Fee Optimality in a Two-Sided Market*

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Abstract

The fees that platforms charge to consumers and merchants may be inefficient due to market power, network externalities, and business-stealing externalities. Using a structural model of platform competition estimated on data covering all major US food delivery platforms, I quantify distortions in platform fees. Consumer fees are nearly optimal due to offsetting market power and offline business stealing distortions. Restaurant commissions, by contrast, are nearly twice their socially optimal levels, primarily because platforms do not fully account for consumer benefits from increased restaurant variety on platforms. I also consider whether platform competition corrects inefficiency in platform fees.

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1 Introduction

Digital platforms that match buyers and sellers offer convenience and variety to consumers. Yet their fees have faced criticism for being both distributionally unfavourable to merchants and allocatively inefficient.[1] This article empirically evaluates whether platform fees are not only too high overall, but also structured in a way that places an excessive burden on sellers.

The setting is the US food delivery industry, which has witnessed particularly contentious debates over platform fees. Leading delivery platforms charge restaurants commissions equal to a share—often around 30%—of sales along with per-transaction fees to consumers. Spurred by restaurant complaints about high commissions, many local governments have imposed commission caps limiting commissions to 15%. These policies provide a natural backdrop for an evaluation of whether platforms' restaurant commissions are excessive.

Several economic forces cause profit-maximizing platforms to set fees that diverge from those maximizing total welfare. First, platform market power drives both consumer fees and restaurant commissions above efficient levels.

Second, platforms internalize network externalities differently than does a social planner. In food delivery, network externalities arise because consumers value restaurant variety and restaurants benefit from platforms with large consumer bases. A social planner's fees account for the cross-side benefits enjoyed by all users on each side of the market. Profit-maximizing platforms, however, focus only on whether fees induce marginal users to participate, ignoring benefits to inframarginal platform users.

Platforms' incomplete internalization of network externalities generates inefficiencies in platform fees. Consider a platform whose loyal consumers strongly value restaurant variety but whose marginal consumers are primarily fee-sensitive. To attract these fee-sensitive marginal consumers while earning a markup above costs, the platform may set low consumer fees and high restaurant commissions. Such a fee structure may inefficiently discourage restaurant participation on the platform given the benefits that the platform's loyal consumers enjoy from restaurant variety.

Beyond the classical distortions from market power and network externalities, I identify sources of inefficiency rooted in business stealing among merchants. Consumers substitute between ordering directly from restaurants ("offline") and ordering through platforms ("online"), which implies that online sales subtract from restaurants' offline sales. Although a restaurant internalizes the effect of its platform sales on its own offline sales, it does not account for the effects on rivals' offline sales. In fact, stealing rivals' offline sales may be a key motivation for restaurants to join platforms.

When platforms raise consumer fees, some customers switch to direct ordering. This substitution benefits merchants by raising their direct orders, limiting the extent to which restaurants steal each others' commission-free offline sales. A social planner would account for this benefit to merchants when setting fees. Profit-maximizing platforms, however, ignore this substitution effect since they earn no revenue from direct orders. This creates an *offline business-stealing distortion* that makes consumer fees inefficiently low from a social perspective.

Another source of inefficiency arises from competition between merchants. When restaurants

[1] Examples include the law suits raised by Epic Games against Apple and Google over app store commissions and debates over credit card fee regulation.

join platforms partly to steal sales from rivals, they may adopt platforms even when the fixed costs of adoption exceed the social benefits from expanded consumer variety. A social planner would account for these adoption costs when setting commissions, using higher rates to discourage socially excessive entry. Profit-maximizing platforms, however, ignore restaurants' adoption costs since they benefit from participation regardless of its social value. This may lead restaurant commissions to be inefficiently low.

Platform competition introduces additional complexity. Although competition typically limits market power, thereby reducing total platform fees, it need not correct inefficiencies in how fees are split between consumers and merchants. Competition may focus on attracting consumers through lower fees. Given the tendency of forces that reduce fees on one side of a two-sided to market to raise fees on the other side—the so-called see-saw effect—increased competition for consumers may raise merchant commissions, potentially exacerbating inefficiency in the split of fees between buyers and sellers.

The distortions affecting each of consumer and merchant fees vary in sign, and economic theory yields no clear predictions about which distortions dominate in determining either whether these fees are too high in absolute level or relative to the fees of the other side. My goal is to empirically determine the extent to which platform fees are inefficient and the sources of inefficiency.

The two primary challenges that I face are in assembling comprehensive data on a platform market and in developing a tractable model of platform competition for use in computing fee distortions. To address the first challenge, I assemble a rich collection of datasets on the US food delivery industry and estimate a structural model of platform competition. The primary dataset is a panel of consumer restaurant orders, which includes ZIP-code-level consumer locations and item-level pricing information. I supplement this with data on all restaurants listed across major delivery platforms, as well as data harvested from platform websites that capture platform fees and estimated delivery times. Together, these sources provide detailed information on pricing, platform participation, and delivery conditions for hundreds of thousands of orders across 14 large US metropolitan areas.

I proceed to formulate a structural model that captures the complex set of responses to platform fee changes. The model has four stages. In the first stage, platforms set restaurant commissions and consumer fees given constant marginal costs of fulfilling orders. Next, restaurants decide whether to join platforms in an incomplete information entry game featuring heterogeneity by geographic location and type (chain versus independent). In choosing which platforms to join, if any, restaurants compare their gains in variable profits from platform adoptions to fixed costs of platform adoption. After joining platforms, restaurants set profit-maximizing prices, which may differ between platform and direct orders. Finally, consumers decide whether to order a restaurant meal, which nearby restaurant to order from, and whether to use a platform in doing so. The model captures the interdependence between consumer and restaurant platform choices: consumers prefer platforms with broader restaurant availability, while restaurants benefit more from joining platforms with high consumer usage. Heterogeneous consumer preferences over platforms govern substitution patterns between platforms and direct ordering.

Estimation proceeds in steps. I first estimate consumer preferences using maximum likelihood, recovering parameters that govern price sensitivity, preferences for restaurant variety, and substitution patterns. I then recover restaurant and platform marginal costs from first-order conditions for optimal pricing. Next, I estimate the restaurant adoption model via the generalized method of moments (GMM), selecting adoption cost parameters to match (i) market-specific platform adoption rates and (ii) the covariance between expected profitability and adoption decisions.

Identification of price sensitivity and network effects is complicated by the endogeneity of platform fees and restaurant networks, which reflect unobserved consumer tastes. I address this by using platform/metro-area fixed effects and exploiting within-metro variation in fees and restaurant networks — variation driven in part by commission caps. To estimate substitution patterns, I leverage the data's panel structure, which traces how consumers switch among ordering options.

Using the estimated model, I compute equilibrium fees arising under competition between profit-maximizing platforms ("privately optimal") and those that maximize total welfare ("socially optimal"). Although profit-maximizing platforms set consumer fees above the socially optimal level, the deviation is modest. On average, consumer fees exceed their welfare-maximizing level by only \$0.29 per order. This small gap reflects the interaction of two opposing forces. Market power pushes consumer fees upward, but this effect is largely offset by an offline business stealing distortion: higher consumer fees induce some customers to switch to direct ordering, which benefits merchants. A profit-maximizing platform ignores this benefit, while a social planner internalizes it. Net distortions from network externalities are also small in magnitude on the consumer side. Thus, the distortions pushing privately optimal consumer fees away from those that are socially optimal are small on net.

By contrast, profit-maximizing commissions are nearly twice as high as those maximizing social welfare, on average. Reducing commissions encourages platform adoption by restaurants, thus benefitting variety-loving consumers. Consumer benefits from increased variety upon commission reductions are about twice the fixed adoption costs associated with increased restaurant uptake of platforms. For restaurants, the benefits of lower commissions are largely offset in equilibrium by increased fixed costs of platform adoption and intensified intra-platform price competition: equilibrium responses reduce restaurant benefits from moving to the socially optimal fees by 73%. Thus, although profit-maximizing platforms charge socially excessive commissions to restaurants, restaurants retain little of the surplus created from correcting this inefficiency.

Having characterized inefficiencies in platform fees, I assess the scope for welfare gains from commission-cap-style regulations that fix restaurant commission rates while allowing platforms to re-optimize their consumer fees. I find that caps set at 15%—the most common level in practice—reduce aggregate welfare. These losses are primarily driven by increases in consumer fees: in response to the cap, platforms shift the burden to consumers, depressing order volumes below efficient levels and leaving fewer consumers available to enjoy the variety gains associated with increased restaurant uptake of platforms. Although 15% commission caps benefit restaurants, restaurants compete away 77% of their direct gains from commission reductions by joining more platforms and reducing their prices.

Not all caps reduce welfare. Less stringent caps—those in the 20–30% range—raise total welfare. Although moderate reductions in commissions lead platforms to raise consumer fees, they also draw more restaurants onto platforms and reduce restaurant prices. These effects more than offset the consumer welfare losses from higher fees, resulting in gains for both consumers and restaurants.

The optimal regulated commission level varies significantly across counties, from 23% at the 10th percentile to 37% at the 90th percentile. I find that optimal restaurant commissions are lower in counties where (i) platform orders strongly reduce direct restaurant sales, (ii) commission reductions generate large consumer welfare gains through expanded restaurant variety, and (iii) restaurants incur relatively low fixed costs to adopt platforms.

Factors (i) and (ii) converge in counties with high restaurant density, making commission caps more likely to be welfare-enhancing in denser markets. In such markets, restaurant ordering is high even without platforms, and hence platforms primarily subtract from direct sales rather than expand total restaurant revenue. At the same time, dense markets offer the greatest potential for variety improvements when commissions fall, as more restaurants are available to join platforms and serve large consumer bases.

Although moderate commission reductions can raise total welfare, the gains are modest compared to two-sided fee regulation. Commission reductions alone yield welfare improvements of up to $0.10 per order, while simultaneously capping consumer fees at baseline levels and reducing commissions to the point that platforms just break even generates gains of $2.30 per order. This dramatic difference reflects two forces. First, constraining overall platform market power produces larger efficiency gains than simply rebalancing fees between consumers and merchants. Second, expanding restaurant participation creates the greatest benefits when consumer fees are low, since a large consumer base can then enjoy the additional variety created by lower commissions.

Last, I examine how platform competition affects fee structures by simulating a regime in which platforms maximize their joint profits, a scenario equivalent to a merger of all active platforms. Under joint profit maximization, consumer fees rise by an average of $0.77 per order, while restaurant commissions fall by 0.7 percentage points. This decline in commissions occurs despite the elimination of competition because the merged platform internalizes positive spillovers across platforms that arise from cost complementarities in restaurant multi-homing: once a restaurant has joined one platform, it is less costly for the restaurant to join incremental platforms. A joint-profit-maximizing platform accounts for this, recognizing that lowering commissions on one platform can increase overall restaurant participation. In contrast, competing platforms do not internalize these cross-platform gains. Without multi-homing or cost complementarities, joint profit maximization would predictably raise fees on both sides.

Although joint profit maximization reduces commissions, it raises overall platform markups and consequently lowers total welfare by -$0.31 per order. This result, taken together with the limited effectiveness of one-sided commission caps compared to two-sided fee regulation, suggests that the main inefficiency in platform pricing lies in the overall fee level, not in the allocation of fees between consumers and merchants.

1.1 Related literature

This article contributes to the literature on platform pricing, pioneered by Rochet and Tirole (2003), Armstrong (2006), and Rochet and Tirole (2006), by estimating distortions in real-world two-sided markets. I quantify standard inefficiencies from market power and network externalities

(Weyl 2010; Tan and Wright 2021), and extend the analysis to settings with seller competition and online/offline substitution. These features, often excluded from canonical models, introduce new distortions. I formalize these distortions in a stylized model that builds on Rochet and Tirole (2006) and Weyl (2010), and quantify them using structural estimates from the US food delivery sector. In studying the welfare consequences of online/offline substitution, I build on Wang and Wright (2024) and Hagiu and Wright (2025).

The article also assesses the impacts of competition on platform fees. Theoretical work highlights the importance of multi-homing behaviour in shaping equilibrium fees under platform competition (e.g., Armstrong 2006; Bakos and Halaburda 2020; Teh et al. 2023). But most empirical studies of platform pricing omit either two-sided pricing or two-sided multi-homing, with Wang (2023) as a notable exception.[2] Using data on both consumer and restaurant platform use together with a model that accommodates flexible patterns of multi-homing, I show that the potential for competition to reduce fee bias depends crucially on merchant multi-homing.

I also analyze food delivery commission caps as a case study in fee regulation. Prior empirical research on platform regulation focuses on payment cards (e.g., Rysman 2007; Carbó-Valverde et al. 2016; Huynh et al. 2022; Wang 2012; Evans et al. 2015, Manuszak and Wozniak 2017, Kay et al. 2018; Chang et al. (2005); Li et al. (2020)). Outside this domain, empirical evidence is sparse. A notable exception is Li and Wang (2024), who study food delivery caps using difference-in-differences methods. I extend their work by analyzing welfare using a structural model.

More broadly, this article contributes to a literature assessing digital platforms' effects on traditional sectors, including ride-hailing (Castillo Forthcoming; Rosaia 2025; Buchholz et al. 2025; Gaineddenova 2022), accommodations (Calder-Wang 2022; Farronato and Fradkin 2022; Schaefer and Tran 2023), media (Kaiser and Wright 2006; Argentesi and Filistrucchi 2007; Fan 2013; Lee 2013; Sokullu 2016; Ivaldi and Zhang 2022), and others (Jin and Rysman 2015; Farronato et al. 2024; Cao et al. 2021). Work on food delivery remains limited (Natan 2024; Lu et al. 2021; Chen et al. 2022; Feldman et al. 2022; Reshef 2020). I add to this literature by documenting how merchant competition can erode the intended benefits of regulation.

Last, this article contributes to the literature on pass-through. Assessing the incidence of regulation requires modelling how commission changes affect consumer fees and restaurant prices. Theoretical work emphasizes the role of demand curvature in shaping pass-through, motivating my use of a flexible demand system (Weyl and Fabinger 2013; Miravete et al. 2023). I also build on empirical evidence from the restaurant industry showing substantial pass-through of cost increases (Cawley et al. 2018; Allegretto and Reich 2018).

2 Illustrative model

Before introducing the full model, I present a stylized model that clarifies sources of inefficiency in platform pricing and guides interpretation of the empirics. This model extends the canonical model of Rochet and Tirole (2006) to account for competition among sellers and substitution between platform ("online") and direct ("offline" or "first-party") ordering.

[2]For example, Rysman (2004) studies Yellow Pages, which are free to consumers; Song (2021) assumes that consumers read at most one magazine; Lee (2013) treats prices as exogenous; and Gentzkow et al. (2024) excludes endogenous consumer fees.

In the stylized model, a monopolist platform facilitates interactions between buyers and sellers. The platform charges per-transaction fees c to buyers and commissions rp_1 to sellers, where p_1 is the seller's price on the platform. Sellers also make sales directly to consumers through an offline channel. Let a denote the benefit that a seller enjoys from an offline sale. The seller's price p_1 may depend on the commission rate r, and the seller's marginal cost of fulfilling a platform order is κ_1. Although seller costs vary, the price p_1 is assumed constant. The platform's sales are $S_1(c, J)$, where J is the number of sellers that have joined the platform. To simplify the analysis, I assume that there is a continuum of sellers and that J is continuous. The number of sellers that join the platform is in turn determined by $J(r, S_1)$, where S_1 are the platform's sales. I assume that the functions S_1 and J admit the inverse demand functions $c(S_1, J)$ and $r(S_1, J)$. Following Weyl (2010), I assume that the platform charges fees that ensure coordination on a selected allocation (S_1, J). Throughout, I use the superscripts "pr" and "so" to denote quantities associated with the allocation maximizing the platform's profits and social welfare, respectively.

Social welfare has three components: platform profits Λ, consumer surplus CS, and restaurant profits RP. First, platform profits are

$$\Lambda = (c(S_1, J) + r(S_1, J)p_1(r(S_1, J)) - mc)\, S_1.$$

Here, mc is the platform's marginal cost of facilitating a sale. Consumer surplus is

$$CS = \int_0^{S_1} Y(x, J)dx - (c + p_1)S_1,$$

where $Y(S_1, J) = c(S_1, J) + p_1(r(S_1, J))$ is the marginal consumer's valuation of platform usage at sales level S_1. Last, restaurant profits are

$$RP = aS_0(S_1) + ([1 - r]p_1 - \bar{\kappa}_1(J))S_1 - KJ.$$

Here, S_0 are total first-party restaurant sales, which I assume depend on online sales. Also, $\bar{\kappa}_1$ is the average marginal cost among the first J restaurants to join the platform and K is the fixed cost of platform membership.

The model enables a comparison between privately and socially optimal consumer fees. The consumer fee maximizing platform profits satisfies

$$c^{\text{pr}} = mc + \mu_B^{\text{pr}} - \tilde{b}_S^{\text{pr}}, \tag{1}$$

where $\mu_B = -S_1/(\partial S_1/\partial c)$ is the inverse semi-elasticity of consumer demand—a measure of buyer-side market power—and $\tilde{b}_S = d(rp_1S_1)/dS_1$ is the effect of additional platform ordering by consumers on the platform's commission revenue from restaurants. By contrast, the consumer fee maximizing social welfare satisfies

$$c^{\text{so}} = mc - \bar{b}_S^{\text{so}} + aD^{\text{so}},$$

where $\bar{b}_S = p_1 - \bar{\kappa}_1$, the mean benefit to restaurants of a platform sales (before commissions) and $D = -{}^{\partial S_0}/_{\partial S_1}$ is the *diversion ratio* — i.e., the rate at which increases in online sales subtract from offline sales. Condition (1) requires that the platform's consumer fee is equal to its marginal cost plus a standard markup arising from market power (μ_B^{pr}) and minus an adjustment $\tilde{b}_S^{\text{pr}}$ reflecting that an increase in sales raises the platform's revenue from the merchant side. The social planner's consumer fee c^{so} does not include a market-power markup but instead depends on the positive externality $\bar{b}_S$ that platform sellers enjoy from a platform sale and the negative externality aD^{so} on restaurants' offline profits of an additional online order. The difference between the socially and privately optimal consumer fees is

$$c^{\text{pr}} - c^{\text{so}} = \underbrace{\mu_B^{\text{pr}}}_{\text{Market power}} - \underbrace{aD^{\text{so}}}_{\text{Offline business stealing}} + \underbrace{\left[\bar{b}_S^{\text{so}} - \tilde{b}_S^{\text{so}}\right]}_{\text{Spence distortion}} + \underbrace{\left[\tilde{b}_S^{\text{so}} - \tilde{b}_S^{\text{pr}}\right]}_{\text{Displacement distortion}} \quad (2)$$

This equation shows that, although market power μ_B^{pr} tends to raise the privately optimal consumer fee above socially optimal levels, the *offline business stealing distortion* has the opposite effect. The offline business stealing distortion is relevant because of between-seller competition. To see why, consider a model in which consumers substitute between platform and direct ordering within each seller, but in which sellers do not compete with each other — a seller subtracts from its own direct sales upon joining the platform, but does not reduce competitors' sales. Then, sellers completely internalize the impact of its platform sales on its direct sales. Under seller competition, though, merchants may join platforms to steal offline business from rivals. In this case, a merchant's platform membership imposes a negative contractual externality on rivals (Segal 1999, Gomes and Mantovani 2025). The offline business stealing distortion reflects this externality, which may be corrected by an increased consumer fee that steers consumers back toward direct ordering.

The equation also features the Spence and displacement distortions that result from network externalities (Weyl 2010, Tan and Wright 2021). The Spence distortion reflects that a social planner internalizes the benefits of attracting new buyers to platform sellers ($\bar{b}_S$) when setting its consumer fee, whereas a profit-maximizing platform internalizes only the benefits for marginal sellers, given that it is these sellers who determine the extent $\tilde{b}_S$ to which the seller earns more seller-side revenue by attracting more buyers.[3] Marginal platform users typically benefit less from interactions with agents on the other side than do inframarginal users, which suggests a positive Spence distortion. As noted by Tan and Wright (2021), however, profit-maximizing platform fees are typically inflated by market power, meaning that their marginal users have higher interaction benefits than those under the social planner's allocation and hence $\tilde{b}_S^{\text{so}} < \tilde{b}_S^{\text{pr}}$. The resulting *displacement distortion* tends to offset the Spence distortion.

The model also suggests scope for distortion in restaurant commissions. The first-order condition for the profit-maximizing value of J is

$$\tilde{b}_B^{\text{pr}} = \mu_S^{\text{pr}}, \quad (3)$$

where $\tilde{b}_B = \partial c/\partial J$ is the marginal consumer's valuation of an additional online restaurant and $\mu_S^{\text{pr}} = -d[r^{\text{pr}} p_1^{\text{pr}}]/dJ$ is the reduction in commission revenue required to attract another merchant to the platform, an inverse measure of the platform's market power on the merchant side. By contrast, the socially optimal J satisfies

$$\bar{b}_B^{\text{so}} S_1^{\text{so}} = K + (\bar{\kappa}')^{\text{so}} S_1^{\text{so}}, \quad (4)$$

where $\bar{b}_B$ is the average consumer valuation of an additional platform seller.[4]

Equation (3) implies that a profit-maximizing platform equalizes the benefits to marginal consumers of an additional restaurant ($\tilde{b}^{\text{pr}}$) with commission revenue losses required to attract a restaurant when assessing a commission reduction. In contrast, equation (4) implies that a social

[3] With seller competition, the model does not yield the result in Weyl (2010) that $\tilde{b}_S$ equals the marginal seller's benefit from a platform interaction. However, $\tilde{b}_S$ still reflects how increased sales encourage platform adoption and thus reflects marginal merchants' gains from platform sales.

[4] Formally, $\bar{b}_B = \int_0^{S_1} \frac{\partial Y}{\partial J}(x, J)dx/S_1$.

planner compares the total benefit $\bar{b}_B^{so} S_1^{so}$ to consumers of an additional restaurant with the costs of increased platform membership increased costs of adoption K and increased marginal costs $(\bar{\kappa}')^{so} S_1^{so}$.

Although (3) and (4) do not yield a decomposition of distortions à la equation(2), they do indicate sources of inefficiency in profit-maximizing platforms' commissions. First, equation (3) implies that market power μ_S^{pr} tends to raise profit-maximizing commissions. Second, the inclusion of competition between sellers raises the possibility for socially excessive entry in the spirit of Mankiw and Whinston (1986): merchants join platforms in part to steal business from rival restaurants rather than creating value for consumers while incurring fixed costs from platform adoption. The social planner accounts for these fixed costs K whereas a profit-maximizing platform does not. This creates scope for the profit-maximizing platform to charge commissions that are too low and insufficiently deter excessive platform adoption by merchants. Last, $\tilde{b}_B^{pr}$ falling below $\bar{b}^{so}$ due to Spence and displacement distortions tends to make commissions socially excessive.

To summarize, a complex set of externalities implies that consumer fees and restaurant commissions may be either too high or too low, both relative to each other and in absolute levels.[5] The goal of this article is to provide a tractable empirical model that captures this complex set of externalities and permits an evaluation of deviations in platform fees from those that are socially optimal.

Role of platform competition The illustrative model features a monopolist platform and thus does not capture how platform competition shapes the gap between privately and socially optimal fees. Online Appendix O.1 describes how the distortions outlined above are extended to a model with multiple platforms. Furthermore, recent research indicates factors that determine how competition affects fees. Teh et al. (2023) show that the effect of platform entry on the balance between consumer and merchant fees depends on whether it intensifies competition more on the buyer or seller side. This, in turn, depends on how entry affects platforms' residual demand elasticities, platforms substitutability from the buyer's perspective, and multi-homing behaviour. One contribution of this article is to estimate the primitives underlying these forces and assess whether competition pushes fees toward or away from the efficient allocation.

3 Data and background

3.1 Industry background

The major US food delivery platforms in 2020–2021 were DoorDash, Uber Eats, Grubhub, and Postmates; their market shares in Q2 2021 were 59%, 26%, 13%, and 2%.[6] These platforms facilitate deliveries of meals from restaurants to consumers, earning revenue from fees charged to consumers and restaurants. Restaurants also set prices for goods sold on platforms. In sum-

[5]Merchant internalization, which arises when merchants consider the average consumer surplus from platform use in choosing whether to join a platform, provides another reason for a fee structure that is unfavourable to merchants (Wright 2012). Although merchant internalization may be relevant in food delivery, I rule it out in my model by specifying that restaurants respond to consumer demand but not to inframarginal consumer surplus.

[6]Uber acquired Postmates in 2020, but did not immediately integrate Postmates into Uber Eats.

mary,

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

where p is restaurant's price, c is the fee, and r is the commission rate. Average order values before fees, tips, and taxes were slightly below $30 across platforms in Q2 2021. I take it that the commission rates for all leading platforms were 30% in areas without caps based on the facts that Uber Eats and Grubhub advertised 30% commissions in 2021 and DoorDash's full-service membership tier featured 30% commissions in April 2021. It is possible that restaurant chains negotiated lower commissions, although I do not observe their contracts with platforms.

Each platform charges various fees that together constitute the consumer fee c. These include delivery, service, and regulatory response fees (e.g., the "Chicago Fee" of $2.50 per order that DoorDash introduced in response to Chicago's commission cap). Service fees—unlike the other fees—are often proportional to order value. There are reasons for platforms to use both fixed and proportional fees. Fixed fees better reflect cost structure—driver costs do not scale with order value—whereas proportional fees reduce merchant markups and enable price discrimination when consumer willingness to pay scales with cost (Shy and Wang 2011, Wang and Wright 2017). A hybrid structure may thus be optimal. Online Appendix O.2 discusses these mechanisms in detail. In the interest of tractability and focus on the division between consumer and merchant fees, I specify a purely fixed consumer fee in my model.

Restaurants that adopt delivery platforms control their menus on these platforms. Their prices on platforms need not equal their prices for direct-from-restaurant orders. Additionally, restaurants typically make an active choice to be listed on platforms.[7] It is common for restaurant locations belonging to the same chain to belong to different combinations of online platforms.

Both restaurants and consumers multi-home (i.e., use multiple platforms). As described by Online Appendix Table O.4. over half of restaurants on DoorDash belong to Uber Eats. Furthermore, consumers sometimes switch between platforms across orders.

In focusing on platform fees, I abstract away from some features of delivery platforms. Although I model consumers and restaurants, delivery also involves couriers. Rather than model couriers, I specify platform marginal costs of fulfilling deliveries that capture courier compensation.[8] In addition, I do not consider restaurants' first-party delivery services separately from their in-store services. This is because first-party delivery has been a minor part of the restaurant industry since the rise of food delivery platforms. I find, using the Numerator data described in Section 3.2, that only 2.6% of first-party restaurant sales were delivered in 2019–2021.

Many local governments introduced commission caps in a staggered fashion after the beginning of the COVID-19 pandemic. Over 70 local governments representing about 60 million people had enacted commission caps by June 2021. Most caps—78% of those introduced before 2022—limited commissions to 15%, although some limited commissions to other levels between 10% and 20%.

[7]Some platforms list restaurants without their consent, although this practice has decreased in popularity and has been outlawed in several jurisdictions. See Mayya and Li (Forthcoming) for a study of nonconsensual listing.

[8]Fisher (2023) finds that courier surplus from gig work in UK food delivery equals about one third of courier wages. This suggests courier welfare impacts of commission regulation that are not accounted for in my study.

Most caps began as temporary measures, but several jurisdictions later made their caps permanent. Some commission caps (19% of those introduced before 2022) excluded chain restaurants. I take these caps' exemption of chains into account in estimating the article's model, although I focus on the more popular form of cap that does not exempt chains in the counterfactual analysis.

Online Appendix Figure O.2 plots the average fees and commission charges over time. Commission revenue consistently exceeded consumer fee revenue in places without caps: at the beginning of 2020, platforms earned on average \$6–8 from restaurant commissions and \$4–5 from consumer fees per order. But the disparity in consumer and restaurant fees contracted in placed with caps.

3.2 Data

Transactions data. This article uses several data sources, the first of which is a consumer panel provided by the data provider Numerator covering 2019–2021. Panelists report their purchases to Numerator through a mobile application that (i) integrates with email applications to collect and parse email receipts and (ii) accepts uploads of receipt photographs. I use Numerator records for restaurant purchases whether placed through platforms or directly from restaurants (including orders placed on premises, pick-up orders, and delivery orders). At the panelist level, these data report ZIP code of residence and demographic variables. At the transaction level, they report basket subtotal and total, time, delivery platform used (if any), and the restaurant from which the order was placed. At the menu-item level, they report menu item names (e.g., "Bacon cheeseburger"), numeric identifiers, categories (e.g., "hamburgers"), and prices.

Numerator provides receipt data for all of its users, but I use only receipts from members of its core panel in most of the empirical analysis. The demographic composition of this core panel is intended to match that of the US adult population. Using data from the American Community Survey (ACS), I find that the demographic profile of the core panel matches the US adult population fairly well.[9] In addition, market shares computed from these data are similar to those computed from an external dataset of payment card transactions; see Online Appendix O.4 for details.

The market definition that I use throughout this article is a metropolitan area, formally a Core-Based Statistical Area (CBSA). I focus on the fourteen large metro areas for which I have detailed fee data: Atlanta, Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York, Philadelphia, Phoenix, Riverside/San Bernardino County, San Francisco, Seattle, and Washington. In Q2 2021, there are 58,208 unique consumers and 447,846 transactions in the sample for these metros. Figure 1 provides platform market shares in each of these metros for Q2 2021.

I supplement the Numerator data with platform/ZIP/month-level estimates of order volumes and average fees for January 2020 to May 2021.[10] Edison provides these estimates, which are based on a panel of email receipts.[11] This dataset also includes estimates of average basket subtotals, delivery fees, service fees, taxes, and tips.

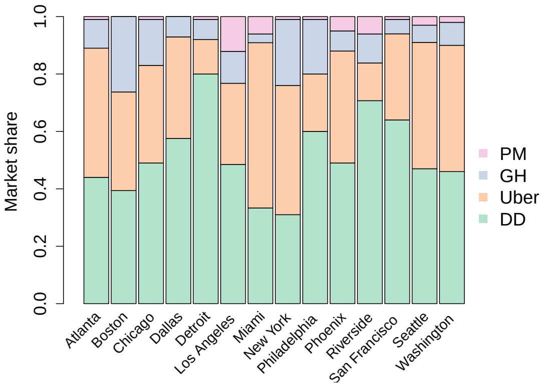
[9] The main exceptions are that individuals younger than 35, individuals older than 64, and high income individuals (over \$125,000 family income) are somewhat underrepresented: their shares in the Numerator panel are 21%, 13%, and 20% whereas their shares in the ACS are 29%, 22%, and 29%. Shares are similar between Numerator and the ACS for marital status, presence of children in household, and race/ethnicity.

[10] I use ZIP rather than ZCTA as shorthand for "ZIP code tabulation area" in this article.

[11] The panel includes 2,516,994 orders for an average of about 148,000 orders a month.

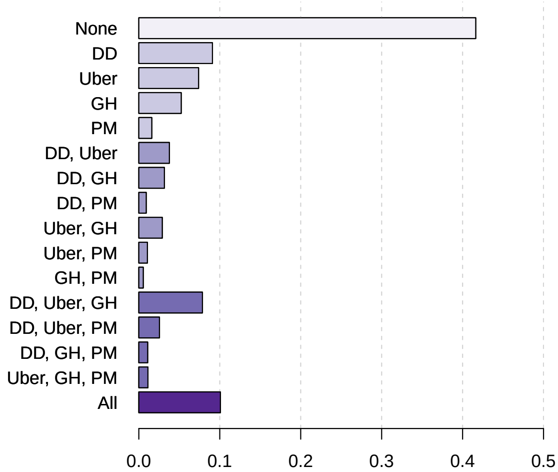
Platform adoption. I obtain data on restaurants' platform adoption decisions from the data provider YipitData. These data record all US restaurants listed on each major platform in each month from January 2020 to May 2021.[12] I obtain data on offline-only restaurants from Data Axle, which provides dataset of a comprehensive listing of US business locations for 2021. In the 14 large metros on which I focus, there were 69,245 restaurants belonging to chains with at least 100 US locations and 354,614 independent restaurants in 2021. Figure 2, which plots the share of these restaurants adopting each possible combination of the four leading platforms in April 2021 within the 14 large metro areas that I will analyze in the empirical analysis, shows that both non-adoption and multi-homing among platform adopters are common in the data.

Figure 1: Market shares, Q2 2021



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

Figure 2: Distribution of restaurants across platform sets, April 2021



Notes: this figure plots the distribution of restaurants across sets of platforms in the 14 metros of focus in April 2021. Deeper shades indicate sets that include more platforms. The total number of restaurants used to construct the figure is 426,058.

Platform fees. I collect data on platform fees in 2021 using a procedure that involves drawing from the set of restaurants in a ZIP and inquiring about terms of a delivery to an address in the ZIP for ZIPs in the 14 metros listed above. The address is obtained by reverse geocoding the coordinates of the ZIP's centre into a street address. Other variables that I record include time of delivery, delivery address, and estimated waiting time. I followed an analogous procedure to collect data on service fees and regulatory response fees; this procedure involves entering an address near the centre of a ZIP, randomly choosing a restaurant from the landing page displayed after entering this address, and inquiring about terms of a delivery from the restaurant.

The resulting fee data provides the basis of the consumer fee indices c_{fz} that I use in estimating the model. These indices, which vary across platforms f and ZIPs z, are sums of (i) hedonic indices of delivery fees that capture systematic differences in these fees across geography and platforms, (ii) service fees, and (iii) regulatory response fees introduced in response to commission caps and other

[12] Note that I estimate my consumer choice model on data from Q2 2021. Because I lack data on restaurant platform adoption in June 2021, I use the May 2021 platform adoption data for both May 2021 and June 2021.

local regulations. Online Appendix O.5 provides details on the computation of these indices.

I also collect data on commission caps including start and end dates covering January 2020 to June 2021 based on a review of news articles. The dataset includes 72 caps active in March 2021.

Demographics. The article also use demographic data from the American Community Survey (ACS, 2014–2019 five-year estimates).

3.3 Restaurant prices

I construct restaurant price indices that vary across platforms and commission rate. Given my focus on platform fees, I specify a detailed model of platforms with a stylized representation of restaurants that abstracts from menu item or quality variation. As such, I design the price indices to capture the pricing dimensions most relevant to platform fees: differences between online and offline orders and responses to commissions. The indices take the form

$$p_{fzt} = \bar{p} \times \exp\left\{\phi_f + \beta r_{fz} + \gamma r_z \times \text{online}_f\right\}. \tag{5}$$

Here, $\bar{p}$ governs the overall price level across ZIPs z, months t, and platforms f; ϕ_f captures differences in prices on platform f relative to direct orders ($f = 0$); β captures how the commission rate r_z affects prices for direct orders; and γ governs how the commission rate affects prices for platform orders ($\text{online}_f = \mathbb{1}\{f \neq 0\}$). The commission rate r_z is defined to be 30% in areas without commission caps and equal to the cap level in areas with commission caps. The formula (5) allows for systematic differences in restaurant prices across platforms f and for commissions to differentially affect direct and platform prices.

I estimate the parameters appearing in (5) via a regression with item, restaurant, and regional fixed effects on the item-level Numerator data. This regression exploits the staggered adoption of commission caps. Appendix A provides details. To summarize, I find that a one percentage point increase in the commission rate raises a restaurant's online prices by 0.63% and does not have a statistically significant effect on a restaurant's prices for direct orders. Under 30% commissions, restaurant prices on DoorDash are predicted to exceed direct-order prices by 14%; under 15% commissions, this gap narrows to 4%. I collect supplementary data on prices directly from restaurants' websites and platform listings that corroborates these findings; see Online Appendix O.6 for details. Last, I do not find substantial differences in prices across the leading platforms.

Price reductions from commission caps could reflect both pass-through of commission reductions and increased competition within platforms, given that caps may encourage platform adoption by restaurants. The article's model will capture both of these mechanisms.

Frictionless transfers between buyers and sellers may make the platform's division of fees between buyers and sellers irrelevant. This situation is called neutrality in the literature on two-sided pricing. I elaborate on sources of non-neutrality in Section 4.3.

3.4 Effects of commission caps

Although the focus of this article is in using a structural model of platform markets to assess the welfare implications of platform fees, I also estimate impacts of commission caps on consumer fees, order volumes, and restaurant uptake of platforms using difference-in-differences (DiD) methods.

The goal of this analysis is to validate hypothesized fee, ordering, and platform adoption responses to commission regulation that play a central role in determining the welfare properties of platform fees. Here, I describe the methods and results in brief, relegating a detailed discussion of the DiD analysis to Online Appendix O.7.

I use a variety of difference-in-differences methods in the analysis but focus on results from the Interaction Weighted (IW) estimator of Sun and Abraham (2021) here. This estimator, which yields estimates of the effects of commission caps on places that introduced caps, corrects problems that arise in the classical two-way fixed effects estimator when treatment is staggered and treatment cohorts vary in their treatment effects. The cross-sectional units in the analysis are ZIPs and the time periods are months. The primary identifying assumption underlying DiD estimation is that, conditional on controls, the outcome in places that enacted commission caps would have followed the same trend as in places that never enacted caps if caps had not been imposed. To make this assumption more tenable, I control for variables related to COVID-19 that may affect both government decisions to enact commission caps and outcomes of interest. The controls include the number of new COVID-19 cases per capita in ZIP z's county in month t, a measure of the stringency of state government responses to COVID-19 (Hallas et al. 2020), and the number of new COVID-19 cases per capita interacted with the Democrat vote share in the 2020 US presidential election. I include this interaction because places with different political proclivities may differentially respond to COVID-19 severity. The treatment variable specified in the baseline analyses is an indicator for a ZIP having a commission cap of 15% or lower.[13] I use data from January 2020 to June 2021, although I provide results for alternative sample periods in Online Appendix O.7. Online Appendix O.7 also contains results for different treatment variables and control groups.

Table 1 summarizes the results. The rows labelled "Consumer fees" provide estimated effects on log average consumer fees. These estimates, which range from 0.069 to 0.249, suggest that platforms do in fact raise their consumer fees when deprived of merchant commission revenue. The rows labelled "# orders" provide estimated effects on the log number of orders placed on delivery platforms ("Platform") and on the log number of direct orders ("Direct"). The results indicate that commission caps reduced the number of orders placed on platforms by about 6.1% and raised the number of orders placed directly from restaurants by 4.5%, suggesting that consumer fee hikes led consumers to substitute from platform ordering to direct ordering. Last, the "# restaurant listings" row provides estimates of effects of commission caps on the number of restaurant listings on platforms per capita. Here, a listing is a restaurant's membership of a platform; a restaurant on both DoorDash and Grubhub, for example, would have two listings. I divide the estimated effect by the mean number of listings per capita so that it may be interpreted as a relative percentage effect. I find that the number of restaurant listings per capita increased by 8.8%, suggesting that commission reductions encouraged more restaurants to join food delivery platforms.

Although the responses described by Table 1 are consistent with the theory of pricing in two-sided markets, their welfare implications are unclear; restaurants, e.g., may earn higher profits due to commission reductions but suffer from sales reductions and increased fixed costs of platform adoption. My goal in developing a model is to account for a complex set of responses to fee regulation in a tractable way and, in doing so, determine the welfare implications of such regulation.

[13]I focus on caps of 15% or lower because 15% is the most common level of caps. I exclude ZIPs with caps greater

Table 1: Difference-in-differences estimates of effects of commission caps

Outcome		Unit	Estimate	SE
Consumer fees	DD	log points	0.249	(0.041)
	Uber	log points	0.069	(0.040)
	GH	log points	0.127	(0.148)
# orders	Platform	log points	-0.061	(0.025)
	Direct	log points	0.045	(0.010)
# restaurant listings		%/100	0.088	(0.009)

Notes: all estimates in the table are from the Interaction Weighted (IW) estimator of Sun and Abraham (2021). The results for consumer fees appear among those for additional estimators in Online Appendix Table O.11. The results for order volumes appear among those for additional estimators in Online Appendix Figure O.7. The result for restaurant listings appears in the "Total listings" row of the "IW" column of Online Appendix Table O.21, which includes table notes that provide additional details on the estimation procedure.

4 Model

4.1 Summary of model

I develop a model of platform competition to empirically analyze the welfare properties of platform fees. Competition in each metro area m is a separate game played by platforms and restaurants. The model's treatment of platforms is detailed whereas its treatment of restaurants is stylized: restaurants systematically differ only in their location (ZIP z) and type (chain versus independent). I distinguish between chain and independent restaurants to allow the model to capture commission caps that exempt chains, which appear in the estimation sample. Each platform, though, has fees, restaurant networks, waiting times, and consumer demand shocks that vary across geography. When it comes to estimation, I match consumers' choices of platforms rather than restaurants. Further, I use detailed platform-specific fee data but restaurant price indices that apply to types of restaurants rather than individual establishments.

The model has four stages. In the first stage, platforms choose commission rates and consumer fees to maximize profits. Restaurants subsequently join platforms. Upon joining platforms, restaurants set prices. Last, consumers choose what to eat. I assume that consumers do not incur costs for adopting platforms, which explains the lack of a consumer platform adoption stage. This assumption is based on the ease with which consumers can join platforms: it is free for consumers to join platforms; platform apps are available for fast installation on mobile devices; users can use single-sign-on accounts (e.g., Google, Facebook, or Apple) to create accounts with minimal hassle; and users can use mobile payments (e.g., Apple Pay) to avoid manually inputting payment information. Based on the ease of creating an account, it would seem unnatural to specify that the consumer must commit to a list of platforms to join before placing orders. With that said, downloading an app and creating an account impose at least some adoption costs. On balance, though, a model without a stage in which consumers adopt platforms fits the setting better.

Two-sided market models often feature multiple equilibria due to network externalities: participation on each side depends on expectations about participation on the other, which can give rise to both low- and high-adoption equilibria. This concern does not arise when consumers can access all platforms without prior adoption, eliminating the risk that restaurants that foresee low consumer

than 15% from the analysis.

participation opt out (and vice versa). Online Appendix O.8 provides a detailed argument.

Although the model captures many central features of the food delivery industry, it abstracts away from others. I assume that consumers have full information of alternatives, and I treat the set of restaurants as fixed. Most significantly, the model is static despite the non-stationary nature of the food delivery industry during the sample period. Section 5 ("Estimation") notes how this may bias my estimates. Here, I highlight two key areas in which I omit dynamic considerations. First, platforms may have dynamic considerations in fee-setting: they may consider how contemporaneous sales and restaurant adoption affect future profitability due to state dependence among platform users and the dynamic nature of competition (e.g., depriving a rival of sales may prompt that rival's exit). My model will not speak to the associated pricing incentives. Second, restaurants may face sunk costs for adoption platforms, making their platform adoption decisions history-dependent and forward-looking. On accounting of ignoring these dynamics, I may understate the persistence of adoption and overstate the responsiveness of restaurants to contemporaneous fee changes.

The remainder of this section details the model stages in reverse order.

4.2 Consumer choice

Consumer i contemplates ordering a restaurant meal at T occasions each month. In each occasion t, the consumer chooses whether to order a meal from a restaurant j or to otherwise prepare a meal, an alternative denoted $j = 0$. A consumer who orders from a restaurant chooses both (i) a restaurant and (ii) whether to order from a platform $f \in \mathcal{F}$ or directly from the restaurant, denoted $f = 0$. Let $\mathcal{G}_j \subseteq \mathcal{F}$ denote the set of platforms on which restaurant $j \neq 0$ is listed; I call $\mathcal{G}_j$ restaurant j's platform subset. The consumer chooses a restaurant/platform pair (j, f) among pairs for which (i) restaurant j is within five miles of the consumer's ZIP and (ii) $f \in \mathcal{G}_j$ to maximize

$$v_{ijft} = \begin{cases} \psi_{if} - \alpha_i p_{jf} + \eta_i + \phi_{i\tau(j)} + \nu_{ijt}, & j \neq 0,\ f \neq 0 \quad \text{(Restaurant order via platform)} \\ -\alpha_i p_{j0} + \eta_i + \phi_{i\tau(j)} + \nu_{ijt}, & j \neq 0,\ f = 0 \quad \text{(Direct-from-restaurant order)} \\ \nu_{i0t}, & j = 0 \quad \text{(Home-prepared meal).} \end{cases}$$

Here, ψ_{if} is consumer i's taste for platform f, p_{jf} is restaurant j's price on platform f, η_i is the consumer's taste for restaurant dining, $\phi_{i\tau(j)}$ is consumer i's tastes for a restaurant of type $\tau(j)$, and ν_{ijt} is consumer i's idiosyncratic taste for restaurant j in ordering occasion t (assumed iid Type 1 Extreme Value). The types $\tau(j)$ that I consider are independent and chain restaurants. Additionally, α_i is consumer i's fee/price sensitivity, which I specify as

$$\alpha_i = \alpha + \alpha_d' d_i,$$

where d_i are observable consumer characteristics including indicators for age under 35 years, for being married, and for having a household income above \$40k.

Consumer i's tastes ψ_{if} for platform f are

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

for $f \neq 0$. Here, δ_{fm} is a parameter governing the mean taste of consumers in metro m for platform f; c_{fz} is platform f's fee to consumers in ZIP z; and W_{fz} is a hedonic waiting time index.

Additionally, the ζ_{if} are persistent idiosyncratic tastes for platforms, specified 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. Here, $\zeta_i^{\dagger}$ governs tastes for the online ordering channel in general whereas $\tilde{\zeta}_{if}$ governs tastes for particular platforms f. The σ scale parameters govern substitution patterns. As $\sigma_{\zeta 1}^2$ grows large, e.g., consumers become polarized in their tastes for food delivery platforms. This reduces the substitutability of platform ordering and direct ordering. Note that, if consumers differ in their initial enrolments in platforms and incur adoption costs for joining food delivery platforms, then the $\tilde{\zeta}_{if}$ preference shocks would capture the identifies of the platforms that the consumer has already joined and the costs of joining other platforms.

I specify consumer i's taste for restaurant meals η_i as

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

where μ_m^{η} governs average tastes for restaurant dining in metro m, d_i are consumer characteristics, and $\eta_i^{\dagger}$ is consumer i's idiosyncratic taste for restaurant dining. I specify that $\eta_i^{\dagger} \sim N(0, \sigma_{\eta}^2)$ independent of all else. Last, I specify $\phi_{i\tau} = \bar{\phi}_{\tau} + \tilde{\phi}_{i\tau}$, where $\tilde{\phi}_{i\tau} \sim N(0, \sigma_{\phi}^2)$.

4.3 Restaurant pricing

The two-sided markets literature recognizes that transfers between platform users can render the division of platform fees between sides of the market irrelevant for real outcomes, a situation known as neutrality. I reject that food delivery fees are neutral given the difference-in-differences evidence that commission caps had real effects on sales and platform adoption.

Non-neutrality requires frictions that limit seller pricing. Three sources of frictions stand out in the food delivery context: platform encouragement of low prices, mis-optimization, and brand image. First, food delivery platforms encourage restaurants to charge relatively low prices for platform-facilitated deliveries and to minimize gaps between in-store and delivery prices.[14] Second, restaurant managers may suboptimally price on platforms. This possibility has support in the literature: Huang (2024) studies pricing by platform sellers on an accomodations platform, finding that prices do not optimally respond to market conditions largely on account of limits in managerial ability to use sophisticated pricing strategies. Additionally, Hobijn et al. (2006) provide evidence of menu costs among restaurants, which would imply incomplete adjustment to changes in commissions. Third, consumers may harbour negative sentiment toward restaurants that charge higher prices online, thus harming these restaurants' brand image.[15] DellaVigna and Gentzkow (2019) suggest that brand image concerns could explain uniform pricing among US retailers.

Rather than analyze explanations for non-neutrality in detail, I specify a pricing model that gives rise to non-neutrality in a reduced-form manner. In the model, restaurants incompletely account

[14] DoorDash's merchant support page, for instance, noted that "While DoorDash doesn't require delivery prices to match in-store prices, we [DoorDash] recommend restaurant price their delivery menu as close to their in-store menu as possible." See here: `https://help.doordash.com/merchants/s/article/How-to-Maximize-Visibility-and-Order-Volume-on-DoorDash?language=en_US`. DoorDash also published an announcement on June 30, 2023 that similarly describes its policy on non-parity: `https://about.doordash.com/en-us/news/menu-pricing`. Uber Eats stated in a media comment that "We strongly encourage restaurant partners to provide the best price possible for consumers while ensuring they have a compelling business opportunity."

[15] This possibility is supported by work in behavioural marketing, including Fassnacht and Unterhuber (2016) and Choi and Mattila (2009).

for platform commissions in pricing, thus limiting the extent of pricing responses to commission rates. An alternative model is one in which restaurants place a negative weight on the difference between platform and direct-order prices in their pricing objective functions. Such a model better describes platform discouragement of gaps in prices between delivery and in-store orders. However, it would do a worse job of describing menu costs. As noted at the end of this section, I consider both models and find that one of incomplete accounting of commissions better fits the data.

I now formally present the restaurant pricing model. Each restaurant sells a standardized menu item. It selects this item's price for first-party orders and separately for each platform to which it belongs. In setting prices, restaurants seek to maximize profits with the proviso that they do not entirely internalize platforms' commission charges in pricing.

Formally, let p_{jf}^* denote the equilibrium price set by restaurant j on platform f. Equilibrium prices solve

$$p_j^* = \arg\max_{p_j} \sum_{f \in \mathcal{G}_j} \left[(1 - \vartheta r_f) p_{jf} - \kappa_{jf}\right] S_{jf}, \tag{6}$$

where κ_{jf} is restaurant j's marginal cost of fulfilling an order on platform f, p_{-j} are other restaurants' prices, and $S_{jf} = S_{jf}(\mathcal{J}_m, p_j, p_{-j}^*)$ (arguments omitted above for brevity) are restaurant j's sales on platform f.[16] Given the small share of direct orders accounted for by first-party delivery, the marginal cost parameter κ_{j0} primarily reflects the restaurant's costs of in-store sales. I impose that restaurant marginal costs are constant within a ZIP/restaurant type pair. The parameter ϑ governs the extent to which restaurants account for platforms' commission charges in their pricing decisions: $\vartheta = 1$ corresponds to full accounting of commissions whereas under $\vartheta = 0$, restaurants set prices that maximize the profits they would earn absent commissions. Although restaurant prices maximize the objective function (6) with incomplete accounting of commissions, restaurant profits include platform commissions fully; see equation (7).

An alternative way to model frictions in restaurant pricing is to add a penalty of the form $\vartheta \sum_f (p_{jf} - p_{j0})^2$ for gaps between platform and direct prices to the objective function in equation (6). I estimated a model of this form, but found that it implied a significant positive relationship between commissions and direct-order prices. Given that I did not find evidence of such a relationship in the item-level price data (see Appendix A), I decided against using this model. Online Appendix O.9 explicitly compares the impacts of commission reductions on prices under the preferred model described by (6) and the alternative model.

4.4 Restaurants' platform adoption choice

Restaurants simultaneously choose which platforms to join in a positioning game in the spirit of Seim (2006). A restaurant j's expected profits from joining platforms $\mathcal{G}$ are

$$\Pi_j(\mathcal{G}, P_m) = \underbrace{\mathbb{E}_{\mathcal{J}_{m,-j}} \left[\sum_{f \in \mathcal{G}} [(1 - r_{fz})) p_{jf}^*(\mathcal{G}, \mathcal{J}_{m,-j}) - \kappa_{jf}] S_{jf}(\mathcal{G}, \mathcal{J}_{m,-j}, p^*) \mid P_m \right]}_{:= \bar{\Pi}_j(\mathcal{G}, P_m)} - K_{\tau(j)m}(\mathcal{G}). \tag{7}$$

The expectation in (7) is taken over rivals' platform adoption decisions $\mathcal{J}_{m,-j}$, which are unknown to restaurant j when it chooses which platforms to join. I use $\bar{\Pi}_j(\mathcal{G}, P_m)$ to denote expected

[16] Online Appendix O.11 provides an expression for sales S_{jf}.

variable profits, i.e., the first term on the righthand side of (7). Rival restaurants' decisions are determined by the probabilities $P_m = \{P_k(\mathcal{G}) : k, \mathcal{G}\}$ with which rival restaurants k choose each platform subset. Additionally, $K_{\tau(j)m}(\mathcal{G})$ is the fixed cost of joining platforms $\mathcal{G}$ for a restaurant of type $\tau(j)$ in metro m. Restaurants correctly anticipate the prices p_{jf} that arise in the model's downstream stages. The fixed costs $K_{\tau(j)m}(\mathcal{G})$ do not represent payments to platforms. Instead, they include costs of contracting with platforms; in maintaining a menu on platforms; and in training staff to interface with platforms. By specifying a separate cost for each platform subset $\mathcal{G}$, I allow for diminishing costs of joining additional platforms. Additionally, I normalize $K_{\tau m}(\{0\})$ to zero for each type τ and for each metro m.

Restaurant j's adoption decision maximizes the sum of expected profits and a disturbance $\omega_j(\mathcal{G})$ representing misperceptions or non-pecuniary motives for adoption:

$$\mathcal{G}_j = \arg\max_{\mathcal{G}:0\in\mathcal{G}} \left[\Pi_j(\mathcal{G}, P_m) + \omega_j(\mathcal{G})\right]. \tag{8}$$

In the welfare analysis, I do not count the $\omega_j(\mathcal{G})$ toward restaurant profits.

A platform adoption equilibrium is a sequence of probabilities $P_m^* = \{P_j^*(\mathcal{G})\}_{j,\mathcal{G}}$ such that

$$P_j^*(\mathcal{G}) = \Pr\left(\mathcal{G} = \arg\max_{\mathcal{G}'} \Pi_j(\mathcal{G}', P_m^*) + \omega_j(\mathcal{G}')\right) \tag{9}$$

for all restaurants j in market m and for all platform subsets $\mathcal{G}$. The right-hand side of (9) is the probability that restaurant j's best response to rivals' choice probabilities P_m^* is to join platform subset $\mathcal{G}$. Thus, an equilibrium is a sequence of choice probabilities that arise when restaurants' best responses to each other's choice probabilities give rise to these choice probabilities. Condition (9) defines P_m^* as a fixed point, and Brouwer's fixed point theorem ensures the existence of an equilibrium. Although existence is ensured, an equilibrium may not be unique. In practice, I do not find multiple equilibria at the estimated parameters.[17]

I specify restaurants' platform adoption disturbances as

$$\omega_j(\mathcal{G}) = \sum_{f\in\mathcal{G}} \sigma_{rc}\omega_{jf}^{rc} + \sigma_\omega \tilde{\omega}_j(\mathcal{G}), \tag{10}$$

where $\omega_j(\mathcal{G})$ are Type 1 Extreme Value deviates drawn independently across j and $\mathcal{G}$. Additionally, the ω_{jf}^{rc} are standard normal deviates drawn independently across restaurants and platforms. The parameter σ_ω governs the variability of platform-subset-specific idiosyncratic disturbances, whereas σ_{rc} governs the extent to which platform subsets are differentially substitutable based on their constituent platforms.

My use of a Seim (2006) positioning game is justified by the facts that (i) equilibria of the game are easier to find than Nash equilibria in complete information games and (ii) complete information entry games suffer from problems related to multiplicity of Nash equilibria reflecting non-uniqueness

[17] In each metro area, I compute equilibria using the algorithm outlined in Online Appendix O.13 from the following initial choice probabilities: (i) the ZIP-specific empirical frequencies of restaurants' platform choices, (ii) probability one of restaurants not joining any platform, (iii) probability one of restaurants joining all platforms, and (iv) the ZIP-specific empirical frequencies of restaurants' platform adoption choices randomly shuffled between platform subsets within each ZIP. I find the same equilibrium in each market using each of these starting points.

in the identities of players that take particular actions. These problems do not arise in my model. One critique of Seim (2006)-style positioning models is that they give rise to *ex post* regret: after players realize their actions, some players would generally like to change their actions in response to other players' actions. This is not a considerable problem here because the large number of restaurants leaves little uncertainty in restaurant payoffs.[18]

4.5 Platform fee setting

In the first stage of the model, each platform f simultaneously chooses its ZIP-level consumer fees $\{c_{fz}\}_z$ and its restaurant commission rate r_{fm} to maximize its expected profits.

Platform f's expected profits are

$$\Lambda_{fm} = \sum_{z \in \mathcal{Z}} \mathbb{E}_{\mathcal{J}_m}[(\underbrace{c_{fz}}_{\substack{\text{Consumer}\\ \text{fee}}} + \underbrace{r_{fz}}_{\substack{\text{Commission}\\ \text{rate}}} \underbrace{\bar{p}^*_{fz}}_{\substack{\text{Restaurant}\\ \text{price}}} - \underbrace{mc_{fz}}_{\substack{\text{Marginal}\\ \text{cost}}}) \times \underbrace{s_{fz}(c_z, \mathcal{J}_m)}_{\text{Sales}}], \tag{11}$$

where s_{fz} are platform f's sales in ZIP z and $r_{fz} = \min\{r_{fm}, \bar{r}_z\}$. Here, $\bar{r}_z$ is the commission cap level in ZIP z and $\bar{r}_z = \infty$ in ZIPs z without caps. The quantity $\bar{p}^*_{fz}$ is the sales-weighted average price charged by a restaurant for a sale on f in ZIP z. Each platform f's profits in a ZIP z depend on its marginal costs mc_{fz}, which represent compensation to couriers. Marginal costs may vary across ZIPs due to regional differences in labour demand and supply conditions. I assume that platforms are price-takers in local labour markets and that their marginal costs do not depend on order volumes. The expectations in (11) are taken over the equilibrium distribution of platform adoption choices $\mathcal{J}_m$, which are governed by the P^*_m probabilities that in turn depend on platform fees. Given that Uber owns both Uber Eats and Postmates, I specify that Uber Eats and Postmates instead maximize their joint expected profits.

5 Estimation

5.1 Estimation of the consumer choice model

Estimation proceeds in steps. The estimator of consumer preferences maximizes the likelihood of consumers' observed sequences of platform choices conditional on covariates. In this model, each consumer i places $T_i \leq T$ orders from restaurants. Recall that T is the maximum number of orders per month in my model. In practice, I define each panelist/month pair as a separate consumer, and set $T = 17$ to the 99th percentile of the number of monthly orders placed by a panelist. The sample includes Numerator core panelists who place at least one order in Q2 2021, excluding consumers who place over T orders. In addition, I restrict the sample to panelists who linked their e-mail accounts to the application that the data provider used to collect e-mail receipts. This leaves a sample of 29,958 panelist/month pairs. The objective function is

$$Ł(\theta, Y_n, X_n) = \sum_{i=1}^{n} \log \left(\int \prod_{t=1}^{T_i} \ell(f_{it} \mid x_i, w_{m(i)}, \Xi_i; \theta) \times \prod_{t=T_i+1}^{T} \ell_0(x_i, w_{m(i)}, \Xi_i; \theta) dH(\Xi_i; \theta) \right), \tag{12}$$

[18] Formally, for any sequence of choice probabilities $\{P_{J,m}\}_{\mathcal{J}=1}^{\infty}$ indexed by the number of restaurants J, the difference between the share of restaurants joining each platform subset (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. Thus, for a large number of restaurants, the integrand in the definition of $\bar{\Pi}_j$ is approximately constant across $\mathcal{J}_{m,-j}$ draws, leaving little scope for ex post regret.

where n is the sample size, $Y_n = \{f_{it} : 1 \le t \le T_i, 1 \le i \le n\}$ contains each consumer's selected platform f_{it} across ordering occasions. Similarly, $X_n = \{x_i, w_{m(i)}\}_{i=1}^n$ contains consumer characteristics x_i (age, marital status, and income) and characteristics $w_{m(i)}$ of the consumer's metro area $m(i)$, including fees, waiting times, and prices. The random vector Ξ_i, which is distributed according to H, includes the platform tastes ζ_i, restaurant dining tastes η_i, and restaurant-type tastes $\tilde{\phi}_{i\tau}$. Additionally, $\ell(f \mid x, \Xi; \theta)$ is the conditional probability that a consumer orders using f (either a platform or $f = 0$, the direct option) whereas $\ell_0(x, \Xi; \theta)$ is the conditional probability that the consumer does not order. Online Appendix O.11 provides expressions for ℓ and ℓ_0.

As the integral in (12) does not have a closed form, I approximate it by simulation with 500 draws of Ξ_i for each consumer. Last, estimation on data from all markets is computationally difficult due to the large number of fixed effects. I therefore estimate the model on data from the largest three metros: those of New York, Los Angeles, and Chicago. I subsequently estimate δ_{fm} and μ_m^η for each remaining metro m by maximizing (12) on data from metro m with respect to these parameters, holding fixed the other parameters at their estimated values.

The estimator maximizes the likelihood of observed platform choices, *not* joint choices of platforms and restaurants. The main reason for using such an estimator is that there are many combinations of restaurants and platforms, even upon aggregating restaurants to the level of a ZIP and type (chain or independent). This means that there are many joint choice outcomes with small probabilities, which are difficult to simulate accurately. Although the estimator circumvents this problem, it does not fully take advantage of the data on restaurant choice.

Identification. The primary endogeneity problem is that unobserved demand shifters affect both demand and fees. My solution is to estimate the demand shifters δ_{fm} as fixed effects, a solution that relies on the assumption that the demand shifters affect demand at the metro level but not at more granular levels of geography. With platform/metro fixed effects specified, estimation of consumer fee sensitivity relies on within-metro fee variation. Fee variation owes to variation in commission cap policies and in local demographics. Note that platform/metro fixed effects similarly address the endogeneity of platforms' restaurant networks.

The data's panel structure permits identification of the scale parameters $\sigma_{\zeta 1}$, $\sigma_{\zeta 2}$, and σ_η governing heterogeneity in 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 $\zeta_i^\dagger \sim N(0, \sigma_{\zeta 1}^2)$ and $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta 2}^2)$. 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 polarized in their tastes for individual platforms and tend to repeatedly choose the same platform, whereas a low value of $\sigma_{\zeta 2}$ generates switching between platforms. Thus, repetition in choice is informative about $\sigma_{\zeta 2}$. Heterogeneity across consumers in the number of orders placed from restaurants is similarly informative about the value of σ_η.

Note that the model rules out state dependence as an explanation for persistence in ordering. Another potential problem is that identification of substitution patterns relies on the assumption that tastes ζ_{if} are stable across orders, which may not have held during 2021 when food delivery was quickly evolving due to the COVID-19 pandemic. If preferences evolved rapidly, then observed switching behaviour may reflect shifting preferences rather than substitutability, leading the model to overstate the degree of substitution across restaurants or platforms.

The model additionally rules out restaurant selection into platform adoption based on demand-side factors other than chain status or geography. This assumption would be violated by, e.g., unobservably higher quality restaurants being more likely to join platforms. In this case, consumers may be more likely to order from platforms because of the high quality of their restaurants, not due to platform quality as captured by ψ_{if}. Thus, selection by high quality restaurants into platform membership could bias upward my estimates of platform quality.

5.2 Estimation of restaurant pricing model

Recall that a restaurant j belonging to the platforms $\mathcal{G}_j$ sets its prices to maximize the objective function in (6), which features incomplete accounting of commissions. For expositional convenience, I introduce $r_0 = 0$ as the commission rate for direct-from-restaurant orders. When where $\mathcal{G}_j = \{f_1, \ldots, f_k\}$, the restaurant's pricing first-order condition is

$$\underbrace{\begin{bmatrix} (1-\vartheta r_{f_1}) S_{jf_1} \\ \vdots \\ (1-\vartheta r_{f_k}) S_{jf_k} \end{bmatrix}}_{=\tilde{S}_j(\vartheta)} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial p_{jf_1}} & \frac{\partial S_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_1}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial p_{jf_k}} & \frac{\partial S_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{=\Delta_p} \left(\underbrace{\begin{bmatrix} (1-\vartheta r_{f_1}) p_{jf_1} \\ \vdots \\ (1-\vartheta r_{f_k}) p_{jf_k} \end{bmatrix}}_{=\tilde{p}_j(\vartheta)} - \underbrace{\begin{bmatrix} \kappa_{jf_1} \\ \vdots \\ \kappa_{jf_k} \end{bmatrix}}_{=\kappa_j} \right) = 0, \tag{13}$$

Note the definitions of $\tilde{S}_j$, Δ_p, $\tilde{p}_j$, and κ_j below the equation above. Solving for κ_j yields

$$\kappa_j(\vartheta) = \tilde{p}_j(\vartheta) + \Delta_p^{-1} \tilde{S}_j(\vartheta). \tag{14}$$

Equation (14) provides the basis of the estimation of both the pricing friction parameter ϑ and marginal costs themselves. I estimate ϑ by GMM under the assumption that restaurant marginal costs κ_{jf} for platform orders are uncorrelated with exposure to commission caps. This assumption holds when areas with systematically low or high restaurant costs are not more likely to adopt commission caps and localities' adoption of commission caps does not impact the physical costs that restaurants incur in preparing meals. Formally, the population moment condition is

$$\mathbb{E}[\tilde{\kappa}_{jf}(\vartheta_0) Z_j] = 0, \qquad f \neq 0 \tag{15}$$

where $\tilde{\kappa}_{jf}(\vartheta) = \kappa_{jf} - \bar{\kappa}_f(\vartheta)$ is the de-meaned marginal cost of restaurant j for orders on platform f, Z_j is an indicator for a commission cap affecting restaurant j, and ϑ_0 is the true value of ϑ. The GMM estimator $\hat{\vartheta}$ sets the empirical analogue of (15) to zero; this empirical analogue averages over both metros m and platforms f.

With an estimate of ϑ in hand, I estimate marginal costs under the assumption that $\kappa_{jf} = \kappa_z^{\text{direct}}$ for $f = 0$ and $\kappa_{jf} = \kappa_z^{\text{platform}}$ for $f \neq 0$, 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 for platform orders may differ from those for direct orders due to differences in the packaging and logistical costs. The costs κ_{jf} that I recover from (14) generally differ across restaurants within a particular platform f due to sampling error. In light of these differences, I use the cross-restaurant average of the κ_{j0} costs recovered from (14) as my estimator of κ_z^{direct}. I similarly use the average κ_{jf} recovered from (14) across platform/restaurant pairs as my estimator of $\kappa_z^{\text{platform}}$.

5.3 Estimation of restaurant platform adoption model

In this section, I outline the estimation of the model of platform adoption by restaurants. Appendix B provides a full technical exposition of the estimator.

I estimate the parameters $K_{\tau m}(\mathcal{G})$ and $\Sigma = (\sigma_\omega, \sigma_{rc})$ governing platform adoption using a two-step generalized method of moments (GMM) estimator. Recall that restaurants adopt platforms to maximize perceived profits given beliefs about rival choices that are consistent with actual choice probabilities. The first step involves estimating conditional choice probabilities (CCPs) as a function of variables affecting restaurant profits. The second step involves setting restaurant beliefs to the estimated CCPs and then fitting model predictions to observed choices.[19]

In the first stage, I specify platform adoption CCPs as a multinomial logit whose parameters I estimate by maximum likelihood. The covariates include: population within five miles of the restaurant; the number of restaurants within five miles; municipality fixed effects; an indicator for an active commission cap; and the shares of the population within five miles that are under 35 years old, married, both under 35 years old and married, and with household income under \$40k. I also include interactions of the demographic shares and the number of nearby restaurants. The first-stage CCPs $\hat{P}_m$ permit computation of each restaurant's probability of joining platforms $\mathcal{G}$ for under parameter values θ^{adopt}. As noted, I estimate θ^{adopt} using a GMM estimator that matches model predictions to two sets of empirical patterns. First, the estimator ensures that the model's predicted share of restaurants joining each possible combination of platforms (e.g., no platforms, only DoorDash, Grubhub and Postmates, etc.) in each metro area equals the analogous observed share. I include moments ensuring that the model matches metro-level adoption probabilities in order to estimate the mean fixed cost parameters $K_{\tau m}(\mathcal{G})$.

The second set of moments are included to pin down $\Sigma = (\sigma_\omega, \sigma_{rc})$. These moments ensure that the model-implied covariances of the log population under 35 years of age within five miles of a restaurant—a shifter of platform adoption—with two measures of platform adoption are equal to the same covariances as computed on the estimation sample. The measures employed are (i) an indicator for whether restaurant j joins any platform and (ii) the number of platforms that the restaurant joins. To understand why these moments are useful in estimating Σ, note that increasing σ_ω and σ_{rc} make 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 smaller values of σ_ω and σ_{rc}. An alternative approach would be to replace the profit shifter D_j with estimated profits. I choose to use demographics D_j rather than estimated profits because the latter are more likely to suffer from measurement error due to sampling error or misspecification error, which would introduce bias.

I aim to characterize a long-run equilibrium using a static model. In practice, however, platform

[19] Singleton (2019) uses a similar estimator to estimate a Seim (2006)-style positioning model.

adoption decisions may be dynamic. If restaurants in the sample have not fully adjusted to a long-run equilibrium, then I risk overstating fixed costs (if non-adoption reflects inertia or perceived risk of platform exit) and understating responsiveness to profitability (if adoption depends more on uncertain long-run returns than on current returns).

5.4 Estimation of platform marginal costs

I estimate platform marginal costs using first-order conditions for the optimality of consumer fees. The first-order conditions for platform f's consumer fees $\{c_{fz}\}_z$ to maximize the expected profits Λ_{fm} as defined in (11) are, stacked in matrix notation,

$$\Delta_f(c_f - mc_f) + \tilde{S}_f = 0, \tag{16}$$

where Δ_f is an $N_z \times N_z$ matrix with the (z, z') entry $(\Delta_f)_{zz'} = d\mathbb{E}_{\mathcal{J}_m}[s_{fz'}]/dc_{fz}$ and S_f is a vector with component z equal to $S_{fz} = \mathbb{E}_{\mathcal{J}_m}[s_{fz}] + \sum_{z' \in \mathcal{Z}} r_{fz'} d\mathbb{E}_{\mathcal{J}_m}[\bar{p}^*_{fz'} s_{fz'}]/dc_{fz}$. Recall that N_z is the number of ZIPs in metro m. Furthermore, c_f and mc_f are N_z-vectors containing platform f's ZIP-specific consumer fees and marginal costs. When Δ_f is non-singular, platform f's marginal costs are given by

$$mc_f = c_f + \Delta_f^{-1} S_f. \tag{17}$$

I estimate mc_f by substituting Δ_f and S_f for estimates of these quantities obtained in (17).[20]

Platforms may maximize long-run profits rather than static profits. If platforms set fees below those maximizing static profits based on the future benefits of contemporaneous fee reductions, then I risk understating platforms' marginal costs. With that said, the marginal costs that I estimate in practice are in line with external information on platform costs (see Section 6.4).

Although the estimation approach relies on the assumption that platforms set their ZIP-specific consumer fees to maximize their profits, I do not assume that platforms choose their commission rates r_m optimally. That platforms set r_m optimally on a market-by-market basis is dubious given that platforms in the sample period advertised constant national commission rates of 30%. In the first part of the counterfactual analysis section, I remain agnostic on platform commission setting and solve for profit-maximizing consumer fees holding a fixed commission rates at various levels; this exercise simulates commission caps that restrict commission rates. In the counterfactual analysis, I solve for profit-maximizing commissions, which equal 34% on average (see Table 6).

6 Estimation results

6.1 Parameter estimates for consumer choice model

Table 2 reports estimates of consumer choice model parameters. Several estimates are noteworthy. First, the estimated scale parameters $\sigma_{\zeta 1}$ and $\sigma_{\zeta 2}$ are sizeable, suggesting that consumers

[20] The procedure requires adjustment for Uber Eats (f) and Postmates (g), who maximize their joint profits $\Lambda_f + \Lambda_g$. The first-order conditions for the consumer fees c_{fz}, c_{gz} are

$$\underbrace{\begin{bmatrix} \Delta_f & \Delta_{fg} \\ \Delta_{gf} & \Delta_g \end{bmatrix}}_{=\bar{\Delta}} (\underbrace{\begin{bmatrix} c_f \\ c_g \end{bmatrix}}_{=\bar{c}} - \underbrace{\begin{bmatrix} mc_f \\ mc_g \end{bmatrix}}_{=\bar{mc}}) + \underbrace{\begin{bmatrix} S_f \\ S_g \end{bmatrix}}_{=\bar{S}} = 0,$$

where Δ_{fg} is an $N_z \times N_z$ matrix with (z, z') entry $d\mathbb{E}_{\mathcal{J}_m}[s_{gz'}]/dc_{fz}$ and S'_f is an N_z-vector with z component $S_{fz} = \mathbb{E}_{\mathcal{J}_m}[s_{fz}] + \sum_{z'} (r_{fz'} d\mathbb{E}_{\mathcal{J}_m}[\bar{p}^*_{fz'} s_{fz'}]/dc_{fz} + r_{gz'} d\mathbb{E}_{\mathcal{J}_m}[\bar{p}^*_{gz'} s_{gz'}]/dc_{fz})$. Assuming non-singularity of $\bar{\Delta}$, the marginal costs of platforms f and g are $\bar{mc} = \bar{c} + \bar{\Delta}^{-1}\bar{S}$.

are divided by both overall taste for online ordering and by tastes for specific platforms. Additionally, the estimated λ demographic effects on platform tastes imply that young and unmarried consumers prefer delivery platforms relative to older and married consumers. The large estimate of σ_η suggests limited substitutability between restaurant ordering and at-home dining. In addition, the α parameter estimates indicate that married and higher income consumers are less price sensitive. Last, platform sales respond to restaurant variety on platforms: the estimated elasticities of platforms' orders with respect to their restaurant listing counts range from 0.78 to 1.32 across platforms in the New York metro.[21]

To evaluate the implications of estimates for ordering behaviour, I compute 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. Across platforms in the New York metro, between 16–24% of these no longer place any restaurant order and an additional 47–57% switch to ordering directly from a restaurant whereas the remainder switch to a different platform. Online Appendix Table O.28 details these results.[22]

Table 2: Consumer choice model parameter estimates

Parameter	Estimate	SE
α	0.24	0.03
α_{young}	-0.01	0.01
α_{married}	-0.02	0.01
$\alpha_{\text{high inc}}$	-0.07	0.01
$\sigma_{\zeta 1}$	1.27	0.09
$\sigma_{\zeta 2}$	0.82	0.09
ρ	0.53	0.47
ϕ_{chain}	0.89	0.14
σ_ϕ	0.87	0.48
σ_η	2.02	0.02

Parameter	Estimate	SE
$\lambda^{DD}_{\text{young}}$	0.60	0.18
$\lambda^{DD}_{\text{married}}$	-0.37	0.20
$\lambda^{DD}_{\text{high income}}$	-0.21	0.24
$\lambda^{Uber}_{\text{young}}$	0.66	0.18
$\lambda^{Uber}_{\text{married}}$	-0.47	0.20
$\lambda^{Uber}_{\text{high income}}$	-0.24	0.20
$\lambda^{GH}_{\text{young}}$	0.34	0.20
$\lambda^{GH}_{\text{married}}$	-0.24	0.21
$\lambda^{GH}_{\text{high income}}$	-0.21	0.20
$\lambda^{PM}_{\text{young}}$	0.51	0.26
$\lambda^{PM}_{\text{married}}$	-0.85	0.24
$\lambda^{PM}_{\text{high income}}$	-0.85	0.16
$\lambda^{\eta}_{\text{young}}$	-0.44	0.25
$\lambda^{\eta}_{\text{married}}$	0.13	0.28
$\lambda^{\eta}_{\text{high income}}$	-1.61	0.14

Notes: this table reports estimates of the parameters of the consumer choice model. The panel on the right reports estimates of parameters related to consumer demographics whereas the panel on the left reports estimates of the other parameters. Estimates of the platform/metro fixed effects δ_{fm} and the metro fixed effects μ^η_m are omitted.

6.2 Estimates of restaurant marginal costs

The first step in estimating restaurant marginal costs involves estimating the ϑ parameter governing the extent to which restaurants account for commissions in price setting. I obtain the estimate $\hat{\vartheta} = 0.638$ (95% confidence inteval = $[0.631, 0.644]$), which implies that restaurants account for about 64% of platform commissions in pricing.[23]

[21] See Online Appendix Table O.27 for details on the computation of these elasticities.

[22] Online Appendix Table O.26 characterizes dispersion in restaurants' total sales gains from joining platforms. The gains vary significantly both within and across metro areas.

[23] I use the bootstrap procedure described in Appendix O.10 to compute this interval, which reflects sampling uncertainty in the sample of restaurants and in the demand estimates but not in the restaurant price indices.

Table 3 describes estimates of restaurant marginal costs κ_{jf} and of the markups implied by the κ_{jf} estimates. Marginal costs are slightly lower for platform orders, which could reflect savings on in-store waiting staff and cleaning. Restaurant markups for direct orders are about 30% their costs. Further, markups on platform orders are larger under commission caps. Markups do not vary much between direct orders placed from restaurants subject and not subject to commission caps. Additionally, restaurants belonging to the same platform have heterogeneous gross, pre-commission markups on account of heterogeneity in costs and demand conditions; Online Appendix Figure O.19 shows that, within each of the leading three platforms, gross markups range from about \$9.50 to \$10.35 between the 5th and 95th percentile. Heterogeneity in gross markups makes Spence and displacement distortions of consumer fees relevant.

Table 3: Restaurant marginal costs and markups (means and standard deviations, \$)

(a) Marginal costs

Channel	No cap	Cap
Direct	16.09±0.34	16.26±0.23
Platform	15.33±0.28	15.51±0.38

(b) Markups

Channel	No cap	Cap
Direct	5.66±0.34	5.56±0.23
Platform	5.00±0.27	5.18±0.23

Notes: the table describes marginal costs κ_{jf} and markups $(1 - r_f)p_{jf} - \kappa_{jf}$ across ZIPs separately for direct orders ($r_0 = 0$) and platform-intermediated orders, and also separately for ZIPs with commission caps and those without caps. The averages are taken over restaurants.

6.3 Estimates of the restaurant platform adoption model

Table 4 reports estimates of the parameters governing platform adoption by restaurants. In interpreting the estimates, note that the average expected revenues of a restaurant that joins all platforms are about \$31,000. The fixed costs are at a monthly level. Panel 4b contains the estimated average costs of platform adoption by platform subset across markets and restaurant types whereas Panel 4c displays average costs by the number of platforms. In both cases, the averages are weighted by restaurant counts. These panels shows that joining a single platform entails a substantial fixed cost, ranging from \$574 tor DoorDash to \$954 for Grubhub, on average. However, joining additional platforms does not systematically raise the platform's fixed adoption costs. Although I estimate that joining two or three platforms is more costly on average than joining one, the differences in the estimates are imprecise. The fact that subsets with three and four platforms are estimated as slightly less costly than those with two platforms likely reflects sampling error. The estimated scale parameter σ_{rc} of platform-specific normal choice disturbances is \$327 whereas the estimated scale parameter σ_{ω} of the platform-subset-specific disturbance is \$287.

6.4 Estimates of platform marginal costs

Table 5 describes the estimated cross-ZIP distribution of platform marginal costs—which reflect courier compensation—and platform markups. 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" (DoorDash calls its couriers "Dashers").[24] This level of pay lines up well with the estimated interquartile range of DoorDash's marginal costs of \$8.56 to \$10.52. Additionally, McKinsey & Company found platform marginal costs of \$8.20

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

Table 4: Estimates of restaurant platform adoption parameters

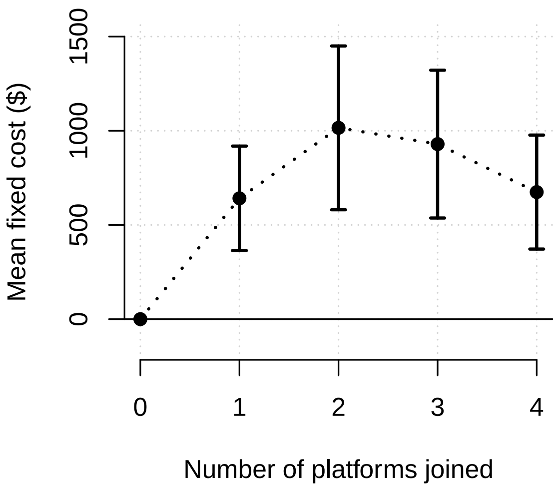
(a) Parameters governing choice disturbance

Parameter	Estimate	SE
σ_ω	287	(70)
σ_{rc}	327	(26)

(b) Mean fixed costs by restaurant type ($)

Platform subset	Estimate	SE
DD	574	(124)
Uber	618	(156)
GH	954	(214)
PM	685	(142)
DD, Uber	967	(195)
DD, GH	968	(222)
DD, PM	820	(171)
Uber, GH	979	(210)
Uber, PM	1202	(272)
GH, PM	1146	(270)
DD, Uber, GH	991	(233)
DD, Uber, PM	1403	(293)
DD, GH, PM	1275	(264)
Uber, GH, PM	1223	(283)
All	675	(154)

(c) Average cost by platform subset size



Notes: Panel 4a reports estimates of the parameters governing the disturbance affecting restaurants' platform adoption decisions. Panel 4b reports estimates of the mean $K_{\tau m}(\mathcal{G})$ fixed costs across markets m for each platform subset $\mathcal{G}$ and restaurant type τ. Panel 4c reports the mean $K_{\tau m}(G)$ across markets m and platform subsets $\mathcal{G}$ with a given number of constituent platforms for each restaurant type. I compute the standard errors appearing in parentheses using the bootstrap procedure described in Appendix O.10.

per order in a 2021 analysis of US food delivery (Ahuja et al. 2021); this figure is close to my mean marginal cost estimates for the leading three platforms.

Table 5: Estimates of platforms' marginal costs ($)

	Marginal costs				Markup			
		Quantiles				Quantiles		
	Mean	0.25	0.50	0.75	Mean	0.25	0.50	0.75
DD	9.38	8.56	9.80	10.52	3.70	3.37	3.71	4.04
Uber	9.31	8.13	9.11	10.39	3.57	3.19	3.56	3.93
GH	9.56	8.00	10.03	10.74	3.34	2.94	3.32	3.71
PM	14.57	12.12	13.83	15.49	3.10	3.14	3.56	4.02

Notes: this table describes the estimated distribution of platforms' marginal costs across ZIPs.

7 Counterfactual analysis

This section proceeds in three parts. First, I compare privately optimal fees—i.e., those chosen by profit-maximizing platforms in equilibrium—to the socially optimal fees that maximize total welfare. This analysis quantifies overall distortions in platform fees and identifies their underlying sources. I next assess the potential for commission regulation of the sort enacted by local governments to correct these distortions. Last, I examine whether platform competition mitigates inefficiencies in fee setting. A caveat of the analysis is that it isolates the pricing margin: I abstract from other possible platform responses to regulation or competition, such as exit, changes in quality, or advertising adjustments.

To implement the counterfactuals, I divide metro areas into counties and compute equilibrium outcomes at the county level. This granular approach increases cross-market variation and facilitates the analysis of how regional characteristics shape fee distortions: although the data include only 14 metro areas, they contain 104 counties. Throughout, I index counties by m.

7.1 Comparison of privately and socially optimal platform fees

I begin the counterfactual analysis by solving for the privately and socially optimal consumer fees and merchant commission rates, allowing both sorts of fees to vary flexibly across platforms and counties. Table 6 reports the cross-county mean and, in parentheses, standard deviations of privately and socially optimal fees.

Table 6: Socially and privately optimal platform fees

Platform	Consumer fee ($)						Restaurant commission (%)					
	Privately optimal		Socially optimal		Difference		Privately optimal		Socially optimal		Difference	
DD	4.36	(1.52)	3.29	(1.81)	1.07	(1.30)	31.01	(4.11)	15.42	(8.54)	15.58	(8.24)
Uber	2.63	(1.37)	2.79	(1.72)	-0.16	(1.69)	37.02	(6.12)	19.93	(6.83)	17.10	(5.61)
GH	2.11	(1.91)	3.14	(1.89)	-1.03	(2.09)	39.28	(6.59)	20.11	(7.22)	19.17	(7.19)
PM	5.51	(1.51)	6.29	(2.29)	-0.78	(2.24)	36.96	(5.33)	18.01	(9.80)	18.96	(8.32)
Total	3.59	(1.55)	3.30	(1.83)	0.29	(1.62)	34.32	(5.24)	17.56	(7.98)	16.77	(7.45)

Notes: this table displays the mean platform consumer fees and restaurant commissions across counties. Each county is weighted by its sales on the indicated platform under the privately optimal fees. The "Total" row averages across platforms, using platforms' total sales under the privately optimal fees as weights. Standard deviations of each reported quantity (weighted by sales) appear in parentheses.

The results show a stark asymmetry: privately optimal consumer fees are close to socially optimal whereas restaurant commissions are about twice their efficient levels.[25] The "Consumer fee ($)" panel of Table 6 shows that the sales-weighted mean difference between privately and socially optimal consumer fees is only $0.29, with all platforms except DoorDash setting consumer fees *below* their welfare-maximizing levels. This contrasts sharply with the result for restaurant commissions: the mean privately optimal commission rate of 34.3% is almost twice the mean socially optimal rate of 17.6%. These patterns are consistent across platforms.[26]

This divergence reflects interdependent dynamics on both sides of the market. First, consumer fees are close to optimal because market power and business stealing distortions off each other. I separately quantify consumer fee distortions using a generalized version of the distortion decomposition formula (2) derived in Section 2. To apply this formula in a setting with platform competition, I evaluate distortions for each platform f individually, holding fixed the fees of its rivals.

Two additional distortions arise in the presence of platform competition. First, an increase in

[25] Total fee levels under profit-maximization are also inefficiently high: the average platform markup (the ratio of platform variable profits to sales) is $3.77 under privately optimal fees, but -$1.50 under socially optimal fees. Negative markups reflect that network externalities make platform subsidization welfare enhancing. Online Appendix Table O.29 provides additional markup results.

[26] In Online Appendix O.14, I investigate sources of cross-county variation in gaps between privately and socially optimal fees by regressing these gaps on potential drivers of this variation as suggested by the illustrative model of Section 2. These drivers reflect platform market power, offline business stealing, and cross-side externalities.

platform f's consumer fee shifts ordering to rival platforms, thus boosting restaurant sales on these rival platforms. A social planner internalizes this benefit to restaurants whereas a profit-maximizing platform does not. This generates an *online business stealing* distortion akin to the offline business stealing distortion. Second, a social planner accounts for the effects of platform f's consumer fees on the profits of all rival platforms $g \neq f$, whereas a platform f that maximizes its own profits does not. This discrepancy gives rise to a *rival profits*. Online Appendix O.1 derives these additional distortions and generalizes the other distortions from the illustrative model.

Despite the additional complexity of the structural model, the generalized distortion decomposition formula closely approximates the total distortion in consumer fees computed by numerically solving for privately and socially optimal fees. The total distortion predicted by summing together the six distortions appearing in the generalized decomposition formula—the market power, offline business stealing, online business stealing, Spence, displacement, and rival profits distortions—correlate at 0.97 with the numerically solved total distortions. Below, I refer to the difference between the total distortion found from solving the model and that predicted by the distortion decomposition formula as "Other," a residual term capturing the extent to which the decomposition is an approximation rather than an exact identity.

Table 7 reports the average contribution of each distortion to the total distortion in consumer fees by platform. For DoorDash, market power raises consumer fees by \$4.35, but this is largely offset by the sum of a \$1.93 offline business stealing distortion and a \$0.95 online business stealing distortion. Displacement more than offsets the Spence distortion, producing only a small net effect from network externalities. The additional rival profits distortion and the unexplained "Other" part of the total distortion are small in magnitude compared to the distortions relating to business stealing and network externalities. As a result, DoorDash's consumer fees exceed the social optimum by only a modest amount. On smaller platforms, market power is weaker while business stealing is stronger, leading to negative net distortions and implying that their consumer fees are inefficiently low on average.[27]

Table 7: Consumer fee distortions (\$)

Distortion	Platform			
	DD	Uber	GH	PM
Market power	4.35	3.81	3.56	3.04
Offline business stealing	-1.93	-1.59	-1.58	-1.39
Online business stealing	-0.95	-1.50	-1.57	-1.76
Spence	2.89	2.72	2.75	2.19
Displacement	-4.19	-4.81	-5.53	-4.32
Rival profits	0.33	0.64	0.64	0.80
Other	0.58	0.58	0.71	0.65
Total	1.07	-0.16	-1.03	-0.78

Notes: "DD" indicates DoorDash; "Uber" indicates Uber Eats; "GH" indicates Grubhub; and "PM" indicates Postmates.

Table 8: Variety and fixed cost effects of commission reductions

Effect	Amount (\$/order)	
	Mean	St. dev.
Variety	0.20	(0.041)
Fixed cost	0.11	(0.040)
Net	0.09	(0.040)

Although the illustrative model does not yield a neat decomposition of commission distortions,

[27] Online Appendix Table O.1 characterizes the power of each distortion in explaining variation in total distortions across counties and platforms. Conditional on all other distortions, the Spence and displacement distortions best explain this variation.

the welfare effects of imposing socially optimal fees clarify why commissions are too high: profit-maximizing platforms fail to internalize consumer gains from expanded restaurant uptake. Table 9a reports that shifting from privately to socially optimal fees yields the total welfare gain of \$3.14 that is driven primarily by consumer gains of \$10.55/order. These gains arise because lower commissions induce a 12.5% reduction in restaurant prices on platforms and substantially restaurant adoption of platforms: as shown in Table 9b, the share of restaurants active on at least one platform rises by 50.7%, and the total number of restaurant listings on platforms increases by 82.0%.

Reductions in commissions raise consumer welfare by encouraging restaurant platform adoption and reducing restaurant prices. However, these responses attenuate restaurants' direct gains from lower commissions. Table 10 decomposes the change in restaurant profits from moving from privately to socially optimal fees, expressed per platform order under the privately optimal fees. The direct effect of the fee change on restaurant profits, holding platform adoption and prices fixed, is \$4.26 gain per order. Accounting for restaurant adoption responses, which entail fixed adoption costs and prompt offline business stealing, reduces the benefit to \$3.59. Similarly, accounting for price responses while holding adoption fixed reduces the benefit to \$2.47. When both adoption and price responses are taken into account, the total profit gain to restaurants falls to just \$0.74 per order, only 17% of the direct benefit. This highlights that most of the gains from lower commissions are competed away, leaving restaurants only modestly better off.[28]

An interaction of the business stealing, Spence, and displacement distortions explain why privately optimal restaurant commissions are inefficiently high. The Spence distortion pushes restaurant commissions above their socially optimal levels when inframarginal consumers benefit more from increased restaurant uptake of platforms than do marginal ones. However, this distortion is offset by a displacement distortion if marginal consumers under privately optimal fees place greater value on seller variety than do marginal consumers under socially optimal fees. This argument applies when privately optimal consumer fees are inefficiently high due to market power, shifting variety-loving consumers who are inframarginal under socially optimal fees into marginal status. Under the estimated model, however, the displacement distortion plays little role in determining restaurant commissions because privately and socially optimal consumer fees do not systematically diverge. As shown by Table 7, this is due to the offline business stealing distortion counteracts market power — the primary reason to expect inefficiently high consumer fees and hence a displacement distortion. As a result, the Spence distortion remains unopposed, leading to restaurant commissions that significantly exceed socially optimal levels.

The fact that the privately optimal commissions far exceed socially optimal levels in turn explains why externalities relating to network externalities do not make consumer fees inefficiently high. Because privately optimal commissions are high, platforms earn substantial restaurant-side revenue from attracting consumers to platforms. This encourages platforms to set low consumer fees, a force that is reflected in the large mean displacement distortions of Table 7.

[28]The findings presented in Online Appendix Figure O.20 corroborate this argument. This figure provides the welfare effects of lowering DoorDash's restaurant commission rate from its privately optimal rate by one percentage point in each county. A marginal commission reduction reduces restaurant profits due to competitive responses (increased platform uptake and price reductions), and raises consumer welfare, in large part due to benefits from increased restaurant variety on platforms. The net effect is positive.

Table 9: Effects of transition from privately to socially optimal fees

(a) Welfare

Quantity	Change ($/order)
Consumer welfare	10.55
Restaurant profits	0.74
Platform profits	-8.14
Total welfare	3.14

(b) Restaurant and consumer responses

Quantity	Change (%)
Restaurant prices	-12.5
Share of restaurants online	50.7
Number of restaurant listings	82.0
First-party orders	-18.5
Platform orders	178.8
Total orders	12.9

Table 10: Decomposition of restaurant profit effects

Responses	Profit change ($/order)
Direct effect of fee changes	4.26
With adoption responses	3.59
With price responses	2.47
Total effect (all responses)	0.74

7.2 Commission regulation

Having established that socially optimal platform fees feature consumer fees similar to those charged by profit-maximizing platforms but substantially lower restaurant commissions, I now assess the potential for commission regulation to move the market closer to this optimum. Specifically, I compute equilibrium outcomes under scenarios in which all platforms' commissions are constrained to various levels $\bar{r}$ while consumer fees remain unconstrained. Throughout, I treat the equilibria under a regulated 30% commission rate as the baseline given that platforms charged this rate in practice in the absence of commission caps.

Figure 4 plots the welfare effects of regulating commission at levels between 15% and 40%, aggregating across markets. The components of welfare included are restaurant profits, platform profits, consumer welfare, and total welfare defined as the sum of these three components.

Although commission caps of 15%—the most common level in practice—lower total welfare, restricting commissions to levels between 20% and 30% is welfare enhancing.[29] Commission reductions in this range raise restaurant profits while having mixed effects on consumer welfare, reflecting the offsetting effects of commission reductions in expanding restaurant variety and raising consumer fees. For small commission reductions, platform ordering and consumer welfare increase because the effects of expanded variety dominate those of higher fees, although this relationship flips for larger commission reductions. Despite the negative impacts of commission reductions on platform profits, the mixed and relatively small effects on consumer welfare and unambiguous positive effects on restaurant profits together imply that moderate commission reductions to levels above 20% boost total welfare. The maximum welfare increase achievable by one-sided commission regulation, though is small at $0.10 (at a 26% commissions).

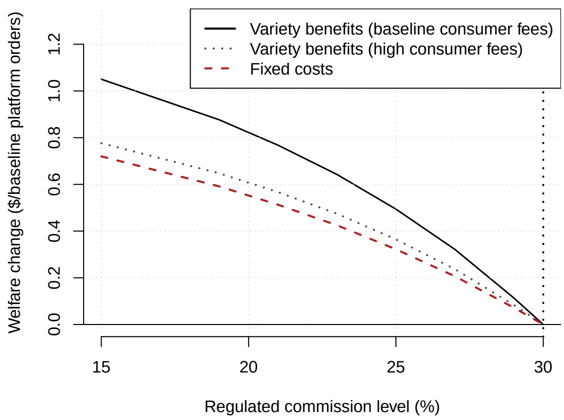
Whereas the socially optimal fee structure involves restaurant commissions roughly half as large

[29] Commission caps of 15% may be attractive to policymakers despite reducing total welfare on the grounds that they increase local welfare defined as the sum of consumer surplus and restaurant profits.

as those chosen by profit-maximizing platforms, halving commissions from 30% to 15% reduces total welfare. This contrast arises because a 15% cap induces higher consumer fees, which reduces platform usage and contracts the pool of consumers who benefit from expanded restaurant variety. To illustrate this mechanism, I compare the consumer value of increased restaurant uptake under the consumer fees and prices prevailing at 30% versus 15% commissions. Specifically, I compute consumer welfare as restaurant adoption rises with lower commissions, holding consumer fees and prices fixed at values under 30% commissions. I also compute the total fixed costs incurred by restaurants when adopting platforms under each commission level, allowing for a direct comparison of the benefits and costs of expanded restaurant uptake of platforms.

Figure 3 presents the results, aggregated across counties and scaled by platform orders under 30% commissions. The solid curve shows the variety benefits under baseline fees and prices, while the dotted grey curve shows variety benefits under the higher consumer fees arising under 15% commissions. The dashed red line plots fixed adoption cost increases. Under the baseline fees, variety benefits far exceed adoption costs. But the fact that the dotted grey curve lies only marginally above the red curve indicates that, under higher consumer fees, the costs of increased restaurant adoption of platforms almost entirely offset the variety benefits, limiting the social value of restaurant platform adoption. Besides reducing consumer welfare by limiting variety benefits, the consumer increases from commission caps directly reduce consumer welfare, contributing to a negative overall impact of 15% commission caps on total welfare.

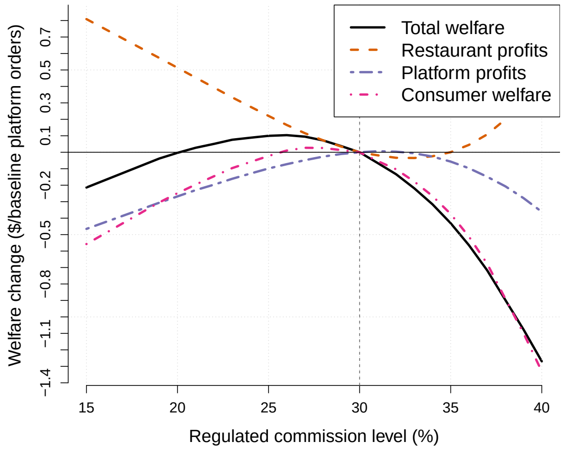
Figure 3: Effects of commission reduction on variety benefits and fixed adoption costs



This figure displays welfare effects of reducing platform commission rates from a 30% baseline to levels between 15% and 30%, aggregated across counties and scaled by the number of baseline platform orders. The "Variety benefits" curves show consumer welfare gains from increased restaurant adoption of platforms due to lower commissions, holding consumer fees and restaurant prices fixed at either their 30% commission levels (baseline consumer fees) or their levels under 15% commission equilibria (high consumer fees). The Fixed costs curve shows the additional fixed costs incurred by restaurants associated with greater platform adoption as commissions fall.

In Section 7.1, I showed that competitive responses largely offset restaurant gains from imposing the socially optimal fees. Restaurants similarly compete away most of their benefits from commission caps. Figure 6a shows that, for a 15% cap, the direct benefit of reduced commission payments to restaurants is $3.73 per order. This falls to $2.11, though, after accounting for higher consumer fees (and thus fewer orders), $1.60 with increased restaurant adoption (which entails fixed adoption costs and offline business stealing), and just $0.80 after restaurants lower prices. Competitive responses also mitigate consumer losses from commission caps. As shown in Figure 6b, fee increases reduce consumer welfare by \$2.68 per order, but this is offset to \$2.17 by greater restaurant adoption and to \$0.56 after additionally accounting for restaurant price reductions.

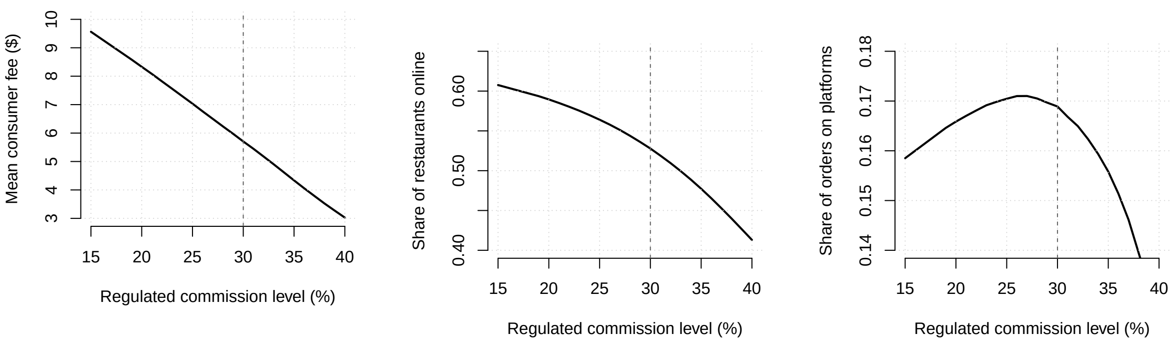
Figure 4: Welfare by regulated commission level



Notes: this figure plots welfare effects of constraining commissions for all platforms at levels between 15% and 40% as a share of the number of platform orders in the 30% commission equilibrium.

Figure 5: Fees, adoption, and ordering by regulated commission level

(a) Consumer fees | (b) Share of restaurants adopting ≥ 1 platform | (c) Share of orders placed on a platform

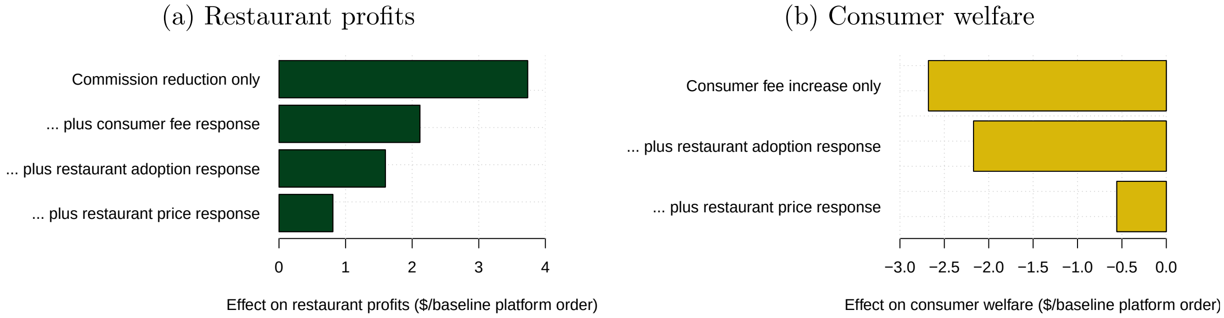


Notes: this plot shows averages of the following variables across counties for various regulated commission levels: consumer fee (\$, mean across platforms weighted by sales), share of restaurants that have adopted at least one platform, and the share of orders placed on a food delivery platform.

Heterogeneity in optimal commission regulation. Table 11, which reports the 10th, 25th, 50th, 75th, and 90th quantiles of regulated commission levels maximizing total welfare and platform profits, reveals cross-county heterogeneity in these optimal rates. The interquartile range of the socially optimal commission caps is 24–28% whereas the corresponding range for platform-optimal commissions is 31–35%. To investigate the determinants of the socially optimal regulated commission rate, I regress this rate r_m^{so} on three county-level characteristics. The chosen characteristics reflect the drivers of socially optimal commissions as suggested by the illustrative model of Section 2.

The first characteristic is a measure of *offline business stealing*, defined as the ratio of the increase in direct sales to the loss in platform sales when platforms become unavailable. The average value

Figure 6: Decomposing welfare effects of 15% commission caps



Notes: Panel (a) reports effects of reducing restaurant commissions from 30% to 15% on restaurant profits. The"Commission reduction only" bar provides the direct effect of lower commissions, holding all other factors fixed at their levels under 30% commissions. Each subsequent bar shows the effect after accounting for an additional equilibrium response (in consumer fees, in restaurant platform adoption, and in prices). Panel (b) shows the corresponding effects on consumer welfare. The "Consumer fee increase only" bar provides the effect of higher consumer fees, holding the other factors fixed at their levels under 30% commissions. The subsequent bars show the effect after accounting for additional equilibrium responses. All effects are measured in dollars per platform order in the 30% commission baseline.

indicates that 60% of platform orders would become direct orders if platforms were abolished. When offline business stealing is high, platform and direct ordering are especially substitutable. This means that the consumer fee increases associated with commission reductions are particularly effective in boosting direct ordering, benefitting restaurants. Thus, I expect a negative relationship between offline business stealing and the socially optimal commission rate.

The additional drivers of r_m^{so} that I consider are changes in platform adoption costs and variety benefits when the regulated commission falls by one percentage point from a 30% baseline. Commission reductions lead restaurants to join more platforms. I compute the per-capita additional fixed platform adoption costs incurred by restaurants due to the one percentage point commission reduction in each county, calling it the *fixed cost change*. Variation in this variable owes to both variation in the efficacy of commission reductions in attracting new restaurants to join platforms and cross-county variation in the magnitude of fixed costs. I also compute per-capita increase in consumer welfare attributable to increases in restaurant platform adoption prompted by the commission reduction, holding fixed consumer fees and prices at their levels under 30% commissions. This yields the *variety change* variable. I expect that counties in which commission reductions especially raise adoption costs to have higher socially optimal commissions, which deter costly platform adoption, and counties in which commission reductions yield especially large variety benefits to consumers to have lower socially optimal commissions.

Table 12 provides results. The estimated coefficient of each of the regressors enumerated above has the hypothesized sign and is statistically significant at 95% level. Furthermore, these three variables alone explain 54% of the cross-county variation in r_m^{so}. In addition to the estimated coefficients, the table contains the following for each regressor k: the R^2 from a regression of r_m^{so} on only regressor k (R_k^2) and (ii) the R^2 from a regression of r_m^{so} on all regressors except k (R_{-k}^2). High values of the former and low values of the latter indicate high explanatory power. All three regressors provide explanatory power, with the bivariate R_k^2 measures ranging from 0.23 for the fixed cost change to 0.40 for the variety change. By both measures, the variety change variable yields the greatest power in explaining cross-county variation in optimal commissions.

These results raise the question of which underlying market features shape the extent of offline business stealing and variety benefits from commission reductions, the two main predictors of optimal commission levels. To explore this, I regress the variety and offline business stealing measures on (i) the log of the average number of restaurants within five miles of a consumer and (ii) the log of population within the same radius. I hypothesize that areas with a higher density of restaurants tend to experience larger variety gains and higher offline business stealing. Variety effects are likely stronger in areas with more local restaurants and hence more potential for expansions in variety. Additionally, I expect offline business stealing to be greater in areas with with high restaurant densities, where baseline restaurant ordering is likely high and thus the scope for platforms to expand restaurant sales is limited.

The results support these hypotheses: restaurant density positively relates to both variety gains and offline business stealing, explaining 51% and 30% of the variation in these variables, respectively. Given the positive relationship between restaurant density and factors associated with lower optimal commissions, denser areas have lower socially optimal commissions. A 10% increase in log restaurant density predicts a 2.5 percentage point drop in the optimal commission rate r_m^{so}. Reflecting that restaurant and population density are highly correlated, the same pattern holds for population density.

Table 11: Heterogeneity in optimal regulated commission rates (%)

Quantity	Percentile				
	10th	25th	50th	75th	90th
Platform-profit maximizing	28	31	32	35	40
Total-welfare maximizing	23	24	26	28	37
Difference	2	5	7	8	9

Notes: this table describes the cross-county distribution of the regulated commission rates maximizing platform profits and total welfare, and of the gap between these rates. The quantiles reported are weighted by county population. The results are based on $N = 104$ counties.

Table 12: Drivers of the socially optimal regulated commission rate

	Outcome: r_m^{so}			
Regressor (k)	Coefficient	SE	R_k^2 (only k)	R_{-k}^2 (all but k)
Offline business stealing	-0.32	(0.08)	0.34	0.46
Fixed cost change	0.96	(0.32)	0.23	0.50
Variety change	-1.00	(0.19)	0.40	0.42
R^2	0.54			

Notes: see the main text for a description of the regression and the definitions of the regressors. "SE" provides classical asymptotic standard errors. "Bivariate R^2" is the R^2 from a bivariate regression of r_m^{so} on the indicated regressor. The sample includes $N = 104$ counties.

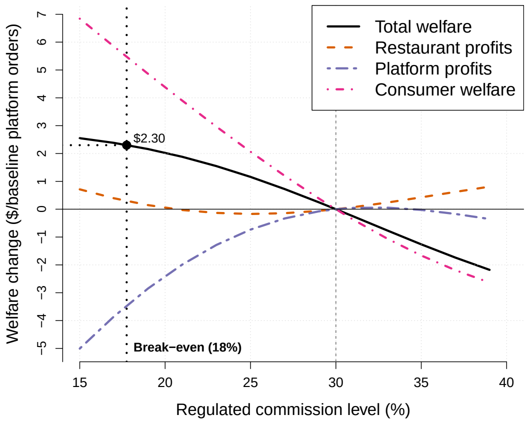
Two-sided regulation. Commission caps affect how fees are split between restaurants and consumers without limiting the combined amount that platforms charge these two sides. The welfare gains from adjusting this split are modest: commission caps can achieve welfare gains of $0.10 per order at best. In contrast, shifting from privately to socially optimal fee levels yields a welfare gain of $3.14 per order. The fact that socially optimal consumer fees are close to those that are privately optimal whereas the socially optimal restaurant commissions are much lower suggests

Table 13: Population density and optimal commission regulation

Regressor	Outcome					
	Offline business stealing		Variety change		r_m^{so}	
log(# restaurants < 5 miles)	0.031		0.037		-0.025	
	(0.005)		(0.004)		(0.005)	
log(population within 5 miles)		0.032		0.041		-0.029
		(0.005)		(0.004)		(0.005)
R^2	0.30	0.27	0.51	0.49	0.21	0.23

Notes: see the main text for a description of the regression and the definitions of the regressors. Classical asymptotic standard errors appear in parentheses. The sample includes $N = 104$ counties.

Figure 7: Welfare under two-sided fee regulation



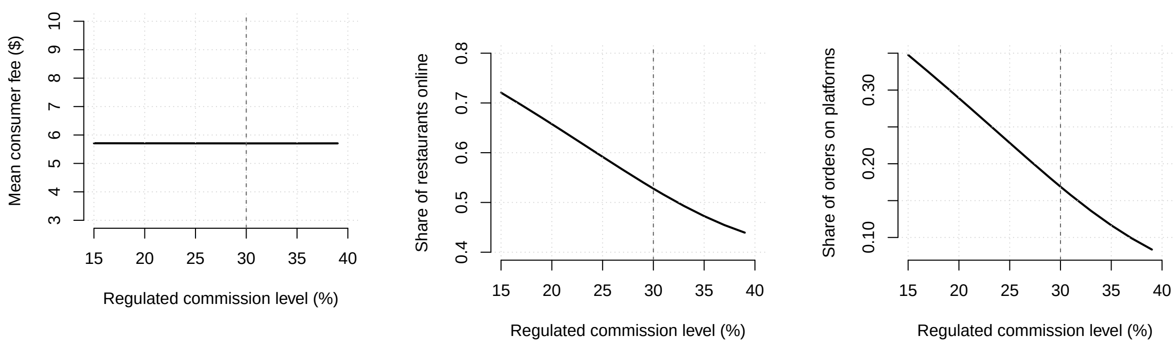
Notes: this figure displays welfare effects of fixing all platforms' commission rates at various levels ranging from 15% to 40% when platforms' consumer fees are fixed at their levels under 30% commission rates. The plot shows welfare results that are aggregated across all counties in the sample and scaled by the number of platform orders in the baseline 30% commissions equilibrium. The dotted black line labelled "Break-even" indicates the regulated commission rate at which platforms earn zero variable profit.

Figure 8: Fees, adoption, and ordering by regulated commission level (fixed consumer fees)

(a) Consumer fees

(b) Share of restaurants adopting ≥ 1 platform

(c) Share of orders placed on a platform



Notes: this plot shows averages of the following variables across counties for various regulated commission levels: consumer fee ($, mean across platforms weighted by sales), share of restaurants that have adopted at least one platform, and the share of orders placed on a food delivery platform.

that a more efficient regulation may pair commission reductions with consumer fee freezes.

To evaluate such two-sided fee regulation, I replicate the analysis underlying Figure 4 but holding consumer fees fixed at their levels under 30% commissions. The results, shown in Figure 7, differ markedly from from those for one-sided commission caps. First, the total welfare gains are larger. At a regulated commission level of 18%—the level at which platform profits fall to zero—total welfare rises by $2.30 per baseline platform order relative to the 30% commission benchmark. One reason for this stark difference is that two-sided regulation directly limits the overall fee level, mitigating distortions from platform market power. Also, as argued in the discussion of Figure 3, fixing consumer fees amplifies consumer gains from expanded restaurant variety.

The distributional impacts of one- and two-sided fee regulations also differ. Most of the welfare gains from two-sided regulation accrue to consumers, whereas restaurants often experience profit losses from such regulation. In contrast, one-sided commission caps primarily benefit restaurants and tend to have smaller—and often negative—effects on consumer welfare. Consumers do better under two-sided regulation because, as shown by Figure 8, it induces restaurant uptake of platforms and restaurant price reductions without boosting fees. Restaurants do not necessarily gain from two-sided fee regulation because it reduces commission-free direct sales, prompts costly increases in platform adoption, and induces price reductions.

7.3 Competition and fee optimality

In one-sided markets, competition typically reduces pricing distortions from market power. In two-sided markets, however, greater competition does not necessarily reduce distortions in how fees are split between consumers and merchants. Teh et al. (2023) show that the effect of entry depends on which side of the market experiences stronger competitive pressure, reflecting the see-saw effect generally present in two-sided markets: lower fees on one side raise fees on the other. If entry especially intensifies competition for merchants, merchant fees fall but consumer fees may rise or remain high. If competition primarily strengthens on the consumer side, the opposite may occur. Teh et al. (2023) show that, when consumer single-homing is high, entry amplifies competition on the consumer side and lowers consumer fees while raising merchant fees. Wang (2023) offers empirical support for this insight. This result resembles that of Armstrong (2006), who demonstrates in a stark model of merchant multi-homing and consumer single-homing that competition reduces consumer prices but does not affect merchant prices. Here, I complement these findings by demonstrating how restaurant multi-homing shapes the fee effects of competition.

I study the effects of competition by simulating a scenario in which the leading four platforms set fees to maximize their joint profits. This scenario corresponds, e.g., to a merger of DoorDash, Uber (which already owns Uber Eats and Postmates), and Grubhub. Comparing outcomes under the current competitive environment to those under counterfactual joint profit maximization highlights the effects of pricing competition among platforms.[30]

Table 14a reports average fees that maximize social welfare, that arise in the competitive *status quo*

[30] Online Appendix Table O.30 reports results from a simulation in which DoorDash operates as a monopolist. The findings align with those under joint profit maximization: monopolizing the market raises consumer fees and reduces commissions. I prefer the joint profit counterfactual as welfare comparisons between the baseline and less competitive regime reflect only the effects of fee changes, not changes in consumer choice sets.

among profit-maximizing platforms, and those that maximize joint platform profits. Compared to the competitive baseline, joint profit maximization raises consumer fees and slightly lowers restaurant commissions. Although this shift moves the fee split closer to the social optimum, it raises the overall level of platform fees. The "Platform markup ($)" row shows that average platform profit per order rises from $3.77 under competition to $4.45 under joint profit maximization. This higher markup outweighs the more efficient allocation of fees in determining welfare: as Table 14b shows, eliminating competition reduces total welfare by $0.31 per order in the competitive equilibria. This loss is driven by consumer surplus, which falls by $0.64 per order. Restaurants, by contrast, benefit from easing platform competition: due to commission reductions, their their profits rise by $0.21/order.

One explanation for why commissions fall under joint profit maximization relates to restaurant multi-homing and diminishing fixed costs of platform adoption. As shown in Table 4, restaurants face substantial fixed costs when joining their first platform but much lower incremental costs when adding a second or third. For example, the average cost of joining DoorDash is $574 for a restaurant not on any platform, compared to just $349 for one already using Uber Eats.

These cost complementarities generate cross-platform spillovers: when one platform lowers its commission and attracts more restaurants, those restaurants face lower incremental costs of joining rival platforms. This makes it easier for rivals to recruit restaurants. Competing platforms do not internalize these spillovers, as each sets fees to maximize its own profits. A single firm controlling all platforms, by contrast, faces an incentive to reduce commissions at each platform in order to promote adoption of other platforms held in common ownership. This dynamic could lead joint profit maximization to lower commissions.

I assess this explanation by computing equilibrium fees in a scenario without cost complementarities. If complementarities explain why commissions fall under joint profit maximization, then removing them should reverse the result that eliminating competition lowers commissions. To eliminate cost complementarities, I replace the fixed costs of multi-homing on a platform set $\mathcal{G}$ with the sum of the fixed costs of single-homing on each platform in $\mathcal{G}$. Formally, I replace the fixed costs $K_{\tau m}(\mathcal{G})$ with new costs $K'_{\tau m}(\mathcal{G})$ defined by

$$K'_{\tau m}(\mathcal{G}) = \sum_{f \in \mathcal{G}} K_{\tau m}(\{f\}), \tag{18}$$

for all restaurant types τ and metros m. For example, I set the fixed cost of adopting both DoorDash and Uber Eats equal to the sum of the costs of joining each individually.

The "No cost complementarity" panel of Table 15 shows that, under joint profit maximization, both consumer fees and restaurant commissions rise absent complementarities. This result establishes that cost complementarities are pivotal in explaining why eliminating competition lowers commission rates. Results from a second counterfactual without restaurant multihoming provide supporting evidence of the role played by cost complementarities in shaping the fee effects of competition. The "No multi-homing" panel, which reports average fees when restaurants are restricted to a single platform, shows that moving from competition to joint profit maximization raises commissions.

Table 14: Effects of joint profit maximization

(a) Fee effects

Quantity	Socially optimal	Privately optimal	
		Competition	Joint max.
Consumer fees ($)	3.30	3.59	4.38
Restaurant commissions (%)	17.6	34.3	33.8
Platform markup ($)	-1.42	3.77	4.45

(b) Welfare effects of moving from competition to joint profit maximization

Welfare component	Effect ($/order)
Consumer welfare	-0.64
Restaurant profits	0.21
Platform profits	0.11
Total welfare	-0.31

Notes: Panel (a) reports sales-weighted average fees of three sorts: (i) those that maximize total welfare ("Socially optimal"), (ii) those arising in competitive equilibria among profit-maximizing platforms ("Competition"), and (iii) those that maximize joint platform profits ("Joint max."). Averages are computed across platform/county pairs using sales from the "Competition" regime as weights . The sales used in the weighted average are sales under fees charged by competing platforms maximizing their own profits. Platform markups are defined as the ratio of platform profits to sales.

Panel (b) reports effects of transitioning from the equilibrium platform fees arising in the status quo of platform competition to the fees that maximize joint platform profits. These effects are in aggregate across counties and scaled by the number of platform orders placed in the "Competition" regime.

Table 15: Profit-maximizing platform fees under alternative multi-homing assumptions

Quantity	No cost complementarity		No multi-homing	
	Competition	Joint max.	Competition	Joint max.
Consumer fees ($)	5.48	5.56	5.23	5.58
Restaurant commissions (%)	25.5	27.7	25.4	27.4

Notes: This table reports sales-weighted average platform fees under two conditions: (i) competition among profit-maximizing platforms ("Competition"), and (ii) joint profit maximization across platforms ("Joint max."). Results are shown for two alternative structural assumptions governing restaurant multi-homing. Under the "No cost complementarity" assumption, the fixed cost of multi-homing equals the sum of the fixed costs of single-homing on each joined platform — i.e., platform adoption costs follow the form specified in equation (18). Under the "No multi-homing assumption," restaurants are restricted to joining a single platform. Under each set of assumptions, the sales weights used in computing averages are those from the "Competition" regime.

8 Conclusion

This article developed and estimated a model of platform competition with the goal of assessing the efficiency of platform fees. I found that US food delivery platforms' consumer fees are approximately optimal. Although market power raises these fees above efficient levels, this distortion is largely offset by the failure of platforms to internalize the social benefit of raising direct ordering via consumer fee increases. Restaurant commissions, by contrast, are about twice as high as is optimal because platforms do not fully account for consumer benefits generated by restaurant variety. Restaurants, though, largely compete away their benefits from commission reductions.

Although restaurant commissions are about twice as high as their efficient levels, regulations that halve commissions are welfare reducing. These regulations prompt consumer fee increases that reduce the pool of consumers available to benefit from expanded restaurant variety on platforms.

A two-sided fee regulation that caps consumer fees while reducing restaurant commissions would be a more effective way of bringing platform fees closer to their efficient levels.

The results suggest subtlety in whether competition remedies fee inefficiencies. Eliminating platform competition slightly reduces restaurant commissions, shifting the ratio of consumer to merchant fees closer to its efficient level and boosting restaurant profits. This occurs because joint-profit-maximizing platforms internalize the cross-platform spillovers from commission reductions, which arise due to cost complementarities in restaurant multi-homing. However, eliminating competition raises the overall level of platform fees and consequently reduces total welfare. Thus, although platform competition harms merchants and exacerbates the bias of platform fees against them, it improves efficiency by curbing market power.

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Appendices

A Restaurant price indices

Here, I discuss the estimation of restaurant price indices that capture cross-platform price differences and the dependence of platform prices on commission rates. I estimate the parameters appearing in (5) via the following regression:

$$\log(p_{jft}) = \psi_j + \psi_{t\times\text{region}(j)} + \phi_f + \beta r_{jt} + \gamma r_{jt} \times \text{online}_f + \varepsilon_{jft}.$$

Here, j is a menu item, f is a platform, t is a month, and region(j) is the region of the restaurant selling j (defined below). Menu items are restaurant/menu item category pairs. I use the most detailed cuisine categories provided by Numerator; examples include bottled soda, corned beef sandwich, milk shakes, and fries.

The fixed effects ψ_j capture heterogeneity across menu items. The $\psi_{t\times\text{region}(j)}$ terms control for time trends in prices that possibly vary across geography. Each state has up to two regions, the parts that never imposed a commission cap policy by June 2021 and those that at some point did. I define p_{jft} as the median price paid for menu item j in month t on platform f. To ensure that the restaurant/item category pairs correspond to unique menu items, I limit the sample to observations for which the interquartile range of prices is less than 5% of the median price and the number of orders underlying the observation is at least 5. I additionally eliminate ZIPs with commission caps that exempted chain restaurants for the analysis. Last, I drop the five chains with the most orders (McDonalds, Chick-Fil-A, Taco Bell, Wendy's, and Burger King) given that large chains are most likely to have negotiated commission rates lower than 30% absent commission caps, which would make their prices less sensitive to commission caps.

Table 16 provides estimates from two specifications: on in r_{jt} is the commission level and another in which it is an indicator for the presence of a commission cap. The results for the first specification, which I use to compute price indices, suggest that a one percentage point increase in the commission rate raises online prices by about 0.61%, with no significant effect on direct-order prices. The results from the second suggest that commission caps reduced platform prices by about 5% without significantly impacting direct-order prices. The results also suggest that prices on platforms are

0.13–0.16 log points (14–17%) higher than those for direct orders. The final rows of Table 16 report DoorDash-to-direct price ratios predicted by the commission-rate regression. These are 14.3% for uncapped (30% commission) areas and 4.0% for 15% commission areas.

Table 16: Restaurant pricing regressions

	Commission level		Cap indicator	
Coefficient	Estimate	SE	Estimate	SE
DoorDash	-0.0555	(0.0529)	0.1320	(0.0109)
Grubhub	-0.0259	(0.0516)	0.1600	(0.0126)
Uber Eats	-0.0456	(0.0529)	0.1420	(0.0118)
Commission rate	-0.0232	(0.0559)	-	-
Commission rate × online	0.6310	(0.1750)	-	-
Commission cap	-	-	0.0029	(0.0075)
Commission cap × online	-	-	-0.0471	(0.0204)
DD/offline ratio (30% comm.)	1.143	0.012	1.141	0.012
DD/offline ratio (15% comm.)	1.040	0.011	1.089	0.025

Notes: the sample size is $N = 5672$. Observations are weighted by the populations of their regions region(j).

To obtain additional pricing evidence, I collected supplementary data on prices from platform and restaurant websites from a random sample of restaurants in December 2022. The advantage of using these data is that it eliminates the need to infer menu items, which are directly observed on restaurant websites, and the data are not selected based on consumer orders. Online Appendix O.6 details the analysis of pricing using these data. I find that prices for platform orders are 13% higher than for direct orders absent commission caps and that 15% caps reduce the gap to 7% (the results from the Numerator approach,14% and 4%, are somewhat similar).

Last, I choose $\bar{p}$ in equation (5) so that the mean price for DoorDash in an area with 30% commissions equals \$21.90, which was the mean DoorDash basket subtotal before tips and taxes in areas without a commission cap in Q2 2021.

B Estimation of platform adoption model

This appendix details the GMM estimator used to estimate the restaurant platform adoption model. Let n_J be the number of restaurants in the sample, and let G_{n_J} denote the n_J-vector of observed platform adoption choices. Additionally, let $\Pi^e_{n_J}$ denote a $n_J \times n_{\mathcal{G}}$ matrix with (j,k) entry equal to restaurant j's expected variable profits from selecting the kth platform subset $\mathcal{G}_k$. Here, $n_{\mathcal{G}}$ is the number of such subsets. Let D_j be the lo population under age 35 within five miles of restaurant j, which serves as a shifter of adoption profitability.

The first set of moment conditions match-model choice probabilities to observed adoption frequencies. Define

$$g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi^e_j, D_j; \theta^{\text{adopt}}) = \mathbb{1}\{m(j) = m, \tau(j) = \tau\} \left(Q_{\tau m}(\mathcal{G}, \Pi^e_j; \theta^{\text{adopt}}) - \mathbb{1}\{\mathcal{G}_j = \mathcal{G}\} \right),$$

for all types τ, markets m, and platform subsets $\mathcal{G}$, where $\tau(j)$ and $m(j)$ are restaurant j's type and market. The predicted choice probability is

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

At the true parameter vector θ_0^{adopt}, we have $\mathbb{E}[g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0$. The corresponding sample moment conditions are

$$\frac{1}{n_J}\sum_{j=1}^{n_J} g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\theta}^{\text{adopt}}) = 0 \qquad \forall \tau, m, \mathcal{G}. \tag{19}$$

I use a second set of moments to target the Σ parameters governing substitution. These moments match covariances between D_j and platform adoption measures in the data 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 joined. These moments are based on

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

where $|\mathcal{G}|$ is the cardinality of set $\mathcal{G}$. Under the true model parameters θ_0^{adopt}, we have $\mathbb{E}[g_\omega(\mathcal{G}_j, \Pi_j^e, D_j; \theta_0^{\text{adopt}})] = 0$. The corresponding sample moment conditions are

$$\frac{1}{n_J}\sum_{j=1}^{n_J} g_{\omega,k}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\theta}^{\text{adopt}}) = 0, \qquad k \in \{1, 2\}. \tag{20}$$

The estimator $\hat{\theta}^{\text{adopt}}$ solves equations (19) and (20). The model is just-identified. Because exactly computing each restaurant's expected profits is computationally intensive, I consider two approximations: (i) simulation-based approximation of expected profits, and (ii) a deterministic approximation using expected counts of adopters by type and ZIP. These two methods yield near-identical results: regressing simulated profits on deterministic approximations yields a coefficient of 1.001 and an R^2 of 1 to three decimal places.

The second approach, which ignores Jensen's inequality, introduces negligible bias due to the large number of competitors (median of 1,448 within five miles) and thus limited variance in adoption shares. I therefore use the deterministic method for both estimation and counterfactuals. See Online Appendix O.13 for further details.