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—typically around 30%—of sales along with per-transaction fees to consumers. Spurred by restaurant complaints about high commissions, many local governments have capped commissions at 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, consider only 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 leading 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 such substitution as 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 payment 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 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. The goal of this article is to empirically determine the extent to which platform fees are inefficient and to quantify the sources of inefficiency.

Two primary challenges are in assembling comprehensive data covering multiple platforms and market sides and in developing a tractable model of platform competition. To address the first challenge, I assemble a rich collection of datasets on the US food delivery industry. 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 capturing fees. 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 adoption to fixed costs of adoption. After joining platforms, restaurants set prices that may differ between platform and direct orders. Finally, consumers decide whether to order a restaurant meal, from which nearby restaurant to order, and whether to use a platform in ordering. 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 the generalized method of moments (GMM), recovering parameters that govern fee sensitivity, preferences for restaurant variety, and substitution patterns. The estimation of fee sensitivity relies on a moment that matches model predictions of sales responses to commission caps to difference-in-differences estimates of these responses. To estimate substitution patterns, I leverage the data's panel structure, which traces how consumers switch among ordering options. I then recover restaurant and platform marginal costs from first-order conditions for optimal pricing. Next, I estimate the restaurant adoption model via GMM, selecting adoption cost parameters to match (i) market-specific platform adoption rates and (ii) the covariance between expected profitability and adoption decisions.

Using the estimated model, I compute equilibrium fees arising under competition between profit-maximizing platforms (*privately optimal*) and those maximizing 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 \$0.49 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, whereas 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 84% higher on average than those maximizing social welfare. 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 more than offset in equilibrium by increased fixed costs of platform adoption and intensified intra-platform price competition: imposing the socially optimal fees benefits restaurants by \$4.14/order absent equilibrium responses but, upon accounting for these responses, leaves restaurants \$0.26/order worse off. Thus, although profit-maximizing platforms charge socially excessive commissions to restaurants, restaurants do not benefit 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: platforms shift the fee burden to consumers in response to caps, 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 23–30% 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 40% 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, which leads platforms to 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 \$0.06 per order, whereas simultaneously capping consumer fees at baseline levels and reducing commissions to the point that platforms just break even generates gains of \$1.81 per order. Two lessons emerge from the analysis. First, expanding restaurant participation creates the greatest benefits when consumer fees are low, as a large consumer base can then enjoy the additional variety induced by lower commissions. Second, the interaction of the division of fees between consumers and merchants and the overall fee level—not simply either in isolation—is crucial in determining the welfare implications of fee regulation. Although the comparison of privately and socially optimally fees implied that platform fees are inefficiently skewed toward merchants, regulation that improves the balance of fees across sides of the market is only welfare enhancing when it also reduces the overall fee level.

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 \$3.50 per order, while restaurant commissions fall by 5.8 percentage points (p.p.). This decline in commissions occurs despite the elimination of competition because the merged platforms internalize positive spillovers 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 may raise uptake of other platforms. In contrast, competing platforms do not internalize these cross-platform gains. I find that cost complementarities are pivotal in explaining why restricting competition reduces commissions: without cost complementarities or restaurant multi-homing, joint profit maximization raises both consumer fees and restaurant commissions.

Although joint profit maximization reduces commissions, it raises overall platform markups and consequently lowers total welfare by \$0.29 per order. This result suggests the overall fee level—not the relative allocation of fees between consumers and merchants—as the relevant dimension of inefficiency in assessing platform competition.

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 I quantify these distortions using an empirical model of 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 (2025) 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 platform 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 scarce. 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

[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.

platform (or *online*) and direct (or *offline*, *first-party*) ordering.

In the stylized model, a monopolist platform facilitates interactions between buyers (or *consumers*) and sellers (or *merchants*). 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 sell directly to buyers through an offline channel. Let a denote the benefit that a seller enjoys from an offline sale. For simplicity, I assume that this benefit is fixed and exogenous. 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 across sellers. The platform's sales are $Q_1(c, J)$, 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 $J(r, Q_1)$. I assume that the functions Q_1 and J admit the inverse demand functions $c(Q_1, J)$ and $r(Q_1, J)$. Following Weyl (2010), I assume that the platform charges fees that ensure coordination on a selected allocation (Q_1, J). Throughout, I use the superscripts "pr" and "so" to denote quantities associated with the fees maximizing the platform's profits and social welfare, respectively.

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

$$\Lambda = (c(Q_1, J) + r(Q_1, J)p_1(r(Q_1, J)) - mc)\, Q_1.$$

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

$$CS = \int_0^{Q_1} Y(x, J)dx - (c + p_1)Q_1,$$

where $Y(Q_1, J) = c(Q_1, J) + p_1(r(Q_1, J))$ is the marginal consumer's valuation of platform usage at sales level Q_1. Last, seller profits are

$$SP = aQ_0(Q_1) + ([1 - r]p_1 - \bar{\kappa}_1(J))Q_1 - KJ.$$

Here, Q_0 are total first-party merchant sales, which I assume depend on online sales Q_1. This dependence is a reduced-form way of modelling the diversion of offline sales into platform orders. Also, $\bar{\kappa}_1$ is the average marginal cost among the first J sellers 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 $\mu_B = -Q_1/(\partial Q_1/\partial c)$ is the inverse semi-elasticity of consumer demand—a measure of buyer-side market power—and $\tilde{b}_S = d(rp_1Q_1)/dQ_1$ is the effect of additional platform ordering by consumers on the platform's commission revenue from sellers. 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 sellers of a platform sales (before commissions) and $D = -{}^{dQ_0}/_{dQ_1}$ 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 sellers' offline profits of an additional online order. The difference between the socially and privately optimal consumer fees is

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

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 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 platform 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 $\tilde{b}_S^{\mathrm{so}} < \tilde{b}_S^{\mathrm{pr}}$. The resulting *displacement distortion* tends to offset the Spence distortion.

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

$$\tilde{b}_B^{\mathrm{pr}} = \mu_S^{\mathrm{pr}}, \tag{3}$$

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

$$\bar{b}_B^{\mathrm{so}} Q_1^{\mathrm{so}} = K + (\bar{\kappa}')^{\mathrm{so}} Q_1^{\mathrm{so}}, \tag{4}$$

where $\bar{b}_B$ is the average buyer valuation of an additional platform seller.[4] Equation (3) implies that a profit-maximizing platform equalizes the benefits to marginal buyers of an additional seller

[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, $\bar{b}_B = (\int_0^{Q_1} \frac{\partial Y}{\partial J}(x, J)dx)/Q_1$.

$(\tilde{b}^{\text{pr}})$ with commission revenue losses required to attract a seller to the platform when assessing a commission reduction. In contrast, equation (4) implies that a social planner compares the total benefit $\bar{b}_B^{\text{so}} Q_1^{\text{so}}$ to buyers of an additional seller with the increased costs of adoption K and increased marginal costs $(\bar{\kappa}')^{\text{so}} Q_1^{\text{so}}$.

Although (3) and (4) do not yield a decomposition of distortions à la equation(2), they do indicate sources of inefficiency in 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 merchants 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, $\tilde{b}_B^{\text{pr}}$ falling below (or above) $\bar{b}_B^{\text{so}}$ due to Spence and displacement distortions tends to make commissions socially excessive (or, respectively, insufficient).

To summarize, a complex set of externalities implies that consumer fees and merchant commissions may be either too high or too low, both relative to each other and in absolute levels.[5] In this article, I 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 disproportionately intensifies competition on the buyer or the seller side. This, in turn, depends on how entry affects platforms' residual demand elasticities, on platforms' substitutability from the buyer's perspective, and on 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 their efficient levels.

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

[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.

both. Restaurants also set prices for goods sold on platforms. In summary,

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

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 quantified below in Section 3.2 and by Online Appendix Table O.3.

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 capped commissions to other levels between 10% and 20%. Most caps began as temporary measures, but several jurisdictions later made their caps permanent.

[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 (2025) 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.

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 study the more popular form of cap not exempting chains in the counterfactual analysis.

Online Appendix Figure O.3 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 places 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 is a metropolitan area (Core-Based Statistical Area, or 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.

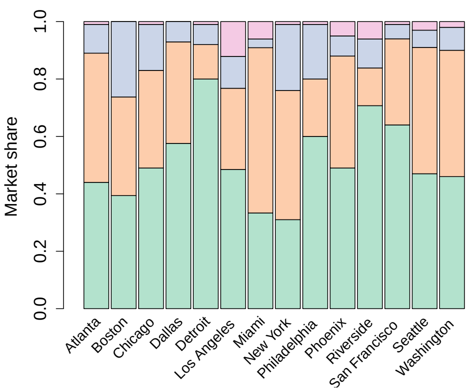
[9]The main exceptions are that individuals younger than 35, individuals older than 64, and high income individuals (over \$125,000 family income) are somewhat underrepresented: their shares in the Numerator panel are 21%, 13%, and 20% whereas their shares in the ACS are 29%, 22%, and 29%. Shares are 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.

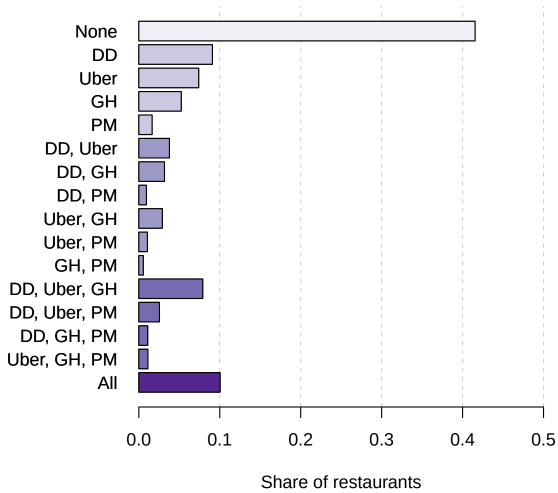
Platform adoption. I obtain data on restaurants' platform adoption decisions from the data provider YipitData. These data record all US restaurants listed on each major platform in each month from January 2020 to May 2021.[12] I obtain data on offline-only restaurants from Data Axle, which provides a comprehensive dataset 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 on which I focus 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 and delivery address. 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 uses demographic data from the American Community Survey (ACS, 2014–2019 five-year estimates).

3.3 Restaurant prices

I construct restaurant price indices that vary by platform 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

$$p_{fzt} = \bar{p} \times \exp\left\{\rho_0 \times \text{online}_f + \rho_1 \times r_{fz} + \rho_2 \left(r_z \times \text{online}_f\right)\right\}. \tag{5}$$

Here, $\bar{p}$ governs the overall price level across ZIPs z, months t, and ordering modes (online and offline); ρ_0 captures differences in prices on online platforms relative to direct orders ($f = 0$, with $\text{online}_f = \mathbb{1}\{f \neq 0\}$); ρ_1 captures how the commission rate r_z affects prices for direct orders; and ρ_2 governs how the commission rate affects prices for platform orders. 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 online and offline ordering channels and for commissions to differentially affect direct and platform prices. I do not measure prices separately across distinct platforms because, as demonstrated in Online Appendix O.3.1, restaurants' prices do not systematically vary across platforms.

I estimate the parameters appearing in (5) via a regression with item, ZIP, and month 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 1 p.p. increase in the commission rate raises a restaurant's online prices by 0.69% and does not have a 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 21%; under 15% commissions, this gap narrows to 9%. I collect supplementary data on prices directly from restaurants' websites and platform listings that corroborates these findings; see Online Appendix O.6 for details.

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 captures both mechanisms. Also, 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 article's primary analysis deploys 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 DiD methods in the analysis but limit discussion here to results from the Interaction Weighted (IW) estimator of Sun and Abraham (2021). This estimator, which yields estimates of the effects of commission caps in 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 indeed 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 restaurants to join 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

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

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.10. The results for order volumes appear among those for additional estimators in Online Appendix Figure O.8. The result for restaurant listings appears in the "Total listings" row of the "IW" column of Online Appendix Table O.20, which includes table notes that provide additional details on the estimation procedure.

in a tractable way and, in doing so, determine the welfare implications of such regulation.

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 by 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, and consumer demand shocks that vary across geography. In estimation, 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 consumer adoption stage fits the setting better.

Two-sided market models often feature multiple equilibria due to network externalities: participation on each side depends on expectations over 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 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). The model will not speak to the associated pricing incentives. Second, restaurants may face sunk costs of adopting 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

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

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, $\phi_{\tau(j)}$ is the mean taste 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 chain and independent restaurants. Additionally, the parameter α governs consumer fee sensitivity.

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

$$\psi_{if} = \delta_{fm} - \alpha c_{fz} + \lambda'_{\text{platform}} d_i + \zeta_{if}.$$

for $f \neq 0$. Here, δ_{fm} is a parameter governing the mean taste of consumers in metro m for platform f; and c_{fz} is platform f's fee to consumers in ZIP z. The demographic characteristics vector d_i includes indicators for consumer i being under the age of 35, being married, and having an income above \$40,000. The $\lambda_{\text{platform}}$ parameters determine how consumers differ in tastes for food delivery platforms on the basis of these demographic variables. 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_ζ scale parameters govern substitution patterns. As $\sigma_{\zeta 1}$ 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 the demographic variables enumerated above, λ_η is a vector of parameters mapping these demographic variables into tastes for restaurant dining, and $\eta_i^\dagger$ is consumer i's idiosyncratic taste for restaurant dining. Last, I specify that $\eta_i^\dagger \sim N(0, \sigma_\eta^2)$ independent of all else. A larger value of σ_η makes consumers more polarized in tastes for restaurant dining, and thus limits substitution between at-home and restaurant dining. Notably for the analysis of platform fees, a large value of σ_η limits the scope for platforms to generate new business for restaurants as opposed to steal offline sales, thus making offline business stealing especially relevant.

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 DiD 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, 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 across geography among US retailers.

[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).

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 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 does 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 it has adopted. 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

$$p^*_j = \arg\max_{p_j} \sum_{f \in \mathcal{G}_j} [(1 - \vartheta r_f) p_{jf} - \kappa_{jf}] \times Q_{jf}(\mathcal{J}_m, p_j, p^*_{-j}), \tag{6}$$

where κ_{jf} is restaurant j's marginal cost of fulfilling an order on platform f, p_{-j} are other restaurants' prices, Q_{jf} are restaurant j's sales on platform f, and $\mathcal{J}_m$ encodes the platform adoption decisions of all restaurants in metro m.[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 pricing: $\vartheta = 1$ 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

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

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

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 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 fact that complete information entry

[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.

games suffer from problems related to multiplicity of Nash equilibria reflecting non-uniqueness 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 those of other players. 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

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

where $\mathcal{s}_{fz}$ 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 stages, beginning with estimation of the consumer choice model via GMM. In the model, each consumer i places $T_i \leq T$ orders from restaurants. Recall that T is the maximum number of orders per month. In practice, I define each panelist/month pair as a separate consumer, and set $T = 10$, the 95th percentile of the number of monthly orders. The sample includes Numerator core panelists who place at least one restaurant order in Q2 2021. I consider only each consumer's first T orders in the case that the consumer places more than T orders. The sample ultimately includes 29,958 panelist/month pairs.

I specify a number of moments equal to the number of parameters. The moments underpinning estimation fall into five groups:

(i) Moments equal to the difference between the data and the model in market-specific aggregate platform ordering volumes (these target the ψ_{fm} and μ_η parameters);

[18] Formally, for any sequence of choice probabilities $\{P_{J,m}\}_{J=1}^{\infty}$ indexed by the number of restaurants J, the difference between the share of restaurants joining each platform 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.

(ii) Moments equal to the difference between the data and the model in channel (i.e., online or offline) ordering frequencies by demographic group (under 35 years of age, married, and income exceeding \$40,000; these target the $\lambda_{\text{platform}}$ and λ_η parameters);

(iii) A moment equal to the difference between the data and the model in chain restaurant order volumes (this targets the ϕ_{chain} parameter);

(iv) A moment equal to the gap between a DiD estimate of the effect of a 15 p.p. commission reduction on sales and the model-predicted effect on sales (this targets the α parameter);

(v) Score-based moments equal to derivatives of the log-likelihood of platform choice with respect to parameters governing the scale of unobserved heterogeneity (these target the $\sigma_{\zeta 1}$, $\sigma_{\zeta 2}$, and σ_η parameters).

Estimation on all markets is computationally difficult due to the large number of fixed effects. I therefore estimate the model on data from the five metros with highest order counts in the sample: New York, Los Angeles, Chicago, Dallas, and Atlanta. I subsequently estimate δ_{fm} and μ_m^η for each remaining metro m as the values of these parameters that lead the model to match platform-specific and offline ordering counts in those metros.

Moment condition (iv) matches the model to quasi-experimental evidence on commission caps' effects on platform sales. I use DiD estimates of the effect of the commission rate on the cost to consumers of ordering on a platform—defined as the sum of platform fees and restaurant prices—and on platform order volumes. This DiD estimation departs from that of Section 3.4 in that it conditions on measures of restaurant uptake of platforms so that the estimated effects isolate the impact of fee and price changes holding platforms' restaurant networks fixed. Table 2 reports the resulting DiD estimates of how the commission rate—assumed to be 0.30 in uncapped regions and equal to the regulated cap level in capped regions—affects log ordering costs and log total platform sales. Moment condition (iv) requires the model's predicted sales response to a 15 p.p. commission reduction to match these empirical responses: specifically, that a 1.95% increase in ordering costs reduces platform sales by 5.72%. Details on the DiD estimation and the construction of moment (iv), as well as the other moments, appear in Appendix B.

Table 2: Difference-in-differences estimates used in consumer choice model estimation

	Ordering cost	Order volume
Commission rate coefficient	-0.13	0.39
	(0.03)	(0.07)
Effect of 15 p.p. commission reduction (%)	1.95	-5.72
	(0.52)	(1.01)

Notes: the "Commission rate coefficient" panel provides DiD estimates of the effect of the commission rate on log ordering cost (defined as the sum of the platform's fee and the price charged by restaurants on the platform) and on log total platform order counts. The "Effect of 15 p.p. commission reduction (%)" row provides, in percentage terms, the effect of a 15 p.p. commission reduction as implied by the coefficients in the first panel. See the main text and Appendix B for details on the DiD estimation.

Identification of unobservable taste heterogeneity. 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 intrinsic 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 $\mathcal{G}_j = \{f_1, \ldots, f_k\}$, the restaurant's pricing first-order condition is

$$\underbrace{\begin{bmatrix} (1-\vartheta r_{f_1})Q_{jf_1} \\ \vdots \\ (1-\vartheta r_{f_k})Q_{jf_k} \end{bmatrix}}_{=\tilde{Q}_j(\vartheta)} + \underbrace{\begin{bmatrix} \frac{\partial Q_{jf_1}}{\partial p_{jf_1}} & \frac{\partial Q_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial Q_{jf_k}}{\partial p_{jf_1}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial Q_{jf_1}}{\partial p_{jf_k}} & \frac{\partial Q_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial Q_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{=\Delta_p} \left(\underbrace{\begin{bmatrix} (1-\vartheta r_{f_1})p_{jf_1} \\ \vdots \\ (1-\vartheta r_{f_k})p_{jf_k} \end{bmatrix}}_{=\tilde{p}_j(\vartheta)} - \underbrace{\begin{bmatrix} \kappa_{jf_1} \\ \vdots \\ \kappa_{jf_k} \end{bmatrix}}_{=\kappa_j} \right) = 0, \tag{12}$$

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

$$\kappa_j(\vartheta) = \tilde{p}_j(\vartheta) + \Delta_p^{-1}\tilde{Q}_j(\vartheta). \tag{13}$$

Equation (13) 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

$$\mathbb{E}[\tilde{\kappa}_{jf}(\vartheta_0)Z_j] = 0, \qquad f \neq 0 \tag{14}$$

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 (14) 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 packaging and logistical costs. The costs κ_{jf} that I recover from (13) 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 (13) as my estimator of κ_z^{direct}. I similarly use the average κ_{jf} recovered from (13) 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 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 fitting model predictions to observed choices upon setting restaurant beliefs to the estimated CCPs.[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 $\mathcal{G}$ 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/type-level adoption probabilities to estimate the 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

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

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 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,

$$\Delta_f(c_f - mc_f) + \tilde{\mathfrak{z}}_f = 0, \tag{15}$$

where Δ_f is an $N_z \times N_z$ matrix with the (z, z') entry $(\Delta_f)_{zz'} = d\mathbb{E}_{\mathcal{J}_m}[\mathfrak{s}_{fz'}]/dc_{fz}$ and $\tilde{\mathfrak{z}}_f$ is a vector with component z equal to $\tilde{\mathfrak{z}}_{fz} = \mathbb{E}_{\mathcal{J}_m}[\mathfrak{s}_{fz}] + \sum_{z' \in \mathcal{Z}} r_{fz'} d\mathbb{E}_{\mathcal{J}_m}[\bar{p}^*_{fz'}\mathfrak{s}_{fz'}]/dc_{fz}$. 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

$$mc_f = c_f + \Delta_f^{-1}\tilde{\mathfrak{z}}_f. \tag{16}$$

I estimate mc_f by substituting Δ_f and $\tilde{\mathfrak{z}}_f$ for estimates of these quantities obtained in (16).[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, 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

[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

$$\underbrace{\begin{bmatrix} \Delta_f & \Delta_{fg} \\ \Delta_{gf} & \Delta_g \end{bmatrix}}_{=\bar{\Delta}} (\underbrace{\begin{bmatrix} c_f \\ c_g \end{bmatrix}}_{=\bar{c}} - \underbrace{\begin{bmatrix} mc_f \\ mc_g \end{bmatrix}}_{=\bar{mc}}) + \underbrace{\begin{bmatrix} \tilde{\mathfrak{z}}_f \\ \tilde{\mathfrak{z}}_g \end{bmatrix}}_{=\bar{\mathfrak{z}}} = 0,$$

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

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 35% on average (see Table 7).

6 Estimation results

6.1 Parameter estimates for consumer choice model

Table 3 reports estimates of consumer choice model parameters. Several estimates are noteworthy. First, the estimated standard deviations of unobserved tastes for online platforms in general $\sigma_{\zeta 1}$ and for specific platforms $\sigma_{\zeta 2}$ are sizeable, equal to \$6.62 and \$5.92 in dollar terms respectively. This indicates considerable polarization in consumer tastes for platform ordering. Additionally, the estimated λ demographic effects on platform tastes imply that younger, unmarried, and higher income consumers prefer delivery platforms relative to their older, married, and lower income counterparts. The large estimate of σ_η suggests limited substitutability between restaurant ordering and at-home dining, and thus scope for offline business stealing distortions. In addition, the α parameter estimate is positive and significant, indicating aversion to platform fees. Last, platform sales respond to restaurant variety on platforms: the estimated elasticities of platforms' orders with respect to their restaurant listing counts range from 0.90–1.41, on average across metros.[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, 14–18% of these no longer place any restaurant order, an additional 54–64% switch to ordering directly from a restaurant, and the remaining 18–34% switch to a different platform (on average across metros). Online Appendix Table O.27 details these results.[22]

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 $\hat{\vartheta} = 0.69$ (with a bootstrap standard error of 0.031), which implies that restaurants account for about 70% of platform commissions in pricing.[23]

Table 4 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 50% of 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

[21] See Online Appendix Table O.26 for details on the computation of these elasticities.

[22] Online Appendix Table O.25 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: Selected consumer choice model estimates

Parameter	Estimate	SE
α	0.13	(0.02)
$\sigma_{\zeta 1}$	0.86	(0.06)
$\sigma_{\zeta 2}$	0.77	(0.04)
ϕ_{chain}	1.14	(0.05)
$\lambda^{\text{young}}_{\text{platform}}$	0.53	(0.05)
$\lambda^{\text{married}}_{\text{platform}}$	-0.28	(0.05)
$\lambda^{\text{high income}}_{\text{platform}}$	0.17	(0.05)
σ_η	2.77	(0.07)
$\lambda^{\text{young}}_{\eta}$	-0.50	(0.06)
$\lambda^{\text{married}}_{\eta}$	0.17	(0.05)
$\lambda^{\text{high income}}_{\eta}$	-0.09	(0.06)

Notes: this table reports estimates of the parameters of the consumer choice model. Estimates of the platform/metro fixed effects δ_{fm} and the metro fixed effects μ^η_m are omitted.

markups on account of heterogeneity in costs and demand conditions; Online Appendix Figure O.20 shows that, within each of the leading three platforms, gross markups range from about \$11.00 to \$11.80 between the 5th and 95th percentile. Heterogeneity in gross markups makes Spence and displacement distortions of consumer fees relevant.

Table 4: Mean restaurant marginal costs and markups (\$)

(a) Marginal costs

Channel	No cap		Cap	
Direct	14.47	(1.50)	14.52	(1.51)
Platform	13.51	(1.46)	13.68	(1.47)

(b) Markups

Channel	No cap		Cap	
Direct	7.29	(1.50)	7.30	(1.51)
Platform	6.41	(1.46)	6.77	(1.47)

Notes: the table reports mean marginal costs κ_{jf} and markups $(1-r_f)p_{jf} - \kappa_{jf}$ 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. Standard errors appear in parentheses.

6.3 Estimates of the restaurant platform adoption model

Table 5 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 \$30,135. The fixed costs are at a monthly level. Panel 5b contains the estimated average costs of platform adoption by platform subset across markets and restaurant types whereas Panel 5c displays average costs by the number of platforms. In both cases, the averages are weighted by restaurant counts. These panel shows that joining a single platform entails a substantial fixed cost; averaging across markets, these are \$1070 and \$1171 for DoorDash and Uber Eats, the two largest platforms. 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 \$367 whereas the estimated scale parameter σ_ω of the platform-subset-specific disturbance is

\$560.

Table 5: Estimates of restaurant platform adoption parameters

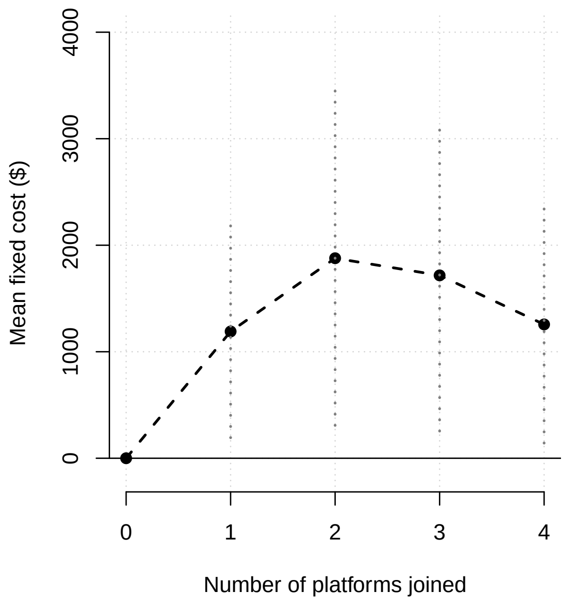
(a) Parameters governing choice disturbance

Parameter	Estimate	SE
σ_ω	560	(244)
σ_{rc}	367	(56)

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

Platform subset	Estimate	SE
DD	1070	(480)
Uber	1171	(493)
GH	1790	(778)
PM	1246	(520)
DD, Uber	1752	(754)
DD, GH	1795	(755)
DD, PM	1502	(658)
Uber, GH	1760	(706)
Uber, PM	2269	(990)
GH, PM	2123	(874)
DD, Uber, GH	1890	(830)
DD, Uber, PM	2511	(1015)
DD, GH, PM	2311	(985)
Uber, GH, PM	2258	(939)
All	1256	(569)

(c) Mean fixed costs by platform subset size



Notes: Panel 5a reports estimates of the parameters governing the disturbance affecting restaurants' platform adoption decisions. Panel 5b reports estimates of the mean $K_{\tau m}(\mathcal{G})$ fixed costs across markets m for each platform subset $\mathcal{G}$. Panel 5c reports the mean $K_{\tau m}(G)$ across markets m and platform subsets $\mathcal{G}$ with a given number of constituent platforms. I compute the standard errors appearing in parentheses using the bootstrap procedure described in Appendix O.10.

6.4 Estimates of platform marginal costs

Table 6 describes the cross-ZIP distribution of estimated 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 \$8.89 to \$10.77. Additionally, McKinsey & Company found platform marginal costs of \$8.20 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.

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

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

Table 6: 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	9.62	8.89	10.18	10.77	3.45	3.28	3.44	3.61
Uber	9.39	8.40	9.24	10.40	3.48	3.29	3.46	3.65
GH	9.72	8.02	10.29	10.82	3.16	2.98	3.13	3.32
PM	13.83	12.05	14.13	15.37	3.92	3.52	3.68	3.86

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

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 7 reports the cross-county mean and, in parentheses, standard deviations of privately and socially optimal fees. As noted earlier, the mean privately optimal platform commission is 35%, higher than the 30% advertised by platforms in practice. I attribute this mismatch to the fact that I specify a static measure of platform profits that does not account for platforms' future gains from a large restaurant network. However, these omitted dynamic concerns are largely orthogonal to the distortions studied in this article.

Table 7: Socially and privately optimal platform fees

	Consumer fee ($)						Restaurant commission (%)					
Platform	Privately optimal		Socially optimal		Difference		Privately optimal		Socially optimal		Difference	
DD	4.16	(1.45)	2.98	(1.66)	1.18	(0.89)	31.87	(4.50)	18.08	(7.10)	13.80	(5.60)
Uber	3.08	(1.18)	2.67	(1.47)	0.40	(1.19)	35.91	(4.98)	19.76	(6.73)	16.15	(5.55)
GH	1.96	(1.73)	2.88	(1.59)	-0.92	(1.85)	39.84	(6.65)	20.18	(7.18)	19.65	(7.52)
PM	5.71	(1.61)	5.43	(1.96)	0.29	(1.71)	37.25	(5.41)	21.17	(10.23)	16.08	(8.80)
Total	3.49	(1.43)	3.00	(1.61)	0.49	(1.27)	34.99	(5.16)	19.21	(7.22)	15.78	(6.20)

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.

Table 7 shows a stark asymmetry: privately optimal consumer fees are close to socially optimal whereas restaurant commissions are markedly higher than their efficient levels.[25] The "Consumer fee ($)" panel of Table 7 shows that the sales-weighted mean difference between privately and socially optimal consumer fees is only $0.49. This contrasts sharply with the result for restaurant commissions: the mean privately optimal commission rate is 84% higher than the mean socially optimal rate of 19.6%. These patterns are consistent across platforms.[26]

This divergence reflects interdependent dynamics across sides of the market. First, consumer fees are close to optimal because market power and business stealing distortions offset each other. I separately quantify consumer fee distortions using a generalized version of the 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 under platform competition. The first reflects that an increase in platform f's consumer fee shifts ordering to rival platforms, thus boosting restaurant sales on these 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 rival platforms $g \neq f$, whereas a platform f maximizing its own profits does not. This discrepancy gives rise to a *rival profits* distortion. 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 8 reports the average magnitude of each distortion in consumer fees by platform. For DoorDash, market power raises consumer fees by $4.35, but this is more than offset by the sum of a $2.83 offline business stealing distortion and a $2.06 online business stealing distortion. Displacement largely offsets the Spence distortion, producing only a small net effect from network externalities. The additional rival profits distortion and the unexplained "Other" 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. The results are qualitatively similar for the other three platforms.

[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.28 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. The results suggest that variation in consumer-side market power, offline business stealing, and network externalities all play a role in explaining heterogeneity in gaps between privately and socially optimal consumer fees. Furthermore, the results suggest that heterogeneity in the variety benefits and fixed cost effects of additional restaurant uptake of platforms best explain the gap between privately and socially optimal commission rates.

Table 8: Consumer fee distortions ($)

Distortion	Platform			
	DD	Uber	GH	PM
Market power	4.35	4.17	3.74	3.32
Offline business stealing	-2.82	-2.60	-2.34	-2.14
Online business stealing	-2.06	-2.33	-2.63	-2.93
Spence	4.53	4.40	4.53	4.62
Displacement	-3.83	-4.40	-5.46	-4.45
Rival profits	0.50	0.64	0.66	0.86
Other	0.50	0.53	0.57	1.02
Total	1.18	0.40	-0.92	0.29

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

Although the illustrative model does not yield a neat decomposition of restaurant commission distortions, 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 $2.72 that is driven primarily by consumer gains of $10.40/order. These gains owe to consumer enjoyment of lower prices and greater variety on platforms: as reported by Table 9b, moving to the lower socially optimal commissions reduces restaurant prices on platforms by 10.5% and boosts the share of restaurants active on at least one platform by 52.0%

Section 2 argued that fixed costs of platform adoption can make additional restaurant uptake socially inefficient. To assess this possibility, I compute the consumer welfare gains and fixed cost increases generated by the rise in restaurant uptake induced by a 1 p.p. reduction in platform commission rates from a baseline with privately optimal fees. Consumer benefits are measured as the change in welfare upon moving to a counterfactual differing from the baseline only in featuring the additional restaurant uptake triggered by the 1 p.p. commission reduction. Table 10 reports these effects relative to baseline platform order volumes. Although lower commissions raise fixed adoption costs by $0.14 per order, the associated variety benefits to consumers amount to $0.27 per order, more than offsetting the additional fixed costs. The fact that commission reductions generate variety benefits exceeding fixed cost increases explains in part why privately optimal restaurant commissions are inefficiently high.

Reductions in commissions raise consumer welfare by encouraging restaurant platform adoption and reducing restaurant prices. However, these responses diminish restaurants' direct gains from lower commissions. Table 11 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 $4.14/order. Accounting for restaurant adoption responses, which entail fixed adoption costs and prompt offline business stealing, reduces the benefit to $2.76. Similarly, accounting for price responses while holding adoption fixed reduces the benefit to $2.24. When both adoption and price responses are taken into account, the total profit gain to restaurants turns to a loss of $0.26 per order. Thus, restaurant gains from reducing commissions to their efficient level are entirely eroded by competitive responses.[27]

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 8, this is because 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 8.

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

(a) Welfare

Quantity	Change ($/order)
Consumer welfare	10.40
Restaurant profits	-0.26
Platform profits	-7.41
Total welfare	2.72

(b) Restaurant and consumer responses

Quantity	Change (%)
Restaurant prices	-10.5
Share of restaurants online	52.0
Number of restaurant listings	84.4
First-party orders	-25.1
Platform orders	159.2
Total orders	9.0

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 absent commission caps.

[27] The findings presented in Online Appendix Figure O.21 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 while raising consumer welfare. The net effect is positive.

Table 10: Variety and fixed cost effects of commission reductions

Effect	Amount ($/order)
Variety	0.27
Fixed cost	0.14
Net	0.13

Notes: this table reports the variety and fixed cost effects of the additional restaurant uptake induced by a 1 p.p. reduction in platform commission rates from the privately optimal baseline. The variety effect is the change in consumer welfare when restaurant adoption levels are changed to those induced by the 1 p.p. commission reduction, holding all other aspects of the baseline fixed. The fixed cost effect is the resulting increase in fixed adoption costs associated with this higher level of restaurant uptake.

Table 11: Decomposition of restaurant profit effects

Responses	Profit change ($/order)
Direct effect of fee changes	4.14
With adoption responses	2.76
With price responses	2.24
Total effect (all responses)	-0.26

Figure 3 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 23% and 30% is welfare enhancing.[28] Commission reductions in this range raise restaurant profits while having relatively small negative effects on consumer welfare, reflecting the offsetting effects of commission reductions in expanding restaurant variety and raising consumer fees as displayed in Figure 4. Despite the negative impacts of commission reductions on platform profits, these effects on consumer welfare and unambiguous positive effects on restaurant profits together imply that moderate commission reductions to levels above 23% boost total welfare. Even at its optimal level—yielding just $0.06/order at a 26% commission rate—one-sided commission regulation delivers only a small welfare improvement, especially when contrasted with the $2.72 per-order gain from fully correcting platform-fee inefficiency (Table 9a).

Whereas the socially optimal fee structure involves reducing restaurant commissions by almost half relative to baseline in which platforms choose commissions to maximize their profits, halving commissions from 30% to 15% reduces total welfare. This contrast arises because a one-sided 15% cap raises 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 benefits from the additional restaurant adoption prompted by commission reductions, holding fixed consumer fees and prices. I also compute the total fixed costs incurred by restaurants when adopting platforms under each commission level, permitting a direct comparison of the benefits and costs of expanded restaurant uptake of platforms.

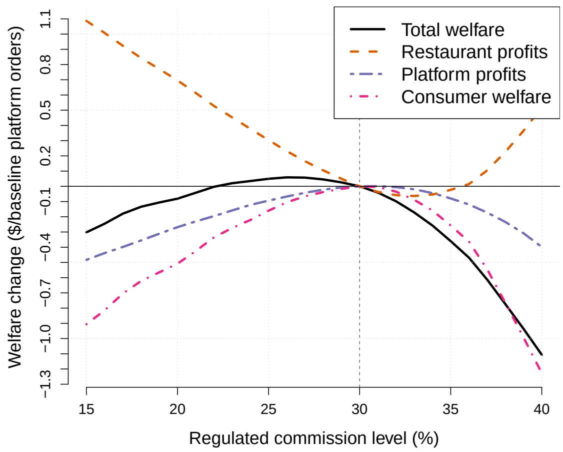
Figure 5 presents the results, aggregated across counties and scaled by platform orders under 30%

[28] 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.

commissions. The solid curve shows the variety benefits under baseline fees and prices, whereas 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.

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 \$4.04 per order. This falls to \$2.89, though, after accounting for higher consumer fees (and thus fewer orders), \$2.28 with increased restaurant adoption (which entails fixed adoption costs and offline business stealing), and just \$0.92 after restaurants lower prices. Competitive responses similarly attenuate consumer losses from commission caps. As shown in Figure 6b, fee increases reduce consumer welfare by \$3.00 per order, but these losses fall to \$2.39 upon accounting for expanded restaurant uptake of platforms and to \$0.46 after additionally accounting for restaurant price reductions.

Figure 3: Welfare by regulated commission level



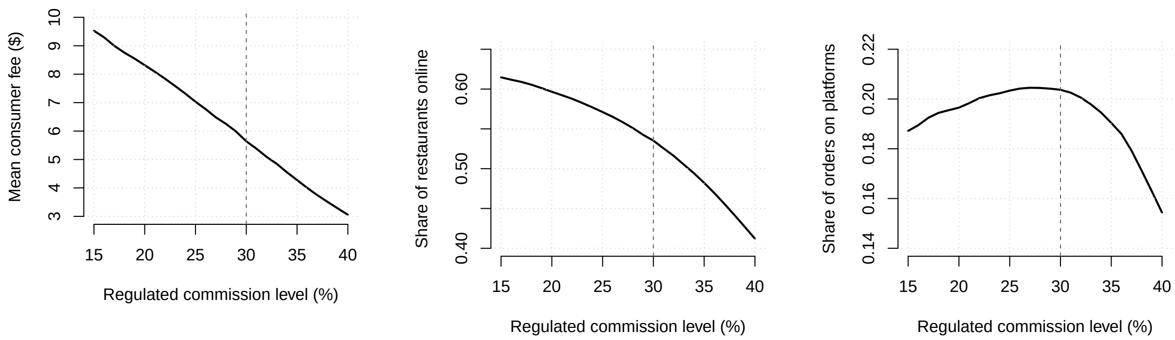
Notes: this figure plots welfare effects of constraining commissions for all platforms at levels between 15% and 40% as a share of the number of platform orders in the 30% commission equilibrium.

Heterogeneity in optimal commission regulation. Table 12, 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 25–30% whereas the corresponding range for platform-optimal commissions is 29–33%. 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 indicates that 60% of platform orders would become direct orders if platforms were abolished.

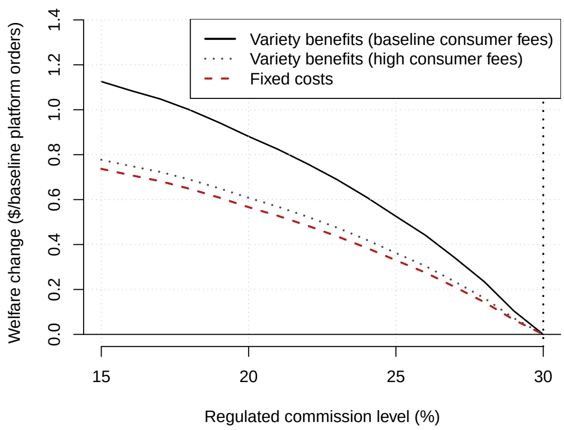
Figure 4: Fees, adoption, and ordering by regulated commission level

(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.

Figure 5: Effects of commission reduction on variety benefits and fixed adoption costs

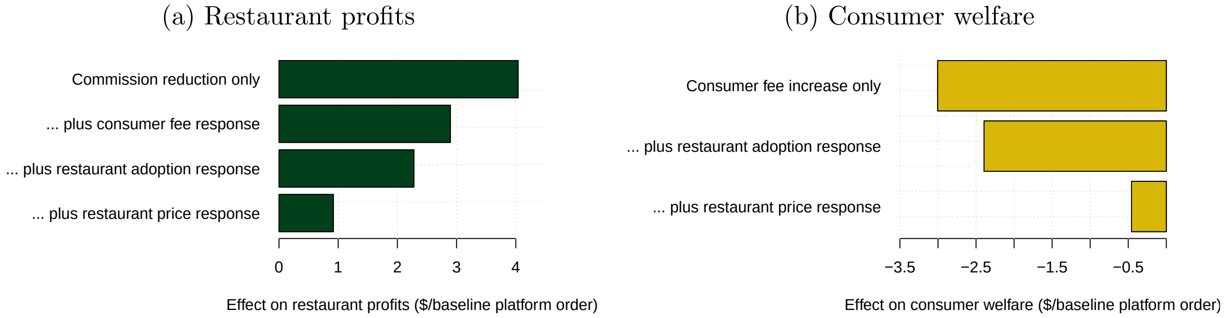


Notes: this figure displays welfare effects of reducing platform commission rates from a 30% baseline to levels between 15% and 30%, aggregated across counties and scaled by the number of baseline platform orders. The "Variety benefits" curves show consumer welfare gains from increased restaurant adoption 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 due to changes in restaurant platform uptake as commissions fall.

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 rate falls by 1 p.p. 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 1 p.p. commission reduction in each county, calling it the *fixed cost change*. I also compute per-capita increase in consumer welfare attributable to increases in restaurant platform adoption prompted by the commission reduction, holding fixed

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.

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 membership among restaurants, and counties in which commission reductions yield especially large variety benefits to have lower socially optimal commissions.

Table 13 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 46% 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 0.18 for the offline business stealing variable to 0.42 for the variety change. By both measures, the variety change variable yields the greatest power in explaining 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 the 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 high restaurant densities, where consumers have ready access to dining at many nearby restaurants absent platforms 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 40% and 27% 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 100% increase in restaurant density predicts a 1.4 p.p. 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. This analysis suggests that commission caps are most effective in enhancing social welfare in dense urban areas.

Table 12: Heterogeneity in optimal regulated commission rates (%)

Quantity	Percentile				
	10th	25th	50th	75th	90th
Platform-profit maximizing	27	29	32	33	38
Total-welfare maximizing	23	25	27	30	40
Difference	0	2	4	5	7

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 13: 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	-0.22	(0.11)	0.18	0.45
Fixed cost change	0.82	(0.46)	0.26	0.45
Variety change	-1.24	(0.26)	0.42	0.34
R^2	0.47			

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.

Table 14: Population density and optimal commission regulation

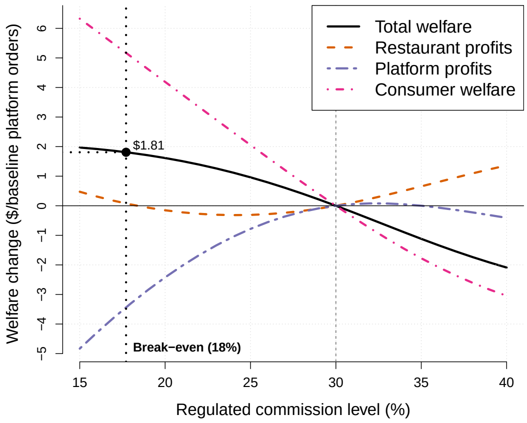
Regressor	Outcome					
	Offline business stealing		Variety change		r_m^{so}	
log(average # restaurants < 5 miles)	0.018		0.020		-0.020	
	(0.003)		(0.002)		(0.004)	
log(population within 5 miles)		0.018		0.021		-0.024
		(0.003)		(0.003)		(0.005)
R^2	0.27	0.23	0.40	0.35	0.18	0.21

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.

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 $0.06 per order at best. In contrast, shifting from privately to socially optimal fee levels yields a welfare gain of $2.72 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 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 3 but holding

Figure 7: Welfare under two-sided fee regulation



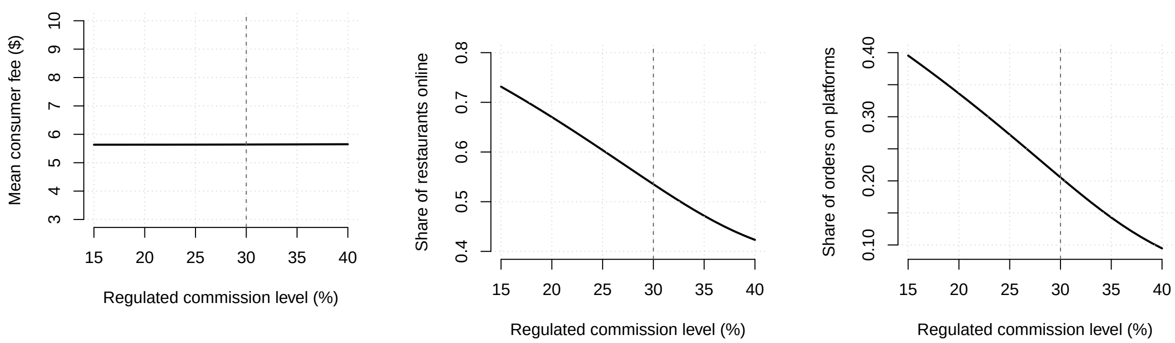
Notes: this figure displays welfare effects of fixing all platforms' commission rates at various levels ranging from 15% to 40% when platforms' consumer fees are fixed at their levels under 30% commission rates. The plot shows welfare results that are aggregated across all counties in the sample and 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.

consumer fees fixed at their levels under 30% commissions. The results, shown in Figure 7, differ markedly 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 $1.81 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 5, holding fixed 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 harm consumers. Consumers do better under two-sided regulation because, as shown by Figure

8, such regulation induces restaurant uptake of platforms and restaurant price reductions without boosting fees. Restaurants do not necessarily gain from two-sided fee regulation because such regulation 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 stemming 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 typical in two-sided markets: lowering fees on one side raises 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. Furthermore, Teh et al. (2023) argue that under high levels of consumer single-homing, entry amplifies competition on the consumer side and lowers consumer fees while raising merchant fees. Wang (2025) 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 to a merger of DoorDash, Uber (which already owns Uber Eats and Postmates), and Grubhub absent an integration of their platforms. Comparing outcomes under the current competitive environment to those under joint profit maximization highlights the effects of pricing competition among platforms.[29]

Table 15a reports average fees that maximize social welfare, that arise in the competitive *status quo* among profit-maximizing platforms, and those that maximize joint platform profits. Compared to the competitive baseline, joint profit maximization raises mean consumer fees by \$2.50 and lowers restaurant commissions by 5.8 p.p. Although this shift moves the division of fees between consumers and restaurants 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 \$3.82 under competition to \$4.44 under joint profit maximization. This higher markup outweighs the more efficient allocation of fees in determining welfare: as Table 15b shows, eliminating competition reduces total welfare by \$0.29 per order in the competitive equilibria. This loss is driven by consumer surplus, which falls by \$0.81 per order. Restaurants, by contrast, benefit from easing platform competition: due to commission reductions, their their profits rise by \$0.36/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 5, restaurants face substantial fixed costs when joining their first platform but much lower incremental costs

[29] Online Appendix Table O.29 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.

when adding a second or third. For example, the average cost of joining Uber Eats is \$1171 for a restaurant not on any platform, compared to an incremental cost of \$581 for one already using DoorDash.

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. But a single firm controlling all platforms faces an incentive to reduce commissions at each platform 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

$$K'_{\tau m}(\mathcal{G}) = \sum_{f \in \mathcal{G}} K_{\tau m}(\{f\}), \tag{17}$$

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 16 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 multi-homing provide supporting evidence of the role played by cost complementarities in shaping the fee effects of competition. When restaurants cannot multi-home, cost complementarities are irrelevant. 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.

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 on average 84% higher than their socially optimal levels because platforms do not appropriately account for consumer benefits generated by restaurant variety. Restaurants, though, largely compete away their benefits from commission reductions.

Although restaurant commissions far exceed 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

Table 15: Effects of joint profit maximization

(a) Fee effects

Quantity	Socially optimal	Privately optimal Competition	Joint max.
Consumer fees ($)	3.00	3.49	5.96
Restaurant commissions (%)	19.2	35.0	29.2
Platform markup ($)	-1.29	3.82	4.44

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

Welfare component	Effect ($/order)
Consumer welfare	-0.81
Restaurant profits	0.36
Platform profits	0.16
Total welfare	-0.29

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 16: Profit-maximizing platform fees under alternative multi-homing assumptions

Quantity	No cost complementarity		No restaurant multi-homing	
	Competition	Joint max.	Competition	Joint max.
Consumer fees ($)	5.70	5.95	5.80	5.81
Restaurant commissions (%)	24.6	26.9	22.9	27.1

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.

effective way of correcting inefficiency in platform fees.

The results suggest subtlety in whether competition remedies fee inefficiencies. Eliminating platform competition 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.

Taken together, the results suggest that the interaction of the division of fees between sides and the overall level of fees is crucial in determining the welfare consequences of market interventions. Reducing the overall level of fees boosts welfare when reductions focus on the restaurant side of the market. However, reducing restaurant commissions without reducing the overall level of fees fails to achieve the welfare gains of simultaneously lowering the fee level and shifting the relative burden of fees toward consumers.

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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 regression

$$\log(p_{ij}) = \psi_j + \psi_{z(i)} + \psi_{t(i)} + \rho_0 \times \text{online}_i + \rho_1 \times r_i + \rho_2 \times (r_i \times \text{online}_i) + \varepsilon_{ij}. \tag{18}$$

Here, i denotes an order placed by a Numerator panelist, j denotes a menu item as identified by Numerator (e.g., "Zaxby's Boneless Wings" or "Subway Turkey Breast Sandwich"), $z(i)$ is the ZIP3 of the consumer who placed the order, and $t(i)$ is the month in which the consumer placed the order. The fixed effects ψ_j capture heterogeneity across menu items whereas $\psi_{z(i)}$ and $\psi_{t(i)}$ capture heterogeneity across regions and time, respectively. I consider online platforms as a single entity rather than modelling prices distinctly for different platforms because restaurants do not generally charge different prices across different platforms. Online Appendix O.3.1 provides evidence of the similarity of menu items' prices across online platforms.

To ensure that the menu items identified by Numerator correspond to unique menu items, I limit the sample to items in which the coefficient of variation of the item's online price and of its offline price in the sample are both under one. To ensure these coefficients of variation are estimated precisely for included items, I further limit the sample to items with at least 100 online orders and 100 offline orders. 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 those most likely to have negotiated commission rates lower than 30% absent commission caps, which would make their prices less sensitive to commission caps.

Table 17 provides estimates from two specifications: one in which r_i 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 1 p.p. increase in the commission rate raises online prices by about 0.69%, with no significant effect on direct order prices. The results from the second suggest that commission caps reduced platform prices by about 9% without significantly impacting direct order prices. The results also suggest that prices on platforms are 0.19 log points (21%) higher than those for direct orders. The final rows of Table 17 report DoorDash-to-direct price ratios predicted by the commission-rate regression. These are 21% for uncapped (30% commission) areas and 9.0% for 15% commission areas.

To obtain additional pricing evidence, I collected supplementary data on prices from platform and

Table 17: Restaurant pricing regressions

Coefficient	Commission level Estimate	SE	Cap indicator Estimate	SE
Online platform	-0.0176	(0.0155)	0.1890	(0.0020)
Commission rate	-0.0091	(0.0084)	-	-
Commission rate × online	0.6940	(0.0532)	-	-
Commission cap	-	-	0.0043	(0.0013)
Commission cap × online	-	-	-0.0934	(0.0080)
Online/offline ratio (30% comm.)	1.210	(0.002)	1.208	(0.002)
Online/offline ratio (15% comm.)	1.090	(0.008)	1.100	(0.009)

Notes: the sample size is $N = 1{,}535{,}913$.

restaurant websites from a random sample of restaurants in December 2022. One advantage of using these data is that they eliminate the need to determine which of the menu items identified by Numerator truly describe a unique menu item. Another advantage is that 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 obtained from the Numerator data analysis in Table 17, 19% and 9%, are 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 details

B.1 Estimation of the consumer choice model

In this appendix, I detail the GMM estimator of the consumer choice model as outlined in Section 5.1. The estimation procedure requires computing consumer choice probabilities that do not have closed forms given the model's multi-dimensional unobserved heterogeneity. Therefore, I approximate the choice probabilities via simulation with 200 draws of unobserved heterogeneity for each consumer.

I now detail the the moment conditions used in estimation. The first set of moment conditions match the model to market-specific platform order counts, specifically counts of orders placed offline ($f = 0$) and of orders placed through each platform f. The moments take the form

$$h^{(\mathrm{i})}_{fm}(\theta; D) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_{if} - y_{if}(\theta)\right). \tag{19}$$

Here, θ is a vector of the consumer choice model parameters and D denotes the dataset of n consumers used in estimation. This dataset includes, for consumer i and ordering outcome f, $\hat{y}_{if}$, the observed number of orders that consumer i placed using f, and $y_{if}(\theta)$, the expected number of orders that consumer i placed using f under the model with parameters θ.

The second set of moments match model-predicted ordering frequencies interacted with consumer demographics to their observed counterparts:

$$h^{(\mathrm{ii})}_{k,\mathrm{platform}}(\theta; D) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_{i,\mathrm{platform}} - y_{i,\mathrm{platform}}(\theta)\right) d_{ik}, \quad h^{(\mathrm{ii})}_{k,\mathrm{offline}}(\theta; D) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_{i,\mathrm{offline}} - y_{i,\mathrm{offline}}(\theta)\right) d_{ik}, \tag{20}$$

where $k \in \{1, 2, 3\}$ and where d_{ik} is the kth component of d_i (which contains indicators for consumer i being under 35 years of age, for being married, and for having an income over \$40,000). Furthermore, the $\hat{y}_{i,\mathrm{platform}}$ and $\hat{y}_{i,\mathrm{offline}}$ are the observed counts of orders that consumer i placed on food delivery platforms and offline whereas $y_{i,\mathrm{platform}}(\theta)$ and $y_{i,\mathrm{offline}}(\theta)$ are the model-implied expectations of these counts.

The next moment condition ensures that the model replicates the share of orders placed at chain restaurants as observed in the data. This moment is

$$h^{(\mathrm{iii})}(\theta; D) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_{i,\mathrm{chain}} - y_{i,\mathrm{chain}}(\theta)\right). \tag{21}$$

Here, $\hat{y}_{i,\mathrm{chain}}$ is the observed number of orders placed at chain restaurants by consumer i whereas $y_{i,\mathrm{chain}}(\theta)$ is the model-implied expected number of chain-restaurant orders.

I now describe moment (iv), the DiD-based moment targeting the fee sensitivity parameter α. I use the Edison ZIP/month/platform-level panel to estimate effects of commission caps via OLS. In estimating impacts on total platform orders, I collapse this dataset to the ZIP/month level. Two distinctions between the regressions of Section 3.4 and those used in constructing moment (iv) are worth noting. First, I enter the commission rate as a continuous treatment. Second, I control for restaurant uptake of platform. By conditioning on a rich set of variables characterizing restaurant adoption, I ensure that my estimates isolate the partial effects of commission caps on fees and sales, holding fixed restaurants' platform adoption decisions. The restaurant adoption controls are the log number of restaurants on each platform and the log number of restaurants on at least one platform within five miles of the focal ZIP. As in the analysis of Section 3.4, I additionally control for variables related to the COVID-19 pandemic.

The outcome variables that I use in the regressions are log sales and log ordering costs, defined as the log average order size inclusive of both restaurant prices and platform fees. The response of this variable to commission caps captures the overall change in the cost to a consumer of ordering on a platform in response to a cap. The sales regression includes ZIP and month fixed effects whereas the ordering cost regression includes fixed effects for ZIP/platform and month/platform interactions.

To simulate the effect of a 15% commission cap on ordering, I construct ordering costs under capped and uncapped regimes using the DiD estimates. The calculation differs for ZIPs with and without a cap in the status quo. Let $\hat{\rho}$ denote the coefficient from the ordering cost DiD regression. For ZIPs without a baseline cap, the ordering cost in the no-cap regime is the observed value whereas the ordering cost under a cap equals this observed cost times $\exp\{-0.15 \times \hat{\rho}\}$, the DiD-implied change from reducing the commission rate by 15 p.p. For ZIPs with a commission cap in the baseline, the ordering cost with a cap is the observed value whereas the counterfactual no-cap cost equals this observed value multiplied by $\exp\{0.15 \times \hat{\rho}\}$. The moment condition is then

$$h^{(\text{iv})}(\theta; D) = \frac{1}{n} \sum_{i=1}^{n} \left(\widehat{\Delta y_{\text{platform}}} - \Delta y_{i,\text{platform}}(\theta) \right),$$

where $\widehat{\Delta y_{\text{platform}}}$ is the DiD estimate of the impact of a 15 p.p. commission reduction on sales and $\Delta y_{i,\text{platform}}(\theta)$ is the reduction in consumer i's expected number of platform orders placed due to the simulated commission cap.

The final group of moments are based on the likelihood of ordering counts across the alternatives of offline ordering and ordering using each platform. Each of these moments is the score of the likelihood with respect to a parameter in the vector $(\sigma_{\zeta 1}, \sigma_{\zeta 2}, \sigma_\eta)$. The likelihood that I use is the likelihood of consumers' sequences of choices between non-ordering, offline ordering, and ordering using each of the four online platforms:

$$\text{Ł}(\theta, Y_n, X_n) = \sum_{i=1}^{n} \log \left(\int \prod_{t=1}^{T_i} \ell(f_{it} \mid x_i, w_{m(i)}, \Xi_i; \theta) \times \prod_{t=T_i+1}^{T} \ell_0(x_i, w_{m(i)}, \Xi_i; \theta) dH(\Xi_i; \theta) \right), \quad (22)$$

where $Y_n = \{f_{it} : 1 \leq t \leq T_i, 1 \leq i \leq n\}$ 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 (ZIP and demographics) and characteristics $w_{m(i)}$ of the consumer's metro area $m(i)$, including fees and prices. The random vector Ξ_i, which is distributed according to H, includes the platform tastes ζ_{if} and restaurant dining tastes η_i. 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.

B.2 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

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

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

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

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

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

where $|\mathcal{G}|$ is the cardinality of set $\mathcal{G}$. 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

$$\frac{1}{n_J}\sum_{j=1}^{n_J} g_{\omega,k}(\mathcal{G}_j, \Pi_j^e, D_j; \hat{\theta}^{\text{adopt}}) = 0, \qquad k \in \{1, 2\}. \tag{24}$$

The estimator $\hat{\theta}^{\text{adopt}}$ solves equations (23) and (24). 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.