Fee Optimality in a Multi-Sided Market*

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Abstract

This article analyzes the efficiency and distributional properties of platform fees in the US food delivery sector. Using a structural model of platform competition estimated on data covering all major delivery platforms, I quantify distortions arising from platform market power, cross-side externalities, and features commonly excluded from canonical models of platform pricing: intra-platform competition, substitution to offline ordering (cannibalization), and platform competition. I find that profit-maximizing platforms' consumer fees are not generally excessive, owing to the fact that a distortion arising from cannibalization largely offsets upward pressure on fees from market power. In contrast, restaurant commissions are nearly twice as high as their welfare-optimal levels. Commission caps improve welfare when set at moderate levels (20–30%) but reduce it at lower levels (e.g., 15%) by raising consumer fees and shrinking the user base that benefits from expanded restaurant variety. Cannibalization explains much of the cross-market variation in the gap between profit-maximizing and welfare-maximizing commission rates. Simulations further show that platform competition tends to reduce consumer fees but raise seller fees, implying that competition does not correct the bias of platform fee structures against merchants.

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1 Introduction

Digital platforms have transformed industries including retail (e.g., Amazon, Alibaba), ride-hailing (Uber), accomodations (AirBnB), advertising (Google), and food delivery (DoorDash). Enabled by advances in information technology, these platforms govern marketplaces that match large numbers of buyers and sellers. Although platforms offer convenience and choice to consumers, merchants often criticize their fee structures as both distributionally unfair and allocatively inefficient. These concerns have surfaced in high-profile lawsuits—including those raised by Epic Games against Apple and Google over app store commissions—as well as in long-standing debates over credit card fees and local municipal efforts to cap food delivery commissions. A key question is not only whether platform fees are too high, but whether they are allocated optimally between consumers and merchants.

Platform fees are central to the functioning—and controversy—of digital markets. Yet evidence on their distributional impacts and efficiency is lacking. This article empirically evaluates whether platform fees disadvantage merchants and reduce social welfare in the context of the US food delivery industry. Leading delivery platforms charge restaurants commissions equal to a share—often around 30%—of sales along with per-transaction fees to consumers. Spurred by restaurant complaints about high commissions, many local governments have imposed commission caps. These policies provide a natural setting to evaluate whether commissions are excessive, both from the perspective of restaurants and from a broader welfare standpoint.

Several competing mechanisms shape the effects of these caps. Lower commissions directly benefit restaurants and encourage more restaurants to join platforms. Although this expands consumer choice, it also raises fixed adoption costs and intensifies competition among restaurants, eroding profits. Commission reductions may also lead restaurants to reduce prices, benefitting consumers but partially offsetting merchants' direct gains from caps. Additionally, depriving platforms of commission revenue may lead them to raise consumer fees, which depresses order volumes. This reduction in sales harms restaurants — unless consumers switch to ordering directly from the restaurant, in which case restaurants avoid paying commissions. Ultimately, the net effects on restaurant profits hinges on the balance of these opposing forces.

From a social efficiency perspective, total platform fees are often excessive due to market power. However, how those fees are divided between consumers and merchants raises more nuanced efficiency questions. Theoretical studies of platform pricing (Weyl 2010, Tan and Wright 2021) indicate that the optimal fee split depends on the structure of cross-side network externalities — i.e., the value users on each side derive from interacting with those on the other. In the food delivery context, network externalities arise because consumers value variety in platforms' restaurant listings and restaurants make more sales on platforms that are popular among consumers. The fees that maximize social welfare fully internalize these network externalities. In contrast, a profit-maximizing platform considers only how fees affect marginal users' decisions to participate, ignoring the welfare of inframarginal users. Although theory suggests scope for network externalities to introduce inefficiencies in platform pricing, there remains no empirical work explicitly estimating these distortions and their welfare effects. This article addresses that gap. It also determines the extent to which features excluded from the canonical model of two-sided model—namely, intra-platform competition among sellers, buyers' ability to transact directly with merchants, and competition between platforms—introduce additional inefficiencies in platform pricing.[1]

To understand the importance of intra-platform competition and offline purchasing, I extend the canonical model to incorporate these aspects of real-world platform markets. In addition to the distortions arising from market power and network externalities, the model features a *cannibalization distortion* that emerges when consumers can buy directly from merchants. A social planner accounts for the fact that higher consumer fees shift demand off-platform, which benefits merchants. A profit-maximizing platform, however, ignores this benefit because it earns no revenue from direct orders. This distortion tends to make profit-maximizing consumer fees inefficiently low.

The model also shows how restaurant commissions can diverge from socially optimal levels. Lower commissions attract more restaurants, boosting platform sales but also generating costs: fixed costs of platform adoption, reduced direct sales, and intensified intra-platform price competition. A social planner accounts for these costs, whereas a profit-maximizing platform does not. This can lead profit-maximizing commissions to be inefficiently low. Market power and distortions arising from network externalities, however, may lead profit-maximizing commissions to be too high. Whether commissions are too high or too low is central to the debate over commission caps, and forms one of the primary empirical questions addressed in this article.

Competition between platforms is another important feature omitted from the canonical model of platform pricing. Although the entry of new platforms is often proposed as a remedy for high fees, its welfare effects are ambiguous. Competitive pressure may focus on the buyer side, leading platforms to lower consumer fees. This benefits consumers, but it puts upward pressure on seller fees as platforms shift margin recovery to the merchant side. As a result, platform competition can intensify distortions that disadvantage merchants even as it improves outcomes for consumers.

To assess the distributional and efficiency effects of regulating platform commissions, I assemble a rich collection of datasets on the US food delivery industry and estimate a structural model of platform competition. The primary dataset is a panel of consumer restaurant orders, which includes ZIP-code-level consumer locations and item-level pricing information. I supplement this with comprehensive data on all restaurants listed across major delivery platforms, as well as scraped data from platform websites that capture order availability, platform fees, and estimated delivery times. Together, these sources provide detailed information on pricing, platform participation, and delivery conditions for hundreds of thousands of potential orders across 14 large US metropolitan areas. I use the data to compute difference-in-differences estimates based on the staggered rollout of commission caps that confirm many of the responses outlined in the theoretical discussion: caps raise consumer fees and reduce platform orders, but also increase restaurant participation and shift some demand to direct-from-restaurant ordering.

The structural model has four stages. In the first stage, platforms set restaurant commissions

[1] I use the terms two-sided, multi-sided, and platform markets interchangeably.

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). After joining platforms, restaurants set profit-maximizing prices, which may differ between platform and direct-from-restaurant orders. Finally, consumers decide whether to order a restaurant meal, which nearby restaurant to order from, and whether to use a platform in doing so. The model captures the interdependence between consumer and restaurant platform choices: consumers prefer platforms with broader restaurant availability, while restaurants benefit more from joining platforms with high consumer usage. Heterogeneous consumer preferences over platforms govern substitution patterns between platforms and direct ordering.

Estimation proceeds in steps. I first estimate consumer preferences using maximum likelihood, recovering parameters that govern price sensitivity, preferences for restaurant variety, and substitution patterns. I then recover restaurant and platform marginal costs from first-order conditions for optimal pricing. Next, I estimate the restaurant adoption model via the generalized method of moments (GMM), selecting adoption cost parameters to match (i) market-specific platform adoption rates and (ii) the covariance between expected profitability and adoption decisions. Identification of price sensitivity and network effects is complicated by the endogeneity of platform fees and restaurant networks, which reflect unobserved consumer tastes. I address this by using platform–metro-area fixed effects and exploiting within-city variation in fees and restaurant presence — variation driven in part by commission cap policies. To estimate substitution patterns, I leverage the panel structure of the data, which traces how consumers switch among ordering options. The estimated model fits key empirical patterns well, including the relationships between platform adoption, platform sales, and local demographics. It also reproduces estimates of commission cap effects consistent with those obtained in the difference-in-differences analysis.

Using the estimated model, I conduct two sets of analyses. The first evaluates commission-cap-style regulations that fix platforms' restaurant commission rates while allowing platforms to re-optimize consumer fees. I find that caps set at 15%—the most common level in practice—reduce aggregate welfare. These losses are primarily driven by increases in consumer fees: in response to the cap, platforms shift the burden to consumers, depressing order volumes below efficient levels. As intended, 15% commission caps benefit restaurants. But restaurant responses largely counteract this benefit: about 77% of restaurants' direct gains from commission reductions are eroded in equilibrium by fixed costs of platform adoption and intensified price competition. In effect, restaurants compete away most of their gains from caps.

Not all caps reduce welfare. Less stringent caps—those in the 20–30% range—raise total welfare. Although moderate reductions in commissions lead platforms to raise consumer fees, they also draw more restaurants onto platforms and reduce restaurant prices. These effects more than offset the consumer welfare losses from higher fees, resulting in gains for both consumers and restaurants. In the sense that commission reductions that prompt consumer fee hikes can raise total welfare, platforms' fee structures are indeed biased against merchants.

An analysis of cross-market heterogeneity in the welfare effects of commission regulation establishes that cannibalization of direct ordering is a key reason why fee structures are biased against merchants. Indeed, the degree to which platform sales displace direct-from-restaurant orders is the market characteristic that best explains the extent to which commissions maximizing platform profits depart from those maximizing aggregate welfare. Commission reductions lead to increased consumer fees, prompting some consumers to switch to offline ordering. This switching mitigates the reduction in restaurant sales that would otherwise result from high consumer fees. The effect is particularly strong in high-cannibalization markets, making commission reductions more welfare-enhancing in these markets. This result establishes the empirical relevance of cannibalization as a determinant of optimal platform pricing — an important feature omitted from canonical models of two-sided pricing.

Although moderate commission reductions can raise total welfare, the gains are modest compared to those achieved by regulations that also cap consumer fees. Whereas commission reductions alone can yield total welfare improvements of about \$0.10 per order, simultaneously capping consumer fees at their baseline level and reducing commissions to the point where platforms earn zero variable profits generates welfare gains of \$2.30 per order. This result reflects two forces. First, regulating overall platform market power yields larger efficiency gains than adjusting the balance of fees between consumers and merchants. Second, the benefits of expanding restaurant participation are greatest when consumer fees are low, as a large consumer base is then available to enjoy the added restaurant variety effected by reduced commissions.

Bias in platform fees can alternatively be defined as the discrepancy in split between consumers and merchant charges between the fees that maximize total welfare (socially optimal fees) and those that emerge in competitive equilibrium among profit-maximizing platforms (privately optimal fees). I assess this form of bias by computing and comparing these two sets of fees. This comparison highlights structural sources of inefficiency in platform pricing and yields a benchmark for fee optimality. Although privately optimal fees exceed their socially optimal levels on both sides of the market, the deviation is much larger for restaurant commissions — consumer fees are slightly excessive on average (by \$0.29), whereas restaurant commissions are, on average, nearly twice as high as those that maximize social welfare. This asymmetry reflects the interaction of opposing forces. Market power drives consumer fees above their efficient level, but this is largely offset by cannibalization: profit-maximizing platforms ignore the benefits to merchants of steering consumers toward offline ordering via high consumer fees. Additionally, the net distortions from network externalities are small. As a result, the socially optimal consumer fee ends up close to the profit-maximizing one. By contrast, there is a substantial welfare value in reducing restaurant commissions, which encourages merchant participation and thus expands consumer choice. Although consumers benefit from expanded restaurant variety under reduced commissions, restaurants capture little of the total welfare gain. The resulting rise in platform adoption entails significant fixed costs and intensifies intra-platform competition — effects that largely neutralize restaurants' direct benefits from lower commissions.

Last, I examine how privately and socially optimal platform fees vary with the degree of platform competition by simulating an alternative regime in which DoorDash—the largest food delivery platform—operates as a monopolist. In this scenario, consumer fees increase by \$1.88 per order, while restaurant commissions fall by 7.21 percentage points. This result reinforces the theoretical prediction that platform competition, by focusing rivalry on the consumer side, can distort fee incidence in ways that favour buyers but impose greater burdens on sellers.

Taken together, the results underscore the importance of accounting for features of real-world platform markets that have henceforth been de-emphasized in models of platform pricing. Although market power and network externalities remain central determinants of inefficiency, distortions arising from cannibalization, intra-platform competition, and platform competition significantly shape both optimal pricing and the welfare effects of regulation.

1.1 Related literature

This article's main contribution is to estimate fee distortions arising in a real-world two-sided market. In doing so, it brings empirical evidence to bear on a literature pioneered by Rochet and Tirole (2003), Armstrong (2006), and Rochet and Tirole (2006) that characterizes profit-maximizing and total-welfare-maximizing platform fees.[2] The first part of my contribution is to quantify distortions leading fees to diverge from socially optimal levels as identified by Weyl (2010) and Tan and Wright (2021), which arise from market power and network externalities. The second is to identify and quantify additional distortions stemming from features excluded from the canonical model of platform pricing — namely, intra-platform competition among sellers, consumers' ability to substitute to direct ordering, and competition between platforms. I identify distortions associated with these features in a stylized extension of the canonical model and quantify them using a structural model estimated on data from the US food delivery industry. The stylized model embeds the insight of Wang and Wright (2024)—that profit-maximizing fees are distorted when platforms fail to account for merchants' off-platform sales—into the framework of Rochet and Tirole (2006) and Weyl (2010). Empirically, I find that seller competition, online/offline substitution, and competition among platforms each materially affect both the nature of pricing distortions and the welfare impacts of fee regulations.

As a related contribution, the article analyzes food delivery commission caps as a case study in platform regulation — their effects, the mechanisms by which they act, and the factors that determine their success. Many empirical analyses of platform regulation have focused on payment card fee regulation — see Rysman (2007), Carbó-Valverde et al. (2016), Huynh et al. (2022), Wang (2023), Evans et al. (2015), Manuszak and Wozniak (2017), Kay et al. (2018), Wang (2012), Chang et al. (2005), and Li et al. (2020). Outside the payment card context, there exists little empirical analysis of fee regulation. Economic research on commission caps in food delivery is, to the best of my knowledge, imited to Li and Wang (2021), who study effects on ordering and fees using difference-in-difference methods. I complement their work by estimating effects on additional outcomes—including consumer ordering and restaurants' platform uptake—and by assessing the implications of commission caps for welfare.

Last, this article contributes to an empirical literature on digital platforms and their effects on

[2] Rysman (2009) and Jullien et al. (2021) provide overviews of this literature.

established industries. Prior work has examined ride-hailing (Castillo 2022, Rosaia 2020, Buchholz et al. 2020, Gaineddenova 2022), short-term accomodations (Calder-Wang 2022, Schaefer and Tran (2020), Farronato and Fradkin (2022)), and entertainment and media (Kaiser and Wright 2006, Argentesi and Filistrucchi 2007, Fan 2013, Lee 2013, Sokullu 2016, Ivaldi and Zhang 2020), among other sectors (Jin and Rysman 2015, Farronato et al. 2020, Cao et al. 2021). Work on the food delivery industry remains relatively limited (Natan 2022, Chen et al. 2022, Lu et al. 2021, Feldman et al. 2022, Reshef 2020). This article adds to the literature by showing that merchants' competitive responses to platform regulation may significantly limit merchants' benefits from regulation.

2 Illustrative model

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

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

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

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

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

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

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

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

Here, S_0 are total first-party restaurant sales, which I assume depend on online sales and the number of sellers that adopt the platform. Also, $\bar{\kappa}_1$ is the average marginal cost among the first

J restaurants to join the platform and K is the fixed cost of platform membership.

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

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

where $\mu_B = -S_1/(\partial S_1/\partial c)$ is the inverse semi-elasticity of consumer demand—a measure of buyer-side market power—and $\tilde{b}_S = d(rp_1 S_1)/dS_1$ is the effect of additional platform ordering by consumers on the platform's commission revenue from restaurants. By contrast, the consumer fees maximizing social welfare satisfy

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

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

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

This equation shows that, although market power μ_B^{pr} tends to raise the privately optimal consumer fee above socially optimal levels, the *cannibalization distortion* has the opposite effect, offsetting market power. The equation also features the Spence and displacement distortions that result from network externalities (Weyl 2010, Tan and Wright 2021). The Spence distortion reflects that a social planner internalizes the benefits of attracting new buyers to platform sellers ($\bar{b}_S$) when setting its consumer fee, whereas a profit-maximizing platform internalizes only the benefits for marginal sellers, given that it is these sellers who determine the extent $\tilde{b}_S$ to which the seller earns more seller-side revenue by attracting more buyers.[3] Marginal platform users typically benefit less from interactions with agents on the other side than do inframarginal users, which suggests a positive Spence distortion. As noted by Tan and Wright (2021), however, profit-maximizing platforms' 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 $\tilde{b}^{\text{so}} < \tilde{b}_S^{\text{pr}}$. The resulting *displacement distortion* tends to offset the Spence distortion.[4]

[3] When sellers steal business from each other, as in the model presented here, each seller's uptake decision is a best response to other sellers' decisions. I sidestep this complication by specifying a reduced-form adoption function $J(r, S)$. However, this reduced-form approach does not yield the result in Weyl (2010) for a model without between-seller competition that the impact $\tilde{b}_S$ of platform orders on the platform's seller-side revenue equals the marginal seller's benefit from a platform interaction. However, $\tilde{b}_S$ still depends on S_1's impact on merchants' platform adoption and hence on marginal merchants' benefits from platform sales.

[4] The Spence and displacement of Weyl (2010) and Tan and Wright (2021) include the derivative $\tilde{b}_S$ of seller-side fee revenue with respect to buyer-side participation. In the canonical model that they study, this derivative equals the marginal seller's benefit from an on-platform interaction with a buyer. This interpretation does not exactly hold in my model due to the introduction of competition among sellers, as noted in the preceding footnote.

Despite the attention received by Spence and displacement distortions in the literature on two-sided market pricing, no empirical research quantifies them in a real-world platform market to confirm their relevance. In the article's empirical analysis, I will quantify each of the distortions in (2) and analyze their implications for platform fee regulation.

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

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

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

$$\bar{b}_B^{\text{so}} S_1^{\text{so}} = K + (\bar{\kappa}')^{\text{so}} S_1^{\text{so}} - a \left(\frac{\partial S_0}{\partial J} \right)^{\text{so}}, \tag{4}$$

where $\bar{b}_B$ is the average consumer valuation of an additional platform seller.[5] Equation (3) implies that a profit-maximizing platform equalizes the benefits to marginal consumers of an additional restaurant ($\tilde{b}^{\text{pr}}$) with commission revenue losses required to attract a restaurant when assessing a commission reduction. In contrast, equation (4) implies that a social planner compares the total benefit $\bar{b}_B^{\text{so}} S_1^{\text{so}}$ to consumers of an additional restaurant with the social costs of increased platform membership: increased fixed costs of platform adoption K, increased marginal costs of platform sales $(\bar{\kappa}')^{\text{so}} S_1^{\text{so}}$, and lost restaurant revenues from offline sales $-a({}^{\partial S_0}/_{\partial J})^{\text{so}}$. Although (3) and (4) do not yield a decomposition of distortions à la equation(2), they do indicate sources of inefficiency in profit-maximizing platforms' commissions. First, equation (3) implies that market power μ_S^{pr} tends to raise profit-maximizing commissions,. Second, the profit-maximizing platform does not take into account the costs K and $(\bar{\kappa}')^{\text{so}} S_1^{\text{so}}$ of restaurants' platform adoption and may charge commissions that are too low as a consequence. The profit-maximizing platform also does not account for merchants' losses in offline revenue $-a({}^{S_0}/_{J})^{\text{so}}$ from merchant platform adoption, which similarly lowers profit-maximizing commissions relative to the socially optimal benchmark. Last, when $\tilde{b}_B^{\text{pr}}$ is lower than $\bar{b}^{\text{so}}$ due to Spence and displacement distortions, commissions will tend to be too high. The question of which of these effects dominate to determine whether profit-maximizing commissions are socially excessive or insufficient is an empirical question that I address in this article.

Comparison to literature The model's primary deviation from the canonical model of Rochet and Tirole (2006) is the introduction of competition between sellers. In the canonical model, each seller interacts with each buyer on the platform, and hence the entry of a new seller does not affect any incumbent seller's sales. The model presented above introduces business stealing: merchants share the S_1 sales made on the platform. This modelling change introduces the possibility for socially excessive entry in the spirit of Mankiw and Whinston (1986). Here, platform adoption may be socially excessive because merchants join platforms in part to steal business from rival restaurants rather than creating value for consumers while incurring fixed

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

costs from platform adoption. The social planner accounts for these fixed costs 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 inefficient platform adoption by merchants.

The introduction of business stealing also makes the cannibalization distortion relevant. 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, the seller completely internalizes the impact of its platform. sales on its direct sales. In contrast, a key motivation for merchants to join platforms in many real-world platform markets is to steal offline business from rival restaurants. When a merchant's online sales subtract from rivals' direct sales, a merchant's platform membership imposes a negative contractual externality on rivals (Segal 1999, Gomes and Mantovani 2025). The cannibalization distortion reflects this externality, which may be corrected by an increased consumer fee that steers consumers back toward direct ordering. Wang and Wright (2024) identify a similar pricing distortion arising from cannibalization in a model in which platforms charge fees only to merchants, and propose fee regulation that neutralizes this distortion.

The article's main model will not capture one notable explanation for a bias in platform fees against sellers: merchant internalization. This phenomenon, as identified by Wright (2012), arises when merchants consider the average surplus that consumers enjoy from using a platform above any consumer-side platform fees when choosing whether to join the platform. Merchant internalization, although possibly relevant in food delivery, does not arise in this article's model because this model features restaurants that consider demand for platforms among consumers but not the surplus of inframarginal consumers when choosing whether to join platforms.

Role of platform competition The illustrative model presented above features a monopolist platform, and thus does not speak directly to the role of platform competition in shaping the gap between privately and socially optimal platform fees. Recent research, however, indicates factors that determine how platform entry affects the balance of platform fees between buyers and sellers. Teh et al. (2023) establish how the impact of platform entry on this balance depends on the extent to which entry intensifies competition over buyers vis-à-vis competition over sellers. The effects of entry on competition over each side of the market in turn depend on entry's impact on the elasticities of residual demand faced by platforms—which drives the impact of entry on buyer-side competition—and on the substitutability of platforms from buyers' perspective—which drives the impact of entry on seller-side competition. One contribution of my article will be to estimate the model primitives that determine how competition affects fees, and use these estimates to understand whether competition shifts the balance of buyer and seller fees toward or away from the socially optimal balance.

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 both consumers and restaurants. 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. Throughout this article, I take it that the commission rates for all leading platforms were 30% in areas without caps — 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—while proportional fees can help curb 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.1 discusses these mechanisms in detail. For tractability and focus, I specify a purely fixed consumer fee in the article's model. This avoids complicating the analysis of fee allocation between the two sides—the article's central concern—with fee structure within each side. Moreover, it was platform fixed fees that responded to commission regulation in practice; modelling fixed fee responses is therefore a way to match the empirical reality.

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 multihome (i.e., use multiple platforms). As described by Online Appendix Table O.7. over half of restaurants on DoorDash belong to Uber Eats. Furthermore, consumers sometimes switch between platforms across orders.

I abstract away from some features of the US food delivery industry due to data limitations and

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

[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 (2021) for a study of nonconsensual listing.

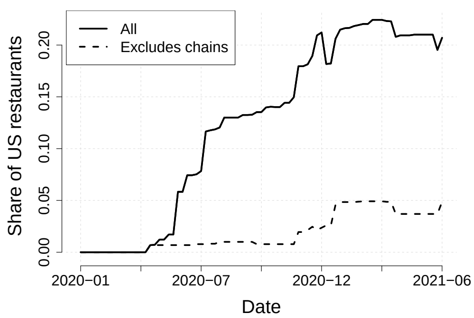
in order to focus on aspects of greater importance in shaping the effects of commission caps. Although I focus on consumers and restaurants, delivery orders also involve couriers. I do not explicitly model couriers, and instead specify platform marginal costs of fulfilling deliveries that capture courier compensation.[8]

Additionally, some platforms offer subscription plans that allow users to pay fixed fees to reduce per-transaction delivery fees. Given that these plans do not reduce regulatory response fees that platforms added in response to caps, their importance is not likely first order and I abstract away from them. I also abstract away from the recommendation and search algorithms that delivery platforms use to direct consumers toward restaurants, focusing instead on platform pricing decisions.

Many local governments introduced commission caps in a staggered fashion after the beginning of the COVID-19 pandemic. Figure 1 displays the share of the US restaurants located in a jurisdiction subject to a cap. Over 70 local governments representing about 60 million people had enacted commission caps by June 2021. Most caps—78% of those introduced before 2022—limited commissions to 15%, although some limited commissions to other levels between 10% and 20%. The first caps were introduced as temporary measures, but several jurisdictions later made their caps permanent.[9] Some commission caps (19% of those introduced before 2022) excluded chain restaurants; the dotted curve in Figure 1 shows the share of US restaurants subject to such caps. I take these caps' exemption of chains into account in estimating the article's model, although I focus on the more popular form of cap that does not exempt chains in the counterfactual analysis.

Online Appendix Figure O.2 plots the average fees and commission charges over time. Commission revenue consistently exceeded consumer fee revenue in places without caps, but the disparity in consumers and restaurant charges contracted in placed with caps.

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



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

[9]These include San Francisco, New York, and Minneapolis. Platforms sued San Francisco and New York City in response to their permanent 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. The demographic composition of Numerator's core panel is close to that of the US adult population as measured with census data. In addition, market shares computed from these data are similar to those computed from an external dataset of payment card transactions; see Online Appendix O.6 for details. The market definition that I use throughout this article is a metropolitan area, formally a Core-Based Statistical Area (CBSA). I focus on the fourteen large metro areas for which I have detailed fee data — those of 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.

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 (before fees, tips, and taxes), delivery fees, service fees, taxes, and tips. I use these estimates in the DiD analysis.

Platform adoption I obtain data on restaurants' platform adoption decisions from the data provider YipitData. These data record all US restaurants listed on each major platform in each month from January 2020 to May 2021.[12] I obtain data on offline-only restaurants from Data Axle, which provides dataset of a comprehensive listing of US business locations for 2021. In the 14 large metros on which I focus, there were 69,245 restaurants belonging to chains with at least 100 US locations and 354,614 independent restaurants in 2021.

Platform pricing I collect data on platform fees in 2021. My procedure for collecting these data involves drawing from the set of restaurants in a ZIP and inquiring about terms of a delivery to an address in the ZIP for ZIPs in the 14 metros listed above. The address is obtained by reverse geocoding the coordinates of the ZIP's centre into a street address. Other variables that I record include time of delivery, delivery address, restaurant characteristics, and estimated

[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.

[12] Note that I estimate my consumer choice model on data from Q2 2021. Because I do not have data on restaurant platform adoption decisions in June 2021, I use the May 2021 platform adoption data for both May 2021 and June 2021.

waiting time. I followed an analogous procedure to collect data on service fees and regulatory response fees; this procedure involves entering a delivery address near the centre of a ZIPs, randomly choosing a restaurant from the landing page displayed after entering this address, and inquiring about terms of a delivery from the restaurant.

The fee data that I collect provide the basis of the consumer fee indices c_{fz} that I use in estimating the structural model. These indices, which vary across platforms f and ZIPs z, are sums of (i) hedonic indices of platforms' 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 local platform regulations. Online Appendix O.3 provides details on the computation of these indices.

I construct a dataset of commission caps including start and end dates based on a review of news articles. The dataset includes 72 caps active in March 2021. Last, I use demographic data from the American Community Survey (ACS, 2014–2019 estimates).

3.3 Restaurant prices

I collected supplementary data on restaurant prices from platform and restaurant websites in December 2022 with the goal of measuring differences in restaurants' prices for direct and for platform orders. To do so, I randomly selected restaurants in various municipalities in the greater New York City metropolitan area: New York, NY (90 restaurants); Hoboken, NJ (10 restaurants); and Bridgeport, New Haven, Hartford, and Stamford, CT (50 restaurants). In doing so, I limited the universe of restaurants from which I selected the sample to those that belonged to at least one of the leading four food delivery platforms. Whereas Hoboken had a commission cap of 15% and New York had a commission cap of 20%, none of the Connecticut municipalities had a commission cap. For each restaurant, I chose a menu item on the restaurant's website and recorded its price on the website. I then determined the price of the same menu item on the restaurant's listing on each food delivery platform to which the restaurant belonged. Let y_{jf} be the ratio of restaurant j's price on platform f to its direct order price. I run the following regression:

$$y_{jf} = \alpha + \beta r_j + \varepsilon_{jf}, \tag{5}$$

where r_j is the commission cap applying to restaurant j, or $r_j = 0.30$ for restaurants j in areas without commission caps (i.e., Connecticut). Here, the parameter α governs the extent to which restaurants charge different prices on platforms than for direct orders independently of the commission level whereas r_j controls pass-through of commissions into platform prices.

Table 1 reports the results of the regression. The bottom two rows of the table show the predicted ratios of platform to direct restaurant prices implied by the regression. The results suggest that a restaurants partially pass through platform commissions into their online prices: a restaurant facing 15% commissions is predicted to charge 3% higher prices on platforms than for direct orders, whereas a restaurant facing 30% commissions is predicted to charge 13% higher prices on platforms.

I use the results reported in Table 1 to construct the restaurant price indices used in the struc-

Table 1: Restaurant prices and commission rates

Parameter	Estimate
α	0.93
	(0.048)
β	0.67
	(0.168)
$\hat{y}_{jf}(r_j = 0.15)$	1.03
$\hat{y}_{jf}(r_j = 0.30)$	1.13

Notes: this table reports results from a regression based on equation (5) as estimated on the restaurant/platform-level panel described in the main text. The $\hat{y}_{jf}(r_j = 0.15)$ row provides the predicted ratio of platform to direct prices under 15% commissions. The $\hat{y}_{jf}(r_j = 0.30)$ row provides the predicted ratio of platform to direct prices under 30% commissions. Classical asymptotic standard errors are reported in parentheses.

tural analysis. In particular, I compute the mean dollar value of a direct-from-restaurant order in each metro m (before taxes, tips, and fees), call it p_m^{off}, and then compute the corresponding online price in ZIP z in market m as $p_z^{\text{on}} = p_m^{\text{off}} \times \hat{y}_{jf}(r_z)$, where $\hat{y}_{jf}(r_z)$ is the predicted ratio of the platform to direct prices in a ZIP with commission cap equal to r_z. Given that the leading platforms advertised commission rates of 30% in the sample period, I assign $r_z = 0.30$ in areas without caps. I use p_m^{off} as the price of a restaurant meal for direct-from-restaurant orders and p_z^{on} as the price of a restaurant meal as ordered on a platform in the structural analysis.

3.4 Effects of commission caps

In a companion article, Sullivan (2024), I estimate the effects of 15% commission caps where they were enacted using difference-in-differences methods. To summarize, the estimates suggest that these caps raised consumer fees by 7–20% across platforms, lowered platform sales by 7%, and raised the share of restaurants adopting at least one platform by 3.9 percentage points. The estimates in Sullivan (2024) also suggest that the increase in direct-from-restaurant sales owing to commission caps mostly offset lost sales on platforms. These estimates are all consistent with the responses to commission caps hypothesized in the introduction.

4 Model

4.1 Summary of model

To analyze the welfare properties of platform fees, I develop a model of platform competition featuring network externalities, onlline/offline substitution, and competition among platform sellers. Competition in each metro area m is a separate game played by platforms and restaurants. The model's treatment of platforms is detailed whereas its treatment of restaurants is stylized — restaurants systematically differ only in their location (ZIP z) and type (chain versus independent). Each platform, though, has fees, restaurant networks, waiting times, and consumer demand shocks that vary richly across geography. When it comes to estimation, I match consumers' choices of platforms rather than restaurants. Further, I use detailed platform-specific fee data but restaurant price indices that apply to types of restaurants rather than individual establishments.

The model has four stages. In the first stage, platforms choose commission rates to maximize profits. Restaurants subsequently join platforms. Upon joining platforms, restaurants set prices. Platforms concurrently set their consumer fees. Last, consumers choose what to eat. I specify that platforms set commissions first because, in practice, they advertise commission rates to restaurants considering membership. Platforms often change their fees after restaurants have joined platforms — this underlies the assumption that platforms set consumer fees after restaurants join platforms.

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

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

4.2 Consumer choice

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

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

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

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

where d_i are observable consumer characteristics including indicators for age under 35 years, for being married, and for having a household income above \$40k.[13] The prices p_{jf} that I take to the data are hedonic price indices capturing systematic variation in restaurant prices across platforms, restaurant types, and geography; see Section 5 for details.

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

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

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

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

where $\zeta_i^\dagger \sim N(0, \sigma_{\zeta 1}^2)$ and $\tilde{\zeta}_{if} \sim N(0, \sigma_{\zeta 2}^2)$ independently of all else. Here, $\zeta_i^\dagger$ governs tastes for the online ordering channel in general whereas $\tilde{\zeta}_{if}$ governs tastes for particular platforms f. The σ scale parameters govern substitution patterns. As $\sigma_{\zeta 1}^2$ grows large, e.g., consumers become polarized in their tastes for food delivery platforms. This reduces the substitutability of platform ordering and direct ordering.

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

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

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

4.3 Restaurant pricing

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

Formally, let $p_{jf}^*(\mathcal{G}_j, \mathcal{J}_{m,-j})$ denote the equilibrium price set by restaurant j on platform f when $\mathcal{J}_{m,-j}$ denotes the platform adoption choices of all restaurants in metro m except j. Equilibrium prices solve

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

where κ_{jf} is restaurant j's marginal cost of fulfilling an order on platform f, p_{-j} are other restaurants' prices, and $S_{jf} = S_{jf}(\mathcal{J}_m, p_j, p_{-j}^*)$ (arguments omitted above for brevity) are restaurant j's sales on platform f.[14] The parameter ϑ governs the extent to which restaurants internalize

[13] I find that age and martial status are the consumer characteristics that best predict usage of food delivery platforms. See Online Appendix Figure O.4.

[14] Online Appendix O.8 provides an expression for sales S_{jf}.

platforms' commission charges in their pricing decisions. When $\vartheta = 1$, restaurants fully internalize commissions and set prices to maximize their profits. When $\vartheta = 0$, restaurants set prices that maximize the profits they would earn absent commission charges.

Incomplete internalization of commissions has several explanations. The main explanation is that restaurants suffer from gaps between first-party and platform prices that arise on account of commissions. Restaurants may seek to avoid such gaps because food delivery platforms encourage restaurants to set prices on their platforms that are similar to those that these restaurants charge for first-party orders. 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." On the same page, DoorDash noted that visibility within its platform depended the extent of price differences between DoorDash and first-party orders.[15] Another explanation for restaurants to avoid gaps between first-party and platform prices is that—as suggested by research in behavioural marketing—consumers tend to find a gap between online and offline prices unfair. Thus, a restaurant that charges higher prices on delivery platforms may lose consumer goodwill and thus profit. Online Appendix O.2 discusses evidence relating to consumer sentiment on online/offline price gaps within a firm. Last, consumers may be unaware that restaurants charge higher prices on delivery platforms and incorrectly infer that the restaurant's first-party prices are as high as their delivery platform prices, thus depressing interest in first-party ordering among such consumers who read the platform's menu on a delivery platform.

An alternative way to model restaurant aversion to gaps between first-party and platform prices is to add a penalty of the form $\vartheta \sum_f (p_{jf} - p_{j0})^2$ for such gaps to the objective function in equation (6). Although I experimented with this approach, I decided against it for two main reasons. First, this objective function does a worse job of capturing reasons other than valuing parity for restaurants to incompletely respond to commissions. These alternative reasons include a lack of restaurant sophistication in pricing. Second, a model with quadratic penalties for deviations between platform prices and first-party prices predicts that platform membership should increase restaurants' offline prices and that that commission caps should lower the offline prices of restaurants that belong to platforms. I failed to find empirical support for these responses.

The multi-sided markets literature—e.g., Rochet and Tirole (2006)—recognizes that transfers between platform users can render the division of platform fees/commissions between sides of the market irrelevant, a situation known as price structure neutrality. That neutrality does not arise here follows primarily from the fact that the adjustment of restaurants' prices on platforms due to changes in platform fees is limited by the presence of non-parity penalties. Additionally, the presence of fixed consumer fees in addition to proportional restaurant commissions also gives rise to non-neutrality, although non-parity penalties alone are sufficient for non-neutrality. See Online Appendix O.2 for additional discussion of this point.

[15]See here: `https://help.doordash.com/merchants/s/article/How-to-Maximize-Visibility-and-Order-Volume-on-DoorDa` `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`.

4.4 Restaurants' platform adoption choice

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

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

The expectation in (7) is taken over rivals' platform adoption decisions $\mathcal{J}_{m,-j}$, which are unknown to restaurant j when it chooses which platforms to join. 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} and fees c_{fz} 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 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 my estimated parameters.[16]

[16] In each metro area, I compute equilibria using the algorithm outlined in Online Appendix O.11 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.

I specify restaurants' platform adoption disturbances as

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

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

My use of a Seim (2006) positioning game is justified by the facts that (i) equilibria of the game are easier to find than Nash equilibria in complete information games and (ii) complete information entry games suffer from problems related to multiplicity of Nash equilibria reflecting non-uniqueness in the identities of players that take particular actions. These problems do not arise in my model. One critique of Seim (2006)-style positioning models is that they give rise to *ex post* regret: after players realize their actions, some players would generally like to change their actions in response to other players' actions. This is not a considerable problem here because the large number of restaurants leaves little uncertainty in restaurant payoffs.[17]

4.5 Platform fee setting

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

Platform f's expected profits are

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

where s_{fz} are platform f's sales in ZIP z and $r_{fz} = \min\{r_{fm}, \bar{r}_z\}$. Here, $\bar{r}_z$ is the commission cap level in ZIP z and $\bar{r}_z = \infty$ in ZIPs z without caps. The quantity $\bar{p}^*_{fz}$ is the sales-weighted average price charged by a restaurant for a sale on f in ZIP z. Each platform f's profits in a ZIP z depend on its marginal costs mc_{fz}, which represent compensation to couriers. Platform marginal costs may vary across locations due to cross-regional differences in local 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.

[17] 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. This suggests that for a large number of restaurants, the integrand in the definition of $\bar{\Pi}_j$ is approximately constant across $\mathcal{J}_{m,-j}$ draws, thus leaving little scope for ex post regret.

5 Estimation

5.1 Estimation of the consumer choice model

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

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

where n is the sample size, $Y_n = \{f_{it} : 1 \leq t \leq T_i, 1 \leq i \leq n\}$ 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 (age, martial status, and income) and characteristics $w_{m(i)}$ of the consumer's metro area $m(i)$, including fees, waiting times, and prices. The restaurant price measures that I use are hedonic price indices that capture systematic variation in the price of a menu item across platforms, restaurant types, and geography. The random vector Ξ_i, which is distributed according to H, includes the platform tastes ζ_i, restaurant dining tastes η_i, and restaurant-type tastes $\tilde{\phi}_{i\tau}$. Additionally, $\ell(f \mid x, \Xi; \theta)$ is the conditional probability that a consumer orders using f (either a platform or $f = 0$, the direct-from-restaurant option) whereas $\ell_0(x, \Xi; \theta)$ is the conditional probability that the consumer does not place an order. Online Appendix O.8 provides expressions for ℓ and ℓ_0.

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

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

The panel structure of my data permits the identification of the scale parameters $\sigma_{\zeta 1}$, $\sigma_{\zeta 2}$, and

σ_η governing heterogeneity in consumer tastes for platforms and restaurant dining. Recall that consumer i's persistent unobserved tastes for platform f are $\zeta_{if} = \zeta_i^\dagger + \tilde{\zeta}_{if}$, where $\zeta_i^\dagger \sim N(0, \sigma_{\zeta 1}^2)$ 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 highly polarized in their tastes for individual platforms. This leads consumers to repeatedly choose the same food delivery platform when using a platform to order a meal. Conversely, when $\sigma_{\zeta 2}$ is low, consumers do not have strong idiosyncratic preferences for platforms, and are more likely to switch between platforms. Thus, repetition in platform choice is informative about the value of $\sigma_{\zeta 2}$. 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 alternative explanation for persistence in ordering. Another potential problem is that identification of substitution patterns relies on the assumption that consumer tastes ζ_{if} are stable across orders, which may not have held during 2021 when the food delivery industry was quickly evolving due to the COVID-19 pandemic. If instead consumers' 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.

Market size. The model yields predictions of sales given counts of consumers in each ZIP. I set the number of consumers in each ZIP so that the model implies platform sales equal to overall sales. Appendix B explains this procedure.

5.2 Estimation of restaurant pricing model

Recall that a restaurant j belonging to the platforms $\mathcal{G}_j$ sets its prices to maximize

$$\sum_{f \in \mathcal{G}_j} \left[(1 - \vartheta r_f) p_{jf} - \kappa_{jf}\right] S_{jf}(\mathcal{J}_m, p), \tag{13}$$

where S_{jf} are restaurant j's sales on platform f, $\mathcal{J}_m$ are the platform adoption decisions of all restaurants in market m, and p contains all restaurant prices. For expositional convenience, I introduce $r_0 = 0$ as the commission rate for direct-from-restaurant orders. When where $\mathcal{G}_j = \{f_1, \ldots, f_k\}$, the restaurant's pricing first-order condition is

$$\underbrace{\begin{bmatrix} (1-\vartheta r_{f_1}) S_{jf_1} \\ \vdots \\ (1-\vartheta r_{f_k}) S_{jf_k} \end{bmatrix}}_{=\tilde{S}_j(\vartheta)} + \underbrace{\begin{bmatrix} \frac{\partial S_{jf_1}}{\partial p_{jf_1}} & \frac{\partial S_{jf_2}}{\partial p_{jf_1}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_1}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial S_{jf_1}}{\partial p_{jf_k}} & \frac{\partial S_{jf_2}}{\partial p_{jf_k}} & \cdots & \frac{\partial S_{jf_k}}{\partial p_{jf_k}} \end{bmatrix}}_{=\Delta_p} \left(\underbrace{\begin{bmatrix} (1-\vartheta r_{f_1}) p_{jf_1} \\ \vdots \\ (1-\vartheta r_{f_k}) p_{jf_k} \end{bmatrix}}_{=\tilde{p}_j(\vartheta)} - \underbrace{\begin{bmatrix} \kappa_{jf_1} \\ \vdots \\ \kappa_{jf_k} \end{bmatrix}}_{=\kappa_j} \right) = 0, \tag{14}$$

Solving for marginal costs yields

$$\kappa_j(\vartheta) = \tilde{p}_j(\vartheta) + \Delta_p^{-1} \tilde{S}_j(\vartheta). \tag{15}$$

Equation (15) provides the basis of the estimation of both the commission internalization parameter and restaurants' marginal costs themselves. I estimate ϑ by GMM under the assumption that restaurants' marginal costs κ_{jf} for platform orders are uncorrelated with restaurants' 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

$$\mathbb{E}[\tilde{\kappa}_{jf}(\vartheta_0)Z_{jf}] = 0, \tag{16}$$

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_{jf} 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 (16) to zero; this empirical analogue averages over both metros m and platforms f.

With an estimate of ϑ in hand, I estimate restaurant 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 of platform orders may differ from those of direct orders due to differences in the packaging and logistical costs. The costs κ_{jf} that I recover from (15) 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 (15) as my estimator of κ_z^{direct}. I similarly use the average κ_{jf} recovered from (15) across platform/restaurant pairs as my estimator of $\kappa_z^{\text{platform}}$.

5.3 Estimation of restaurant platform adoption model

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

I estimate the parameters $K_{\tau m}(\mathcal{G})$ and $\Sigma = (\sigma_\omega, \sigma_{rc})$ governing restaurants' platform adoption decisions using a two-step generalized method of moments (GMM) estimator. Recall that restaurants adopt platforms to maximize perceived profits given beliefs regarding rivals' choices that are consistent with actual choice probabilities. The first stage of estimation involves estimating restaurants' conditional choice probabilities (CCPs) as a function of variables affecting their profits. The second stage involves setting restaurant beliefs to the estimated CCPs and then fitting model predictions to observed choices.[18]

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 nearby population with the of demographic shares and

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

with the number of nearby restaurants.

The first-stage CCPs $\hat{P}_m$ permit computation of each restaurant's probability of joining platforms $\mathcal{G}$ for under parameter values θ^{adopt}. As noted, I estimate θ^{adopt} using a GMM estimator that matches model predictions to two sets of empirical patterns. First, the estimator ensures that the model's predicted share of restaurants joining each possible combination of platforms (e.g., no platforms, only DoorDash, Grubhub and Postmates, etc.) in each metro area equals the analogous observed share. I include moments ensuring that the model matches metro-level platform adoption probabilities in order to estimate the mean fixed cost parameters $K_{\tau m}(\mathcal{G})$.

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

I aim to characterize the long-run equilibrium of the food delivery industry using a static model. In practice, however, restaurant platform adoption decisions may be dynamic—shaped by both past adoption and expectations about future conditions. Restaurants in the sample may not have fully adjusted to a long-run equilibrium. If so, I risk overstating fixed costs (if non-adoption reflects inertia or perceived risk that platforms may exit) and understating responsiveness to short-term profitability (if adoption depends more on uncertain long-run returns than on current returns).

5.4 Estimation of platform marginal costs

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

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

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

f's marginal costs are given by

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

I estimate mc_f by substituting Δ_f and S_f for estimates of these quantities obtained in (17).[19]

Platforms may maximize long-run profits rather than static profits, which creates a problem for estimation when long-run profits depend on contemporaneous fees (due, e.g., to state dependence or strategic effects). If platforms set fees below those maximizing static profits based on the future benefits of contemporaneous fee reductions, then I risk understating platforms' marginal costs. With that said, the marginal costs that I estimate in practice are in line with external information on platform costs (see Section 6.3).

Although the estimation approach detailed above relies on the assumption that platforms set their ZIP-specific consumer fees to maximize their profits, I do not assume that platforms choose their commission rates r_m optimally. That platforms set r_m optimally on a market-by-market basis is dubious given that the leading 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 second part of the counterfactual analysis, I solve for profit-maximizing commission rates, which may differ from the 30% set by leading platforms in the sample period.

6 Estimation results

6.1 Parameter estimates for consumer choice model

Table 2 reports estimates of consumer choice model parameters. Several estimates are noteworthy. First, the estimated scale parameters $\sigma_{\zeta 1}$ and $\sigma_{\zeta 2}$ are both sizeable, suggesting that consumers are divided by both overall taste for online ordering and by tastes for specific platforms. Additionally, the estimated λ demographic effects on platform tastes imply that young and unmarried consumers prefer delivery platforms relative to older and married consumers. The large estimate of σ_η suggests limited substitutability between restaurant ordering and at-home dining. In addition, the α parameter estimates indicate that married and higher income consumers are less price sensitive. Figure 2 plots the distribution of estimated own-fee elasticities across metros; these elasticities range from 0.5 to 2.5 for DoorDash, Uber Eats, and Grubhub, the three platforms with sizeable national market shares. Last, platform sales respond to restaurant variety on platforms — the estimated elasticities of platforms' orders with

[19] 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

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

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

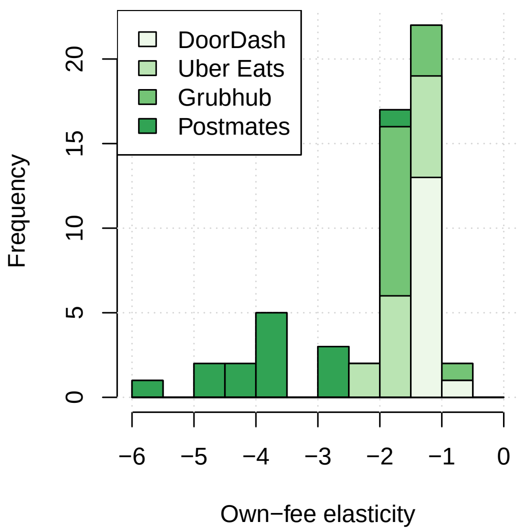
respect to their restaurant listing counts range from 0.57 to 0.97 across platforms in the New York metro.[20] Price sensitivity α_i governs the extent to which consumers value low fees relative to restaurant variety. The mean α_i for DoorDash across metros is 0.209 when weighting by sales and 0.220 when weighting by the change in sales when fees are infinitesimally reduced. The similarity of average fee sensitivity and marginal consumers' fee sensitivities here casts doubt on the presence of a Spence distortion that commission caps could correct.

Table 2: Consumer choice model parameter estimates

Parameter	Estimate	SE
α	0.28	0.01
α_{young}	0.01	0.01
α_{married}	-0.07	0.01
$\alpha_{\text{high inc}}$	-0.06	0.01
$\sigma_{\zeta 1}$	2.02	0.04
$\sigma_{\zeta 2}$	1.28	0.02
ρ	0.51	0.19
ϕ_{chain}	-0.84	0.11
σ_{ϕ}	1.02	0.06
$\lambda^{\text{DD}}_{\text{young}}$	0.71	0.14
$\lambda^{\text{DD}}_{\text{married}}$	-1.29	0.15
$\lambda^{\text{DD}}_{\text{high income}}$	-0.16	0.15
$\lambda^{\text{Uber}}_{\text{young}}$	0.82	0.13
$\lambda^{\text{Uber}}_{\text{married}}$	-1.62	0.14
$\lambda^{\text{Uber}}_{\text{high income}}$	-0.35	0.14
$\lambda^{\text{GH}}_{\text{young}}$	0.54	0.16
$\lambda^{\text{GH}}_{\text{married}}$	-1.14	0.15
$\lambda^{\text{GH}}_{\text{high income}}$	-0.32	0.16
$\lambda^{\text{PM}}_{\text{young}}$	0.80	0.19
$\lambda^{\text{PM}}_{\text{married}}$	-1.40	0.21
$\lambda^{\text{PM}}_{\text{high income}}$	-1.03	0.20
σ_{η}	2.03	0.01
$\lambda^{\eta}_{\text{young}}$	-0.35	0.20
$\lambda^{\eta}_{\text{married}}$	-1.12	0.21
$\lambda^{\eta}_{\text{high income}}$	-1.23	0.21

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.

Figure 2: Distribution of own-fee elasticities across markets



Notes: this figure plots stacked histograms of platform-specific own-fee elasticity estimates across metro areas.

To evaluate the estimates and understand their implications for ordering behaviour, I compute substitution patterns predicted by the model. First, Table 3 provides the shares of consumers substituting to each platform and to making no purchase among those who substitute away from a platform f upon a uniform increase in f's consumer fees. The estimates show that, across platforms, between 21% and 34% of platforms' consumers who substitute away from ordering on a platform no longer place any restaurant order. An additional 33–40% switch to

[20]See Online Appendix Table O.24 for details on the computation of these elasticities and for cross-elasticity estimates.

ordering directly from a restaurant whereas the remainder switch to a different platform. The estimates additionally suggest that cannibalization is an important consideration for restaurants in determining whether to join platforms. On average across markets, the loss of direct sales by a restaurant that has previously not joined any platform from joining DoorDash equals 25% of the restaurant's overall gain in sales from joining this platform. Although joining platforms raises a restaurant's overall sales, it also shifts sales from the commission-free direct channel to the commission-subject platform channel.

Table 3: Between-platform diversion ratios for the New York metro

	Quantity response for...					
Platform	No purchase	Direct	DD	Uber	GH	PM
DD	0.29	0.39	-1.00	0.20	0.11	0.01
Uber	0.35	0.43	0.10	-1.00	0.11	0.01
GH	0.29	0.39	0.10	0.20	-1.00	0.01
PM	0.20	0.34	0.12	0.22	0.12	-1.00

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

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

where $c_{f'm}$ is a vector of the consumer fees charged by f' across all ZIPs within m; s_{fm} are alternative f's sales in m. Each column provides diversion ratios $d_{ff'}$ for a particular alternative f whereas each row provides diversion ratios $d_{ff'}$ for a particular platform f whose consumer fees increase across m.

6.2 Estimates of restaurant marginal costs

Table 4 describes restaurant markups implied by the κ_{jf} estimates. Independent restaurant markups for direct orders are about a sixth of their prices. Further, markups on platform orders are larger under commission caps. Markups, however, do not vary substantially between chain and independent restaurants. Nor do they vary much between direct orders placed from restaurants subject and not subject to commission caps.

Table 4: Restaurant markups (means and standard deviations, \$)

(a) Chain restaurants

Channel	No cap	Cap
Direct	4.67±0.42	4.51±0.27
Platform	3.51±0.32	3.93±0.25

(b) Independent restaurants

Channel	No cap	Cap
Direct	4.86±0.40	4.74±0.31
Platform	3.79±0.32	4.17±0.35

Notes: the table describes markups $(1 - r_f)p_{jf} - \kappa_{jf}$ across ZIPs separately for direct orders ($r_0 = 0$) and platform-intermediated orders, and also separately for ZIPs with commission caps and those without caps. The averages are taken over restaurants. Note that the average direct-from-restaurant price is \$18.08 for independent restaurants and \$16.27 for chain restaurants.

6.3 Estimates of platform marginal costs

Table 5 describes the estimated cross-ZIP distribution of platform marginal costs—which reflect courier compensation—and platform markups. As of September 2022, DoorDash's website stated that "Base pay from DoorDash to Dashers ranges from \$2–\$10+ per delivery depending on the estimated duration, distance, and desirability of the order" (DoorDash calls its couriers "Dashers").[21] This level of courier pay lines up well with the estimated interquartile range of DoorDash's marginal costs of \$7.08 to \$9.72. Additionally, McKinsey & Company found platform marginal costs of \$8.20 per delivered order in a 2021 analysis of the US food delivery industry (Ahuja et al. 2021); this figure is close to my mean marginal cost estimates for the leading three platforms.

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

	Marginal costs				Markup			
		Quantiles				Quantiles		
	Mean	0.25	0.50	0.75	Mean	0.25	0.50	0.75
DD	9.82	8.93	10.39	11.14	3.35	3.06	3.30	3.59
Uber	9.78	8.57	9.75	11.01	3.20	2.89	3.18	3.47
GH	10.05	8.08	10.72	11.34	2.96	2.60	2.92	3.27
PM	14.51	12.59	14.88	16.25	3.37	2.88	3.18	3.49

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

6.4 Estimates of the restaurant platform adoption model

Table 6 reports estimates of the parameters governing platform adoption by restaurants in the scale of thousands of dollars. In interpreting the estimates, note that the average expected variable profits of a restaurant that joins no online platform in my sample is roughly \$12,500. The fixed cost estimates are at a monthly level. Panel 6c displays average costs by the number of platforms joined across platform subsets and metros. This plot shows that costs increase at a diminishing rate as restaurants join more platforms and level off considerably at two platforms joined. The estimated scale parameter σ_{rc} of restaurants' platform-specific normal choice disturbances is \$350 whereas the estimated scale parameter σ_{ω} of the platform-subset-specific disturbance is \$290, which maps to a standard deviation of \$372.

7 Counterfactual analysis

This section has two parts. In the first, I evaluate regulations on restaurant commissions under which platforms optimally re-adjust their consumer fees. The goals of this first part are to evaluate the welfare impacts of enacted commission regulations and to assess the scope for alternative regulations to both benefit restaurants and boost total welfare. In the second part, I explicitly compute privately and socially optimal platform fees and commissions. Although this part is less directly policy relevant, it characterizes sources of inefficiency in platform pricing in a manner that is more closely connected to the article's theoretical content. The goal of this part is to empirically characterize various pricing distortions and determine the relative importance of price level inefficiency owing to market power and price structure inefficiency owing to distortions unique to multi-sided markets. In this second part, I also assess how the competitive landscape interacts with pricing distortions and the scope for competition to achieve goals of commission regulation. Note also that I focus in this article on platform

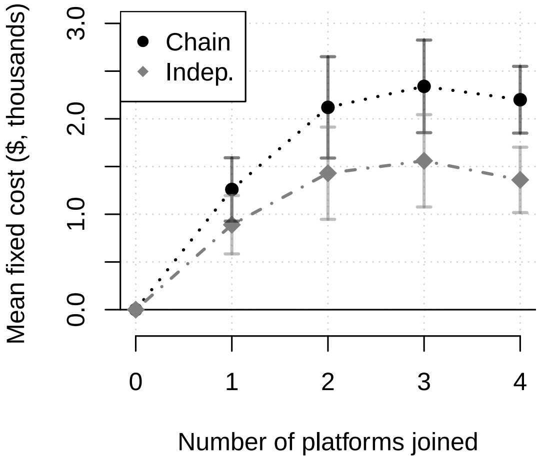
[21] See https://help.doordash.com/consumers/s/article/How-do-Dasher-earnings-work.

Table 6: Estimates of restaurant platform adoption parameters

(a) Parameters governing choice disturbance

Parameter	Estimate	SE
σ_ω	0.29	(0.07)
σ_{rc}	0.35	(0.03)

(c) Average cost by platform subset size



(b) Mean fixed costs by restaurant type

Platform subset	Chain		Indep.	
DD	1.76	(0.15)	0.80	(0.11)
Uber	0.86	(0.16)	0.79	(0.15)
GH	2.28	(0.23)	1.31	(0.20)
PM	1.23	(0.19)	0.81	(0.14)
DD, Uber	2.68	(0.28)	1.26	(0.19)
DD, GH	1.68	(0.26)	1.22	(0.22)
DD, PM	2.32	(0.20)	1.26	(0.18)
Uber, GH	1.21	(0.23)	1.15	(0.22)
Uber, PM	2.38	(0.27)	1.63	(0.28)
GH, PM	1.75	(0.33)	1.51	(0.29)
DD, Uber, GH	2.33	(0.24)	1.62	(0.25)
DD, Uber, PM	1.95	(0.31)	1.64	(0.30)
DD, GH, PM	2.69	(0.27)	1.77	(0.28)
Uber, GH, PM	2.03	(0.32)	1.59	(0.29)
All	2.20	(0.18)	1.36	(0.17)

Notes: Panel 6a reports estimates of the parameters governing the disturbance affecting restaurants' platform adoption decisions. Panel 6b reports estimates of the mean $K_{\tau m}(\mathcal{G})$ fixed costs across markets m for each platform subset $\mathcal{G}$ and restaurant type τ. Panel 6c reports the mean $K_{\tau m}(G)$ across markets m and platform subsets $\mathcal{G}$ with a given number of constituent platforms for each restaurant type. I compute the standard errors appearing in parentheses using the bootstrap procedure described in Appendix C.

pricing and abstract away from responses to fee regulation other than in pricing, ordering, and platform adoption; other responses that may be relevant in practice include platform exit, quality responses, and changes in platform advertising.

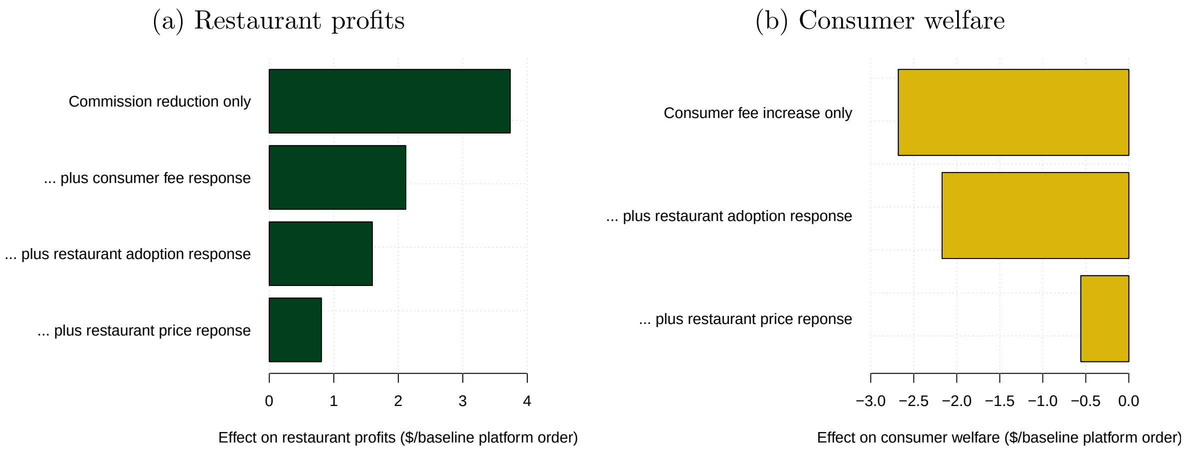
7.1 Commission regulation

To evaluate commission regulation, I compute equilibria of the model when all platforms' commissions are constrained to equal various levels $\bar{r}$. Rather than compute equilibria at the metro area level, I divide metros into counties and compute county-specific equilibria. This granular approach facilitates the study of how regional characteristics affect privately and socially optimal platform prices, as dividing metros into counties raises the amount of variation across markets: the sample includes 14 metro areas but 104 counties.

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

15% commission caps. The first substantive conclusion is that commission caps of 15%–the most common level in practice—achieve their intended goal of benefitting restaurants but reduce total welfare. Restaurant profits rise by $0.81 per order in the baseline 30% equilibrium upon a 15% commission cap, but this benefit to restaurants comes at the expense of consumers and

Figure 3: Decomposing welfare effects of 15% commission caps



platforms. Figure 5, which shows the effects of regulated commission changes on consumer fees, restaurants' platform adoption, and platform sales as a share of all restaurant orders, reveals why consumers and platforms lose out from 15% commission caps. Although reducing commissions to 15% from the 30% baseline boosts restaurants' uptake of platforms by about 15 percentage points, it boosts consumer fees by $3.86. The net effect is to reduce consumer welfare and—as illustrated by Figure 5c—shift consumers away from platform ordering, thus reducing platform revenues. Consumer losses stand at $0.56/order whereas platform losses are $0.47/order, implying total welfare losses of $0.21/order.

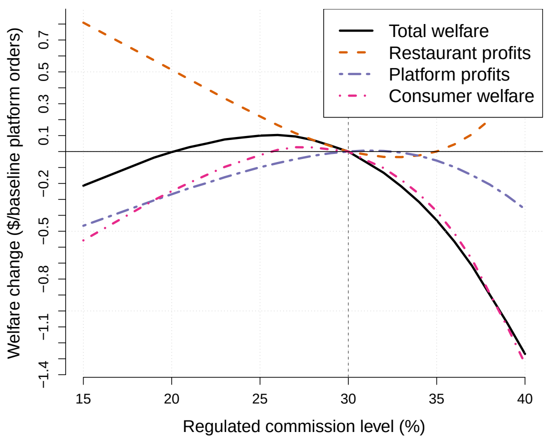
Although commission caps reduce welfare, the reduction of $0.22 per order in the baseline is somewhat small because equilibrium responses to commission caps largely neutralize their welfare effects. Figure 3a provides a decomposition of the effect of a 15% commission cap on restaurant profits. The direct benefit to restaurants of cutting commissions to 15%—holding consumer fees, restaurants' adoption choices, and restaurant prices fixed—is $3.73 per order. The "plus consumer fee response" shows that the reduction in orders associated with platforms' fee hikes reduces restaurants' benefit from the cap to $2.11. Increased restaurant adoption of platforms in response to the commission cap entails fixed costs and cannibalization of commission-free first-party orders that further reduces restaurants' benefit to $1.60 per order. Last, restaurants reduce their prices in response to commission caps, which further reduces their benefit from caps to $0.80. Thus, the combination of fee hikes resulting from caps and intensified restaurant competition on platform adoption and pricing dimensions largely undo restaurants' direct benefits from commission reductions.

Whereas competitive responses limit restaurants' gains from commission caps, they attenuate consumers' losses. Figure 3b shows a decomposition of the consumer welfare effects of a 15% commission cap. Consumer losses from platforms' fee responses to the cap amount to $2.68 per platform order. However, commission caps lead to increased platform uptake of platforms that limit consumer losses to $2.17 and also to restaurant price reductions that further reduce consumer losses to $0.56.

The direct benefit to restaurants of cutting commissions to 15%—holding consumer fees, restaurants' adoption choices, and restaurant prices fixed—is \$3.73 per order. The "plus consumer fee response" shows that the reduction in orders associated with platforms' fee hikes reduces restaurants' benefit from the cap to \$2.11. Increased restaurant adoption of platforms in response to the commission cap entails fixed costs and cannibalization of commission-free first-party orders that further reduces restaurants' benefit to \$1.60 per order. Last, restaurants reduce their prices in response to commission caps, which further reduces their benefit from caps to \$0.80. Thus, the combination of fee hikes resulting from caps and intensified restaurant competition on platform adoption and pricing dimensions largely undo restaurants' direct benefits from commission reductions. Restaurants' equilibrium responses to caps similarly attenuate consumer losses from commission regulation.

Moderate commission reductions are welfare enhancing. Although 15% commission caps reduce total welfare, reducing commissions to levels between 20% and 30% is welfare enhancing. Commission reductions in this range raise restaurant profits while having the offsetting effects on consumer welfare noted above: raising restaurant variety on platforms and raising platforms' consumer fees. Figure 5 shows the magnitude of these responses. It also indicates that for commission reductions to levels above 25%, the variety effect dominates the fee effect on ordering: these commission reductions boost the share of restaurant orders made on platforms. Figure 4 similarly shows that commission reductions to levels above 25% have small positive effects on consumer welfare relative to a 30% commission baseline. Commission reductions always hurt platforms, but the benefits to consumers and especially to restaurants are large enough for slight commission reductions to levels above 25% to boost total welfare. In fact, even larger commission reductions to levels as low as 20% boost total welfare despite harming consumers, as the benefits to restaurants are significant whereas consumers' losses are small due to the fact that increased restaurant variety offsets consumer losses from higher fees.

Figure 4: Welfare by regulated commission level

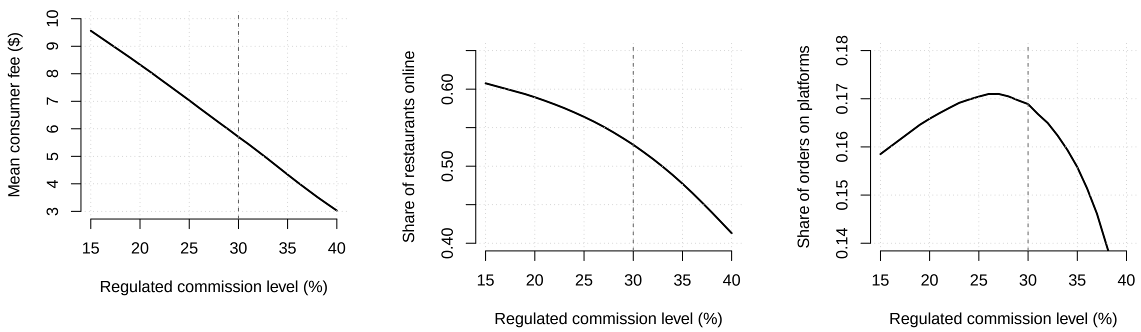


Notes: this plot provides welfare effects of capping commissions at levels between 30% and 0% as a share of the number of platforms orders in the 30% commission equilibrium.

Heterogeneity in optimal commission regulation. Figure 6 reveals substantial cross-county variation in the commission rates that maximize total welfare, platform profits, and consumer welfare.

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

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



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

The interquartile range of the socially optimal commission caps is 24-28%, while the corresponding range for platform-optimal commissions is 31-35%, indicating a consistent upward bias in the latter.

To explain this discrepancy, I define $\Delta_j = r_j^{\text{pr}} - r_j^{\text{so}}$ as the difference (in percentage points) between the platform-optimal and the welfare-optimal commission rates in county j. I then regress Δ_j on a set of county-level characteristics that may explain this wedge. These characteristics are:

- Diversion ratio: the ratio of the increase in direct restaurant orders to the decrease in platform orders following a uniform increase in consumer fees. A higher diversion ratio implies that shifting the fee burden from merchants to consumers leads to an especially large increase in restaurants' direct sales. Thus, I hypothesize the diversion ratio to have an inverse relationship with the socially optimal commission rate (and thus a positive relationship with Δ_j). I compute the diversion ratio at the 30% commission equilibrium.
- Effect of commission reductions on fixed costs: the increase in fixed adoption costs incurred by restaurants when the regulated commission rate falls by 1% from a 30% baseline. When reducing commissions entails larger fixed cost increases, relatively high commission are socially optimal. That is, higher fixed costs imply a lower r_j^{so} and thus a lower Δ_j.
- Effect of commission reductions on variety benefits: the increase in consumer welfare from the increase in restaurants' uptake of platforms that occurs when the regulated commission level falls by 1% from a 30% baseline. When consumers experience a greater benefit from enhanced restaurant variety upon a commission reduction, the optimal commission level should be lower and thus Δ_j should be higher.[22]

[22] In computing this variable, I fix consumer fees and prices at the 30% commission equilibrium's consumer fees and prices. I then compute welfare at these fees and prices under (i) restaurants' platform uptake in the 30% commission equilibrium and (ii) restaurants' platform uptake in the 15% commission equilibrium.

- Effect of restaurant variety on sales: the increase in platform sales owing to the increase in restaurants' uptake of platforms that occurs when the regulated commission level falls from 30% to 29%. When commission reductions are successful in attracting restaurants that boost platform sales, platforms benefit from relatively low commissions. Thus, the profit-maximizing commission rate and thus Δ_j should positive correlate with this variable.[23]

Table 7 provides results from the regression. The estimated coefficient of each of the regressors enumerated above has the hypothesized sign and is statistically significant at 95% level. Furthermore, these variables alone explain 50% of the cross-county variation in Δ_j. The results validate the relevance of the distortions suggested by the illustrative model of Section 2 and—given the general nature of these distortions—have broad implications for commission regulation. In assessing whether commissions are excessive in similarly organized platform markets, policymakers should consider the extent of cannibalization of direct sales, fixed costs of platform adoption, and consumer enjoyment of variety on platforms.

Given that the extent to which platform sales cannibalize direct-from-restaurant sales, the question of what determines the cannibalization rate naturally arises. I hypothesize that cannibalization is especially strong in areas with many restaurants — in these areas, consumers are likely to frequent restaurants irrespective of the availability of delivery platforms. This is because (i) restaurant dining is more attractive in these areas due to the variety of restaurants available and (ii) a high density of restaurants in an area is more likely to arise when the locals enjoy restaurant food. This hypothesis is corroborated by the fact that the single best predictor of the cannibalization rate is the local density of restaurants defined as the average number of restaurants within five miles, with the average taken across residents of a county. Table 8 presents the results of a regression of the cannibalization rate defined above on log restaurant density. This regressor alone explains 56% of cross-county variation in cannibalization. It also relates positively to the cannibalization rate: a 1% increase in local restaurant density is associated with an approximately 0.37 percentage point increase in the cannibalization rate.

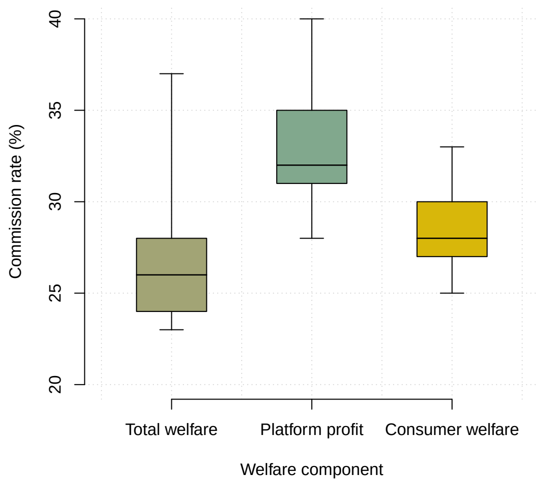
Table 7: Drivers of heterogeneity in gap between commission rates maximizing social welfare and platform profits

Regressor	Coefficient	SE	Bivariate R^2
Cannibalization	0.26	(0.05)	0.27
Fixed cost change	-0.58	(0.12)	0.00
Variety change	1.37	(0.47)	0.15
Sales change	-5.12	(2.48)	0.17
R^2	0.42		

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 Δ_j (the difference between the commission rate maximizing total welfare and that maximizing platform profits) on the indicated regressor. The sample includes $N = 104$ counties.

[23] In computing this variable, I fix consumer fees and prices at the 30% commission equilibrium's consumer fees and prices. I then compute total platform sales at these fees and prices under (i) restaurants' platform uptake in the 30% commission equilibrium and (ii) restaurants' platform uptake in the 15% commission equilibrium.

Figure 6: Heterogeneity in optimal commission level



Notes: this plot describes the cross-county distribution of commission cap levels maximizing each of (i) total welfare, (ii) platform profits, and (iii) consumer welfare. The five summary statistics illustrated by each box-and-whiskers plot are the 5th, 25th, 50th, 75th, and 95th quantiles (weighted by county population).

Table 8: Restaurant density largely determines the cannibalization rate

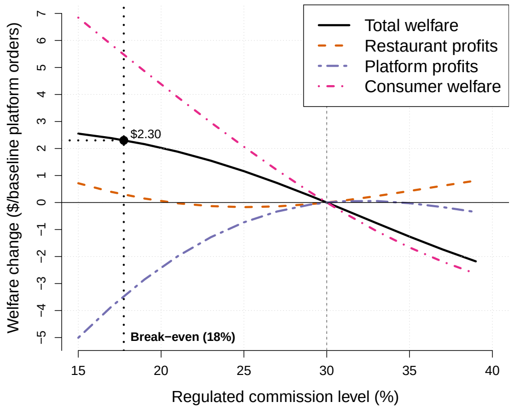
Regressor	Coefficient	SE
log(average # restaurants $<$ 5 miles)	0.37	0.03
R^2	0.56	

Two-sided regulation. Commission caps constrain the structure of platform fees—-specifically, the split between restaurant commissions and consumer fees—without limiting the overall fee level (i.e., the total charge to consumers and restaurants combined). The scope for welfare improvements from adjustments to this split is modest: the most that total welfare could be boosted by a commission cap is about \$0.10 per order.

This limited impact reflects that commission caps address only distortions in the relative balance between commission and fee levels, rather than the overall level of platform fees. By contrast, two-sided regulation that limits both restaurant commissions and consumer fees could also address distortions arising from platform market power. The welfare gains from curbing market power may exceed those from only rebalancing fees between the two sides of the market. Moreover, the benefits of reducing commissions are amplified when consumer fees are lower and platform ordering is consequently high. In this scenario, more consumers take advantage of the increased restaurant variety effected by commission reductions, boosting the consumer welfare gains from increased restaurant uptake of platforms.

To evaluate two-sided fee regulation, I replicate the analysis underlying Figure 4 but holding consumer fees fixed at their levels under 30% commissions. The results, shown in Figure 7, differ markedly from from those for one-sided commission caps in both the level and decomposition of welfare effects. First, the total welfare gains from two-sided regulation are substantially

Figure 7: Welfare under two-sided fee regulation



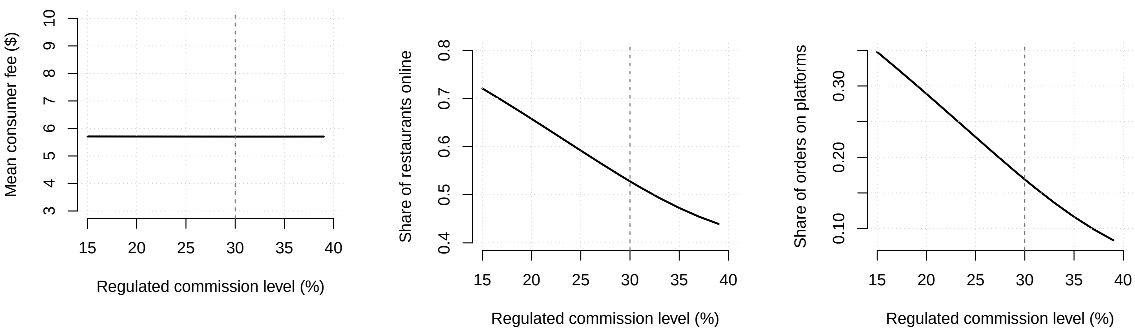
Notes: this figure displays welfare effects of fixing all platforms' commission rates at various levels ranging from 15% to 40% when platforms' consumer fees are fixed at their levels under 30% commission rates. The plot shows welfare results that are aggregated across all counties in the sample and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

larger. At a regulated commission level of 18%—the commission level at which platform profits fall to zero, as marked by a dotted line in Figure 7—total welfare rises by $2.30 per baseline platform order relative to the 30% commission benchmark. This compares to a maximum gain of only about $0.10 per order under optimal one-sided regulation. A key reason for this stark difference is that two-sided regulation directly limits the overall fee level, mitigating distortions from platform market power.

Second, the distributional impacts differ. Under two-sided regulation, most of the welfare gains accrue to consumers, while the effects on restaurant profits are modest and vary in sign depending on the commission level. In contrast, one-sided commission caps primarily benefit restaurants and tend to have smaller—and often negative—effects on consumer welfare. Consumers benefit more under two-sided regulation because it induces restaurant uptake of platforms and restaurant price reductions leads restaurants to reduce prices. As shown by Figure 8, this leads to an increase in the share of orders placed on platforms. The displacement of restaurants' direct (commission-free) sales by platform sales, however, partly explains why restaurants do not necessarily gain from two-sided fee regulation. Restaurants also compete away much of the benefit from lower commissions in equilibrium in the manner discussed above, further reducing their gains from two-sided regulation. Meanwhile, consumer gains from expanded restaurant choice are amplified under two-sided regulation, as fixed consumer fees lead to higher platform usage relative to the case under one-sided commission caps in which fees rise. With more consumers using platforms, the value of increased restaurant variety rises.

7.2 Comparison of privately and socially optimal platform fees

There are two notions of bias in platform fees, each with its own advantages. First, we may consider fees as biased against merchants when a regulated reduction in merchant commissions—without corresponding limits on consumer fees—raises total welfare. This concept in useful for assessing the potential for regulation to improve efficiency by rebalancing fees between the two sides of the market.

Bias can alternatively be defined as the discrepancy between the fee split that maximizes social welfare and the one chosen by profit-maximizing platforms—specifically, when the socially optimal outcome places a relatively smaller burden on merchants. Although less directly relevant for policy design, this notion is useful for diagnosing the structural sources of pricing distortions. Furthermore, the socially optimal fees involved in the notion provide a benchmark for evaluating platform fees. To assess bias in this latter sense, I compare platform fees constituting an equilibrium of the model in which each platform sets fees to maximize its own profits with those maximizing social welfare. For brevity, I will refer to these as the *privately optimal* and *socially optimal* fees, respectively.

Table 9 presents mean socially and privately optimal for each platform. The first panel, Table 9a, presents the results for consumer fees. It shows that the mean difference between privately and socially optimal consumer fees is only \$0.29 on average across platforms, with platforms other than DoorDash having privately optimal consumer fees that fall *below* their socially optimal levels. The results for consumer fees contrast with those for restaurant commission rates as This relatively small difference contrasts with the results on commission rates reported in Table 9b, which show that the mean privately optimal commission rate of 34.32% is almost twice the mean socially optimal rate of 17.56%. The results are similar across platforms. Thus, profit-maximizing platforms' fees are biased against merchants in the sense introduced above.

The overall level of fees under profit-maximizing platforms is also much higher than is socially optimal. The final pane, Table 9c, reports mean markups, defined as the ratio of platform variable profits to sales. Whereas profit-maximizing platforms earn markups of \$3.77 per order, on average, the presence of network externalities makes it is socially optimal to subsidize platform usage; the mean socially optimal aggregate markup is -\$1.50.

Table 9: Socially and privately optimal platform fees

(a) Consumer fee ($)

Platform	Privately optimal	Socially optimal	Difference
DD	4.36	3.29	1.07
Uber	2.63	2.79	-0.16
GH	2.11	3.14	-1.03
PM	5.51	6.29	-0.78
Total	3.59	3.30	0.29

(b) Restaurant commission rate (%)

Platform	Privately optimal	Socially optimal	Difference
DD	31.01	15.42	15.58
Uber	37.02	19.93	17.10
GH	39.28	20.11	19.17
PM	36.96	18.01	18.96
Total	34.32	17.56	16.77

(c) Markup ($)

Platform	Privately optimal	Socially optimal	Difference
DD	3.64	-1.73	5.37
Uber	3.98	-1.11	5.08
GH	3.89	-1.09	4.99
PM	3.69	-1.10	4.80
Total	3.77	-1.50	5.27

Notes: this table displays the mean platform consumer fees, restaurant commissions, and aggregate markups 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. The markup is defined as the ratio of platform profits to the number of orders placed on the platform.

Having quantified the overall discrepancies between privately and socially optimal fees, I now decompose the distortions that account for the gap in consumer fees. This decomposition is based on equation (2) in the illustrative model, which involves a monopolist platform. To apply the decomposition to a competitive setting, I compute distortions for each platform, holding the fees of rival platforms fixed. The decomposition includes four distinct distortions: market power, which drives consumer fees above the social optimum; cannibalization, which exerts downward pressure on fees, as platforms do not internalize the losses that restaurants incur when orders shift from direct to platform-based channels; and two distortions related to network externalities — Spence and displacement distortions.

Table 10 reports the mean magnitudes of the distortions across counties for each platform. Market power raises DoorDash's consumer fees by $4.35, on average. This upward distortion, however, is mostly offset by the cannibalization distortion, which reduces DoorDash's fees by $2.89. The displacement distortion identified by Tan and Wright (2021) more than offsets the Spence distortion, resulting in a slight net downward pressure from network externalities. These opposing effects explain why DoorDash's profit-maximizing consumer fees only slightly exceed the welfare-maximizing benchmark. For the other, smaller platforms, the market power distortion is smaller whereas the cannibalization distortion is larger; the contributes to negative net distortions for these platforms.

Although the illustrative model does not yield a neat decomposition of merchant commission distortions, the welfare effects of moving to socially optimal fees indicate why commissions are too high: the profit-maximizing platform fails to internalize the variety gains to consumers from expanding platform adoption by restaurants and has limited incentive to encourage such

Table 10: Decomposition of consumer fee distortions

Distortion	Platform			
	DoorDash	Uber Eats	Grubhub	Postmates
Market power	4.35	3.81	3.56	3.04
Cannibalization	-2.89	-3.12	-3.17	-3.17
Spence	2.94	2.80	2.88	2.99
Displacement	-3.33	-3.65	-4.30	-3.64
Total	1.07	-0.16	-1.03	-0.78

adoption using commission reductions due to merchant-side market power. Table 11a reports the welfare effects of moving from the privately optimal fees to the socially optimal fees. The total welfare gain of \$3.14 is driven primarily by consumer gains of \$10.55/order. These gains reflect two restaurant responses to reduced commissions: a 12.5% reduction in restaurant prices on platforms and a large increase in restaurant participation on platforms. Table 11b, which reports these responses, shows that the share of restaurants active on at least one platform rises by 50.7% whereas the total number of restaurant listings on platforms rises by 82.0%. These responses benefit consumers, but—consistent with the discussion of Figure 3a—attenuate the direct benefits to restaurants direct from lower commissions.

The results highlight an important conceptual distinct between the notion of bias in platform fees and the distribution of welfare impacts. Although the fee structure is biased against merchants, consumers are the primary beneficiaries of correcting that bias.

The analysis of optimal fees bolsters the case for two-sided fee regulation. Recall that—as showed in Figure 7—freezing consumer fees while reducing commissions to 18%—the level at which platform profits (excluding fixed costs) fall to zero—yielded a \$2.30/order welfare gain. This suggests that most of the efficiency gains from moving to socially optimal fees could be captured through a commission cap paired with a prohibition on resulting consumer fee increases.[24]

Table 11: Effects of transition from privately to socially optimal fees

(a) Welfare

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

(b) Restaurant responses

Quantity	Change (%)
Restaurant prices	-12.5
Share of restaurants online	50.7
Number of restaurant listings	82.0

7.3 Competition and fee optimality

In standard one-sided markets, entry tends to reduce pricing distortions arising from market power. In two-sided markets, however, platform entry does not generally eliminate distortions

[24] An important caveat is that such regulation could prompt platform exit, quality reductions, or increased advertising, each of which could reduce welfare.

in how fees are divided between consumers and merchants. In a model of competing symmetric platforms, Teh et al. (2023) show that the impact of entry on platform fee structures depend on the extent to which entry intensifies competition on each side of the market. Entry may especially strengthen competition for merchants, thus driving down merchant fees; this downward pressure on merchant fees tends to exert upward pressure on consumer fees due to the see-saw effect arising in two-sided markets (Rochet and Tirole 2003). Alternatively, entry may especially intensify competition for consumers, reducing consumer fees and exerting upward pressure on merchant fees. Which side sees a greater intensification of competition upon entry depends on the patterns of consumer substitution across platforms and the nature of consumer multihoming. When most consumers multihome, platforms compete more aggressively for merchants, l eading to lower fees for sellers. Conversely, when most consumers singlehome, platforms compete for exclusive access to buyers to raise their merchant-side market power—raising the merchant share of platform fees and possibly the overall level of merchant fees. The possibility that platform competition can raise merchant fees has empirical support. Wang (2023) shows that, in the payment cards industry, competition between payment networks tends to raise the fees that these networks charge to merchants.

Rather than simulate the impacts of platform entry, which would require making arbitrary assumptions about the characteristics of the new entrant, I simulate a scenario in which DoorDash—the largest food delivery platform in the US—becomes a monopolist. Comparing outcomes under the current competitive environment to those under this counterfactual DoorDash monopoly reveals the effects of platform entry.

Table 12 shows the effects of making DoorDash a monopolist on DoorDash's consumer fees and restaurant commissions across counties, on average across counties. Monopolization tends to boost the privately optimal consumer fees while lowering restaurant commissions. This result owes to the fact that monopolization reduces competition over consumers, which in turn raises DoorDash's consumer fees. In a see-saw effect, this puts downward pressure on restaurant commissions to the point that merchant commissions fall. Although monopolization reduces platform competition over merchants, which tends to raise commissions, the negative see-saw effect dominates so that restaurant commissions fall under a DoorDash monopoly.

The analysis described above has the shortcoming that the fee effects of platform competition critically depend on the nature of buyer multihoming (Teh et al. 2023). Although I allow consumers to show at any mix of food delivery platforms across consecutive eating occasions, the model—unlike Teh et al. (2023) and Wang (2023)—does not feature a stage in which consumers chose which food delivery platforms to adopt (i.e., which applications to download and accounts to create) so that, at the ordering stage, there are some consumers who cannot shop at multiple platforms. I choose not to include a consumer adoption stage because food delivery applications are free and simple to install so that the costs of joining a platform is minimal. Determining the relevance of a consumer adoption stage to the fee effects of competition, though, is a worthwhile direction for future empirical research.

Table 12: Effects of monopolization on DoorDash fees

Quantity	Privately optimal	Socially optimal
Consumer fee ($)	1.88	0.10
Restaurant commission (pp)	-7.21	0.02

8 Conclusion

This article developed a model of competing food delivery platforms and estimated it using a rich collection of datasets characterizing consumer behaviour, restaurant participation on food delivery platforms, and pricing in the US food delivery industry. Using the model, it conducted analysis of distortions in platform fees and the scope for regulation to correct these distortions.

A major theme of the results is that competition among platform sellers—a phenomenon omitted from the canonical model of platform pricing—shape the welfare implications of platform fees. In the analysis of commission caps, I showed that restaurants' competitive responses to caps offset most of their direct benefits from reduced commissions. Similarly, moving to the socially optimal fees—which involve similar levels of consumer fees and much lower commissions than under profit-maximizing platforms—primarily benefits consumers rather than restaurants because commission reductions lead restaurants to join more platforms and to reduce their prices on platforms, responses that reduce restaurant profits but boost consumer welfare.

Another major theme in the results is the importance of online/offline substitution, another feature excluded from the canonical model. The extent to which platform ("online") sales cannibalize direct ("offline") sales—or *cannibalization*—is a powerful predictor of the extent to which platform fee structures are biased against merchants. When cannibalization is high, there is a larger social benefit to reducing commissions and boosting consumer fees, as this prompts more consumers to switch from platform ordering to direct ordering, providing a benefit to restaurants that profit-maximizing platforms to not internalize. Online/offline substitution gives rise to the related *cannibalization distortion*, which tends to make profit-maximizing consumer fees too low. I find that this distortion explains why consumer fees are not generally socially excessive. Furthermore, online/offline substitution explains why restaurants enjoy limited benefits from regulations that keep consumer fees fixed while reducing commissions: such regulation induces consumers to shift from direct ordering—for which restaurants pay no commissions—to platform ordering.

Besides indicating the importance of seller competition and online/offline substitution, my article is the first to simultaneously quantify the market power, Spence, and displacement distortions in a real-world platform market. Although market power is significant, it is mostly offset on the consumer side by the cannibalization distortion. Furthermore, the Spence and displacement distortions identified by Weyl (2010) and Tan and Wright (2021) largely offset each other, implying small overall distortions in consumer fees.

Bibliography

Ahuja, Kabir, Vishwa Chandra, Victoria Lord, and Curtis Peens. 2021. "Ordering in: The rapid evolution of food delivery." `https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/ordering-in-the-rapid-evolution-of-food-delivery`.

Argentesi, Elena, and Lapo Filistrucchi. 2007. "Estimating Market Power in a Two-Sided Market: The Case of Newspapers." *Journal of Applied Econometrics* 22 (7): 1247–1266.

Armstrong, Mark. 2006. "Competition in two-sided markets." *The RAND Journal of Economics* 37 (3): 668–691.

Buchholz, Nicholas, Laura Doval, Jakub Kastl, Filip Matějka, and Tobias Salz. 2020. "The value of time: Evidence from auctioned cab rides." NBER Working Paper 27087.

Calder-Wang, Sophie. 2022. "The distributional impact of the sharing economy on the housing market." Unpublished working paper.

Cao, Guangyu, Ginger Zhe Jin, Xi Weng, and Li-An Zhou. 2021. "Market Expanding or Market Stealing? Platform Competition in Bike-Sharing." *RAND Journal of Economics* 52 (4): 778–814.

Carbó-Valverde, Santiago, Sujit Chakravorti, and Francisco Rodríguez-Fernández. 2016. "The role of interchange fees in two-sided markets: an empirical investigation on payment cards." *The Review of Economics and Statistics* 98 (2): 367–381.

Castillo, Juan Camilo. 2022. "Who benefits from surge pricing?", Unpublished working paper.

Chang, Howard, David S. Evans, and Daniel D. Garcia Swartz. 2005. "The effect of regulatory intervention in two-sided markets: an assessment of interchange-fee capping in Australia." *Review of Network Economics* 4 (4): .

Chen, Manlu, Ming Hu, and Jianfu Wang. 2022. "Food delivery service and restaurant: friend or foe?" *Management Science.*

Evans, David S., Howard Chang, and Steven Joyce. 2015. "The impact of the US debit-card interchange fee regulation on consumer welfare." *Journal of Competition Law and Economics* 11 (1): 23–67.

Fan, Ying. 2013. "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market." *American Economic Review* 103 (5): 1598–1628.

Farronato, Chiara, Jessica Fong, and Andrey Fradkin. 2020. "Dog eat dog: measuring network effects using a digital platform merger." NBER Working Paper 28047.

Farronato, Chiara, and Andrey Fradkin. 2022. "The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry." *American Economic Review* 112 (6): 1782–1817.

Feldman, Pnina, Andrew E. Frazelle, and Robert Swinney. 2022. "Managing relationships between restaurants and food delivery platforms." *Management Science*, Forthcoming.

Fisher, Jack. 2023. "Worker Welfare in the Gig Economy." Unpublished working paper.

Freyaldenhoven, Simon, Christian Hansen, and Jesse M Shapiro. 2019. "Pre-event trends in the panel event-study design." *American Economic Review* 109 (9): 3307–3338.

Gaineddenova, Renata. 2022. "Pricing and efficiency in a decentralized ride-hailing platform." Unpublished working paper.

Gomes, Renato, and Andrea Mantovani. 2025. "Regulating platform fees under price parity." *Journal of the European Economic Association* 23 (1): 190–235.

Hallas, Laura, Ariq Hatibie, Saptarshi Majumdar, Monika Pyarali, Rachelle Koch, Andrew Wood, and Thomas Hale. 2020. "Variation in US states' responses to COVID-19." `https://www.bsg.ox.ac.uk/research/publications/variation-us-states-responses-covid-19`.

Huynh, Kim P., Gradon Nicholls, and Oleksandr Scherbakov. 2022. "Equilibrium in two-sided markets for payments: consumer awareness and the welfare cost of the interchange fee." Bank of Canada Staff Working Paper, No. 2022-15.

Ivaldi, Marc, and Jiekai Zhang. 2020. "Platform Mergers: Lessons from a Case in the Digital TV Market." CEPR Discussion Paper No. DP14895.

Jin, Ginger Zhe, and Marc Rysman. 2015. "Platform pricing at sports card conventions." *Journal of Industrial Economics* 63 (4): 704–735.

Jullien, Bruno, Alessandro Pavan, and Marc Rysman. 2021. "Two-sided markets, pricing, and network effects." In *Handbook of Industrial Organization, Volume 4*, edited by Ho, Kate, Ali Hortaçsu, and Alessandro Lizzeri Volume 4. of Handbook of Industrial Organization 485–592, Elsevier.

Kaiser, Ulrich, and Julian Wright. 2006. "Price structure in two-sided markets: Evidence from the magazine industry." *International Journal of Industrial Organization* 24 (1): 1–28.

Kay, Benjamin S., Mark D. Manuszak, and Cindy M. Vojtech. 2018. "Competition and complementarities in retail banking: Evidence from debit card interchange regulation." *Journal of Financial Intermediation* 34 91–108.

Lee, Robin S. 2013. "Vertical integration and exclusivity in platform and two-sided markets." *American Economic Review* 103 (7): 2960–3000.

Li, Bin Grace, James McAndrews, and Zhu Wang. 2020. "Two-sided market, R&D, and payments system evolution." *Journal of Monetary Economics* 115 180–199.

Li, Zhuoxin, and Gang Wang. 2021. "Regulating powerful platforms: evidence from commission fee caps in on-demand services." Available at SSRN: https://ssrn.com/abstract=3871514.

Lu, Haozhe, Mingyang Sun, and Yimin Zeng. 2021. "Will the food delivery industry be monopolized?" In *Proceedings of the 2021 International Conference on Financial Management and Economic Transition (FMET 2021)*, 95–100, Atlantis Press.

Mankiw, N Gregory, and Michael D Whinston. 1986. "Free entry and social inefficiency." *The RAND Journal of Economics* 48–58.

Manuszak, Mark D., and Krzysztof Wozniak. 2017. "The impact of price controls in two-sided markets: evidence from US debit card interchange fee regulation." Finance and Economics Discussion Series 2017-074. Washington: Board of Governors of the Federal Reserve System.

Mayya, Raveesh, and Zhuoxin Li. 2021. "Growing platforms by adding complementors without consent: evidence from on-demand food delivery platforms." NET Institute Working Paper No. 21-14.

Natan, Olivia. 2022. "Choice frictions in large assortments." Unpublished working paper.

Reshef, Oren. 2020. "Smaller slices of a growing pie: the effects of entry in platform markets." Working paper. Washington University in St. Louis.

Rochet, Jean-Charles, and Jean Tirole. 2003. "Platform Competition in Two-Sided Markets." *Journal of the European Economic Association* 1 (4): 990–1029.

Rochet, Jean-Charles, and Jean Tirole. 2006. "Two-sided markets: a progress report." *RAND Journal of Economics* 37 (3): 645–667.

Rosaia, Nicola. 2020. "Competing Platforms and Transport Equilibrium: Evidence from New York City." Working paper.

Rysman, Marc. 2007. "An Empirical Analysis of Payment Card Usage." *The Journal of Industrial Economics* 55 (1): 1–36.

Rysman, Marc. 2009. "The Economics of Two-Sided Markets." *Journal of Economic Perspectives* 37 (3): 125–143.

Schaefer, Maximilian, and Kevin Ducbao Tran. 2020. "Airbnb, Hotels, and Localized Competition." Unpublished working paper.

Segal, Ilya. 1999. "Contracting with externalities." *The Quarterly Journal of Economics* 114 (2): 337–388.

Seim, Katja. 2006. "An empirical model of firm entry with endogenous product-type choices." *RAND Journal of Economics* 37 (3): 619–640.

Shy, Oz, and Zhu Wang. 2011. "Why do payment card networks charge proportional fees?" *American Economic Review* 101 (4): 1575–1590.

Singleton, John D. 2019. "Incentives and the supply of effective charter schools." *American Economic Review* 109 (7): 2568–2612.

Sokullu, Senay. 2016. "A semi-parametric analysis of two-sided markets: an application to the local daily newspapers in the USA." *Journal of Applied Econometrics* 31 (843-864): .

Sullivan, Michael. 2024. "Price Controls in a Multi-Sided Market." Unpublished working paper.

Tan, Hongru, and Julian Wright. 2021. "Pricing distortions in multi-sided platforms." *International Journal of Industrial Organization* 79 102732.

Teh, Tat-How, Chunchun Liu, Julian Wright, and Junjie Zhou. 2023. "Multihoming and Oligopolistic Platform Competition." *American Economic Journal: Microeconomics* 15 (4): 68–113. 10.1257/mic.20210324.

Wang, Chengsi, and Julian Wright. 2024. "Regulating platform fees." *Journal of the European Economic Association* jvae040.

Wang, Lulu. 2023. "Regulating Competing Payment Networks." Unpublished working paper.

Wang, Zhu. 2012. "Debit card interchange fee regulation: some assessments and considerations." *FRB Economic Quarterly* 98 (3): 159–183.

Wang, Zhu, and Julian Wright. 2017. "Ad valorem platform fees, indirect taxes, and efficient price discrimination." *The RAND Journal of Economics* 48 (2): 467–484.

Weyl, E. Glen. 2010. "A Price Theory of Multi-sided Platforms." *American Economic Review* 100 (4): 1642–1672.

Wright, Julian. 2012. "Why payment card fees are biased against retailers." *The RAND Journal of Economics* 43 (4): 761–780.

Appendices

A Estimation of platform adoption model

In this appendix, I provide a technical exposition of the GMM estimator of 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 whose (j,k) entry is equal to restaurant j's expected variable profits from selecting the kth platform subset $\mathcal{G}_k$, where $n_{\mathcal{G}}$ is the number of subsets. Last, let D_j be the log of the population under age 35 within five miles of j; I use D_j as a shifter of the profitability of platform adoption.

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

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

for all τ, m, and $\mathcal{G}$, where $\tau(j)$ and $m(j)$ are restaurant j's type and market, respectively. Additionally,

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

is the probability that restaurant j chooses platforms $\mathcal{G}$. Under the true model parameters θ_0^{adopt}, profits Π^e_j, and CCPs, $\mathbb{E}[g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi^e_j, D_j; \theta_0^{\text{adopt}})] = 0$. The corresponding sample moment conditions are

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{\tau m \mathcal{G}}(\mathcal{G}_j, \Pi^e_j, D_j; \hat{\theta}^{\text{adopt}}) = 0 \qquad \forall \tau, m, \mathcal{G}. \tag{18}$$

I target the Σ parameters that govern substitution patterns with additional moments. Each moment equalizes the covariance of D_j and a measure of platform adoption as computed on 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

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

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

$$\frac{1}{n_J} \sum_{j=1}^{n_J} g_{\omega,k}(\mathcal{G}_j, \Pi^e_j, D_j; \hat{\theta}^{\text{adopt}}) = 0, \qquad k \in \{1, 2\}. \tag{19}$$

The estimator $\hat{\theta}^{\text{adopt}}$ is the vector of parameter values that solves (18) and (19). Given that that the model is just-identified, one problem that arises is that exactly computing restaurants' expected profits given beliefs about a large number of rivals' decisions is computationally prohibitive. Two approximations that reduce the computational burden are available: (i) approximation of the integral defining expected profits by simulation and (ii) an alternative approximation that involves computing profits at the expected number of restaurants of each type and ZIP that adopt each platform subset. These approximations yield near-identical results: a regression of expected profits from the first on those from the second yields a coefficient of 1.001 and an R^2 of one up to three decimal places. The latter approximation, which ignores Jensen's inequality, introduces minimal bias because variability in the realized distribution of restaurants across platform subsets is low due to the large number of competing restaurants; the median number of restaurants within five miles of a particular restaurant is 1448 in the metros that I study. Given that this latter approximation involves a lower computational burden than simulation, I use it in estimation and in solving counterfactuals. See Online Appendix O.11 for details.

B Market size

I set the number of consumers in each ZIP and the distribution of their demographic types (i.e., ages, marital statuses, and incomes) using a combination of the Edison, Numerator, and ACS data. I tentatively set the number of consumers in each ZIP to the ACS estimate of the ZIP's population. I then set the distribution of consumers across demographic types equal to the distribution among Numerator panelists in the ZIP. For ZIPs with fewer than 10 panelists, I instead set the distribution equal to that in the sets of ZIPs within five miles. Next, I compute an equilibrium in prices conditional on observed restaurant platform adoption, fees, and commissions in April 2021. The ratio of the number of platform orders in the metro from the Edison sales estimates dataset for April 2021 to the expected number of orders in this equilibrium provides a factor by which I multiply each ZIP's tentative number of consumers. After scaling by this factor, the model's predictions of metro-level sales align with the Edison estimates.

C Bootstrap procedure

This appendix describes the article's bootstrap procedure. The procedure has, first, a parametric part that involves drawing from the estimated asymptotic distribution of the consumer choice model estimator. I estimate the asymptotic variance of this estimator using the outer product of the gradients estimator. I then take $B = 100$ draws from the associated estimate of the asymptotic distribution of $Z = \sqrt{n}(\hat{\theta}^{\text{cons}} - \theta_0^{\text{cons}})$, where θ_0^{cons} is the true choice model parameter vector, $\hat{\theta}^{\text{cons}}$ is the maximum likelihood estimator, and n is the sample size. Let Z^b denote the bth draw, and let $\hat{\theta}^{\text{cons},b} = \hat{\theta}^{\text{cons}} + n^{-1/2}Z^b$. I estimate restaurants' and platforms' marginal costs, call them $\hat{mc}^b$, under each $\hat{\theta}^{\text{cons},b}$. For each b, I also take a bootstrap draw of restaurants within ZIP and type. Let $\mathcal{J}^b$ denote the bth draw. I proceed to estimate the parameters of the platform adoption game at $\{\hat{\theta}^{\text{cons},b}, \mathcal{J}^b, \hat{mc}^b\}$ for each b, obtaining estimates $\hat{\theta}^{\text{adopt},b}$ for each b. The standard errors that I report for these parameters are the standard deviations of the parameters across bootstrap replicates. I similarly estimate the weights h_{fm} at $\{\hat{\theta}^b, \hat{mc}^b, \hat{\theta}^{\text{adopt},b}\}$ for each b, yielding estimates $\hat{h}^b_{fm}$. Last, I solve for equilibria at each b and take the standard deviation of outcomes across replicates b to obtain standard errors.