) = \sum_{i=1}^{n} \log \left(\int \prod_{t=1}^{T_i} \ell(f_{it} \mid x_i, w_{m(i)}, \Xi_i; \theta) \times \prod_{t=T_i+1}^{T} \ell_0(x_i, w_{m(i)}, \Xi_i; \theta) dH(\Xi_i; \theta) \right), \tag{18}$$

where $Y_n = \{f_{it} : i, 1 \leq t \leq T_i\}$ contains each consumer i's selected platform f_{it} across ordering occasions t. Similarly, $X_n = \{x_i, w_{m(i)} : 1 \leq i \leq n\}$ contains observable consumer characteristics

x_i and characteristics $w_{m(i)}$ of consumer i's metro area $m(i)$ that affect consumer i's ordering decisions. The x_i vector includes consumer i's ZIP, age, marital status, and household income. The w_m vector includes the configuration of restaurants across platform portfolios in each ZIP of market m as well as the platform fees c_{fz}, waiting times W_{fz}, and restaurant prices p_{jf} in market m. The random vector Ξ_i includes the persistent channel tastes $\zeta_i^\dagger$, the persistent platform tastes $\tilde{\zeta}_{if}$, and the unobservables $\eta_i^\dagger$ governing tastes for restaurant orders. The taste unobservables Ξ_i are distributed according to the distribution function H, which depends on the model parameters θ. Additionally, $\ell(f \mid x, \Xi; \theta)$ is the probability that a consumer chooses to order from platform f given explanatory variables x, taste unobservables Ξ, and model parameters θ, whereas $\ell_0(x, \Xi; \theta)$ is the probability that the consumer does not order from a restaurant given these conditioning variables. Online Appendix O.8 provides expressions for ℓ and ℓ_0.

Under my chosen parametric assumptions, ℓ and ℓ_0 have closed forms: they are sums of products of logit choice probabilities. Integrals of logit-type choice probabilities over continuously distributed unobserved heterogeneity Ξ_i, however, generally lack closed forms. My case is no exception: the integral in (18) has no closed form. I approximate this integral by simulation with 300 draws of Ξ_i for each consumer i in my sample. Last, estimating my model on data from all markets and including platform/metro fixed effects δ_{fm} and metro-specific tastes μ_m^η for restaurant orders is computationally difficult due to the large number of parameters involved. I limit the number of parameters by estimating the model on data from the largest three metros: those of New York City, Los Angeles, and Chicago. I subsequently estimate the δ_{fm} and μ_m^η parameters for each remaining metro m by maximizing the likelihood function (18) as computed on data from metro m with respect to these parameters. In doing so, I hold fixed the other model parameters at their estimated values.

Identification. A primary identification concern in demand estimation is price endogeneity owing to unobserved demand shifters that affect firms' pricing incentives. The standard solution to the price endogeneity problem, which follows Berry et al. (1995), is to use instrumental variables that shift prices without shifting structural demand unobservables. In this approach, demand for each product in each market is assumed to be affected by a scalar unobservable interpretable as unobserved product quality that affects demand through a linear index. I make a similar assumption in my specification of the platform taste indices ψ_i, with the similarity stemming from the fact that my δ_{fm} fixed effects are market-specific unobservable tastes for platforms. The fact that I possess data with significant within-market variation allows me estimate the δ_{fm} as parameters. The within-market variation in price in my data is partly attributable to variation in commission cap policies and in local demographics within a market.

A concern related to price endogeneity in markets with network externalities is the endogeneity of platforms' networks. This problem arises in my setting because unobservables shifting demand for platforms affect restaurants' decisions to join platforms. The fixed effects approach with which I address my price endogeneity problem also addresses this network endogeneity problem: I identify effects of restaurants' platform adoption decisions on concern ordering using variation in platforms' networks of restaurants within a metro. Intramarket variation in the distribution of restaurants across platform portfolios owes partly to variation in commission cap policies and local demographics within markets.

The panel structure of my data permits the identification of the scale parameters $\sigma_{\zeta 1}$, $\sigma_{\zeta 2}$, and σ_η governing heterogeneity in consumer tastes for platforms and restaurant dining. Recall that consumer i's persistent unobserved tastes for platform f are $\zeta_{if} = \zeta_i^\dagger + \tilde{\zeta}_{if}$, where $\zeta_i^\dagger \sim N(0, \sigma_{\zeta 1})$ and $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta 2})$. When $\sigma_{\zeta 1}$ is large, consumers are polarized in their tastes for ordering through platforms. This leads consumers to either repeatedly order meals through platforms or repeatedly order meals directly from restaurants. Repetition in the choice to order through a platform is consequently informative about the value of $\sigma_{\zeta 1}$. Similarly, a large value of $\sigma_{\zeta 2}$ implies that consumers are highly polarized in their tastes for individual platforms. This leads consumers to repeatedly choose the same food delivery platform when using a platform to order a meal. Conversely, when $\sigma_{\zeta 2}$ is low, consumers do not have strong idiosyncratic preferences for platforms, and are more likely to switch between delivery platforms. Thus, repetition in platform choice is informative about the value of $\sigma_{\zeta 2}$. Last, σ_η controls polarization among consumers in tastes for restaurant dining. When consumers are highly polarized in their tastes for restaurant meals, they tend to either frequently order from restaurants or rarely order from restaurants. Thus, heterogeneity across consumers in the number of orders placed from restaurants is informative about the value of σ_η. Note that state dependence alternatively explains persistence in consumer ordering; my model rules out this possibility.

Market size. The consumer choice model presented by Section 4.2 yields predictions of sales given counts of consumers in each ZIP. I set the number of consumers in each ZIP so that my model implies platform sales equal to those that I observe in my data. Appendix C explains this procedure in detail.

5.2 Estimation of restaurant marginal costs

The profits of a restaurant j that adopts platform portfolio $\mathcal{G}_j$ are

$$\sum_{f \in \mathcal{G}_j} \left[(1 - r_f)p_{j0} - \kappa_{jf}\right] S_{jf}(\mathcal{J}_m, p), \tag{19}$$

where S_{jf} are restaurant j's sales on platform f, $\mathcal{J}_m$ are the platform adoption decisions of all restaurants in market m, and p contains the prices of all restaurants in market m. In (19) and what follows, I introduce the commission r_0 of the direct-from-restaurant platform and set it to zero for expositional convenience. The first-order condition for restaurant profit maximization is

$$\underbrace{\begin{bmatrix} (1-r_{f_1})S_{jf_1} \\ (1-r_{f_2})S_{jf_2} \\ \vdots \\ (1-r_{f_k})S_{jf_k} \end{bmatrix}}_{=\tilde{S}_j} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial p_{jf_1}} & \frac{\partial S_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_1}} \\ \frac{\partial S_{jf_1}}{\partial p_{jf_2}} & \frac{\partial S_{jf_2}}{\partial p_{jf_d}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial p_{jf_k}} & \frac{\partial S_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{=\Delta_p} \left(\underbrace{\begin{bmatrix} (1-r_{f_1})p_{jf_1} \\ (1-r_{f_2})p_{jf_2} \\ \vdots \\ (1-r_{f_k})p_{jf_k} \end{bmatrix}}_{=\tilde{p}_j} - \underbrace{\begin{bmatrix} \kappa_{jf_1} \\ \kappa_{jf_2} \\ \vdots \\ \kappa_{jf_k} \end{bmatrix}}_{=\tilde{\kappa}_j} \right) = 0, \tag{20}$$

where $\mathcal{G}_j = \{f_1, \ldots, f_k\}$. Solving for marginal costs yields

$$\tilde{\kappa}_j = \tilde{p}_j + \Delta_p^{-1} \tilde{S}_j. \tag{21}$$

Equation (21) provides the basis of my estimation of restaurant marginal costs. My estimation procedure begins with the computation of the right-hand side of (21) at the estimated parameters of the consumer choice model and the observed restaurant prices. I compute this quantity for each restaurant j in a market m. In addition, I assume that

$$\kappa_{jf} = \begin{cases} \kappa_z^{\text{direct}}, & f = 0 \\ \kappa_z^{\text{platform}}, & f \neq 0, \end{cases}$$

where κ_z^{direct} is a restaurant's cost of preparing a meal for a direct order and $\kappa_z^{\text{platform}}$ is the cost of preparing a meal for a platform order. Marginal costs of preparing platform orders may differ from those for direct orders due to differences in the packaging of delivery orders and to costs of communicating with delivery platforms. Both commissions and higher costs could explain a gap between prices for platform-intermediated orders and those for direct orders. Additionally, the greater the extent to which a difference in costs explains this gap, the less scope there remains for commission reductions to narrow the gap. The costs κ_{jf} that I recover from (21) generally differ across restaurants within a particular platform f due to sampling error in my estimates of the consumer choice model parameters. In light of these differences, I use the cross-restaurant average of the κ_{j0} costs recovered from (21) as my estimator of κ_z^{direct}. I similarly use the average κ_{jf} recovered from (21) across pairs of platforms $f \neq 0$ and restaurants j locating on these platforms as my estimator of $\kappa_z^{\text{platform}}$.

5.3 Estimation of platform marginal costs

I estimate platform marginal costs from first-order conditions for the optimality of platforms' consumer fees. This procedure follows the standard approach for estimating marginal costs in the differentiated products literature following Berry et al. (1995). Within a ZIP z, platforms' consumer fees solve the following system of first-order conditions:

$$(\mathcal{H} \odot \Delta_c)(c_z + r_m \odot p_z - mc_z) + \mathcal{s}_z = 0,$$

where c_z is a vector containing each platform's consumer fee in ZIP z, r_m is a vector containing each platform's commission rate, p_z is a vector including the sales-weighted average restaurant price in the ZIP on each platform f, and mc_z is a vector containing each platform f's marginal cost mc_{fz}. The vector $\mathcal{s}_z$ similarly contains each platform f's sales in z. The $\odot$ operator denotes entry/component-wise multiplication.[29] Letting F denote the number of online platforms, Δ_c is an $F \times F$ matrix whose (f, f') entry is $\partial \mathcal{s}_f / \partial c_{f'z}$. The $\mathcal{H}$ matrix also has dimension $F \times F$; its

[29] My exposition follows Conlon and Gortmaker (2020).

(f, f') entry indicates whether f and f' have the same owner.[30] Therefore,

$$mc_z = c_z + r_m \odot p_z + (\mathcal{H} \odot \Delta_c)^{-1} \mathfrak{s}_z. \tag{22}$$

I estimate mc_z by substituting the observables c_z, r_m, and p_z and Δ_c and $\mathfrak{s}_c$ as evaluated at the estimated consumer choice model parameters into the right-hand side of (22).

5.4 Estimation of parameters governing platform adoption by restaurants

I estimate the parameters K_m and $\Sigma = (\sigma_\omega, \sigma_{rc})$ governing restaurants' platform adoption decisions using a conditional choice probability generalized method of moments (CCP-GMM) estimator. Recall that, as stated by (13), restaurants choose platform portfolios to maximize their profits given beliefs that are consistent with actual choice probabilities. The first stage of my estimation procedure involves estimating restaurants' CCPs as a function of state variables affecting their profits. The second stage involves setting restaurants' choice probabilities to the estimated CCPs and subsequently fitting the model's prediction of restaurants choices to observed choices. A desirable feature of CCP estimators is that they do not require finding an equilibrium for each trial parameter vector considered by an estimation algorithm. Singleton (2019) similarly uses a CCP estimator to estimate a model of firm positioning based on that of Seim (2006).

For the CCP stage of the CCP-GMM estimator, I specify restaurants' conditional probabilities of joining platform portfolios as a multinomial logit, and I estimate the parameters of this logit by maximum likelihood. The covariates that I include in the logit are: the population of the region within five miles of the restaurant; the number of restaurants within five miles of the restaurant; municipality fixed effects; an indicator for a commission cap being in effect in the restaurant's area; and the shares of the population within five miles that are under 35 years of age, married, both under 35 years of age and married, and that have an annual household income under \$40,000. I also include interactions of the overall population with the population shares of demographic groups and with the total number of restaurants.

Given first-stage CCPs $\hat{P}_m$, it is straightforward to compute each restaurant's probability of joining a platform portfolio $\mathcal{G}$ for a trial value of parameter values θ^{adopt}, where θ^{adopt} includes the common fixed costs of platform adoption $\{K_m(\mathcal{G})\}_{\mathcal{G},m}$ as well as the Σ parameters. I estimate θ^{adopt} using a GMM estimator.[31] Defining this GMM estimator requires some new notation. Let n_J be the number of restaurants in the estimation sample, and let G_{n_J} denote the n_J-vector of observed platform portfolio choices. Additionally, let $\Pi^e_{n_J}$ denote a $n_J \times n_{\mathcal{G}}$ matrix whose (j, k) entry is

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

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

[31] I do not use a maximum likelihood estimator on account of the finite-sample problems of maximum likelihood estimation, which are well documented in the industrial organization literature on entry games. These problems relate to the fact that the maximum likelihood objective function highly penalizes the assignment of near-zero probabilities to outcomes that occur in the data; see Pakes et al. (2007) and Collard-Wexler (2013) for more detailed explanations. Both of these papers use estimators that fit the model to aggregated data moments rather than predictions for individual observations. By using a GMM estimator, I take a similar approach.

equal to restaurant j's expected variable profits from selecting the kth platform portfolio $\mathcal{G}_k$. Here, $n_{\mathcal{G}}$ is the number of platform portfolios. Last, let D_j be the log of the population under the age of 35 residing within five miles of j. I use D_j as a shifter of the profitability of platform adoption.

My GMM estimator is based on moment conditions that match the model's predictions to the data. The first set of moment conditions match the model's predictions of aggregated choice probabilities to empirical frequencies. These conditions involve the functions

$$g_{m\mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) = \mathbb{1}\{m(j) = m\} \left(Q(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) - \mathbb{1}\{\mathcal{G}_j = \mathcal{G}\} \right) \qquad \forall m, \mathcal{G},$$

where $m(j)$ is restaurant j's market and

$$Q(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) = \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \left[\bar{\Pi}_j(\mathcal{G}', \hat{P}_m) - K_m(\mathcal{G}) + \omega_j(\mathcal{G}) \right] \mid \theta^{\text{adopt}} \right)$$

is the probability that restaurant j chooses platform portfolio $\mathcal{G}$. Note that, when θ_0^{adopt} are the true model parameters and Π_j^e is computed using restaurants' true conditional choice probabilities, the law of iterated expectations implies $\mathbb{E}[g_{m\mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0$. The corresponding sample moment conditions are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{m\mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0 \qquad \forall m, \mathcal{G}. \tag{23}$$

I target the Σ parameters that govern substitution patterns by including additional moment conditions. Each of these moment conditions equalizes the covariance of D_j and a measure of platform adoption as computed on the estimation sample and as predicted by the model. The two measures of platform adoption that I use are (i) an indicator for whether the restaurant joins any online platform and (ii) the number of online platforms that a restaurant joins. These moment conditions are based on the functions

$$\begin{aligned} g_{\omega,1}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) &= D_j \times \left(\mathbb{1}\{\mathcal{G}_j \neq \{0\}\} - (1 - Q(\{0\}, \Pi_j^e; \theta^{\text{adopt}})) \right) \\ g_{\omega,2}(\mathcal{G}_j, \Pi_j^e, D_j; \theta^{\text{adopt}}) &= D_j \times \left(|\mathcal{G}_j| - \sum_{\mathcal{G}} |\mathcal{G}| \times Q(\mathcal{G}, \Pi_j^e; \theta^{\text{adopt}}) \right), \end{aligned}$$

where $|\mathcal{G}|$ is the cardinality of set $\mathcal{G}$. When θ_0^{adopt} are the true model parameters that generate $\mathcal{G}_j$, and when Π_j^e is computed using the true CCPs,

$$\mathbb{E}[g_\omega(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0. \tag{24}$$

The sample moment conditions corresponding to (24) are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{\omega,k}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0, \qquad k \in \{1, 2\}. \tag{25}$$

Increasing σ_ω makes restaurants less responsive to expected profits when choosing which platforms to join. Given that a higher population of young people—who are especially likely to enjoy platforms—boosts the profit gains from joining platforms, a larger covariance between D_j and platform adoption suggests a smaller value of σ_ω. The moment conditions in (24) are also informative about σ_{rc} because responses of the share of restaurants on platforms and of the average number of portfolios joined differentially depend on σ_ω and σ_{rc}. Increasing σ_{rc} makes platform portfolios with more overlap more substitutable, and portfolios with less overlap less substitutable. This means that restaurants that do not belong to any platform are more likely to substitute to a portfolio with one platform than one with multiple platforms when σ_{rc} is high. Thus, for a fixed increase in the share of restaurants belonging to at least one online platform, the average number of platforms joined increases by less when σ_{rc} is larger.

A natural alternative to using the moment condition (24) in the GMM estimation would be to replace the profit shifter D_j with estimated profits. This approach is problematic when expected profits are mismeasured. Such mismeasurement could owe to both sampling error in my demand estimates and to misspecification error. Whereas the relationships between restaurant decisions and expected profit estimates are attenuated by measurement error, the relationship between restaurant decisions and local demographics is unlikely to be attenuated as long as the American Community Survey precisely estimates regional demographics. Matching an attenuated empirical relationship between platform adoption and prices may yield an underestimate of restaurants' responsiveness to the profitability of platform adoption, i.e., an overestimate of σ_ω.[32]

The sample moment condition corresponding to (24) is

$$\frac{1}{n_J}\sum_{j=1}^{n_J} g_\omega(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\kappa}) = 0. \tag{26}$$

My estimator $\hat{\kappa}$ is the vector of parameter values that solves equations (23) and (26). Given that that the number of equations across (23) and (26) is equal to the number of parameters that I estimate, it is generally possible to solve these equations exactly.

5.5 Estimation of restaurant-network weights in platform objective functions

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

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

Manipulating the first-order condition for this problem yields

$$h_{fm} = -\left(\frac{\partial J_f}{\partial r_{fm}}\right)^{-1} \frac{\partial \bar{\Lambda}_{fm}}{\partial r_{fm}}. \tag{27}$$

[32] An analogy to the linear regression model illustrates this point. In the linear regression setting, the OLS estimator equalizes the covariance between the dependent variable and the regressor with the covariance between the model's fitted value and the regressor. This estimator is subject to attenuation bias when the regressor is mismeasured. The instrumental variables estimator instead equalizes the covariance between the dependent variable and an instrumental variable with the covariance between the model's fitted value and the instrument. When the instrument is independent of the measurement error in the regressor, this estimator is not subject to attenuation bias. In my setting, the variable D_j plays the role of an instrumental variable that shifts the profitability of platform adoption (given that younger people are more likely to use online food delivery) without suffering from the mismeasurement problems plaguing my measure of expected profits.

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 (27) 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.

6 Estimation results

6.1 Parameter estimates for consumer choice model

Table 9 reports estimates of consumer choice model parameters. Recall the scale normalization that $\gamma = 1$, which implies that all estimates are interpretable as ratios over γ. Several estimates are noteworthy. First, the scale parameter $\sigma_{\zeta 1}$ of persistent idiosyncratic tastes for online ordering is large, indicating significant dispersion across consumers in tastes for online ordering. The scale parameter of idiosyncratic tastes $\sigma_{\zeta 2}$ is smaller but also sizeable, suggesting that consumers are divided by both overall taste for online ordering and by tastes for specific platforms. Additionally, the estimated demographic effects λ^f_{age} and $\lambda^f_{\text{married}}$ imply that—as suggested by Figure 7—young and unmarried consumers prefer delivery platforms relative to older and married consumers. The parameters $\lambda^\eta_{\text{young}}$ and $\lambda^\eta_{\text{married}}$ govern differences in tastes for restaurant orders between demographic groups; we see that young consumers and unmarried consumers have lower tastes for restaurant orders that are not placed on platforms. In addition, the fact that α_{LowInc} is positive indicates that low-income consumers are more price-sensitive than their higher-earning counterparts, although this difference in price sensitivity is small. Consumers are estimated to prefer platforms with lower waiting times, as the estimated disutility τ of waiting time (in hours) is positive and statistically significant. Last, the large estimate of σ_η suggests limited substitutability between restaurant ordering and at-home dining.

To assess the reasonableness of my estimates and to understand ordering behaviour, I check my estimates' implications for substitution patterns. First, Table 10 provides the shares of consumers substituting to each platform and to making no purchase among those who substitute away from a platform f upon a uniform increase in f's consumer fees. The estimates show that, across platforms, between 25% and 40% of platforms' consumers who substitute away from ordering on a platform no longer place any restaurant order. An additional 24–34% switch to ordering directly from a restaurant whereas the remainder switch to ordering from a different platform.

Next, I compute price elasticities that account for variation in fees across ZIPs. Each of these elasticities is a percentage change in a platform f's sales from a uniform price increase by platform

Table 9: Selected estimates of consumer choice model parameters

Parameter	Estimate	SE
α	0.228	0.003
α_{LowInc}	0.009	0.001
$\sigma_{\zeta 1}$	3.38	0.02
$\sigma_{\zeta 2}$	1.67	0.01
τ	0.97	0.08
$\lambda^{\text{DD}}_{\text{young}}$	1.19	0.02
$\lambda^{\text{DD}}_{\text{married}}$	-0.87	0.02
$\lambda^{\text{Uber}}_{\text{young}}$	1.06	0.02
$\lambda^{\text{Uber}}_{\text{married}}$	-1.07	0.02
$\lambda^{\text{GH}}_{\text{young}}$	0.70	0.02
$\lambda^{\text{GH}}_{\text{married}}$	-0.63	0.02
$\lambda^{\text{PM}}_{\text{young}}$	0.89	0.03
$\lambda^{\text{PM}}_{\text{married}}$	-1.98	0.03
σ_{η}	2.110	0.005
$\lambda^{\eta}_{\text{young}}$	-0.68	0.01
$\lambda^{\eta}_{\text{married}}$	0.18	0.01

Notes: this table reports estimates of the parameters of the consumer choice model. Estimates of the platform/metro fixed effects δ_{fm} and the metro fixed effects μ^{η}_{m} in consumer tastes for restaurant dining are omitted from the table.

f' in a metro m that is a percentage of the average fee charged by f' in m.[33] Table 11 reports estimates of these elasticities for the Chicago metro area; the estimated own-fee elasticities range from -0.96 to -3.05 across platforms. Note that, unlike in the case of one-sided markets, elasticities under one in absolute value do not contradict profit maximization under non-negative marginal costs. This is because the effective marginal cost that platforms consider in setting consumer fees are marginal costs net of restaurant commissions.

I similarly define network elasticities as the percentage change in platforms' sales in response to a uniform percentage increase in the number of new restaurants on platform f across ZIPs in a metro m.[34] Table 12 reports the resulting estimates of network elasticities of demand for the Chicago metro area. Network externalities are substantial: a percentage increase in the number of

[33]Formally, I compute

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

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; $\jmath_{fm}$ are platform f's sales in m; and I have suppressed the dependence of $\jmath_{fm}$ 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.

[34]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

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

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

restaurants on a platform leads to a 0.48–1.10% increase in ordering on that platform.

Table 10: Between-platform diversion ratios for the Chicago metro

	Quantity response for...					
Platform	No purchase	Direct	DD	Uber	GH	PM
DD	0.40	0.34	-1.00	0.17	0.07	0.02
Uber	0.38	0.31	0.21	-1.00	0.07	0.02
GH	0.30	0.29	0.22	0.17	-1.00	0.02
PM	0.25	0.24	0.24	0.19	0.09	-1.00

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

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

where $c_{f'm}$ is a vector of the consumer fees charged by f' across all ZIPs within m; $\mathcal{s}_{fm}$ are alternative f's sales in m; and I have suppressed the dependence of $\mathcal{s}_{fm}$ on all variables except the consumer prices charged by platform f'. The sales of the no-purchase alternative are defined as the number of ordering occasions in which the consumer makes no purchase. Each column provides diversion ratios $d_{ff'}$ for a particular alternative f whereas each row provides diversion ratios $d_{ff'}$ for a particular platform f whose consumer fees increase across m.

Table 11: 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. Computation of these responses are discussed in the main text.

Table 12: 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. Computation of these responses are discussed in the main text.

Figure O.12 in Online Appendix O.11 reports average sales differences between restaurants that belong to online platforms versus those that only fulfill orders directly from consumers. The figure shows that, on average across ZIPs and relative to restaurants that do not belong to any platform, the sales of a restaurant that joins DoorDash, the most popular platform, are 29% higher.

6.2 Estimates of restaurant marginal costs

Table 13 describes the restaurant markups implied by my estimates of κ_{jf}. Restaurants' markups on platforms are much larger where commission caps are in effect. Their markups for direct orders are about a fifth of their prices. Additionally, the estimated costs for direct orders and platform-intermediated orders are similar; they differ by only one cent on average across ZIPs.[35]

Table 13: Restaurant markups ($)

Means ± std. dev. across ZIPs by channel, policy

Channel	No cap	Cap
Direct	4.34±0.02	4.33±0.02
Platform	1.96±0.15	3.60±0.12

Notes: the table describes markups $(1-r_f)p_{jf}-\kappa_{jf}$ across ZIPs separately for direct orders (for which the commission rate is $r_0 = 0$) and platform-intermediated orders, and also separately for ZIPs with commission caps and those without caps. Note that the average price for a direct-from-restaurant order is $21.89 (standard deviation: $1.17).

6.3 Estimates of platform marginal costs

Table 14 describes the estimated cross-ZIP distribution of platform marginal costs of fulfilling orders. It also reports the implied cross-ZIP distributions of platform markups $c_{fz}+r_{fm}\bar{p}^*_{fz}-mc_{fz}$. Courier compensation is the primary component of platform marginal costs. As of September 2022, DoorDash's website stated that "Base pay from DoorDash to Dashers ranges from $2–$10+ per delivery depending on the estimated duration, distance, and desirability of the order"; ("Dashers" is DoorDash's name for its couriers).[36] This level of courier pay seems consistent with the estimated interquartile range of DoorDash's marginal costs of $7.08 to $9.72.

Table 14: Estimates of platforms' marginal costs ($)

Platform	Marginal costs				Markup			
	Mean	25th %ile	Median	75th %ile	Mean	25th %ile	Median	75th %ile
DD	8.20	7.08	8.79	9.72	5.90	5.38	5.86	6.43
Uber	8.08	6.95	8.04	9.13	5.83	5.44	5.84	6.22
GH	9.39	7.40	9.87	10.94	4.52	4.26	4.58	4.91
PM	13.98	11.86	14.21	15.72	4.79	4.27	4.80	5.37

6.4 Estimates of restaurant platform adoption model

Table 15 reports estimates of the parameters governing platform adoption by restaurants. In interpreting these parameters, note that the average expected variable profits of a restaurant that joins no online platform across ZIPs in my sample is roughly $12,500 a month. Given that I set the market size so that platform sales equal their observed sales for April 2021, my fixed cost estimates are interpretable as costs incurred to join platform portfolios for that month. The three lowest of the estimated fixed costs $K_m(\mathcal{G})$ are those for platform portfolios including a single platform, which is to be expected if joining multiple platforms is more costly than joining a single one. I compute the standard errors reported by Table 15 using the bootstrap procedure described in Appendix D. The estimated scale parameter of restaurants' idiosyncratic $\tilde{\omega}_j(\mathcal{G})$ disturbances of joining the platforms in $\mathcal{G}$ is about $650, which implies a standard deviation of about $834. This is smaller

[35] Figure O.16 in Online Appendix O.7 reports the distribution of the estimated difference $\kappa_z^{\text{platform}} - \kappa_z^{\text{direct}}$, which concentrates in [-$2.00, $2.00].

[36] See https://help.doordash.com/consumers/s/article/How-do-Dasher-earnings-work.

than the fixed costs of joining platform portfolios. The parameter σ_{rc}, which controls the variance of random coefficients on platform membership of portfolios, is statistically significant.

Table 15: Estimates of restaurant platform adoption parameters ($'000s/month)

Parameter	Estimate	SE
σ_ω	0.65	0.04
σ_{rc}	0.34	0.03
Fixed cost: DD	1.45	0.07
Fixed cost: Uber	1.52	0.07
Fixed cost: GH	2.34	0.10
Fixed cost: PM	1.56	0.08
Fixed cost: DD, Uber	2.32	0.11
Fixed cost: DD, GH	2.33	0.11
Fixed cost: DD, PM	2.00	0.08
Fixed cost: Uber, GH	2.29	0.12
Fixed cost: Uber, PM	3.04	0.15
Fixed cost: GH, PM	2.97	0.14
Fixed cost: DD, Uber, GH	2.68	0.11
Fixed cost: DD, Uber, PM	3.12	0.15
Fixed cost: DD, GH, PM	3.05	0.14
Fixed cost: Uber, GH, PM	2.99	0.14
Fixed cost: All	1.89	0.06

Notes: the table reports estimates of parameters governing restaurants' platform adoption decisions and, in the "SE" column, their standard errors as computed using the bootstrap procedure described in Appendix D. The table reports these parameters in thousands of dollars. The "Fixed cost" parameters are cross-metro averages of fixed costs of joining the various platform portfolios. The platforms included in the portfolio corresponding to each row are indicated in the "Parameter" column.

6.5 Estimates of restaurant-network weights in platform objective functions

Table 16 provides medians and interquartile ranges of the cross-metro distribution of my estimates of the weights h_{fm} that platforms place on their restaurant networks in setting commission rates. These estimates suggest that platforms' dynamic considerations in commission-setting are significant — beyond the benefit of a restaurant on a platform's contemporaneous profits, platforms value the addition of a restaurant to their network by $850–$1044 on median across metros.

Table 16: Estimates of restaurant-network weights ($)

(a) Cross-metro distribution of estimated weights

Platform	Quantile		
	25%	Median	75%
DD	740	850	979
Uber	550	606	671
GH	966	1059	1066
PM	992	1044	1195

(b) Standard errors for cross-metro median weights

Platform	SE
DD	44
Uber	30
GH	34
PM	67

Notes: this table reports medians of the estimated h_{fm} weights taken across metros m for each leading platform m. I compute standard errors for median weights across metros using the bootstrap procedure described in Appendix D.

7 Counterfactual analysis

This section uses my model to evaluate commission caps. It also evaluates alternative policies intended to bolster restaurant profitability, and the impact of delivery platforms on the restaurant industry. I evaluate commission caps by comparing baseline equilibria without commission caps to equilibria under caps. Rather than perform this section's counterfactual analyses on the full metro areas on which I estimate my model, I perform them on the core municipality of each metro area and, in the case of New York's metro area, on Manhattan. Limiting attention to metro areas' core subregions reduces the computational cost of computing equilibria.

I compute equilibria in my model's various stage games using a combination of algorithms that Online Appendix O.10 describes in detail. To summarize, I find equilibria in restaurant prices and platforms' consumer fees by iterating on equations implied by first-order conditions for optimal pricing; I find equilibria in restaurants' platform adoption game by iterating on the fixed-point condition (14), using the realized ZIP-specific distributions of restaurants across platform portfolios as an initial value for the probabilities P_m; and I find equilibria in restaurants' commission-setting game using a Newton algorithm.

7.1 Evaluation of 15% commission caps

Table 17: Welfare effects of 15% commission cap (% of platform revenue)

(a) Restaurant price response

Outcome	Mean	SE	Median	SE	Min.	Max.
Consumer welfare (fees/prices only)	-3.62	0.06	-3.83	0.07	-4.18	-2.67
Consumer welfare (total)	-2.24	0.06	-2.30	0.09	-2.68	-1.45
Restaurant profits	1.25	0.04	1.13	0.08	0.04	2.65
Platform variable profits	-1.64	0.05	-1.66	0.07	-2.05	-1.01
Total welfare	-2.63	0.10	-2.31	0.11	-3.83	-1.77

(b) No restaurant price response

Outcome	Mean	SE	Median	SE	Min.	Max.
Consumer welfare (fees/prices only)	-25.88	0.08	-28.75	0.23	-31.73	-18.47
Consumer welfare (total)	-22.40	0.09	-24.78	0.32	-28.58	-14.48
Restaurant profits	9.20	0.08	7.81	0.21	4.07	15.60
Platform variable profits	-18.34	0.12	-21.00	0.45	-23.09	-11.51
Total welfare	-31.54	0.20	-33.48	0.62	-41.48	-21.80

Notes: all welfare and profit figures are expressed as shares of platform revenues in the absence of commission caps. The "(fees/prices only)" row gives the change in dollarized expected utility relative to the baseline equilibrium when fees and prices are set to their levels in an equilibrium under the commission cap while restaurants' platform adoption probabilities are held 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. I compute the means and medians across regions wherein I simulate commission caps, and I weight each region by its population. I compute standard errors using a bootstrap procedure with 100 replicates.

Table 17 summarizes annual welfare effects of commission caps as shares of platform revenue in baseline equilibria without commission caps. Table 17a reports results for the case in which restaurant prices respond to commission caps whereas Table 17b reports results for the case in which

Table 18: Fee and price effects of a 15% commission cap

Outcome	Mean	Median	Min.	Max.
Fee	5.25	5.36	4.48	5.74
Restaurant price	-4.72	-4.83	-5.22	-3.94
Net change	0.52	0.53	0.50	0.55
Fees (fixed prices)	4.28	4.34	3.68	4.68

Notes: the table summarizes market-level average effects of a 15% commission cap on (i) platform fees (ii) restaurants prices for platform orders in each market in dollar terms across markets. The market-level effects that are summarized by means (unweighted), medians (unweighted), minima, and maxima are sales-weighted averages taken across platforms and restaurants. The "Fees (fixed prices)" row reports average effects of a 15% commission cap on fees in a scenario in which restaurants cannot adjust their prices upon the imposition of the cap.

restaurant prices are held fixed at their levels in the baseline equilibrium. The "Consumer welfare (total)" row describes the overall effects of caps on consumer welfare, whereas the "Consumer welfare (fees/prices only)" row describes effects of a cap that do not account for changes in restaurant membership of platforms.

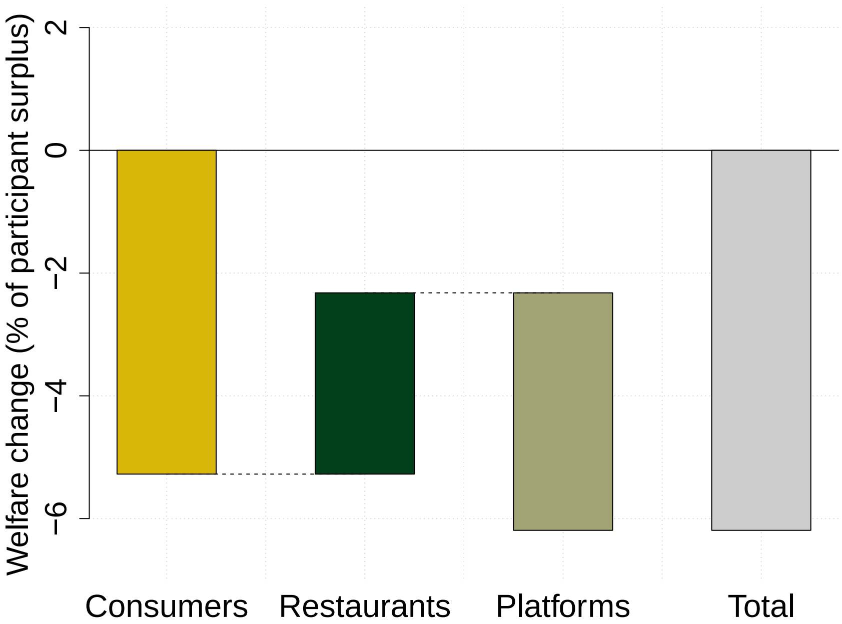
Caps boost restaurant profits while reducing total welfare. This finding holds regardless of whether restaurant prices respond to commission caps. Both consumers and platforms suffer from commission caps, and their losses are similar in magnitude. A failure of restaurants to optimally adjust their prices upon the imposition of a commission cap magnifies the welfare effects of the cap; the estimated median effect of a cap on consumer welfare is over 10 times greater when restaurant prices do not respond to the cap. Note that, per order placed on a platform in the baseline equilibrium, the the mean consumer welfare loss is \$0.28, the mean restaurant profit gain is \$0.15, the mean platform profit loss is \$0.20, and the mean total welfare loss is \$0.33. When restaurant prices do not adjust, these figures are \$2.72 for consumer welfare losses, \$1.09 for restaurant profit gains, \$2.24 for platform profit losses, and \$3.87 for total welfare losses.

Figure 9 plots the effects of commission caps on consumer welfare, restaurant profits, and platform profits as a share of participant surplus from delivery platforms, defined here as the sum of consumer surplus and of restaurant surplus from platforms.[37] The figure shows that commission caps reduce consumer surplus by over 5% of total surplus from food delivery platforms, raise restaurant profits by about 3% of total surplus, and reduce platform profits by about 4% of total surplus. Summing over these effects, total welfare falls by over 6% in the metro areas that I study when they all impose commission caps.

Recall that I estimate the effects of caps with and without restaurant price adjustments because I do not observe large price adjustments to commission caps in my data. The lack of observed price adjustment may reflect uniform or zone pricing by restaurants, or uncertainty about the longevity of caps. Given that commission charges primarily explain why restaurants charge higher prices on platforms (recall that I do not find a meaningful difference between average restaurant marginal costs for platform-intermediated and direct-from-restaurant orders), I expect that a permanent national commission cap would eventually induce a restaurant price response as occurs in the

[37] As detailed in Section 7.5, I use my model to estimate the participant surplus associated with delivery platforms, i.e., the difference in joint consumer and restaurant welfare between an economy with platforms (and no commission caps) and one without platforms. Online Appendix O.7 provides an analogue of Figure 9 that reports caps' welfare effects as a share of the sum of participant surplus from platforms and platforms' variable profits.

Figure 9: Welfare effects of 15% commission cap relative to participant surplus from platforms



Notes: this figure plots the ratio of the welfare effects on consumer welfare, restaurant profits, and platform profits of a 15% commission cap (as reported in Table 17a) and the total surplus from food delivery platforms. Participant surplus from platforms is the effect of platforms' availability on the sum of consumer welfare and restaurant profits (i.e., the "Total welfare: upper bound" row in Table 21). I add both welfare effects of caps and participant surplus across metro areas to obtain the quantities reported in the figure. Note that the figure provides cumulative welfare changes when consumers' changes are considered first, then restaurants, and then platforms.

setting whose results appear in Table 17a. The results suggest that restaurants would benefit from colluding to maintain their prices at pre-cap levels upon a commission cap's introduction. These higher prices, however, reduce consumer welfare. They also reduce platform profits partly because platform sales experience a greater decline when restaurants do not reduce their prices on platforms once a cap is introduced.

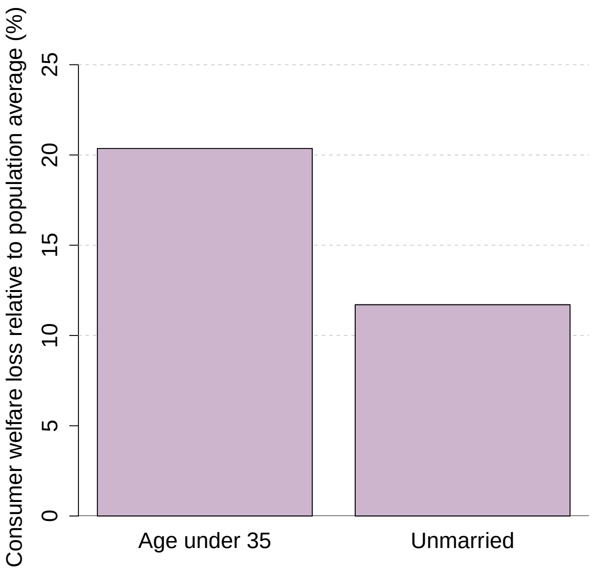
Another noteworthy result presented by Table 17 is that failing to account for the benefit to consumers of increased restaurant uptake of platforms leads the researcher to dramatically overstate consumer welfare losses from commission caps. Indeed, the loss in consumer welfare across markets is about 70% greater when this benefit is not accounted for, as a comparison of the "Consumer welfare (fees/prices only)" and "Consumer welfare (total)" rows of Table 17a reveals.

Table 18 summarizes the average effects of commission caps on fees and prices. This table summarizes metro-level sales-weighted averages taken across platforms and restaurants. The "Restaurant price" row describes effects on the prices that restaurants post on platforms, not on their prices for direct-from-restaurant orders. Caps raise platform fees by between \$4.48 and \$5.74. The resulting increase in the consumer's cost of placing an order, however, is offset by a decrease in restaurants' prices on delivery platforms. Indeed, a comparison of the tables shows that the overall cost of ordering, defined as the sum of the platform's fee and the restaurant's price, increases by about 50 cents for each market/platform pair.

The effects of commission caps on consumer welfare depend on consumer characteristics. Figure 10 reports the ratio of the mean welfare loss from a 15% commission cap among consumers in various demographic groups relative to the overall mean consumer welfare loss. Young consumers and unmarried consumers experience greater-than-average losses due to their greater usage of food delivery platforms.

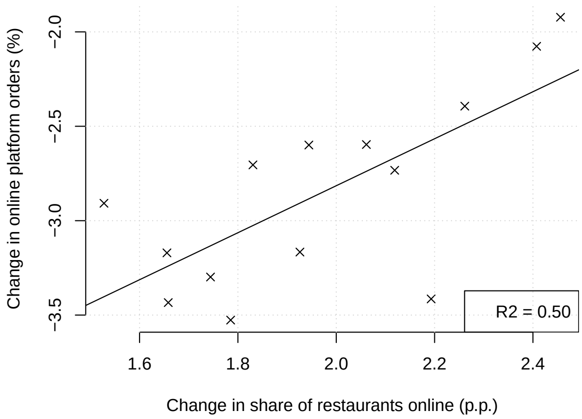
Figure 11 plots commission caps' effects on (i) the number of orders placed on platforms and (ii) the share of restaurants joining a platform across metros. The models' predicted effects are similar to the difference-in-differences estimates of commission caps' effects as reported by Section 3 Additionally, the figure shows that differences in caps' effects on restaurant uptake of platforms largely explain differences in effects on ordering among metro areas.

Figure 10: 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.

Figure 11: Cross-metro comparison of commission caps' sales and platform adoption effects

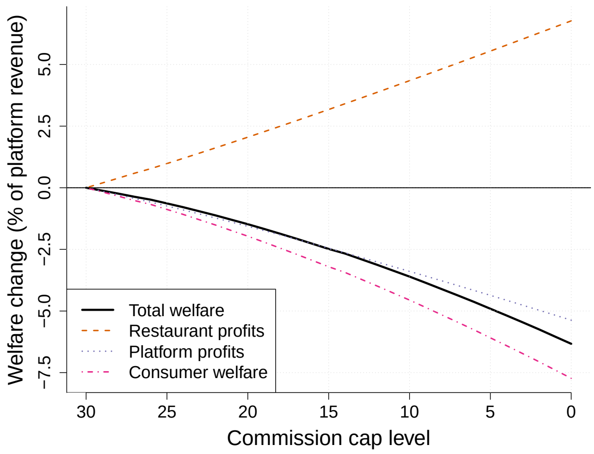


Notes: each point provides the estimated effect of a 15% commission cap on the share of restaurants that join at least one online platform and on overall online platform sales. The solid lines are ordinary least squares regression lines, and the R^2 of the regression is displayed in the lower right corner.

7.2 Alternative commission caps

Negative effects of 15% commission caps on consumer welfare and total welfare do not rule out positive effects of capping commissions at higher or lower levels. To determine how the effects of alternative caps compare to those of 15% caps, I compute equilibria under caps from 0% to 29% and compare them to the baseline equilibrium wherein commission rates equal 30%. Figure 12 provides results for the Los Angeles. Lowering the cap level monotonically raises restaurant profits while lowering platform profits, consumer welfare, and total welfare. This finding applies to all of the metro areas that I analyze. Thus, the signs of the estimated welfare effects of the 15% commission cap do not depend on the 15% level of the cap, but instead broadly apply to commission caps.

Figure 12: Welfare effects of alternative commission caps in Los Angeles



Notes: this plot provides welfare effects of cappping commissions at levels between 30% and 0% as a share of total platform revenue in the baseline equilibrium.

7.3 Taxing commissions

It is plausible that policies other than commission caps could increase restaurant profits with more favourable overall welfare effects than caps. One such policy is a tax on platform commissions whose revenues are remitted to restaurants. Besides directly providing revenue to restaurants, a commission cap penalizes commissions as a revenue source for platforms relative to consumer fees, which could lead platforms to reorient their price structures away from commissions and toward fees. The tax that I consider is a share $\mathfrak{t}$ of a platform's commission earnings. Recalling the expression for platform f's profits in (16), platform f's tax obligations are

$$\mathfrak{t} \times \sum_{z \in \mathcal{Z}_m} r_{fz} \bar{p}^*_{fz} \mathfrak{s}_{fz}.$$

I set the tax rate $\mathfrak{t}$ so that the government's revenue from the tax absent a pricing response by platforms is equal to restaurants' profit gains from a 15% commission cap. This yields $\mathfrak{t} = 1.8\%$ for Los Angeles, the city on which I focus my analysis of a commission tax.

Table 19 provides effects of a 15% commission cap and the commission tax relative to the baseline equilibrium for Los Angeles. Note that the sum of the change in restaurant profits and the change in government revenue is similar for each policy. Consumers and platforms, however, are better off under the tax. Although a tax alters platform pricing incentives, it does not do so as dramatically as a cap; responses in fees and commissions to a tax are relatively small, and thus reductions in consumers' platform orders and consumer welfare are small. Thus, when the government transfers proceeds from a commission tax to restaurants, the tax can lead to a comparable increase in restaurant profits as a cap with more favourable overall welfare effects.

Table 19: Comparison of commission cap and commission tax

Change in...	Cap	Tax
Avg. consumer fee ($)	5.62	0.60
Avg. commission rate (p.p.)	-15.00	-1.36
Avg. platforms adopted (%)	4.58	0.43
Shr. adopting a platform (p.p.)	1.93	0.18
Platform orders (%)	-3.17	-0.26
Restaurant profits ($ p.c.)	3.18	0.26
Platform profits ($ p.c.)	-2.45	-2.10
Consumer welfare ($ p.c.)	-3.25	-0.25
Government revenue ($ p.c.)	0.00	2.79
Total welfare ($ p.c.)	-2.53	0.69

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 compares the effects of policies in Los Angeles. "Avg. consumer fee" and "Avg. commission rate" are averages of fees and commissions, respectively, taken across platforms with weights equal to platforms' sales in the baseline equilibrium. "Avg. platforms adopted" gives the change in the average number of online platforms that a restaurant in the market adopts. "Shr. adopting a platform" gives the percentage point change in the share of restaurants that join at least one online platform. The symbol "(%)" appearing after a variable's name indicates that the table provides the percentage rather than absolute change in that variable.

7.4 Value of multihoming

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 20 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 20: 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.

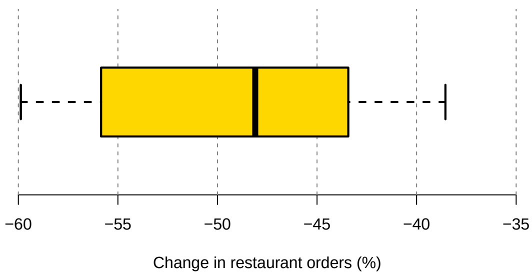
7.5 Effects of online platforms on the restaurant industry

Although food delivery platforms offer a valuable service to consumers, the effect of platforms on restaurant profitability is *a priori* ambiguous. Platforms raise restaurant sales, but sales on platforms may cannibalize restaurants' commission-free sales made directly to consumers. Platform membership also entails fixed costs. To evaluate the effects of platforms on the restaurant industry, I consider a counterfactual in which platforms are eliminated. Savings on platform fixed costs should be accounted for in an analysis of the overall welfare effects of eliminating platforms. Rather than estimate fixed costs, I compute welfare outcomes under two scenarios: (i) platform fixed costs are equal to zero, and (ii) platform fixed costs are equal to platform variable profits. Changes in total welfare under these scenarios provide sharp lower and upper bounds on the total welfare effects of eliminating platforms when both platform profits and platform fixed costs are non-negative.

My estimates of the welfare and profit effects of eliminating platforms account for differential reliability and costs between deliveries made by restaurants' own delivery services and those delivered by online platforms. Consumers may prefer to receive deliveries from platforms rather than restaurants' own delivery services because deliveries from platforms may be more reliable than deliveries made directly by restaurants. These preferences impart a positive effect of delivery platforms on consumer welfare. My model captures these preferences through the δ_{fm} fixed effects, which are common across consumers in a market, and the consumers' idiosyncratic ζ_{if}. Additionally, restaurants may face differential costs of fulfilling orders that they deliver themselves versus those delivered through platforms. My model partially accounts for these differential costs through the $K_m(\mathcal{G})$ fixed costs of platform adoption, which are net of the fixed costs of not joining any online platform, and the differential marginal costs of fulfilling orders directly versus those placed on platforms.

Figure 13 reports the cross-metro distribution of changes in the number of orders placed at restaurants in an economy without food delivery relative to the number of orders placed on platforms in the baseline equilibrium. This plot shows that in about half of cases, a restaurant order placed on a platform is no longer placed when platforms are eliminated. Thus, platforms have a substantial market expansion effect. Table 21 summarizes the welfare effects of eliminating food delivery platforms.[38] Even though platforms boost restaurant order volumes, they reduce restaurant profits. This reflects that platform adoption boosts a restaurant's profits largely at the expense of its rivals. This situation is analogous to a firm's ability to profit from undercutting its rival's prices despite the fact that an industry-wide agreement to sustain high prices could raise the sum of firm profits. My results suggest that restaurant collusion against platform membership would be profitable for restaurants. Eliminating platforms, however, comes at a substantial cost to consumers and eliminates platforms' profits.

Figure 13: Effects of eliminating delivery platforms on restaurant orders



Notes: this figure reports the effects of eliminating delivery platforms on restaurant orders across metros. The reported changes are relative to platform orders in the baseline equilibrium. The plotted points are the cross-metro minimum effect, the 0.25, 0.50, and 0.75 quantiles of the effects across metros, and the cross-metro maximum effect.

Table 21: Welfare effects of eliminating delivery platforms (dollars per capita, annual)

Outcome	Mean	Median	Min.	Max.
Consumer welfare	-66.98	-69.09	-103.04	-29.80
Restaurant profits	17.88	18.58	6.52	34.62
Platform variable profits	-58.06	-58.23	-94.26	-29.12
Total welfare: lower bound	-107.16	-98.88	-178.44	-50.72
Total welfare: upper bound	-49.10	-41.76	-84.17	-21.60

Notes: this table summarizes effects of abolish food delivery platforms across markets using cross-market medians (unweighted), minima, and maxima. 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.

8 Conclusion

This paper evaluates restrictions on food delivery platforms' commission charges to restaurants using a model of platform competition and a rich collection of datasets characterizing the US food delivery industry. My model captures the responses that drive the effects of caps: responses restaurants' platform adoption decisions, of restaurant prices, and of platform fees. These responses in turn depend on the network externalities that consumers and restaurants exert on each other. My model is novel in the empirical literature on platform pricing in that it includes pricing between the end users of a platform (i.e., restaurant pricing to consumers) and that it nests a positioning model to capture endogenous platform membership by restaurants. Several aspects of my results

[38] See Online Appendix O.11 for market-specific results.

are noteworthy: caps boost restaurant profits while reducing consumer welfare and platform profits; a failure of restaurants to adjust their prices upon the imposition of a cap magnifies the effects of caps; and consumer welfare losses are significantly larger when network externalities are not taken into account. Additionally, a tax on commissions leads to a comparable gain in restaurant profits without the negative overall welfare effects of a commission cap.

This study raises several directions for future research. First, platforms may charge agents membership fees in addition to transaction fees. Since the sample period considered by my paper, food delivery platforms have increasingly marketed subscription plans that allow consumers to pay flat fees to reduce their per-transaction delivery fees. Platforms could similarly charge restaurants membership fees in addition to (or in place of) commissions. The implications of these alternative price structures is a promising topic for future research. Another direction for future research involves the role of payments between platforms' end users, and the effects of these payments—and any platform policies that limit them—on platform markets. The role of such payments has been analyzed by the theoretical literature on multi-sided markets, and my paper provides an empirical demonstration of these payments' importance. Indeed, price setting allows restaurants to pass through changes in platforms' commissions to their prices, and my model suggests that commission caps may induce restaurant price reductions that offset platforms' consumer fee increases. I expect that the effects reported in this study, for example, would differ significantly if platforms limited restaurant to charge the same prices on platforms as they do for direct-from-restaurant orders. Last, my study holds fixed the population of restaurants. Changes in restaurants' profitability, however, are likely to affect restaurants' entry and exit decisions. I leave the extension of my model to account for restaurant entry and exit as a topic for future research.

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Appendices

A Delivery fee measures

I estimate the conditional expectation in (2) using a linear regression of the form

$$df_{kfz} = x_k'\beta_f + w_z'\mu_f + \phi x_k^{\text{dist}} w_z^{\text{dens}} + \epsilon_{kfz}, \tag{28}$$

where w_z are characteristics of ZIP z and x_k^{dist} and w_z^{dens} are scalar components of x_k and w_z, respectively, that are explained at the end of this paragraph. Additionally, ϵ_{kfz} is an unobservable that is mean-independent of x_k and w_z, f, and z.

The observable characteristics included in w_z are municipality indicators; county indicators; CBSA indicators; local density defined as the population within five miles of ZIP z; and several variables measuring the demographic composition of the area within five miles of z.[39] Last, x_k^{dist} is the delivery distance for order k and w_z^{dens} is the local density of z; I included variables' interaction in (28) to capture the possibility that the cost of increasing an order's distance depends on population density due to traffic congestion. It is important to include a rich set of geographical features so that the fee indices flexibly capture fee differences across geography.

There are several problems in estimating (28) by ordinary least squares (OLS): OLS is prone to overfitting in settings with many regressors, and using OLS would require a somewhat arbitrary selection of a noncollinear set of geographical indicators to include in w_z. I therefore use the Lasso to estimate (28).[40] The Lasso estimator minimizes the sum of squared residuals plus the L_1 norm of the coefficient vector times a penalization parameter. The use of the Lasso may be justified by its reduction of overfitting relative to OLS and its compatibility with collinear regressors. In my setting, the Lasso provides a data-driven method for selecting geographical indicators for inclusion in w_z based on their relevance in predicting delivery fees. I select the value of the penalization parameter using k-fold cross validation, with $k = 10$.

Upon estimating the parameters (β_f, μ_f, ϕ_f) of (28) with a Lasso estimator separately for each platform f, I compute the delivery fee measure $\widehat{DF}_{fz}$ as

$$\widehat{DF}_{fz} = \bar{x}'\hat{\beta}_f + w_z'\hat{\mu}_f + \hat{\phi}_f \bar{x}_k^{\text{dist}} w_z^{\text{dens}}.$$

I set $\bar{x}$ to the average x_k across all orders in my sample. Additionally, I estimate each regression on observations recorded in the second quarter of 2021.

B Restaurant price measures

This appendix describes the construction of the restaurant price measures that I use in estimating my model. I define a measure $p_{f\mathcal{G}z}$ for each combination of a platform f, a platform portfolio $\mathcal{G}$ (that is, a subset of the online platforms), and a ZIP z. Variation in the $p_{f\mathcal{G}z}$ measures across platforms, platform portfolios, and ZIPs reflects variation in the price of a fixed menu item offered by a restaurant chain across platforms, across ZIPs z, and across restaurant locations with different platform portfolios $\mathcal{G}$. I estimate a menu item's relative price across platforms, locations on different platform portfolios, and locations in different regions using a Lasso regression with item fixed effects and log price as the dependent variable. The Lasso selects which interactions of platform, platform portfolio, and geography are empirically relevant in explaining menu items' prices. With menu items' relative prices in hand, I obtain absolute prices by fixing the price of an order from Uber Eats in the New York City metro area from a restaurant that belongs only to Uber Eats to the average size of an Uber Eats order in New York before fees and taxes.

I now describe the construction of the restaurant price measures in detail. Let ι denote a menu item and t denote a transaction. Additionally, let f and m denote the platform and metro, respectively, of the transaction in question. Similarly, let $\mathcal{G}$ denote the platform portfolio of the restaurant from

[39] These variables include the shares of the population in various age groups, the share of the population over 15 years of age that is married, and the shares of the population over 18 years of age having achieved various levels of educational attainment.

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

which the consumer placed an order. Consider the equation

$$\log p_{\iota f \mathcal{G} m t} = \varphi_\iota + \vartheta_{f \mathcal{G} m} + \epsilon_{\iota f \mathcal{G} m t}, \tag{29}$$

where $p_{\iota f \mathcal{G} m t}$ is the observed transaction price of the item ι, φ_ι are item fixed effects and $\vartheta_{f \mathcal{G} m}$ are platform/platform portfolio/metro fixed effects. I interpret the $\epsilon_{\iota f \mathcal{G} m t}$ as measurement error. When $\epsilon_{\iota t} = 0$ yields, we have (suppressing the transaction subscript)

$$\frac{p_{\iota f \mathcal{G} m}}{p_{\iota f' \mathcal{G}' m'}} = e^{\vartheta_{f \mathcal{G} m} - \vartheta_{f' \mathcal{G}' m'}}. \tag{30}$$

Thus, the ϑ fixed effects provide the relative price of a menu item on a particular combination of platform, platform portfolio, and metro to the price of the same item on any other combination of these three variables.

Defining price indices in levels at the level of a platform, platform portfolio, and metro triple requires fixing one of the $p_{\iota f \mathcal{G} m}$ prices; once such a price is fixed, (30) and the ϑ fixed effects allow me to compute $p_{\iota f \mathcal{G} m}$ for all remaining $(f, \mathcal{G}, m)$ triples. In practice, I fix the price of an order on Uber Eats from a restaurant that belongs only to Uber Eats in New York City's metro area to the average basket size for an order from Uber Eats in New York City's metro area. Note that Uber Eats is the largest delivery platform in New York City's metro area, which is the largest metro area in the United States. This average basket size is \$29.50.

I estimate the ϑ fixed effects in (29) using the Lasso. In particular, I specify ϑ as a linear combination of fixed effects for interactions of platforms, platform portfolios, and metros:

$$\vartheta_{f \mathcal{G} m} = \Upsilon_f + \Upsilon_{\mathcal{G}} + \Upsilon_m + \Upsilon_{f \mathcal{G}} + \Upsilon_{fm} + \Upsilon_{\mathcal{G} m} + \Upsilon_{f \mathcal{G} m}. \tag{31}$$

I then estimate the Υ parameters using the Lasso. Note that the collinearity of the fixed effects does not preclude the application of the Lasso, which selects the granularity of the fixed effects to manage a bias/variance trade-off. I select the penalization parameter entering the Lasso objective function using 10-fold cross-validation. Rather than estimate (29) directly, I estimate the equation after applying the within transformation $x_{\iota t} \mapsto x_{\iota t} - (1/T_\iota) \sum_{t'} x_{\iota t'}$ to both sides of the equation, where T_ι is the number of transactions for item ι and the sum is taken over all transactions of item ι. The within transformation removes the item-level fixed effects φ_ι from (29). I estimate the transformed equation via the Lasso on all transactions in the Numerator data in the second quarter of 2021 that were placed in one of the 14 metro areas on which my paper's analysis focuses. This yields estimates $\hat{\Upsilon}$ of the the Υ fixed effects appearing in (31). I substitute these $\hat{\Upsilon}$ estimates into (29) in the place of the Υ parameters to obtain estimates $\hat{\vartheta}$ of the ϑ fixed effects. My restaurant price indices are then

$$p_{f \mathcal{G} m} = p_{f_0 \mathcal{G}_0 m_0} e^{\vartheta_{f \mathcal{G} m} - \vartheta_{f_0 \mathcal{G}_0 m_0}},$$

where f_0 denotes Uber Eats, $\mathcal{G}_0$ denotes the platform portfolio containing no online platform other than Uber Eats, and m_0 is the New York City metro area. As suggested above, $p_{f_0 \mathcal{G}_0 m_0} =$ \$29.50.

I now discuss several caveats in the computation of the indices. First, I lack item-level data on Postmates orders. Consequently, I set the price indices for Postmates equal to those for Uber

Eats. In particular, when f_1 is Postmates and f_0 is Uber Eats, I set $p_{f_1 \mathcal{G} m} = p_{f_0 \mathcal{G}^* m}$, where $\mathcal{G}^*$ is equal to $\mathcal{G}$ with membership of Postmates and Uber Eats interchanged. That is, $\mathcal{G}^*$ includes Postmates (Uber Eats) if and only if $\mathcal{G}$ includes Uber Eats (respectively, Postmates), and $\mathcal{G}$ and $\mathcal{G}^*$ each contain DoorDash and Grubhub if and only if the other set does. Another concern is that restaurant prices depend on the presence of a commission cap. I do not detect a difference in menu items' prices on online platforms between areas with and without commission caps using my item fixed-effects approach. One explanation for this finding is that most of the items that I observe being purchased repeatedly across platforms, and can therefore use in an analysis with item fixed effects, are sold by chain restaurants. Chains may practice uniform or zone pricing; that is, they may not condition their prices on local demand and cost conditions, including the presence of a local commission cap. Uniform and zone pricing policies by chain retailers have been documented in the industrial organization literature; see DellaVigna and Gentzkow (2019) and Adams and Williams (2019). I alternatively check for a difference between restaurants' prices on platforms between areas with and without commission caps by manually collecting data on restaurant prices. In particular, I randomly drew 20 and 10 restaurants on each of DoorDash and Uber Eats in each CBSA, respectively and found the price of an item from their menu on each delivery platform to which they belong. I also found the price of the same item for direct-from-restaurant orders. Collecting these data manually between July 21 and August 18, 2021 yielded a dataset of 593 prices for menu items on platforms for which a direct-from-restaurant price is available. A platform/menu item level regression of the ratio of the platform-intermediated price to the direct-from-restaurant price on an indicator for a commission cap being in place with platform and CBSA fixed effects included yields a coefficient of -7.02% (standard error: 2.94%) on the commission cap indicator. I adjust my estimated markup of platform-intermediated prices over direct-from-restaurant prices by this amount in computing my restaurant price measures. In particular, I set the restaurant price index for online platform f, platform portfolio $\mathcal{G}$, and metro m to

$$p_{f\mathcal{G}m}^{\text{cap}} = p_{0\mathcal{G}m} \left[\frac{p_{f\mathcal{G}m}}{p_{0\mathcal{G}m}} - 0.0702 \right]$$

for ZIPs z where commission caps are in effect.

Figure 14 displays the median and interquartile range of restaurant price indices across metros m and portfolios $\mathcal{G}$ for each platform f. Table 22 reports results from a regression of the price indices $p_{f\mathcal{G}m}$ on platform indicators and the number of online platforms in $\mathcal{G}$. Together, Figure 14 and Table 22 show that there is a systematic difference between direct-order prices and online platform prices, but not between the prices charged by restaurants across different online platforms.

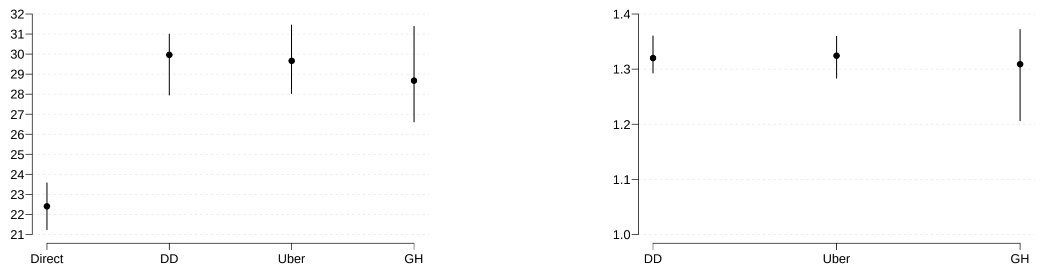
Table 22: Comparison of restaurant price indices

	Estimate	SE
Intercept	29.68	0.41
Platform: direct	-7.30	0.33
Platform: Grubhub	-0.94	0.37
Platform: Uber	0.08	0.37
Platform portfolio size	0.03	0.13

Notes: this table provides estimates from an ordinary least squares regression of the restaurant price indices $p_{f\mathcal{G}m}$ on (i) platform f indicators and (ii) the number of online platforms included in $\mathcal{G}$. DoorDash is the omitted platform.

Figure 14: Restaurant price indices (medians and interquartile ranges)

(a) Level (b) Relative to direct price



Notes: Panel (b) reports the median and interquartile range of each platforms' price indices divided by the respective direct price indices.

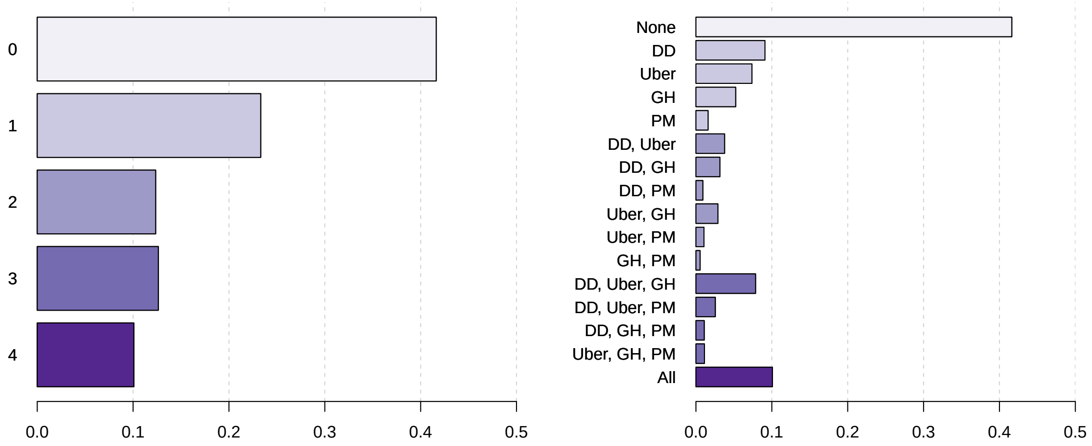
C Market size

I set the number of consumers in each ZIP and distribution of these consumers' demographic types (i.e., their ages, marital statuses, and incomes) using a combination of the Edison platform/ZIP-level estimates of sales volumes, the Numerator panel, and the 2019 American Community Survey (ACS). For each metro m, I tentatively set the number of consumers in each ZIP to the ACS estimate of the ZIP's population. I then set the distribution of consumers across demographic types equal to the distribution among Numerator panelists residing in the ZIP. For ZIPs with fewer than 10 Numerator panelists, I instead set the distribution equal to that in the collection of ZIPs within five miles of the ZIP in question. Next, I compute an equilibrium in restaurant prices conditional on observed platform adoption decisions, fees, and commissions in April 2021. The ratio of the number of platform orders in the market from the Edison transactions dataset for April 2021 to the expected number of platform orders in this equilibrium provides the factor by which I multiply each ZIP's number of consumers. After scaling up the tentative number of consumers in each ZIP by this market-level factor, my model's predictions of metro-level sales align with the Edison estimates. As noted in Section 2.2, the Edison sales estimates align with DoorDash's earnings reports and the Consumer Expenditure Survey.

D Bootstrap procedure

This appendix describes the bootstrap procedure that I use to compute standard errors. This procedure has features of the parametric bootstrap and of the nonparametric bootstrap. The parametric part involves drawing from the estimated asymptotic distribution of the consumer choice model estimates and using these draws as inputs in later stages of estimation. The nonparametric part primarily involves sampling with replacement from the population of restaurants. Recall that I estimate my consumer choice model via maximum likelihood. I estimate the asymptotic variance of my maximum likelihood estimator using the outer product of the gradients estimator. I then take $B = 100$ draws from the associated estimate of the asymptotic distribution of $Z = \sqrt{n}(\hat{\theta}^{\text{cons}} - \theta_0^{\text{cons}})$, where θ_0^{cons} is the true choice model parameter vector, $\hat{\theta}^{\text{cons}}$ is the maximum likelihood estimator,

Figure 15: Distribution of restaurants across platform sets, April 2021



(a) Number of adopted platforms

(b) Identities of adopted platforms

Notes: this figure plots the distribution of restaurants across sets of portfolios (e.g., joining no online platform, joining only DoorDash, joining Uber Eats and Grubhub) in the 14 markets listed in Table 1 in April 2021. Deeper shades indicate sets that include more platforms.

and n is the sample size. Let Z^b denote the bth draw, and let $\hat{\theta}^{\text{cons},b} = \hat{\theta}^{\text{cons}} + n^{-1/2}Z^b$. I estimate restaurants' and platforms' marginal costs, call them $\hat{mc}^b$ under each $\hat{\theta}^{\text{cons},b}$. For each b, I also take a standard bootstrap draw of restaurants within each market, where each market is defined by its ZIP and its platform portfolio choice. Let $\mathcal{J}^b$ denote the bth draw. I proceed to estimate the parameters of restaurants' platform adoption game at $\{\hat{\theta}^{\text{cons},b}, \mathcal{J}^b, \hat{mc}^b\}$ for each b. This procedures yields estimates $\hat{\theta}^{\text{adopt},b}$ of the parameters of restaurants' platform adoption game for each bootstrap replicate b. The standard errors that I report for these parameters are the standard deviations of the parameters across bootstrap replicates. I similarly estimate the weights h_{fm} at $\{\hat{\theta}^b, \hat{mc}^b, \hat{\theta}^{\text{adopt},b}\}$ for each b, which yields estimates $\hat{h}^b_{fm}$ of these weights for each b. Last, I solve for equilibria at each b and take the standard deviation of outcomes across replicates b to obtain the standard errors for results from counterfactual simulations.

E Additional data description

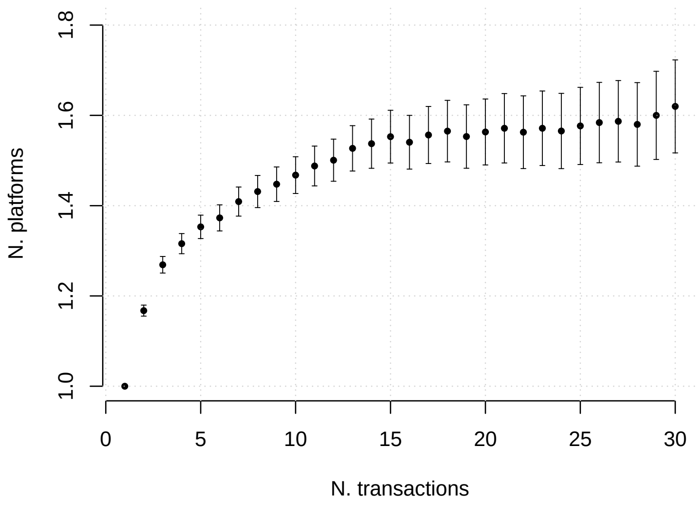
This appendix provides additional descriptive analyses of my study's data. First, Table 23 decomposes the four major platforms' fee indices into their constituent components as specified by the main text: indices of delivery fees, service fees, and regulatory response fees.

Table 23: 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 16: Average cumulative numbers of platforms used by consumers



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

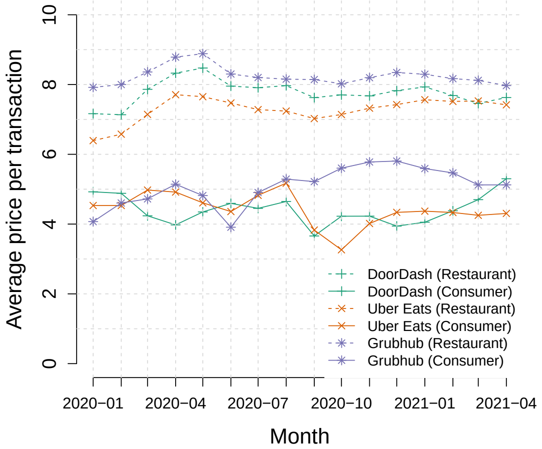
Table 24: Evaluation of state dependence

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

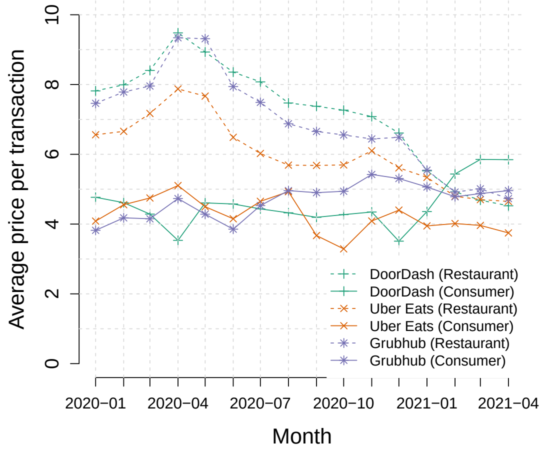
Notes: the "# switches" columns report the average number of switches between online platforms among consumers buying from k unique platforms within τ orders from online platforms. The "# switches (Shuffled data)" column report average numbers of switches as defined above as when each consumer's purchasing sequence is randomly shuffled. I conducted the analysis on Numerator data from the 14 markets listed in Table 1 in Q2 2021.

Sources of within-market fee variation. 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 run these regressions first including only platform fixed effects and then including fixed effects for all platform/market pairs. This second regression is useful for understanding whether commission caps and demographic differences provide variation in fees within markets. Table 25 provides the results. Even after including platform/CBSA fixed effects and thereby limiting ourselves to within-market variation in fees, the presence of a commission cap provides variation in fees. Additionally, the demographic variables included as controls provide variation in fees: areas with higher proportions of young people and married people tend to have lower fees, as do areas with higher population densities.

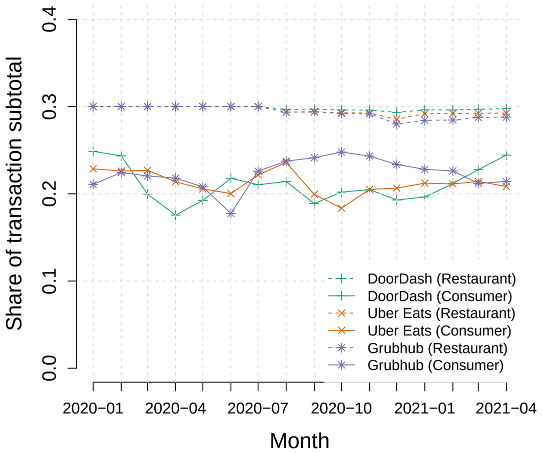
Figure 17: Platforms' average fees and commissions in regions with and without a commission cap as of May 2021



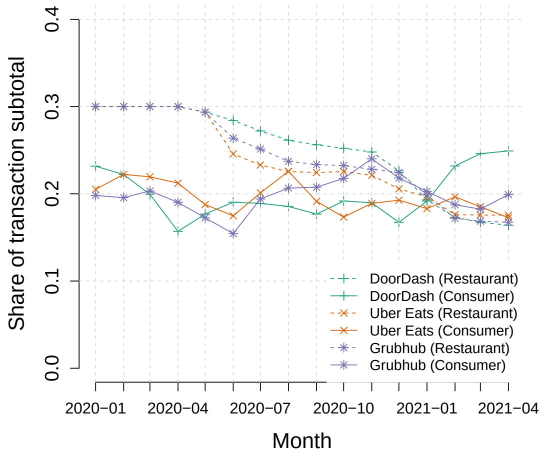
(a) Average prices per transaction: no cap



(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 25: 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: these tables provide results from regressions on a dataset of fees in ZIPs within the markets analyzed by my study. Each of the $N = 17220$ observations 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.