UNITE AND CONQUER:
Seller Collusion in Multi-Sided Markets*

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Abstract

This paper explores online marketplace dynamics using a game-theoretic model. We uncover a strong platform provider incentive for fostering seller collusion, particularly in markets with fixed fees alongside proportional charges. Platforms exhibit a preference for seller price coordination when buyer demand is inelastic or highly elastic, demonstrating a u-shaped pattern. Fixed fees consistently reinforce the platform's inclination for supply-side pricing coordination, hinting at potential hub-and-spokes cartels. Policy implications emphasize the impact of negative demand shocks and established user bases on platform behavior, underlining the importance of distinguishing between two-sided and supply-side network effects. These findings remain robust even without seller-induced network effects. In an era dominated by price-matching algorithms, our results suggest the potential for supra-competitive pricing. Additionally, we propose that these insights offer an alternative approach for mitigating the adverse effects of price-matching algorithms on competition by adjusting platform fees—a novel avenue for policymakers contending with the challenges of regulating such algorithms.

JEL Classification codes: D40, L10, L40
Keywords: Multi-sided markets, platforms, seller collusion, platform design, marketplace design, marketplace governance

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1 Introduction

In an increasingly digitized economy, consumers can access a growing range of products and services via online marketplaces. Examples range from e-commerce marketplaces like Amazon and eBay, over accommodation websites such as Airbnb or Booking.com, to mobile app stores and many more. Such *multi-sided* marketplaces add value to sellers by attracting many consumers beyond local markets. Similarly, consumers may benefit from greater product variety. This gives rise to positive indirect network effects: a growing number of buyers attracts more sellers and vice versa.

Given the growing economic relevance of online marketplaces, it's unsurprising that high-profile antitrust cases involving anti-competitive seller behavior have surged. [see, e.g., OECD, 2018].[1] Further, the use of price matching algorithms is now fairly established in digital marketplaces, and their growing popularity is likely to amplify this number [Calvano et al., 2020; Ezrachi and Stucke, 2019; CMA, 2021].[2] However, existing legal frameworks are often ill-adapted to counteract their anti-competitive consequences [Gal, 2023, forthcoming; Bhadauria and Vyas, 2018], and many regulators and supranational bodies express concerns about the resulting tacit "agreements" among sellers [OECD, 2017; Gal, 2023, forthcoming; Bernhardt and Dewenter, 2020; Gal, 2019; Ezrachi and Stucke, 2019]. Overall, this suggests that the number of actual cases is far greater than those that have been prosecuted yet.

In this paper, we investigate how a platform's marketplace design choices affect sellers' incentive to collude and whether such a platform has an incentive for self-regulation. Building on a game-theoretic model, we first derive the optimal pricing choices of an (online) marketplace providing platform. In particular, we carve out the platform's optimal fee level when sellers compete and when they collude. By doing so, we stress the importance of the platform's fee on sellers's incentives to collude. Based on this channels, we then probe on sellers' incentives to coordinate on prices and study how such a platform can manipulate their' incentives to steer their competitive behavior its own favour. Ultimately, we provide conditions under which a platform is able to correct sellers' anti-competitive behavior.

[1] Cases are numerous. For instance, several sellers in the DVD and Blu-Ray segment on Amazon were recently pleaded guilty by the US Department of Justice (DoJ) [2022] for price fixing. Similarly, the Italian Competition Authority (AGCM) [2020] fined resellers in the earphone segment on Amazon. Other famous cases involve the use of pricing algorithms to mitigate competition, such as in the posters and picture frames online market as investigated and prosecuted by the British Competitions and Markets Authority (CMA) [2016] or the DoJ [2015, 2016]. Moreover, the CMA [2018] finds evidence for the "widespread use of algorithms to set prices, particularly on online platforms" [p.3].

[2] While some scholars distinguish between collusion that involves a deliberate implementation via a dedicated code (collusion by code) and collusion as a consequence of algorithmic pricing (algorithmic collusion), we abstract from this debate in the paper and label both incidences as algorithmic collusion.

Perhaps unsurprisingly, we find that a platform can indeed affect sellers' ability to collude through its marketplace design choices and the fee it imposes. In particular, given that the platform can ration users and has the ability to manage seller markups within its marketplace, it can govern and, hence, steer seller competition in its own favour. Moreover, by varying the imposed usage fee, the platform is also able to manipulate sellers' profit margins at the potential risk of decreasing overall buyer demand: if sellers compete, increasing usage fees may be passed on to buyers, resulting in higher prices. Ultimately, this renders the platform less attractive to buyers. Hence, if sellers compete, the platform may ration buyers by raising usage fees since it decreases the extend of positive indirect network effects on the platform.

In addition, by looking at transaction fees (or per-unit fees) the platform can also have an incentive to encourage seller collusion –and this incentive is especially strong whenever buyer demand is either entirely inelastic or very elastic. Particularly when buyer demand is very elastic, the platform has to trade off whether extracting profits from sellers outweigh the profits from the overall volume in its marketplace by exploiting its underlying network effects. Intuitively, given that a retail platform can only make profits by extracting (parts of) the seller surplus when buyer demand is inelastic, its own profits are maximized whenever most of the buyer surplus is captured by the sellers. As a result, when demand is inelastic, the platform first tries to maximize seller profits by encouraging them to charge the highest possible price (which may be attained through collusion), only to extract these profits in a subsequent step via its fee. This creates a motive for the platform to establish a *hub-and-spoke cartel* [Ezrachi and Stucke, 2016]: the platform has an incentive to centrally coordinate sellers' price setting (e.g., by giving price recommendations to sellers or even by internalizing their price setting) to charge higher prices.[3]

Alternatively, when buyers are very responsive to changes in prices, the platform needs to leave some surplus to buyers. However, as some of that surplus will be absorbed by the sellers due to a double marginalization problem, setting a higher fee will hence crowd out more buyer demand. Thus, when comparing seller competition with seller collusion, it can generate higher profits under price coordination because it does not need to care about crowding out buyers anymore when charging a higher fee. Therefore, if buyers react strongly to price changes, the platform can make greater profits from seller collusion. Interestingly, this results still holds when the platform accounts for the incentive compatibility constraint of sellers to collude.

We also extend our analysis to different types of fees (including royalty fees, fixed

[3] Leading potential candidates to be classified as hub-and-spokes cartels in the landscape of digital markets may include Amazon's [2023] 'Automate Pricing' and Airbnb's [2023] 'Smart Pricing' tools. The CMA [2021] reports that also other sharing economy platforms employ similar tools that allow sellers to delegate their pricing decisions to the platform or even require them to do so.

fees, and two-part tariffs) as well as other types of competition and introduce network effects on the supply side. In contrast to a proportional fee (like a per-unit fee or royalties), the platform's preferred conduct is always seller collusion when it employs a fee that involves a fixed part (e.g., membership fees or a two-part tariff). Moreover, when network effects on both sides matter, the platform has no incentive to actively promote price coordination: since the number of active sellers is positively correlated with the number of active buyers in the marketplace, higher prices decrease the number of buyers and therefore also the number of sellers, which reduces the overall number of transactions on the platform.

The remainder of this paper is organized as follows. In Section 2, we discuss the related literature. Section 3 outlines the basic model and describes the timeline of the game. The model features three types of agents: buyers, sellers, and a monopoly platform. Sellers provide horizontally differentiated goods on the platform. The platform then decides on its usage fee. Subsequently, Section 4 studies platform governance choices through the lens of the previously described model. We discuss extensions and robustness check to our analysis in Section 5. Potential policy implications are drawn in Section 6. Section 7 concludes.

2 Related Literature

This paper contributes to various strands of the literature in industrial organization studying multi-sided markets. This includes the literature on pricing in multi-sided markets, platform governance, platforms managing (seller) competition, and platform regulation as the literature studying the feasibility of seller coordination.

Platform Pricing in Multi-Sided Markets A substantial part of the literature studying multi-sided markets primarily focuses on the interplay between a platform's underlying network effects and pricing decisions [Caillaud and Jullien, 2003; Rochet and Tirole, 2003, 2006; Armstrong, 2006; Armstrong and Wright, 2007; Weyl, 2010]. Typically discussed pricing models in the previous literature include *transaction* (or per-unit) fees, *fixed membership* fees, *royalty* fees (also called ad valorem or revenue-sharing fees), or *two-part tariffs*. Building on these theories, we additionally investigate platform pricing affects seller's ability and their incentives to collude.

Platform Governance While considering pricing aspects, we also contribute to the more recent literature that studies platform governance decisions [see, e.g., Boudreau, 2010; Parker and Van Alstyne, 2018; Hagiu and Spulber, 2013; Edelman and Wright, 2015; Hagiu and Wright, 2019; Teh, 2022; Schlütter, 2020; Johnen and Somogyi, 2021; Rhodes et al., 2023].

However, most of these works examine implications of innovation on platforms [Boudreau, 2010; Parker and Van Alstyne, 2018; Hagiu and Spulber, 2013; Edelman and Wright, 2015; Hagiu and Wright, 2019]. Teh's paper [2022] comes closest to ours, by examining how a platform's fee structure affect may affect seller competition. But in contrast to his paper, our focus lies on seller collusion, hence platform pricing decisions are fully endogenous in our model. Moreover, we can also extend our analysis to allow for indirect network effects on both sides. Yet, if we neglect cross-group network effects between buyers and sellers, our models coincide.

Schlütter [2020] studies the effect of *price parity clauses* (PPCs) used as a design element on seller collusion on a platform that acts as an intermediary (thereby neglecting any type of indirect network effects). Although exploring PPCs is not the primary goal of this paper, our baseline model features sellers' outside option normalized to zero. Hence, one possible way of interpreting sellers' outside option in our framework is that sellers expect to make the same profits across all available distribution channels. However, we discuss the role of sellers' outside options more broadly in Section 5.

In another paper, Johnen and Somogyi [2021] look at the role of *drip pricing* as a marketplace design tool. In their model, online platforms have the ability to indicate additional product attributes (such as shipping and return policies) in advance or at the end of a buyer's purchasing process. While Johnen and Somogyi [2021] mainly focus on the question of why specific product attributes tend to be shrouded in online marketplaces, this paper aims to shed light on the interplay between implemented marketplace design and seller competition.

Managing Seller Competition Due to its overlap with the literature on platform governance, we also relate to the literature that studies platforms managing competition among sellers [Belleflamme and Peitz, 2019; Anderson and Bedre-Defolie, 2021; Padilla et al., 2022; Nocke et al., 2007; Hagiu, 2009; Teh, 2022; Schlütter, 2020]. In most of these papers, the number of sellers on the platform is determined endogenously by the platform's pricing decision, which, in turn, can be affected by other exogenous factors (such as cross-group network effects or consumer preferences). For instance, Belleflamme and Peitz [2019] and Karle et al. [2020] study a platform imposing membership fees and its consequences on the number of sellers (thereby also the degree of competition between sellers). Closely related, Edelman and Wright [2015], Hunold et al. [2018] and Schlütter [2020] abstract from network effects to explore PPCs restricting sellers to charge lower prices elsewhere than via the platform.

In contrast to these works, and similar to the work by Teh [2022], our approach enables the separation of pricing decisions from other design features like product variety or information disclosure to analyze their impact on total welfare. In fact, if we neglect potential cross-group network effects between buyers and sellers, our model is identical to the one proposed by Teh [2022]. Different to Teh [2022], however, we model sellers' choices on "how to compete" more explicitly, in addition to a platform's preferences over its marketplace design.

Although related, another literature stream looks at a very distinctive setting where platforms can sell their own products [Anderson and Bedre-Defolie, 2021; Padilla et al., 2022]. Here, a platform acts not only a marketplace manager but also as a competitor to third-party sellers. In such setting, platforms face a trade-off between maximising profits via the management of network effects and via selling its own products, oftentimes resulting in an incentive for *self-preferencing*: the platform favors its own products by foreclosing buyer demand to third-party sellers. Our setting, on the other hand, abstracts from this possibility and focuses on platforms who first *design* and then *manage* their marketplace.

Algorithmic Collusion on Platforms Another related strand of the literature focuses on seller collusion in multi-sided markets based on the use of price matching algorithms [Calvano et al., 2020, 2021; Klein, 2021; Miklós-Thal and Tucker, 2019; Ezrachi and Stucke, 2019; Hansen et al., 2021; Rhodes et al., 2023]. In a set of simulation studies, for instance, Calvano et al. [2020, 2021] find that when sellers use algorithms to price their products, tacit collusion is almost certain to arise, independent of cost or demand asymmetries, the number of sellers, and uncertainty. Moreover, such cartels remain stable over time, even though seller algorithms have not been initially trained nor instructed to do so.

In a more recent paper, Rhodes et al. [2023] investigate algorithmic collusion, both theoretically and experimentally, in a setting very similar to ours. Their primary question revolves around whether elevating the prominence of specific sellers can diminish price coordination among them. Their findings reveal that platforms can indeed disrupt seller cartels, even when sellers are infinitely patient. However, our research diverges from theirs in one fundamental way: we extend the inquiry beyond this aspect and study whether a platform possesses an incentive to actively promote competition within its marketplace.

Most of these works, however, neglect network effects between buyers and sellers. Therefore, their main focus lies on the feasibility of seller cartels without direct coordination among the colluding parties. Our work, on the other hand, provides a more theoretical perspective on seller collusion and highlights mechanisms in which a platform can encourage seller collusion. In particular, we show that platforms can be motivated by the *hub-and-spoke* argument [Ezrachi and Stucke, 2019] to establish some form of price coordination among sellers when buyer demand is very elastic. In addition, we explore how other marketplace design features of a platform may shape seller competition.

Regulating Online Platforms Finally, there is a growing scrutiny on the regulatory side about harmful commercial practices by established online platforms (oftentimes called tech giants or gate keepers).[4] Such practices include, e.g., (potential) *killer acquisitions* [Hemphill, 2020; Cunningham et al., 2021; Motta and Peitz, 2021] as suspected after Meta's acquisition of Giphy,[5] *self-preferencing* by Amazon and Google (i.e., favoring their own products over third-party seller products on their marketplaces) [Hagiu et al., 2022], *predatory pricing* by Amazon [Khan, 2016], or *misleading sales tactics* by Booking.com to put pressure on consumers [Teubner and Graul, 2020]. We contribute to this debate by stressing how network effects may incentivise a platform to exploit its dominance in designing and regulating its marketplace to encourage seller collusion.

3 Theoretical Framework

This section outlines the model. We first describe competition on the platform level and then explain seller competition within the platform's marketplace. Next, we explain how network effects arise in this framework before providing the timeline of the game.

3.1 Competition and Network Effects on the Platform

To understand how a platform's pricing decisions may shape seller competition and how the platform may benefit from it, we propose a simple model in the spirit of Armstrong [2006] and Johnen and Somogyi [2021] featuring three types of agents: a monopoly platform, sellers, and buyers. We assume that there are $N^S \in \mathbb{N}$ sellers and $N^B \in [0, 1]$ buyers on the platform.

Buyers interact with sellers via the platform, and sellers provide horizontally differentiated goods in the marketplace. Quality differences in goods can thus be seen as products of sellers who compete in different markets, while sellers in the same market provide imperfect substitutes. Hence, a pair blue trainers shares the same market with a pair of red trainers, but not with a pair of red boots. However, to simplify things, we assume without loss of generality that there is only one product category. Also, for the sake of tractability, we assume that sellers' outside option is homogeneous and normalized to zero.[6] Buyers have an idiosyncratic stand-alone utility $u^B \in \mathbb{R}$ from joining

[4] See, e.g., New York Times [2020]. An example of regulators' concerns about, and (soon-to-be) implemented actions against, such practices can be found in, e.g., the *Digital Markets Act* by the European Commission [2022].

[5] See, e.g., Financial Times [2021].

[6] This homogeneity assumption about the sellers' outside option implies that increasing the number of buyers also increases the benefit for sellers without attracting more sellers in equilibrium. Hence, all sellers with a non-negative profit will join the platform in equilibrium. This limits the extend of cross-group network effects and simplifies the demand system without eliminating these network effects.

the platform that follows some continuous distribution F with support $[0, 1]$.[7] They endure no cost of joining the platform. Further, let $v \in \mathbb{R}_{++}$ be buyers' homogeneous valuation for goods within the marketplace.[8] Sellers charge a price $p \in \mathbb{R}_{+}$. Thus, a buyer's utility from joining the platform is

$$U^B = u^B + (v - p) * N^S. \tag{1}$$

Similarly, a seller's benefit from joining the platform is equal to the total profits π that she can make in the marketplace:

$$U^S = \pi * N^B. \tag{2}$$

The valuations U^B and U^S capture two common assumptions. First, it is assumed that each buyer interacts with every seller on the platform and vice versa, such that their expected perceived per-user benefit is $(v - p)$ and π, respectively. Hence, the platform can manage indirect network effects on the buyer side, namely buyers benefit from the presence of a greater number of sellers . In addition, each additional interaction is assumed to have the same marginal value to each user group.

We focus on a platform charging a transaction (or per-unit) fee $f \in \mathbb{R}_{+}$.[9] Without loss of generality, we further assume that the platform does not impose any fees on buyers [Weyl and Fabinger, 2013]. Hence, the outlined model is most applicable to retail platforms or cases where buyers cannot observe fees born by sellers.

We model the platform in a way similar to Armstrong [2006] or Johnen and Somogyi [2021]. As mentioned above, the platform charges f to sellers and has no marginal costs. We assume that the platform cannot discriminate among sellers or buyers. Total platform profits can then be summarized as

$$\Pi_P(f) = f * N^S * N^B. \tag{3}$$

Hence, the platform faces a trade-off between charging a higher transaction fee f and maximizing overall trading volume $N^S * N^B$ on its marketplace.

[7] Assuming $u^B \sim F[0, 1]$ captures the idea that each buyer has an individual outside option that is randomly distributed. Also, we do not impose any restrictions on the sign of u^B, it can thus be either, positive (i.e., buyers enjoy being on the platform –e.g., for reputational or personal reasons– even though they might not buy anything), zero (e.g., buyers simply want to make the best deals, but they derive no stand-alone utility merely from being on the platform), or negative (e.g., buyers generally dislike the platform but use it to purchase goods since it provides the best value-for-money).

[8] We assume that buyers' valuation for goods is sufficiently large such that the market is covered (see Assumptions A1 below). Note, however, that together with the homogeneous valuation v for goods, the specification of u^B allows for indirect network effects on the buyer side.

[9] While our subsequent analysis features a model of transaction fees, we provide an extension to various other fee structures. Namely, in Section 5, we discuss how our results relate to royalty fees, fixed membership fees and two-part tariffs.

3.2 *Competition among Sellers*

Sellers compete in a Salop [1979] fashion: there is a continuum of buyers and $N^S \in \mathbb{N}$ sellers who provide horizontally differentiated goods in this one-dimensional product space. They are symmetric and equally distributed across a circular city with a perimeter equal to one. Moreover, they have no marginal costs. Let $\tau \in \mathbb{R}_+$ be the product-differentiation parameter and let $p_i \in \mathbb{R}_+$ be the price charged by seller i and $p_{-i} \in \mathbb{R}_+$ be the price charged by i's competitors $N^S \setminus \{i\}$, respectively. The total profits of seller i are then given by

$$\pi_i(p_i, p_{-i}) = (p_i - f - c) * d_i(p_i, p_{-i}), \tag{4}$$

where $d_i(p_i, p_{-i}) = 1/N^S + (p_{-i} - p_i)/\tau$ is seller i's demand.

Buyers, on the other hand, have a particular taste or idea about the product they want to purchase but observe these horizontally differentiated goods. Hence, they bear a disutility from their ideal and the actual product which is proportional to τ. Alternatively, following the convention of the spatial economics literature, we can interpret τ as the transportation cost that buyers incur in order to purchase the product of seller i. For the sake of tractability, we assume linear transportation costs. As discussed above, buyers' willingness to pay is homogeneous and equal to $v \in \mathbb{R}_{++}$. Also for the sake of simplicity, their outside option consists of not buying (can be relaxed). For ease of presentation, we assume that this outside option is at the sellers' locations [see, e.g., Bénabou and Tirole, 2016; Heidhues and Kőszegi, 2018].[10]

3.3 *Network Effects on the Platform*

The total number of users on the platform is subject to indirect network effects (or cross-group externalities). In particular, while buyers exhibit such network effects, the total number of sellers on the platform is fixed.[11] To see this, note that the number of sellers is given by

$$N^S = N^S(p, N^B) = \Pr[\pi(p) * N^B \geq 0]. \tag{5}$$

Since by assumption their outside option is homogeneous and normalized to zero, sellers always join the platform as long as they can generate non-negative profits. Hence, in equilibrium either all N^S sellers join or not.

[10] One way of interpreting this assumption is that buyers first have to go to a seller (facing transportation costs τ), and *then* decide whether to buy or not. As a result, τ only influences the level of competition between sellers without affecting the attractiveness of seller i's product relative to the outside option for any given buyer.

[11] Consequently, there is no market entry or exit from the seller side. In Section 5, we relax this assumption and discuss how our results change when sellers are subject to indirect network effects and have a heterogeneous outside option.

In contrast to sellers, buyers prefer lower prices and a greater presence of sellers on the platform. The platform thus has an incentive to increase the total number of interactions in its marketplace. Similar to the number of sellers, the total number of buyers on the platform is given by

$$N^B = N^B(p, N^S) = \Pr[u^B + (v - p) * N^S \geq 0], \tag{6}$$

with

$$\frac{\partial N^B}{\partial p} < 0 \quad \text{if } N^S > 0 \qquad \text{and} \qquad \frac{\partial N^B}{\partial N^S} \geq 0 \quad \forall p \leq v. \tag{7}$$

The first partial derivative in expression 7 states that, everything else equal, buyers prefer lower prices given the existence of sellers on the platform. The second partial derivative reflects indirect network effects on the buyer side: as long as prices do not exceed buyers' willingness to pay, they prefer a larger number of sellers. Given that sellers provide horizontally differentiated goods, this also provides a microfoundation for buyers' taste for variety.

3.4 *Timeline of the Game*

The timeline of the game is as follows: First, the monopoly platform makes a design choice and decides its pricing strategy. Second, buyers and sellers decide whether to join the platform or not. Third, sellers decide on whether to compete or to collude. In case of no collusion, sellers compete in the manner as outlined above. In case of collusion, sellers coordinate to charge the highest price possible (i.e., the monopoly price).[12] Buyers then decide whether to purchase goods via the platform or not. We solve this model by studying subgame perfect equilibria and then use backward induction.[13]

4 Competition and Platform Governance

Based on the model above, this section describes a platform's governance decisions given sellers' ability to collude. In particular, we establish a platform's best response to set transaction fees when sellers compete and when they collude. Moreover, we also show under which conditions the platform actually prefers seller collusion over competition within its marketplace. Before, however, we discuss possible market equilibria.

[12] In principle, colluding sellers could agree to charge *any* price above the marginal costs. However, we later show in Section 5 that results remain qualitatively unchanged when sellers have this option.

[13] Since the platform commits to fees before the sellers decide on their conduct, and since fees are public knowledge, there is no need to model beliefs explicitly in this environment.

4.1 Market Equilibria

On the platform, sellers compete by providing horizontally differentiated goods. Based on the model outlined in Section 3, buyers decide to purchase a good as long as their willingness to pay is greater than the price they face. Similarly, sellers offer their products on the platform as long as they can make non-negative profits. This introduces a trade-off for the platform in its governance decision: To maximize volume in the marketplace, the platform has an incentive to keep prices low enough such that it maximizes the number of buyers. At the same time, however, the platform generates profits from imposing its transaction fee, which increases the overall price and hence may crowd out buyers.

Given this trade-off, we first describe the set of market equilibria to start with our analysis. We then study the effects of this trade-off in more detail. The following lemma shows that, depending on buyers' willingness to pay and transportation costs, a marketplace is either competitive or features local monopolies.

Lemma 1 (Competitive Equilibria)**.** *There exists a unique market equilibrium. In particular, the marketplace is* competitive *if*

$$v > f + \tau/N^S. \tag{8}$$

Alternatively, the marketplace features local monopolies *if* $v < f + \tau/N^S$*. Moreover, both cases* coinincide *whenever* $v = f + \tau/N^S$*.*

Proof. We proof this lemma by contraposition. Given buyers' outside option (i.e., not buying) is at the seller's location, a buyer purchases a good from seller i iff $v - p_i - \tau x_i \geq 0 \iff v \geq p_i$.

Suppose first that $v < f + \tau/N^S$. Then, seller i's best response

$$\pi_i(p_i, p_{-i}) = (p_i - f) * d_i \tag{9}$$

is to maximize profits with respect to p_i, where p_{-i} denotes the price set by seller i's rivals along the Salop circle and $d_i = 1/N^S + (p_{-i} - p_i)/\tau$ denotes i's demand. Since sellers are symmetric, profit maximization reveals that the optimal price charged by all sellers satisfies

$$p^{com} \equiv p_i = f + \tau/N^S, \tag{10}$$

and they all obtain the same market share $d_i = 1/N^S$ for all $i \in N^S$. But, since buyers' participation constraint reads $v \leq f + \tau/N^S$, not all buyers along the Salop circle will purchase (i.e., buyer rationing). Given that buyers are uniformly distributed across the Salop circle, however, there exist at least one buyer at seller i's location, who will buy from seller i as long as $p_i \leq v$. Thus, the profit maximizing price is $p^{mon} \equiv v$, yielding a profit of $\pi^{mon} = (v - f)/N^S$ for each seller. As a result, if v is sufficiently low or τ is sufficiently large, sellers will act as local monopolies.

Conversely, suppose it holds that $v > f + \tau/N^S$. Then, if seller i sets a price $p_i > p^{com}$, this leads to a loss in market share (i.e., $d_i < 1/N^S$) and hence lower profits. Therefore, if $v > f + \tau/N^S$, sellers compete along the Salop circle with $p_i = p^{com}$ and $\pi^{com} \equiv \pi_i = \tau/(N^S)^2$ for all $i \in N^S$.

Finally, if $v = f + \tau/N^S$, the profit maximizing price resulting from competition is equal to the monopoly price, i.e., $p^{com} = p^{mon} = v$ for all $i \in N^S$ due to symmetry. Hence, both cases coincide. □

Lemma 1 shows that there are two types of competitive equilibria, depending on whether Condition 8 is met. In particular, when buyers' willingness to pay v is sufficiently high (or transportation costs τ are sufficiently low), there is demand around the Salop circle. Moreover, sellers are distributed around the Salop circle at equal distance from each other. Then, the competitive outcome is equal to Bertrand competition with imperfect substitutes: charging a price that exceeds the competitive price p^{com} leads to a loss in demand, leading to lower profits. Hence, charging p^{com} constitutes an equilibrium.

Alternatively, if v is sufficiently low (or τ sufficiently large), buyers 'movements' are locally bounded. Hence, the Salop circle is not entirely covered. Then, for each seller i, the optimal strategy is to charge the monopoly price $p_i = p^{mon} = v$ since there is at least one buyer at seller i's location who is willing to buy the product. As a result, sellers act as local monopolies within whenever $v < f + \tau/N^S$.

Regardless of the competitive equilibrium, sellers seek to maximize profits. Therefore, to link profits and prices within each equilibrium, the following corollary carves out their underlying relationship:

Corollary 1 (From Lemma 1)**.** *Let p^{mon} and and p^{com} be the monopoly and competitive price, respectively. Then,*

i) if the marketplace is competitive, it holds that $p^{mon} > p^{com} \iff \pi^{mon} > \pi^{com}$.

ii) if the marketplace features local monopolies, it holds that $p^{mon} < p^{com} \iff \pi^{mon} < \pi^{com}$.

Proof. Take a competitive marketplace. Then $p^{mon} = v > f + \tau/N^S = p^{com}$, where the inequality stems from Lemma 1 since sellers compete in that marketplace. However, if seller i is the only seller in the market, i's profits are maximized at $p_i = p^{mon}$. Hence, $\pi^{mon} > \pi^{com}$. Conversely, by a similar reasoning, if sellers act as local monopolies, then $p^{mon} = v < f + \tau/N^S = p^{com}$ and $\pi^{mon} < \pi^{com}$. □

Corollary 1 displays how prices and profits differ in general when comparing seller competition with local seller monopolies. In particular, sellers have no incentive to compete in the monopolistic equilibrium: Given that buyers' willingness to pay is sufficiently low (or transportation costs are too high), sellers act as local monopolies and charge the highest price possible $p^{mon} = v$.

As mentioned earlier, however, this differs starkly when buyers have a high willingness to pay: in a competitive marketplace, sellers are exposed to the Bertrand trap. Even though charging higher prices would result in greater profits for each seller, charging a lower price leads to a competitive advantage and, hence, allows them to gain a greater market share by attracting more demand.

However, it is important to note that this also provides scope for sellers to create a cartel. In fact, once sellers can coordinate on prices, they can generate greater profits from forming a collusive agreement than when competing with each other. As an additional corollary from Lemma 1, we can thus state:

Corollary 2 (From Lemma 1)**.** *Only in a competitive marketplace, sellers have an incentive to collude since $\pi^{mon} > \pi^{com}$.*

Proof. A necessary condition for collusion is that sellers can make greater profits when charging a collusive price. Assume that if sellers collude, they charge a collusive price $p^{coll} = p^{mon} > p^{com}$. The first statement of Corollary 1 shows that $\pi^{mon} > \pi^{com}$ whenever sellers compete. Hence, only in a competitive market sellers have an incentive to collude. □

As a result, collusion can only arise in a *competitive* marketplace. Therefore, for the remaining part of the paper, we thus assume that $p^{mon} > p^{com}$ to rule out the economically uninteresting case of the monopolistic equilibrium:[14]

A1. $p^{com} < p^{mon}$.

Following this, we next study a monopoly platform's governance decisions. Particularly, we first examine the platform's strategies when sellers compete, followed by the same analysis when sellers collude. We then look at whether a platform has an incentive to manipulate competition in its marketplace to foster price coordination among sellers.

4.2 *Seller Competition*

When sellers compete in the marketplace, they make profits equal to $\pi^{com} = \tau/(N^S)^2$ and charge prices $p^{com} = f + \tau/N^S$. The platform then maximizes profits with respect to the fees it imposes. Thus, the platform's problem formally reads:

$$\begin{aligned} \max_f \Pi_P &= f * N^B(p(f), N^S) * N^S \\ \text{s.t.} \quad p(f) &= p^{com} = f + \frac{\tau}{N^S} \end{aligned} \tag{11}$$

[14] Notice that this assumption is equivalent to say that buyers prefer seller competition over collusion. Moreover, it also gives a reasonable justification to focus on marketplaces of retail platforms.

Based on the maximization problem above, the following proposition replicates the result by Rochet and Tirole [2003]; Armstrong [2006] of a profit-maximizing monopoly platform: since the platform manages indirect network effects across users, it is able to charge fees above marginal costs (here equal to zero). Further, setting a transaction fee that is too high is inefficient since this would reduce buyer demand, which in turn reduces the total volume in its marketplace, and hence decreases profits. Also, for the remaining part of the paper, we are going to drop arguments for the sake of disposition whenever it creates no confusion, and use labels of *com* or *coll* in sub- or superscripts to refer to a particular statistic in a competitive or collusive equilibrium, respectively.

Proposition 1 (Platform Pricing (Seller Competition))**.** *Suppose Lemma 1 holds and that sellers compete. Then, the monopoly platform's best response to maximize profits is*

$$f^{com} = -\frac{N^B_{com}}{dN^B_{com}/dp} \quad \text{and} \quad \eta^B_{com} = \frac{f}{N^B_{com}}\frac{dN^B_{com}}{dp} \tag{12}$$

being the elasticity of buyers' demand with respect to prices on the platform.

Proof. The platform maximizes profits with respect to its transaction fees, i.e.,

$$\max_f \Pi_P = f * N^B(p(t), N) * N^S, \tag{13}$$

whose first order condition (while neglecting arguments for a moment) solves

$$N^B_{com} * N^S * + N^S * f * \frac{dN^B_{com}}{df} = 0. \tag{14}$$

Given that sellers charge $p^{com} = f + \tau/N^S$, they make profits $\pi^{com} = \tau/(N^S)^2 > 0$, so in equilibrium all sellers join the platform. Moreover, since seller profits are independent of f, also $dN^S/df = 0$. This reduces the first order condition to

$$N^B_{com} + f * \frac{dN^B_{com}}{df} = 0, \tag{15}$$

where, after rearranging terms, we can derive both

$$\frac{N^B_{com}}{-dN^B_{com}/dp} = f \equiv f^{com} \quad \text{and} \quad \frac{f}{N^B_{com}}\frac{dN^B_{com}}{dp} \equiv \eta^B_{com}, \tag{16}$$

which concludes the proof. □

Notice that $N^B_{com} > 0$ and $dN^B_{com}/df < 0$. Therefore, Proposition 1 tells us that in equilibrium, the platform charges a positive transaction fee f^{com}. Moreover, if sellers compete, they charge a price $p(f) = f + \tau/N^S$ and make profits equal to $\tau/(N^S)^2$. Hence a double marginalization problem exists: the platform is unable to extract seller profits completely since sellers pass on higher transaction fees to buyers.

In addition, Proposition 1 also reveals further important comparative statics. For instance, a higher number of sellers N^S allows the platform to charge a higher transaction fee. In fact, a greater number of sellers implies tougher competition between sellers, which results in lower prices and ultimately leads to lower profits for each seller. Tougher competition thus reduces the extent of the platform's double marginalization problem but also increases marketplace volume. Moreover, buyers benefit from more sellers due to indirect network effects. In turn, the platform can then exploit these two effects by setting a larger transaction fee.

Conversely, and by the same reasoning, rationing sellers is costly for the platform since reducing the number of sellers results in less competition. Sellers then can charge higher prices which entails greater profits for them but also reduces overall marketplace volume: first, because sellers pass on the imposed fees to buyers, and second, because less buyers join the marketplace overall. Hence, also double marginalization becomes a more prevalent issue for the platform. To counteract such events, the platform would have to decrease its fees.

Additionally, improving product comparability (e.g., by decreasing τ) has two effects. First, by making products appear more similar or displaying similar item for a given product search, seller competition becomes more fierce. This results in lower prices, which increases buyer demand on the platform. Second, also sellers' profits decrease, which reduces issues of double marginalization. Together, this allows the platform to set higher transaction fees.

Finally, increases in the elasticity of buyer demand around the competitive price p^{com} force the platform to set lower transaction fees. Intuitively, when buyer demand is responsive to prices, the platform must leave more surplus to buyers because else it is crowding out demand. Since sellers pass on fees to buyers, the platform thus has to reduce its fee to prevent buyers from leaving. Alternatively, the platform may try to increase buyers' stand-alone benefit u^B to counteract their increased sensitivity to prices by, e.g., providing or improving add-on services.

4.3 Seller Collusion

This previous subsection looked at a marketplace equilibrium where sellers compete. In that case, sellers charge prices $p^{com} = f + \tau/N^S$ and make profits $\pi^{com} = \tau/(N^S)^2$. Given that sellers compete, Proposition 1 characterizes the platform's optimal pricing strategy. As shown above, the optimal fee f^{com} extracts some surplus from sellers while still allowing for cross-group externalities such that the overall number of trades is maximized. However, since $\pi^{com} > 0$, the platform faces an issue of double marginalization that limits its ability to extract all surplus. Hence, a platform may find employing transaction fees an inefficient tool.[15]

Contrary to the previous case, where sellers could not coordinate on prices, we now study an equilibrium where sellers have the ability to collude. In particular, we first look at the equilibrium of an infinitely repeated collusion game. In that part of the game, sellers –being symmetric and having the same discount factor for future profits– decide whether to coordinate on prices or to compete in the above fashion. Strikingly, we find that a platform may shape sellers' incentives to coordinate on prices and therefore also collusion stability via its imposed fee. We then carve out the platform's optimal fee level in case of seller collusion.

Based on Corollary 2, a necessary condition for seller collusion is that they can obtain higher profits (i.e., $\pi^{coll} > \pi^{com}$) if they coordinate on prices. Thus, given Assumption A1, we look at an infinitely-repeated game in discrete time with periods $k = 0, ..., \infty$ where sellers have a common discount factor $\delta \in (0, 1)$ and aim to maximize the discounted stream of (future) profits:

$$\sum_{k=0}^{\infty} \delta^k \pi(p). \tag{17}$$

Notably, the platform does not participate in the collusive agreement but may have a preferred conduct (i.e., seller competition or collusion). Moreover, by choosing its fee, the platform can influence how sellers act in its marketplace. Finally, the platform sets a symmetric transaction fee at the beginning of the first period that remains constant over time.

As before, we solve for subgame-perfect Nash equilibria in this infinitely-repeated subgame between sellers. To simplify the demonstration of our results, we assume sellers coordinate on the monopoly price $p^{coll} \equiv p^{mon}$.[16]

We are now going to model seller collusion by looking at grim trigger strategies [Friedman, 1971] – that is, once a seller deviates from the collusive scheme, all sellers play their competitive strategies and earn π^{com} profits.Suppose now that sellers form a cartel that coordinates on prices charging the collusive price p^{coll}. Hence, once the cartel is formed, each colluding seller obtains $\pi^{coll} > \pi^{com}$. Then, if one seller decides to deviate from the collusive scheme, the deviator sets a price p^{Dev} to maximise deviation profits. Thus, collusion is an infinitely repeated prisoner's dilemma. The following lemma summarizes this result:

[15] In Section 5, we discuss further pricing tools that the platform could impose. As we show, having a fixed fee or a two-part tariff may eliminate double-marginalization completely when sellers compete.

[16] In principle, colluding sellers could agree on any price between p^{com} and p^{mon}. Hence, it does not necessarily hold that $p^{coll} = p^{mon}$, resulting in an infinite number of possible equilibria, as suggested by the Folk Theorem [Friedman, 1971]. However, in Section 5, we generalize our findings by relaxing this assumption and show that they still hold when colluding sellers have the possibility to charge a price $p^{coll} \in [p^{com}, p^{mon})$.

Lemma 2 (Deviator strategy). *Suppose all sellers coordinate to play p^{coll}. Now, if one seller deviates from the collusive scheme by playing p^{Dev}, the deviator's then obtains a market share d^{Dev} and generates profits π^{Dev} such that*

$$p^{Dev} = p^{coll} - \frac{p^{coll} - p^{com}}{2} \; ; \; d^{Dev} = \frac{1}{N^S} + \frac{p^{coll} - p^{com}}{2\tau} \; ; \; \pi^{Dev} = \pi^{coll} + \frac{(\pi^{coll} - \pi^{com})^2}{4\pi^{com}}. \quad (18)$$

Proof. Suppose $N^S - 1$ sellers play p^{coll} and one seller deviates by playing p^{Dev}. Denote this seller's profits, market share, and prices with superscript Dev. Then, the deviator's best response p^{Dev} maximizes

$$\pi^{Dev}(p^{Dev}, p^{coll}) = (p^{Dev} - f) * \left(\frac{1}{N^S} + \frac{p^{coll} - p^{Dev}}{\tau} \right), \quad (19)$$

where p^{coll} is the price charged by the remaining $N^S - 1$ sellers. Then, after taking the problem's first order conditions, this yields p^{Dev}, d^{Dev}, and π^{Dev} as stated above. □

Proposition 2 shows that a deviating seller chooses a price below the cartel price p^{coll}. By doing so, she is able to gain a greater market share $d^{Dev} > 1/N^S$, which maximizes her profits. As a result, deviating from the collusive agreement may be profitable. Thus, sellers' incentive compatibility constraint to stick to the collusive regime is

$$\pi^{mon} + \sum_{k=1}^{\infty} \delta^k \pi^{mon} \; \geq \; \pi^{Dev} + \sum_{k=1}^{\infty} \delta^k \pi^{com}. \quad (20)$$

In other words, sellers cartelize if the profits from sticking to the collusive agreement exceed the profits from deviating once and playing competitive strategies for the remaining future.

Further, given the incentive compatibility constraint for collusion, we can rearrange terms in Expression 20 to obtain a lower bound for the common discount factor under which collusion is always stable:

$$\delta \; \geq \; \delta^* \equiv \frac{\pi^{Dev} - \pi^{mon}}{\pi^{Dev} - \pi^{com}}. \quad (21)$$

Hence, collusion is only stable if $\delta \geq \delta^*$. In other words, sellers need to be sufficiently "patient" to collude. Notably, $\pi^{mon} = \pi^{mon}(f)$ and therefore $\pi^{Dev} = \pi^{Dev}(f)$, also the critical discount factor $\delta^* = \delta^*(f)$, while π^{com} is independent of transaction fees f. Thus, the platform is able to influence the stability of seller collusion by raising or lowering its fee. To provide some further insights on this, we show in the next Proposition how collusion stability relates to the transaction fee imposed by the platform in more detail:

Proposition 2 (Collusion incentives). *Denote δ^* the critical discount factor for which colluding is subgame perfect. For π^{Dev} and π^{mon} as defined in Proposition 2 and Corollary 1, respectively, it holds that $\delta^*(f)$ is monotonically decreasing in f.*

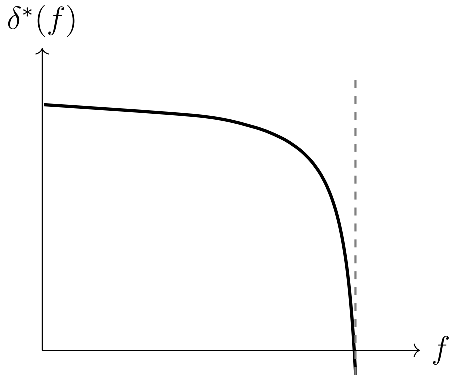

Figure 1: Threshold value or the discount factor δ^* depending on transaction fees f.

Proof. Notice that a necessary condition for collusion is that the discount factor of the cartelizing sellers is large enough:

$$\delta \geq \delta^*(f) \equiv \frac{\pi^{Dev}(f) - \pi^{mon}(f)}{\pi^{Dev}(f) - \pi^{com}}. \tag{22}$$

In combination with the results in Lemma 2, we can thus simplify the enumerator to $\pi^{Dev}(f) - \pi^{mon}(f) = (\pi^{mon}(f) - \pi^{com})^2/(4\pi^{com})$. Moreover, the denominator can be reduced to $\pi^{Dev}(f) - \pi^{com} = (\pi^{mon}(f) - \pi^{com})^3/(4\pi^{com})$. Differentiating with respect to f then yields

$$\frac{d\delta^*(f)}{df} = -\frac{5}{N^S} \frac{\pi^{mon}(f) - \pi^{com}}{4\pi^{com}} < 0. \tag{23}$$

□

Proposition 2 shows that if sellers collude, a higher transaction fee reinforces sellers' incentives to collude once again. In fact, higher transaction fees reduce both deviator profits as well as profits under collusion. Yet, deviator profits decrease faster than collusion profits. Therefore, higher transaction fees render the sellers' outside option of collusion (i.e., to compete) relatively less attractive. As a result, a higher transaction fee can thus reinforces sellers' incentives to collude. Figure 1 illustrates the relationship between sellers' collusion incentives and transaction fees imposed by the platform.

How will the platform react if sellers collude? The following Lemma establishes that the platform's best response is to adjust its transaction fees once a seller cartel has been implemented:

Lemma 3 (Platform Pricing (Seller Collusion))**.** *Suppose Lemma 1 holds and that sellers collude. Then, the monopoly platform's best response to maximize profits is*

$$\tilde{f}^{coll} = v. \tag{24}$$

Proof. Suppose sellers charge $p^{coll} = v$ and obtain $\pi^{coll} = (v - f)/N^S$. Moreover, it holds that $dN^B_{coll}/df = 0$, so higher fees do not crowd buyers anymore as long as $f < v$. Hence, it must be that $f \leq v$. In addition, also $dN^S/df = 0$, so any $f < v$ is inefficient since a setting higher fee increases profits but does not crowd out sellers. As a result, the platform's optimal fee is $\tilde{f}^{coll} \equiv f = v$. □

When sellers collude, buyer demand on the platform is minimized: they charge $p^{coll} = v$, making buyers indifferent between realizing their outside option and purchasing. Consequently, colluding sellers act like a monopoly and can so extract all buyer surplus, which also limits indirect network effects on the buyer side. However, because indirect network effects are already limited, colluding sellers earn $\pi^{coll} = (v - f)/N^S$, so the platform's best response is to extract this surplus once again by charging $\tilde{f}^{coll} = v$ irrespective of potential network effects. As a result, by charging $\tilde{f}^{coll}$, the platform can eliminate its double double marginalization problem, acting like a vertically integrated firm when sellers collude.

4.4 *Collusion or Competition*

Suppose the monopoly platform can now decide whether sellers collude or compete. In that case, which equilibrium will the it prefer? Notably, the platform's preferred conduct depends on its profits in the given scenario. Irrespective of the sellers' participation constraint to collude, it turns out that the platform prefers seller collusion whenever buyers' have a high willingness to pay v or demand is sufficiently elastic around p^{com}:

Lemma 4 (Preferred Conduct). *The monopoly platform prefers seller collusion iff*

$$v > -\frac{N^B_{com}}{dN^B_{com}/dp} * \frac{N^B_{com}}{N^B_{coll}}. \tag{25}$$

Proof. The platform prefers seller collusion iff

$$\Pi^{coll}_P > \Pi^{com}_P \iff \tilde{f}^{coll} * N^B_{coll} * N^S > f^{com} * N^B_{com} * N^S. \tag{26}$$

Moreover, together with the results from Proposition 1 and Lemma 3, we can rewrite this statement as

$$v * N^B_{coll} > -\frac{N^B_{com}}{dN^B_{com}/dp} * N^B_{com}, \tag{27}$$

which, after rearranging terms, yields the expression as shown in the Lemma. □

A higher willingness to pay v implies less elastic demand. Hence, given that buyers react less sensitively to changes in prices, the platform may prefer the sellers charging the highest price possible. In principle, when sellers compete, they charge prices equal to $p^{com} = f + \tau/N^S$, passing on the fees f to buyers. In principle, the platform could increase its feed such that $p^{coll} = v$, but then it still faces the issue of double marginalization when sellers compete. On the other hand, when sellers collude, they charge p^{coll} by themselves, and the platform can re-extract that surplus from the sellers once again via its fee $\tilde{f}^{coll}$.

Additionally, when the number of buyers is sufficiently price sensitive around p^{com}, a higher fee crowds out a great number of buyers (again due to the pass-through of f). Thus, when buyers are very sensitive towards prices around p^{com}, the platform's preferred conduct is seller collusion.

Even though price coordination among sellers may be preferred, encouraging them to collude can still be challenging for the platform. Notably, the result of Lemma 4 neglects sellers' incentive compatibility constraint to collusion: As stated in Corollary 2, a necessary condition for seller collusion is $\pi^{mon} > \pi^{com}$. But as shown in Lemma 3, the platform optimal fee under collusion eliminates double marginalization. Therefore, the platform's incentives to foster collusion may diminish once it respects sellers' incentive compatibility constraint and double marginalization.

However, as we show next, a platform may still favor seller collusion even when it must maintain its double marginalization problem. In fact, similar to the previous Lemma, its preference for collusion depends on buyers' willingness to pay and their sensitivity towards prices around p^{com} as well (although stricter). However, before stating our main result, we first derive the platform's optimal pricing strategy to seller collusion in compliance to the incentive compatibility constraint:

Proposition 3 (Platform Pricing (Collusion, IC))**.** *For any $\epsilon < v - \tau/N^S$, and in compliance to the incentive compatibility constraint (Corollary 2), the platform's optimal pricing strategy with respect to seller collusion is*

$$f^{coll} = v - \epsilon - \frac{\tau}{N^S}. \tag{28}$$

Proof. In Lemma 4, it was established that the optimal fee level maximizes platform profits while preventing a crowding out of users. Moreover, the incentive compatibility constraint in Corollary 2 read $v > f + \tau/N^S$. Hence, for f to be optimal, it must hold $v - \tau/N^S > f$, which implies that there exists and $\epsilon \in \mathbb{R}_{++}$ such that $f = v - \epsilon - \tau/N^S$. Moreover, any $f \leq 0$ is strictly dominated by an $f > 0$. Thus, $\epsilon < v - \tau/N^S$. □

Proposition 4 (Preferred Conduct (IC))**.** *Given the sellers' incentive compatibility constraint for collusion (Corollary 2) and for any $\epsilon < v - \tau/N^S$, the platform's preferred conduct is seller collusion iff*

$$v > \epsilon + \frac{\tau}{N^S} - \frac{N^B_{com}}{dN^B_{com}/dp} * \frac{N^B_{com}}{N^B_{coll}}. \tag{29}$$

Proof. Denote the platform's profits in the competitive and the collusive equilibrium by Π^{com}_P and Π^{coll}_P, respectively. As in Lemma 4, a monopoly platform prefers seller collusion whenever $\Pi_P^{coll} > \Pi_P^{com}$. Together with the result of Proposition 3, we can rewrite this inequality as

$$f^{coll} * N_{coll}^B > f^{com} * N_{com}^B \iff \left(v - \epsilon - \frac{\tau}{N}\right) * N_{coll}^B > -\frac{N_{com}^B}{dN_{com}^B/dp} * N_{com}^B, \tag{30}$$

which, after re-arranging terms, yields the expression in the Proposition. □

As shown in Proposition 1, when sellers compete, they pass on the imposed fee to buyers via their prices, which in turn crowds out buyer demand in the marketplace. Hence, when buyers reacts strongly to prices, the platform's profits when sellers compete are lower than its profits when sellers collude. Therefore, when buyer demand is very elastic, the platform prefers seller collusion.

Moreover, and in line with Lemma 4, Proposition 4 shows that a platform is inclined towards price coordination among sellers whenever buyers' willingness to pay is sufficiently large. A large willingness to pay for goods is equivalent to say that buyers' reservation prices are high.

Interestingly, taken together these two points suggest that a platform's preference for seller collusion follows a u-shaped pattern depending on buyer demand elasticity: when buyer demand is inelastic, sellers could charge a higher price without crowding out much demand. But since extracting buyer surplus under competition turns out to be inefficient for the platform (due to double marginalization), the platform prefers seller collusion. In this case, sellers capture all buyer surplus, which the platform then re-extracts once again via its fee. As a result, the platform prefers seller collusion when buyer demand is very inelastic or buyers have a large willingness to pay.

Given that the platform's profits under collusion exceed profits under competition when demand is either very elastic or very inelastic, it can thus have an incentive to encourage seller collusion, depending on demand characteristics. Consequently, given the platform's ability to design and to govern its marketplace, it may seize to exploit this relationship. This gives rise to a novel theory of harm for seller collusion in online marketplaces that sheds light on the question of whether online platforms as marketplace designers are accountable, at least in parts, for consumer harming practices that involve price coordination among sellers in their marketplaces. Following this result, we first discuss extensions and robustness checks of our model before highlighting potential consequences for policymakers and managers in the next section.

5 Extensions and Limitations

Our baseline analyses explored the implication of a platform's marketplace design decisions on competition between sellers and their incentives to collude. In this section, we expand the scope of our analysis in several directions.

We previously studied a platform that levies transaction costs. However, we can generalize our results from Section 4 to other platform pricing models, such as royalty fees, fixed membership fees, and two-part tariffs. Notably, most of our results remain qualitatively unchanged. In fact, some findings become even more pronounced if the platform uses different pricing models. In particular, if the platform's fee structure includes a fixed component (as it is the case for membership fees or a two-part tariff), platform always prefers seller collusion.

Royalty Fees or Revenue Sharing Our previous analysis focused on a retail platform imposing transaction fees, i.e., a fee that must be paid for every unit sold via its marketplace. Given this pricing scheme, we found that a platform's preference for seller collusion follows a u-shaped pattern in the elasticity of buyer demand. In addition, the platform may favor seller collusion even though it means that it must maintain double marginalization and, hence, cannot extract the whole surplus.

Yet, another popular pricing strategy among online marketplaces are royalty fees or revenue-sharing models. As we show in Section A.1.1, our previous findings remain unchanged if the platform employs royalty fees to fund its marketplace. To see this, notice that under royalty fees, the platforms takes a share of the total revenue created in its marketplace. Thus, even though there exists a wedge between prices on the seller and the buyer side, the platform's total profit still depends on the volume in the entire marketplace. Consequently, the platform thus takes buyer demand elasticity into account when setting its optimal fee, which makes its choice for the preferred conduct depend on it. Therefore, our analysis is robust to royalty fees.

Fixed Membership Fees Another popular pricing strategy employed by online platforms are fixed fees. Unlike per-unit or royalty fees, fixed fees adopted by a platform exclusively hinge on the aggregate number of users within a specific user group. Consequently, in the context of a retail platform, such a strategy entails the platform deriving its revenue from the equilibrium participation of sellers on the platform. This approach primarily disregards potential ramifications on the buyer side and, in turn, does not prioritize maximizing the transaction volume within its marketplace.

To accommodate such concerns, we expand our model to fixed fees in Section A.1.2. While most of our findings remain consistent when the platform imposes fixed fees on sellers, the platform consistently leans toward fostering price coordination among sellers. This inclination is primarily driven by the platform's desire to encourage sellers to set higher prices, which can then be collected by the platform through its fixed fee. Furthermore, as the fixed fee operates like a fixed cost in sellers' profit functions, it emerges as an efficient pricing tool for the platform due to its ability to mitigate double marginalization. Nonetheless, our analysis reveals that even in cases where double marginalization is permitted, the platform consistently favors seller collusion over embracing a regime of fair competition.

Two-Part Tariff Finally, in Section A.1.3, we delve into the ramifications of an online platform's adoption of a two-part tariff, a pricing strategy which encompasses both fixed and variable fees. This strategic pricing approach empowers the platform to fine-tune its fee structure in response to the distinctive dynamics of the market.

Remarkably, also for a two-part tariff our analysis uncovers a preference within online marketplaces for seller collusion. This inclination arises primarily from the efficacy of the fixed fee component as a surplus-extraction tool, surpassing the variable fee in its impact. Consequently, even in the context of a two-part tariff, the platform consistently favors the establishment of seller collusion as the dominant form of conduct.

In conclusion, our examination of other conventional pricing strategies within the online platform context underscores a recurring theme: the inherent incentive for these multi-sided markets to establish price coordination among sellers. This observation resonates deeply with our overarching theory of harm, suggesting that in multi-sided markets, the platform's pursuit of profit often leads to strategies that prioritize seller coordination and revenue extraction over fostering competitive dynamics. This insight further highlights the nuanced complexities of pricing strategies in online platforms and the imperative need for regulatory scrutiny to ensure fair and competitive market outcomes.

Other Types of Competition Our preceding analysis has predominantly focused on sellers offering differentiated goods and engaging in price-based competition. Nevertheless, an intriguing question arises: can our findings be extended to scenarios featuring homogeneous goods or a different competitive landscape? In order to be able to address these questions, we expand our analytical framework to encompass a setting where sellers engage in quantity-based competition, as explored in Section A.2.

Our investigations reveal a remarkable consistency in results even when transitioning from a competition à la Salop to a Cournot competition framework. This notable stability underscores the robustness of our theoretical constructs. Importantly, it corroborates our novel theory of harm, which posits that multi-sided platforms, irrespective of the specific competitive dynamics among sellers, often exhibit a predisposition toward strategies favoring seller coordination and revenue maximization. This theoretical resilience further reinforces the imperative of regulatory scrutiny in multi-sided markets to ensure the preservation of competitive forces and the prevention of potential harm stemming from platform behavior.

Different Collusive Prices (Folk Theorem) In our previous analysis, we simplified our assumptions by considering that colluding sellers, in their price coordination efforts, tacitly agreed to charge the monopoly price. However, it is important to recognize that colluding sellers may opt for prices that deviate from the monopoly price for a multitude of strategic reasons. These reasons may include evading regulatory scrutiny, deterring potential new entrants, or reducing the risk of defection from the collusion arrangement. Consequently, the pricing landscape becomes more nuanced, with colluding sellers having the flexibility to select prices anywhere between the competitive and monopoly levels, resulting in an infinite spectrum of possible collusive equilibria [Friedman, 1971].

Nevertheless, in Section A.3, our analysis demonstrates the robustness of our findings even when considering the complexities arising from the *Folk Theorem*. Specifically, we establish that our results maintain their qualitative character across a broad range of collusive equilibria where prices fall within the spectrum spanning from competitive to monopoly prices. This resilience underscores the enduring implications of our research within the intricate dynamics of collusive behavior in multi-sided markets.

Indirect Network Effects and Idiosyncratic Outside Option for Sellers We previously made the simplifying assumption that there are no indirect network effects affecting sellers. However, to comprehensively capture the two-sided nature of online marketplaces, one might ask: what if sellers are subject to network effects as well? In Section A.4, we expand the depth of our model by introducing two key modifications to accommodate network effects on both sides.

First, we introduce a dynamic where buyers' transportation cost becomes contingent upon the number of buyers who join the platform in equilibrium. Consequently, sellers' profits exhibit a positive correlation with the quantity of buyers in the marketplace. Second, to accommodate these network effects, we assume that each seller possesses a unique external option and that engaging in the marketplace incurs an exogenous fixed cost denoted as $F \in \mathbb{R}_{++}$.[17] Consequently, only those sellers capable of generating profits surpassing F will participate in the marketplace.

Remarkably, our investigation reveals that in marketplaces where both sides are influenced by indirect network effects, the platform lacks the incentive to actively promote collusion among sellers. This outcome stems from the intricate dynamics of indirect network effects. To elaborate further, consider that if (colluding) sellers raise their prices, the overall number of buyers diminishes. This, in turn, leads to a reduction in the number of sellers due to the presence of indirect network effects. Consequently,

[17] This fixed cost F may encompass entry barriers, the aggregate expenses associated with establishing a business, or alternative distribution channels such as other platforms.

raising prices yields a detrimental impact on participation levels, undermining any rationale for fostering collusion among sellers.

As a result, this nuanced observation refines our theory of harm, emphasizing that the incentives for collusion may differ significantly in marketplaces where indirect network effects influence both buyers and sellers, as opposed to those where such effects can be neglected on the seller side.

6 Policy Implications

The rapid evolution of digital markets has lead to unprecedented opportunities and challenges for economists, policymakers, and market participants alike. In a landscape where online platforms serve as intermediaries connecting buyers and sellers, the dynamics of competition have taken on novel dimensions. In that, our research unveils a particularly intriguing result: the latent incentives for platforms to facilitate or tolerate seller collusion under certain market conditions. In this section, we discuss potential cases in which such behaviour is more likely to arise and carve out implications for policymakers.

6.1 Two-Sided or One-Sided Network Effects

Firstly, one crucial consideration is the need for policymakers to be meticulous in assessing whether a marketplace is subject to indirect network effects on both sides or solely on the buyer side. As our analysis (and our extension in Section 5) have shown, potentially harmful practices by the platform may arise primarily in marketplaces where indirect network effects are limited to the buyer side. This distinction is vital in shaping regulatory approaches and underscores the importance of a nuanced understanding of network effects in multi-sided markets.

As our results suggest, the presence of network effects, both direct and indirect, can significantly influence market outcomes. This necessitates a nuanced approach to antitrust and competition policies that considers the intricate interplay of a platform's pricing strategies and potential collusion among sellers. In particular, given that a platform may want to encourage sellers to coordinate on supra-competitive prices under certain circumstances, it can do so effectively by raising its (per-unit or royalty) fees. Thus, following our analysis, regulatory authorities should remain vigilant in monitoring platforms' pricing strategies and should be prepared to adapt traditional measures of market concentration to account for these complexities.

6.2 Negative Buyer Demand Shocks

Secondly, regulators and policymakers should be more cautious with marketplaces that recently faced a negative buyer demand shock. In principle, because negative buyer demand shocks result in a stronger elasticity. Based on Proposition 4, and depending on the change in buyer demand, the platform may have two potential strategies it can pursue. First, if the demand shock is small enough such that buyer demand remains sufficiently inelastic, Proposition 1 shows that it is optimal for the platform to set a lower transaction fee to increase overall volume in its marketplace. In turn, this makes collusion to sellers more attractive, but the critical discount factor also increases, as shown in Lemma 2, making collusion ultimately less likely. Alternatively, it can try to increase users' stand-alone benefit from joining the marketplace by offering or improving additional services like shipping or handling returns and refunds.

Second, if a shock is sufficiently large such that buyer demand becomes sufficiently elastic, it is optimal for the platform to set a very high transaction fee such that sellers are more likely to coordinate on prices. Then, once sellers collude, they capture all the surplus, and the platform extracts this surplus from the sellers via its imposed fee. Alternatively, the platform may be able to coordinate sellers' pricing strategies centrally by providing them with price recommendations, encouraging the use of centralized pricing tools or even by internalizing itself their pricing decisions. Policymakers and other authors usually refer to this alternative strategy as a *hub-and-spoke* cartel, which is suspected to be more prevalent once sellers use price-matching algorithms [see, e.g., Ezrachi and Stucke, 2019; CMA, 2018]. Indeed, large online marketplaces like Amazon and Airbnb feature centralized pricing tools to give concrete price recommendations. In addition, the CMA [2021] reports that other sharing economy platforms employ similar tools that allow sellers to delegate their pricing decisions to the platform or even require them to do so.[18]

Thus, in the contemporary landscape of digital commerce, it becomes increasingly important for competition authorities to exercise scrutiny when confronted with seller collusion in online marketplace, particularly in the wake of negative demand shocks. As our theoretical framework suggests, negative demand shocks may incentivize online platforms to leverage their influential roles in shaping their marketplace, thereby fostering an environment conducive to coordinated pricing behavior among sellers to the detriment of final consumers.

[18] The online marketplace Amazon [2023] offers its sellers its internalized pricing called 'Automate Pricing' together with a detailed step-by-step manual on how to employ it. Likewise, Airbnb [2023] offers a very similar tool (also with instructions) called 'Smart Pricing'. And even though it does not offer its own tool to automate seller prices, Expedia's online platform Vrbo [2023] encourages hosts to use a tool called 'MarketMaker' to make "make more competitive decisions". In a similar way, Fiverr [2023], an online platform that connects freelancers with clients, provides detailed information about how to set appropriate prices. Indeed, as its first point, Fiverr encourages freelances to "Take a Look at the Competition" when setting their prices.

6.3 *Platform Maturity and Established User Base*

Similarly, all else equal, seller collusion should be more common on already well-established platforms, since young platforms tend to maximize buyer surplus to attract more buyers. Hence, they would charge a lower transaction fee, making collusion less likely. Moreover, given that the platform's marketplace also provides a new environment for sellers, coordination on prices is even less likely. Thus, seller collusion should be less of an issue on platforms without an established user base.

Conversely, if a platform has already matured or has a well-established user base, it does not need to attract additional buyers anymore. Hence, indirect network effects are less detrimental, so that it can charge a higher transaction fee. But then, as Lemma 2 shows, increasing transaction fees also increases sellers' incentives to collude. Moreover, the platform can avoid potential double marginalization problems when sellers collude. Therefore, collusion should be more common once a mature platform has an already established user base.

Consequently, regulators should thus be concerned about mature platforms with an already well-established user base, abusing their dominant position in their own marketplace. As put forward by the CMA [2021], particular focus should hence be directed towards platforms in the sharing economy that already have many users and employ specific tools to regulate seller prices.

7 Discussion and Conclusion

Even though our present analysis is subject to various simplifications, our model establishes that online marketplaces do not necessarily act in favour of their users. In this paper, we have delved into the intricate dynamics of online marketplaces, shedding light on the incentives that drive platform providers and sellers within these multi-sided ecosystems. Our theoretical exploration has yielded several critical insights that hold significant implications for understanding the behavior of online platforms and shaping effective policies in the digital commerce realm.

One of our key findings revolves around the platform's incentive to encourage seller collusion in online marketplaces. We have shown that this incentive is contingent on the nature of the platform's fee structure, particularly whether it incorporates a fixed fee component alongside proportional fees like per-unit charges or royalties. Our analysis indicates the nuanced relationship between platform incentives and buyer demand elasticity, revealing that platforms tend to prefer price coordination among sellers when buyer demand is either unresponsive to price changes or highly elastic, suggesting a u-shaped relationship. Furthermore, the inclusion of a fixed fee component, akin to membership fees or two-part tariffs, consistently reinforces the platform's drive to foster pricing coordination on the supply side. This result naturally raises the prospect of platforms potentially internalize sellers' pricing decisions in form of a hub-and-spokes cartels within their marketplaces, a phenomenon with far-reaching implications for market competition and consumer welfare.

Our findings offer new insights for policymakers when navigating through the regulatory landscape of digital marketplaces. We highlight the potential implications of negative demand shocks, emphasizing that they can exacerbate the platform's incentive to promote collusion. Moreover, we underscore the significance of considering whether a platform has already established a substantial user base, as this factor can significantly influence the platform's strategic behavior.

However, it is crucial to recognize that the robustness of these findings hinges on the presence of indirect network effects solely on the buyer side. We have demonstrated that this effect dissipates when sellers themselves are subject to indirect network effects, emphasizing the importance of distinguishing between two-sided network effects and those specific to the supply side. The precise distinction is key for policymakers striving to develop targeted regulatory approaches that effectively address the dynamics of online marketplaces.

Lastly, our results remain pertinent in the context of the adoption of price-matching algorithms, as these algorithms can serve as a proxy for seller collusion incentives. The overarching implication is that the adoption of such algorithms may lead to supra-competitive prices, underscoring the enduring relevance of our findings in the aspiring digital landscape.

In conclusion, our research contributes valuable insights into the complex interplay of incentives within online marketplaces, shedding light on the platform's drive to foster seller collusion. These findings not only deepen our understanding of digital commerce dynamics but also offer essential guidance for policymakers aiming to strike a balance between fostering innovation, safeguarding competition, and protecting consumer interests in the digital age. Recognizing the nuanced factors at play within these multi-sided ecosystems is paramount to achieving equitable and efficient outcomes in the realm of online marketplaces.

Bibliography

AGCM (2020): "ICA: investigation launched against Apple and Amazon for banning the sale of Apple- and Beats-branded products to retailers who do not join the official programme," Available under https://en.agcm.it/en/media/press-releases/2020/7/I842.

AIRBNB (2023): "Smart Pricing - Airbnb Help Center," https://www.airbnb.com/help/article/1168, online; accessed September 18, 2023.

AMAZON (2023): "Automate Pricing: Adjust pricing quickly and automatically," https://sell.amazon.com/tools/automate-pricing, online; accessed September 18, 2023.

ANDERSON, S. P. AND Ö. BEDRE-DEFOLIE (2021): "Hybrid platform model," Tech. rep., CEPR Discussion Paper No. DP16243.

ARMSTRONG, M. (2006): "Competition in two-sided markets," *RAND Journal of Economics*, 37, 668–691.

ARMSTRONG, M. AND J. WRIGHT (2007): "Two-sided markets, competitive bottlenecks and exclusive contracts," *Economic Theory*, 32, 353–380.

BELLEFLAMME, P. AND M. PEITZ (2019): "Managing competition on a two-sided platform," *Journal of Economics & Management Strategy*, 28, 5–22.

BÉNABOU, R. AND J. TIROLE (2016): "Bonus culture: Competitive pay, screening, and multitasking," *Journal of Political Economy*, 124, 305–370.

BERNHARDT, L. AND R. DEWENTER (2020): "Collusion by code or algorithmic collusion? When pricing algorithms take over," *European Competition Journal*, 16, 312–342.

BHADAURIA, S. S. AND L. VYAS (2018): "Algorithmic Pricing & Collusion; The Limits of Antitrust Enforcement," *Nirma ULJ*, 8, 87.

BOUDREAU, K. (2010): "Open platform strategies and innovation: Granting access vs. devolving control," *Management Science*, 56, 1849–1872.

CAILLAUD, B. AND B. JULLIEN (2003): "Chicken & egg: Competition among intermediation service providers," *RAND Journal of Economics*, 309–328.

CALVANO, E., G. CALZOLARI, V. DENICOLO, AND S. PASTORELLO (2020): "Artificial intelligence, algorithmic pricing, and collusion," *American Economic Review*, 110, 3267–97.

CALVANO, E., G. CALZOLARI, V. DENICOLÓ, AND S. PASTORELLO (2021): "Algorithmic collusion with imperfect monitoring," *International Journal of Industrial Organization*, 79, 102712.

CMA (2016): "Decision of the Competition and Markets Authority: Online sales of posters and frames," https://assets.publishing.service.gov.uk/media/57ee7c2740f0b606dc000018/case-50223-final-non-confidential-infringement-decision.pdf.

——— (2018): "Pricing algorithms: Economic working paper on the use of algorithms to facilitate collusion and personalised pricing," Research and analysis, Competition and Markets Authority, available under https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf.

——— (2021): "Algorithms: How they can reduce competition and harm consumers," Research and analysis, Competition and Markets Authority, available under https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers#executive-summary.

CUNNINGHAM, C., F. EDERER, AND S. MA (2021): "Killer acquisitions," *Journal of Political Economy*, 129, 649–702.

DOJ (2015): "Plea Agreement: United States of America v. David Topkins," Available under https://www.justice.gov/atr/case/us-v-david-topkins.

——— (2016): "Plea Agreement: United States of America v. Daniel William Aston and Trod Limited," Available under https://www.justice.gov/atr/case/us-v-daniel-william-aston-and-trod-limited.

——— (2022): "Three Amazon Marketplace Sellers Plead Guilty to Price Fixing DVDs and Blu-Ray Discs in Ongoing Investigation," Available under https://www.justice.gov/opa/pr/three-amazon-marketplace-sellers-plead-guilty-price-fixing-dvds-and-blu-ray-discs-ongoing.

EDELMAN, B. AND J. WRIGHT (2015): "Price coherence and excessive intermediation," *Quarterly Journal of Economics*, 130, 1283–1328.

EUROPEAN COMMISSION (2022): "Regulation (EU) 2022/1925 of the European Parliament and of the Council of 14 September 2022 on contestable and fair markets in the digital sector and amending Directives (EU) 2019/1937 and (EU) 2020/1828 (Digital Markets Act) (Text with EEA relevance)," Legislative Body: CONSIL, EP.

EZRACHI, A. AND M. E. STUCKE (2016): "Virtual competition," *Journal of European Competition Law & Practice*, 7, 585–586.

——— (2019): "Sustainable and unchallenged algorithmic tacit collusion," *Northwestern Journal of Technology and Intellectual Property*, 17, 217.

FINANCIAL TIMES (2021): "UK regulator expected to block Meta's Giphy deal," *Kate Beioley and Javier Espinoza*, https://www.ft.com/content/662c8e3f-4909-4bec-9131-c0237bb4897d.

FIVERR (2023): "Know Your Worth: How to Price Your Services," https://blog.fiverr.com/post/know-your-worth-how-to-price-your-services, online; accessed September 18, 2023.

FRIEDMAN, J. W. (1971): "A non-cooperative equilibrium for supergames," *Review of Economic Studies*, 38, 1–12.

GAL, M. (2023, forthcoming): "Limiting Algorithmic Coordination," *Berkeley Technology Law Journal*.

GAL, M. S. (2019): "Algorithms as illegal agreements," *Berkeley Technology Law Journal*, 34, 67–118.

HAGIU, A. (2009): "Two-sided platforms: Product variety and pricing structures," *Journal of Economics & Management Strategy*, 18, 1011–1043.

HAGIU, A. AND D. SPULBER (2013): "First-party content and coordination in two-sided markets," *Management Science*, 59, 933–949.

HAGIU, A., T.-H. TEH, AND J. WRIGHT (2022): "Should platforms be allowed to sell on their own marketplaces?" *RAND Journal of Economics*, 53, 297–327.

HAGIU, A. AND J. WRIGHT (2019): "Controlling vs. enabling," *Management Science*, 65, 577–595.

HANSEN, K. T., K. MISRA, AND M. M. PAI (2021): "Frontiers: Algorithmic collusion: Supra-competitive prices via independent algorithms," *Marketing Science*, 40, 1–12.

HEIDHUES, P. AND B. KŐSZEGI (2018): "Behavioral industrial organization," *Handbook of Behavioral Economics: Applications and Foundations 1*, 1, 517–612.

HEMPHILL, C. S. (2020): "What role for antitrust in regulating platforms?" *Communications of the ACM*, 63, 36–38.

HUNOLD, M., R. KESLER, U. LAITENBERGER, AND F. SCHLÜTTER (2018): "Evaluation of best price clauses in online hotel bookings," *International Journal of Industrial Organization*, 61, 542–571.

JOHNEN, J. AND R. SOMOGYI (2021): "Deceptive features on platforms," *CEPR Discussion Paper*, No. DP16175.

KARLE, H., M. PEITZ, AND M. REISINGER (2020): "Segmentation versus agglomeration: Competition between platforms with competitive sellers," *Journal of Political Economy*, 128, 2329–2374.

KHAN, L. M. (2016): "Amazon's antitrust paradox," *Yale Law Journal*, 126, 710.

KLEIN, T. (2021): "Autonomous algorithmic collusion: Q-learning under sequential pricing," *RAND Journal of Economics*, 52, 538–558.

MIKLÓS-THAL, J. AND C. TUCKER (2019): "Collusion by algorithm: Does better demand prediction facilitate coordination between sellers?" *Management Science*, 65, 1552–1561.

MOTTA, M. AND M. PEITZ (2021): "Big tech mergers," *Information Economics and Policy*, 54, 100868.

NEW YORK TIMES (2020): "'This Is a New Phase': Europe Shifts Tactics to Limit Tech's Power," *Adam Satariano*, https://www.nytimes.com/2020/07/30/technology/europe-new-phase-tech-amazon-apple-facebook-google.html.

NOCKE, V., M. PEITZ, AND K. STAHL (2007): "Platform ownership," *Journal of the European Economic Association*, 5, 1130–1160.

OECD (2017): "Algorithmic-facilitated Coordination – Note by Michal Gal," Directorate for financial and enterprise affairs, competition committee, OECD, available under https://one.oecd.org/document/DAF/COMP/WD(2017)26/en/pdf.

——— (2018): "Implications of E-commerce for Competition Policy - Background Note," Directorate for financial and enterprise affairs, competition committee, OECD, available under https://one.oecd.org/document/DAF/COMP(2018)3/en/pdf.

PADILLA, J., J. PERKINS, AND S. PICCOLO (2022): "Self-Preferencing in Markets with Vertically Integrated Gatekeeper Platforms," *Journal of Industrial Economics*, 70, 371–395.

PARKER, G. AND M. VAN ALSTYNE (2018): "Innovation, openness, and platform control," *Management Science*, 64, 3015–3032.

RHODES, A., J. P. JOHNSON, AND M. WILDENBEEST (2023): "Platform design when sellers use pricing algorithms," *Econometrica*.

ROCHET, J.-C. AND J. TIROLE (2003): "Platform competition in two-sided markets," *Journal of the European Economic Association*, 1, 990–1029.

——— (2006): "Two-sided markets: a progress report," *RAND Journal of Economics*, 37, 645–667.

SALOP, S. C. (1979): "Monopolistic competition with outside goods," *The Bell Journal of Economics*, 141–156.

SCHLÜTTER, F. (2020): "Managing Seller Conduct in Online Marketplaces and Platform Most-Favored Nation Clauses," Tech. rep., Working Paper.

TEH, T.-H. (2022): "Platform governance," *American Economic Journal: Microeconomics*, 14, 213–54.

TEUBNER, T. AND A. GRAUL (2020): "Only one room left! How scarcity cues affect booking intentions on hospitality platforms," *Electronic Commerce Research and Applications*, 39, 100910.

VRBO (2023): "About MarketMaker - Help," https://help.vrbo.com/articles/What-is-MarketMaker, online; accessed September 18, 2023.

WEYL, E. G. (2010): "A price theory of multi-sided platforms," *American Economic Review*, 100, 1642–72.

WEYL, E. G. AND M. FABINGER (2013): "Pass-through as an economic tool: Principles of incidence under imperfect competition," *Journal of Political Economy*, 121, 528–583.

A Appendix – Extensions

Below, we provide a set of extensions to our baseline model, as discussed in Section 5. Although most our results are quite robust to these considerations, we discuss how alternative pricing strategies and types of competition as well as the Folk Theorem relate our findings, and how to introduce supply-sided network effects as well as platform competition.

A.1 Other Pricing Strategies

Our main analysis studied a platform's pricing behavior and incentives to encourage collusion among sellers when it employs a per-unit fee structure. In this section, we look how our results relate to alternative pricing strategies. Especially, we show that our results remain qualitatively unchanged when the platform sets a royalty fee, a fixed membership fee, and a two-part tariff.

A.1.1 Royalty Fees

In this section, we show that our results from the transaction fee model can also be extrapolated to a model of royalty fees. More specifically, the both the effect of the raising fees on sellers' incentive to collude and the platform's u-shaped preference for seller collusion still hold in a model featuring a revenue-sharing scheme.

To start, let us formally denote by $f_R \in [0, 1]$ the share of revenue whose value is retained by the platform. Also, let platform profits be characterized by

$$\Pi^P = f_R * \pi * N^B * N^S s \tag{31}$$

Sellers' prices and profits, on the other hand, are thus equal to $p_R^{com} = \tau/N^S$ and $\pi_R^{com} = (1 - f_R)\tau/(N^S)^2$, respectively, when sellers compete, and $p^{coll} = v$ and $\pi_R^{coll} = (1 - f_R)v/N^S$ when they collude. As a result, Lemma 1 as well as Corollaries 1 and 2 remain unchanged.

The next proposition shows that under royalty fees, a monopoly platform can eliminate double marginalization when sellers compete:

Proposition 5 (Royalties – Platform Pricing (Seller Competition))**.** *Suppose Lemma 1 holds and that sellers compete. Then, the monopoly platform's profit maximizing fee satisfies* $f_R^{com} = 1$.

Proof. The platform's optimization problem reads

$$\begin{aligned} \max_{f_R} \ \Pi^P = & f_R * \pi_R^{com} * N^B(p_R^{com}, N^S) * N^S \\ \text{s.t. } & 0 \geq (1 - f_R)\frac{\tau}{(N^S)^2}, \end{aligned} \tag{32}$$

which is maximized at $f_R^{com} \equiv f_R = 1$, since sellers have no marginal costs. □

As the Proposition above shows, when sellers compete, the platform charges a royalty fee that extracts all the surplus from the sellers.

We next study a seller collusion game as outlined in Section 4.3. The following Lemma shows that also under royalty fees, a deviating seller charges a price that is between the competitve and the collusive price, thus gets a larger market share and therefore higher profits:

Lemma 5 (Royalties – Deviator strategy). *Suppose all sellers coordinate to play p^{coll}. Now, if one seller deviates from the collusive agreement by playing p_R^{Dev}, the deviator then obtains a market share d_R^{Dev} and generates profits π_R^{Dev} such that*

$$p_R^{Dev} = p^{coll} - \frac{p^{coll} - p_R^{com}}{2} \;\; ; \;\; d_R^{Dev} = \frac{1}{N^S} + \frac{v - \tau/N^S}{2\tau} \;\; ; \;\; \pi_R^{Dev} = \pi_R^{coll} + \frac{(\pi_R^{coll} - \pi_R^{com})^2}{4\pi_R^{com}}. \quad (33)$$

Proof. This proof is analogous to the proof of Lemma 2. □

And even though also sellers' competitive profits p_R^{com} depend now on the level of the transaction fee (in contrast to proportional fees), sellers' incentives to collude increase in the level of the imposed royalty fees as well:

Proposition 6 (Royalties – Collusion Incentives). *Denote δ_R^* the critical discount factor for which collusion is sustained. For π_R^{Dev}, π_R^{mon}, and π_R^{com}, it holds that $\delta_R^*(f_R)$ is monotonically decreasing in f_R.*

Proof. This proof is analogous to the proof of Proposition 2. □

Finally, the next two Propositions show the platform's optimal pricing strategy once sellers collude, and its preferred conduct. In particular, our results remain qualitatively unchanged if the platform charges royalty fees instead of transaction fees:

Proposition 7 (Royalties – Platform Pricing (Collusion, IC)). *Suppose Propostion 2 holds and that sellers collude. Then, for there exists $\epsilon < 1$, the platform's profit maximizing royalty fee is $f_R^{coll} = 1 - \epsilon$.*

Proof. From Proposition 2, a necessary condition for seller collusion is $\pi_R^{coll} > \pi_R^{com}$. Further, it follows from Proposition 5 that $\pi_R^{com} = 0$. Hence, the profit-maximizing fee must satisfy $\pi_R^{coll} = (1 - f_R^{coll})v/N^S > 0$, hence $f_R^{coll} < 1$. Moreover, since $v/N^S > 0$, this implies that there exists an $\epsilon < 1$ such that $f_R^{coll} = 1 - \epsilon$. □

Proposition 8 (Royalties – Preferred Conduct (IC)). *Given that seller's incentive compatibility constraint for collusion (Corollary 2) is satisfied, the platform's preferred conduct is seller collusion iff*

$$v > \frac{\tau}{N^S} \frac{N_{com}^B}{N_{coll}^B} \frac{1}{1-\epsilon}. \quad (34)$$

Proof. This proof is analogous to the proof of Proposition 4. In particular, $\Pi_P^{coll} > \Pi_P^{com} \iff$

$$(1-\epsilon) * \pi_R^{coll} * N_{coll}^B \ > \ \pi_R^{com} * N_{com}^B, \tag{35}$$

which, after rearranging terms, yields the inequality in the above Proposition. □

A.1.2 Fixed Membership Fees

The main result of this section is that under fixed membership fees, the platform will virtually always prefer seller collusion. The reason is that in contrast to transaction fees and royalty fees, the platform's profit do not depend on the total volume in its marketplace, but only on the total number of sellers. Thus, it limits the platform's focus on revenue generated via the sellers. However, to support this claim, we first characterize sellers' strategies when the platform levies a fixed fee. Next, we show that the platform can charge a higher fee to colluding sellers.

Suppose first that the platform charges a fixed fee f_m. The next Proposition characterizes seller prices and profits:

Proposition 9 (Fixed Fee – Platform Pricing (Seller Competition))**.** *If the platform charges a fixed membership fee F and sellers compete, then sellers charge $p_F^{com} = \tau/N^S$. The platform charges $f_F^{com} = \tau/(N^S)^2$ and sellers obtain $\pi_F^{com} = 0$.*

Proof. We first derive sellers' optimal prices and profits, and then prove that the platforms optimal fee F is equal to $\tau/(N^S)^2$. Firstly, from Lemma 1, $p^{com} = f + \tau/N^S$, where f is the proportional fee levied by the platform. Hence for our purpose, $f = 0$ such that $p_F^{com} = \tau/N^S$. Moreover, also from Lemma 1, $\pi_F^{com} = \tau/(N^S)^2$, thus total profits under fixed fees become $\pi_F^{com} = \tau/(N^S)^2 - F$.

Secondly, since $\Pi_P = F * N^S$ subject to $F \leq \pi_F^{com}$, it follows from the first step of the proof that Π_P is maximized when $F = \tau/(N^S)^2$ and therefore $\pi_F^{com} = 0$. This completes the proof.

□

Since sellers provide horizontally differentiated goods, they can charge a mark-up to achieve prices above marginal costs (zero here) – extracting some of the surplus from the buyers. But since a fixed fee represents a fixed cost for sellers, the platform can re-extract this surplus via its fee from the sellers to maximize profits.

On the other hand, when seller collude, they can charge the monopoly price $p^{coll} = v$ (as seen in Lemma 1). Thus, seller profits are equal to $\pi_F^{coll} = v/N^S - f$. Again, the platform may set its fee to re-collect all the surplus that sellers have captured from consumers, i.e., $f_F^{coll} = (v-c)/N^S$. Thus $\pi_F^{coll} = 0$. However, this would violate sellers' participation constraint to collude. Thus, the platform needs to set f_F^{coll} such that $\pi_F^{coll} = \epsilon_F > 0$. The next Proposition summarizes these results:

Proposition 10 (Fixed Fee – Platform Pricing (Seller Collusion, IC))**.** *If the platform charges a fixed membership fee F and sellers collude, then sellers charge $p^{coll} = v$, and there exists an $\epsilon_F \in \mathbb{R}_{++}$ such that the platform charges $f_F^{coll} = (v - \epsilon_F)/N^S$ and sellers obtain $\pi_F^{mon} = \epsilon_F$ for any $v - \tau/N^S > \epsilon_F > 0$.*

Proof. We structure this proof in two parts. The first part derives the optimal prices irrespective of the participation constraint for sellers to collude and is analog to the proof of Proposition 9. The second part adjusts these findings with respect to the participation constraint. For this, notice that collusion requires that $\pi_F^{coll} > \pi_F^{com} = 0$. Thus $f_F^{coll} < v/N^S$ because else $\pi_F^{coll} = 0$. This implies that there exists $\epsilon_F > 0$ and $f_F^{coll} = v/N^S - \epsilon_F/N^S$. Note that the platform sets f_F^{coll} as long as $f_F^{coll} > f_F^{com} \iff v - \tau/N^S > \epsilon_F$. □

Notice that Proposition 10 is conditional on the size of ϵ_F. But given Assumption A1, this condition is always satisfied.

Finally, since we study a retail platform, it can charge only the seller side. Thus, the platform takes only the total number of sellers into account (and ignores network effects). Therefore, under fixed membership fees, the platform's profits are given by

$$\Pi^P = F * N^S. \tag{36}$$

Therefore, the platform only cares about the total number of sellers and the fee it charges to them. But since both the charged fee and the numbers of sellers are greater under collusion (because $\pi_F^{coll} > \pi_F^{com}$), the platform can generate greater profits under collusion. Hence, whenever the platform employs fixed fees, it will prefer seller collusion.

Proposition 11 (Fixed Fee – Preferred Conduct)**.** *Under fixed membership fees, the platform always prefers seller collusion.*

Proof. Given it charges a fixed membership fee, a monopoly platform's profits are characterized by

$$\Pi^P = F * N^S.$$

Moreover, from Lemma 10, it holds that $f_F^{coll} > f_F^{com}$. Hence, holding the number of (colluding) sellers constant, $\Pi_P^{coll} > \Pi_P^{com}$. □

A.1.3 Two-part tariff

Employing a two-part tariff fee structure, the platform levies both a fixed fee and a proportional fee. Denote the fixed fee and the proportional fee of the two-part tariff by $F_{TPT} \in \mathbb{R}_{++}$ and $f_{TPT} \in \mathbb{R}_{++}$, respectively. As established previously, a fixed fee is a more efficient tool to extract surplus from sellers compared to a proportional fee. And given that a two-part tariff involves a fixed fee, also the results remain qualitatively unchanged. Hence, also under a two-part tariff, the platform would prefer collusive prices.

In contrast to a fixed fee, however, the platform does not need to incentivize sellers to collude to reach such an outcome: instead, the platform can achieve collusive prices by setting proportional fees such that sellers' prices parallel the collusive price v, and then set the fixed fee to eliminate any double marginalization. As a result, for the platform employing a two-part tariff is an even more efficient tool to extract rents, but also the worst outcome in terms of welfare. Together, this implies that a two-part tariff with collusive prices is always the most preferred pricing scheme for the platform because it can fully extract both buyer and seller surplus. The following two Propositions summarizes these findings:

Proposition 12 (TPT – Platform Pricing (Seller Competition))**.** *Under a two-part tariff, the platform's optimal per-unit fee and fixed fee are $f_{TPT} = v - \tau/N^S$ and $F_{TPT} = \tau/(N^S)^2$, respectively. Moreover, seller profits are $\pi^{com}_{TPT} = 0$ and buyer surplus is minimized.*

Proof. This proof is conducted in two steps. As a first step, recall from Lemma 1 that $p^{com}_{TPT} = f_{TPT} + \tau/N^S$ and $p^{coll} = v$. Suppose now the platform charges a two-part tariff. Then, it can set the variable part of the tariff f_{TPT} such that $p^{com}_{TPT} = p^{coll}_{TPT} \iff f_{TPT} + \tau/N^S = v \iff f_{TPT} = v - \tau/N^S$, which minimizes buyer demand and, hence, buyer surplus.

As a second step, and based on the first step, sellers profit margin then equals $\pi^{com}_{TPT} = \tau/(N^S)^2 - F_{TPT}$, from which it follows that $F_{TPT} = \tau/(N^S)^2$ eliminates double marginalization and maximizes the platform's profits. $\square$

Proposition 13 (TPT – Preferred Conduct (IC))**.** *When the platform can employ a two-part tariff, its preferred conduct is seller collusion*

Proof. We prove this statement by contraposition. Before starting, however, notice that from Propositions 9 and 10, it follows that the optimal fixed fees are and $F = \pi^{coll}_F$ under seller competition and $f^{com}_m = \pi^{com}$ under seller collusion, respectively.

Suppose now that the platform does not play according to pricing strategy outlined in Proposition 12. Then, the platform can set variable fees to parallel either f^{com}_{TPT} when sellers compete, or f^{coll}_{TPT} when sellers collude (notice that from Proposition 1 and Lemma 3, it follows that f^{coll}_{TPT} is never optimal once sellers compete, and f^{com}_{TPT} is never optimal once they collude).

Thus, potential candidates for an optimal strategy are the two-part tariffs $(F_{TPT} = F^{coll}, f_{TPT} = f^{coll})$ and $(F_{TPT} = F^{com}, f_{TPT} = f^{com})$. Now, if the statement in Proposition 13 is false, then

$$\Pi^{com}_P > \Pi^{coll}_P \iff \pi^{com} * N + f^{com} * N * N^B_{com} > \pi^{coll} * N + f^{coll} * N * N^B_{coll}, \quad (37)$$

which can be rearranged to

$$\pi^{coll} - \pi^{com} < f^{com} * N^B_{com} - f^{coll} * N^B_{coll}. \tag{38}$$

Notice that the left-hand side is positive. Moreover, notice that $N^B_{com} > N^B_{coll}$, hence there exist a $z \in \mathbb{R}_{++}$ such that $N^B_{com} = N^B_{coll} + z$. Thus, the expression above can be rewritten as

$$\pi^{coll} - \pi^{com} \; < \; N^B_{com} * (f^{com} - f^{coll}) - f^{mon} z, \tag{39}$$

where the right-hand side is negative. But since, $\pi^{coll} - \pi^{com} > 0$, this is a contradiction. Hence, offering a two-part tariff of $(F_{TPT} = F^{coll}, f_{TPT} = f^{coll})$ must be optimal. □

A.2 Cournot Competition

Although our baseline model considers sellers who provide horizontally differentiated goods, we can extend this model to a setting that features homogeneous goods where sellers compete in quantities instead of prices. To see this, suppose that sellers compete à la Cournot. Formally, suppose there is a finite number of sellers N^S, where each seller $i \in N^S$ produces a quantity $q_i \in \mathbb{R}_+$ and $Q = \sum^{N^S_{i=1}} q_i$. For the sake of simplicity, assume that sellers are symmetric and face no marginal costs. Further, let the inverse demand function of buyers be

$$P(Q) = A - bQ, \tag{40}$$

where $A \in \mathbb{R}{++}$ is the reservation price and $b \in \mathbb{R}{++}$ a parameter for demand sensitivity.

Then, in the Cournot equilibrium sellers charge $p = (A + N^S f)/(N^S + 1)$, sell units of $q_i = (A - f)/(b(N^S + 1))$ and make profits equal to $\pi_i = (1/b) * ((A - f)/(N^S + 1))^2$.

In relation to Proposition 1, the following Lemma shows that when a platform employs a transaction fee f, results from the competitive equilibrium remain qualitatively unchanged:

Proposition 14 (Cournot – Platform Pricing (Seller Competition))**.** *Suppose that sellers compete à la Cournot. Then, the monopoly platform's best response to maximize profits is*

$$f^{com}_{Cournot} = \frac{N^B}{-dN^B/df} \quad \textit{and} \quad \eta^B_{Cournot} = -\frac{f^{com}_{Cournot}}{N^B}\frac{dN^B}{df}. \tag{41}$$

Proof. This proof is analogous to the proof of Proposition 1. □

In addition, if sellers collude, they maximize joint profits. In particular, they agree on the monopoly price and commonly sell the associated quantity:

Lemma 6 (Cournot – Collusive Equilibrium)**.** *In the Cournot model, if sellers collude, their prices $p^{coll}_{Cournot}$, quantities $q^{coll}_{Cournot}$ and profits $\pi^{coll}_{Cournot}$ are, respectively:*

$$p^{coll}_{Cournot} = \frac{A + f}{2} \quad ; \quad q^{coll}_{Cournot} = \frac{A - f}{2bN^S} \quad ; \quad \pi^{coll}_{Cournot} = \left(\frac{A - f}{2}\right)^2 \frac{1}{bN^S}. \tag{42}$$

Proof. Colluding sellers act like a single monopoly and maximize joint profits with respect to the price. Hence, given the inverse demand function $p = A - bQ$, the first order condition yields prices, quantities and profits equal to the one in the proposition above. □

In contrast to the model with horizontal differentiation, however, a deviator chooses a price that is slightly below the collusive price and caters the entire market. To see this, let $\epsilon \in \mathbb{R}_{++}$ be the increase in sold united with respect to the total quantity from collusion. The following Proposition outlines the deviator's strategy:

Proposition 15 (Cournot – Deviator Strategy)**.** *In the Cournot model, if a seller deviates from the collusive agreement, its price, quantity and profits, respectively, are:*

$$p^{Dev}_{Cournot} = \frac{A+f}{2} - \epsilon b \quad ; \quad q^{Dev}_{Cournot} = \frac{A-f}{2b} - \epsilon \quad ; \quad \pi^{Dev}_{Cournot} = \left(\frac{A-f}{2}\right)^2 \frac{1}{b} - \epsilon^2 b. \tag{43}$$

Moreover, a seller has an incentive to deviate as long as $\epsilon < (N^S - 1)(q^{coll}_{Cournot})^2$.

Proof. Suppose a seller deviates and sets the price $p^{Dev}_{Cournot}$, which is slightly below $p^{coll}_{Cournot}$. Then, it follows from the inverse demand function that the sold quantity is equal to $q^{Dev}_{Cournot}$. Together, this implies that a deviator's profits are equal to $\pi^{Dev}_{Cournot} = (A - f0^2/(4b) - \epsilon^2 b$.

Finally, it is easily verified that $\epsilon < (N^S - 1)(q^{coll}_{Cournot})^2$ implies $\pi^{Dev}_{Cournot} > \pi^{coll}_{Cournot}$. This concludes the proof. □

Next, we show that also Proposition 2 remains qualitatively unchanged when switching to the Cournot model. In particular:

Proposition 16 (Cournot – Collusion Incentives)**.** *Denote δ^* the critical discount factor δ that enables collusion. For $\pi^{Dev}_{Cournot}$, $\pi^{coll}_{Cournot}$ and $\pi^{com}_{Cournot}$ as defined above, it holds that $\delta^*(f)$ is monotonically decreasing in f.*

Proof. The critical discount factor for the Cournot model is defined as

$$\delta^* = \frac{\pi^{Dev}_{Cournot} - \pi^{coll}_{Cournot}}{\pi^{Dev}_{Cournot} - \pi^{com}_{Cournot}}, \tag{44}$$

which, when plugging in $\pi^{Dev}_{Cournot}$, $\pi^{coll}_{Cournot}$ and $\pi^{com}_{Cournot}$, yields

$$\frac{\left(\frac{A-f}{2}\right)^2 \frac{N^S-1}{N^S} - (\epsilon b)^2}{\left(\frac{A-f}{2}\right)^2 \frac{(N^S+1)^2-4}{(N^S+1)^2} - (\epsilon b)^2}.$$

Moreover, its derivative with respect to f is

$$\frac{\partial \delta^*(f)}{\partial f} = -\left(\frac{A-f}{2}\,\epsilon b\right)^2 \frac{\frac{(N^S-1)^2-4}{(N^S-1)^2} - \frac{N^S-1}{N^S}}{(\pi^{Dev}_{Cournot} - \pi^{com}_{Cournot})^2}, \tag{45}$$

where the first term is negative and the denominator of second term is positive. Moreover, also the second term's enumerator is positive since $N^S(2+N^S) > 1$, so $\partial\delta^*/\partial f < 0$. $\square$

Given that sellers collude, we next characterize the platform's best response to seller collusion. Notice, however, that when sellers compete in quantities, they take the imposed fee into account when jointly maximizing their profits and setting their prices. As a result, it is possible that even under the monopoly price, buyer demand is not minimized in Cournot competition.[19] Thus, a higher platform fee may crowd out further demand, which may force the platform to reduce its fee:

Proposition 17 (Cournot – Platform Pricing (Seller Collusion))**.** *Suppose sellers collude. Then, the monopoly platform's best response to maximize profits is*

$$f^{coll}_{Cournot} = \frac{N^B_{coll}}{-dN^B/df} \quad \textit{and} \quad \eta^B_{coll} = -\frac{f^{coll}_{Cournot}}{N^B_{coll}} * \frac{dN^B}{df}. \tag{46}$$

Additionally, in comparison to Lemma 14, it holds that $f^{coll}_{Cournot} < f^{com}_{Cournot}$ *whenever* $N^B_{coll}/N^B_{com} < (N^S+1)/(2N^S)$.

Proof. When sellers collude, the platform's profits are

$$\Pi^P = f * N^S * N^B_{coll}. \tag{47}$$

Taking its derivative with respect to f yields the first order condition, which after rearranging terms, leads to

$$f^{coll}_{Cournot} = \frac{N^B_{coll}}{-dN^B_{coll}/df}. \tag{48}$$

Lastly, notice that $N^B_{com} > N^B_{coll}$ and that $\frac{-dN^B_{coll}/dp^{coll}_{Cournot}}{-dN^B_{com}/dp^{com}_{Cournot}} = \frac{N+1}{2N^S} < 1$. Hence,

$$f^{coll}_{Cournot} > f^{coll}_{Cournot} \quad \Longleftrightarrow \quad \frac{N^B_{coll}}{N^B_{com}} > \frac{N^S+1}{2N^S}. \tag{49}$$

$\square$

Finally, also the platform's preferences over collusion remain mostly unchanged. However, since the difference between the fees in the collusive and the competitive equilibrium depends now on the number of sellers, also the platform's preference over the competition structure now depends on the number of sellers in the marketplace:

Proposition 18 (Cournot – Preferred Conduct)**.** *Let* N^B_{coll} *and* N^B_{com} *be the number of buyers in the collusive and the competitive equilibrium, respectively, and* $^S N$ *the number of sellers. The platform prefers seller collusion over seller competition iff* $2N^S/(N^S+1) > (N^B_{com}/N^B_{coll})^2$.

[19] That is to say, a higher price leads to a finite decrease in buyer demand. Hence, $dN^B_{coll}/dp \neq -\infty$, which contrasts the model with horizontally differentiation.

Proof. The platform prefers seller collusion over competition whenever $\Pi_P^{coll} > \Pi_P^{coll}$. Substituting the results for $f_{Cournot}^{com}$ and $f_{Cournot}^{coll}$ from Propositions 14 and 17, respectively, we can rewrite this condition as

$$f_{Cournot}^{coll} * N^S * N_{coll}^B > f_{Cournot}^{com} * N^S * N_{com}^B \iff \frac{2N^S}{N^S+1} > \left(\frac{N_{com}^B}{N_{coll}^B}\right)^2 . \tag{50}$$

□

A.3 Folk Theorem

Generally, sellers can coordinate on any price $p^{coll} \in [p^{com}, p^{mon}]$ when colluding. Consequently, there are infinite collusive equilibria, as suggested by Folk Theorem [Friedman, 1971]. While we conveniently assumed in the main part of our paper that when sellers collude, they coordinate on the monopoly price p^{mon}, the following lemma establishes that the results of Lemma 2 can be generalized to hold under the Folk Theorem.

Lemma 7 (Folk Theorem)**.** *Suppose sellers can coordinate on prices $p^{coll} \in [p^{com}, p^{mon}]$. Then there exists an $\alpha \in [0,1]$ such that collusive price and profits are given by*

$$p^{coll} = \alpha p^{mon} + (1-\alpha)p^{com} \quad ; \quad d^{coll} = \frac{1}{N^S} \quad ; \quad \pi^{coll} = \alpha \pi^{mon} + (1-\alpha)\pi^{com}. \tag{51}$$

Moreover, a deviator's price, demand, and profits, respectively, are given by

$$p^{Dev} = p^{com} + \alpha\frac{p^{mon}-p^{com}}{2} \quad ; \quad d^{Dev} = \frac{1}{N^S} + \alpha\frac{p^{mon}-p^{com}}{2\tau} \quad ;$$
$$\pi^{Dev} = \pi^{coll} + \alpha^2\frac{(\pi^{mon}-\pi^{com})^2}{4\pi^{com}}. \tag{52}$$

Proof. Colluding sellers can charge any price $p^{coll} \in [p^{com}, p^{mon}]$. If all sellers collude to play p^{coll}, there exist $\alpha \in [0,1]$ such that

$$p^{coll} = \alpha p^{mon} + (1-\alpha)p^{com} \quad ; \quad d^{coll} = \frac{1}{N^S} \quad ; \quad \pi^{coll} = \alpha \pi^{mon} + (1-\alpha)\pi^{com}. \tag{53}$$

Suppose now that while $-i$ sellers collude while i deviates to play p^{Dev}. Then, i's best response reads

$$\pi^{Dev} = (p^{Dev} - f) * \left(\frac{1}{N^S} + \frac{p^{coll}-p^{Dev}}{\tau}\right), \tag{54}$$

which yields

$$p^{Dev} = p^{com} + \alpha\frac{p^{mon}-p^{com}}{2} \quad ; \quad d^{Dev} = \frac{1}{N^S} + \alpha\frac{p^{mon}-p^{com}}{2\tau} \quad ;$$
$$\pi^{Dev} = \pi^{coll} + \alpha^2\frac{(\pi^{mon}-\pi^{com})^2}{4\pi^{com}}. \tag{55}$$

□

A.4 Indirect Network Effects and Idiosyncratic Outside Option for Sellers

The main part of the analysis focused on a retail platform absent of network effects on the supply side for the sake of simplicity. However, we can easily embed indirect network effects of the supply side in this framework by allowing for two additional features: first, seller's profits must be increasing in the total number of buyers on the platform, and second, sellers have an idiosyncratic outside option or face an individual cost to set up their business.

First, seller profits need to increase in the total number of buyers. Hence, sellers benefit from the presence of more buyers. In fact, our model is able to capture this if we let buyers' transportation cost τ be monotonically increasing in the number of buyers N^B who join the platform in equilibrium. Thus, buyers' updated transportation costs are then equal to τN^B.[20] Due to the fact that N^B enters only as a multiplicative factor to the transportation cost τ, most of our initial results remain unchanged (in particular, Lemma 1 and Corollaries 1 and 2).

Second, we assume that each seller i has an idiosyncratic outside option $\mathcal{F}_i \in \mathbb{R}$ following a continuous distribution with support over $[\underline{\mathcal{F}}, \overline{\mathcal{F}}]$ where $\underline{\mathcal{F}}, \overline{\mathcal{F}} \in \mathbb{R}$ and $\underline{\mathcal{F}} < \overline{\mathcal{F}}$. Hence, one can interpret $\mathcal{F}_i$ as another distribution channel for sellers, like a brick and mortar store or another platform. Although we are going to call $\mathcal{F}_i$ as seller i's idiosyncratic outside option for the remaining part of the analysis, one can also think of it as a seller specific cost to set up their business. Given that third-party online sellers oftentimes reside in countries different from the platform or consumers, $\mathcal{F}_i$ may thus reflect different requirements that happen in the background of a buyer's purchasing process.[21] Hence, a necessary condition for sellers to join the platform is that their profits (which now depend on N^B) are greater than $\mathcal{F}_i$ for all i.

Finally, denote sellers' cost of joining the platform by $\mathcal{F} \in [\underline{\mathcal{F}}, \overline{\mathcal{F}}]$. Then, sellers' updated utility from joining the platform is equal to

$$U^S = \pi * N^B - \mathcal{F}_i, \tag{56}$$

so they join the platform as long as $\mathcal{F}_i \geq \mathcal{F}$. To see this, notice that since each seller's outside option is idiosyncratic and either above $\underline{\mathcal{F}}$ or below $\overline{\mathcal{F}}$, sellers can be ordered along their individual $\mathcal{F}_i$. Thus, by the Intermediate Value Theorem, there exist an $\mathcal{F} \in [\underline{\mathcal{F}}, \overline{\mathcal{F}}]$ such that $\mathcal{F}_i \geq \mathcal{F} \in [\underline{\mathcal{F}}, \overline{\mathcal{F}}]$ for some sellers and below for others.

In the following, we show that also the other main results of our analysis can be imported to a framework where sellers have an idiosyncratic outside option and their total number is subject to indirect network effects. The only difference to our previous findings, however, is that now, due to indirect network effect, the platform also takes

[20] In other words, the perimeter of the Salop circle can be "scaled" by N^B.

[21] For instance, these requirements can be country-specific (e.g., warehousing and storing), contract related (e.g., shipping and reselling), or internal (e.g., organizational procedures).

the price elasticity of sellers into account when setting its fees. In particular, one can show that most of the intuition and the results of Proposition 1 remains valid, and similar to Rochet and Tirole [2003], it also reflects indirect network effects on on the seller side:

Proposition 19 (NE – Platform pricing (Seller Competition)). *Suppose Lemma 1 holds and that sellers compete. Then, the monopoly platform's profit maximizing fee is*

$$f_{NE}^{com} = -\frac{N_{com}^S * N_{com}^B}{N_{com}^S \frac{dN_{com}^B}{df} + N_{com}^B \frac{dN_{com}^S}{df}}$$

$$\text{where} \quad \eta_{NE}^B = \frac{f^{com}}{N_{com}^B}\frac{dN_{com}^B}{df} \text{ and } \eta_{NE}^S = \frac{f^{com}}{N_{com}^S}\frac{dN_{com}^S}{df}. \tag{57}$$

Proof. The first order condition of the platform's maximization problem solves

$$N_{com}^S * N_{com}^B + f\left(N_{com}^S \frac{dN_{com}^B}{df} + N_{com}^B \frac{dN_{com}^S}{df}\right) = 0. \tag{58}$$

which, after solving for f, gives the optimal fee level when sellers compete. □

Proposition 19 reflects that in a competitive equilibrium, the platform charges a relative markup equal to $1/(\eta_{NE}^B + \eta_{NE}^S)$. Thus, in addition to the elasticity of buyer demand, the platform also takes the elasticity of the number of sellers into account when supply-side network effects are present.

What is the platform's optimal fee level when sellers collude? Unchanged in the presence of seller network effects, colluding sellers charge a price $p^{coll} = v$. Then, due to network effects, both the number of sellers and the number of buyers is reduced to a minimum.

Proposition 20 (NE – Collusion incentives). *Denote δ^* the critical discount factor δ that enables collusion. Then, it holds that $\delta^*(f)$ is monotonically decreasing in f if and only if*

$$\pi_{NE}^{mon} + \pi_{NE'}^{com} > 2\pi_{NE}^{com}, \tag{59}$$

where $\pi_{NE'}^{com} = \tau/(N_{coll}^S)^2 * N_{com}^B$.

Proof. Before starting with the proof, notice first that a deviator plays and gets

$$p_{NE}^{Dev} = \frac{v + \tau/N_{coll}^S * N_{coll}^B}{2} \quad \text{and} \quad \pi_{NE}^{Dev} = \pi_{NE}^{coll} + \frac{(\pi_{NE}^{coll} - \pi_{NE'}^{com})^2}{4\pi_{NE'}^{com}}, \tag{60}$$

respectively, where $\pi_{NE'}^{com} = \tau/(N_{coll}^S)^2 * N_{coll}^B$. Notice further that the collusion enabling discount factor is

$$\delta^*(f) = \frac{\pi_{NE}^{Dev}(f) - \pi_{NE}^{coll}(f)}{\pi_{NE}^{Dev}(f) - \pi_{NE}^{com}}, \tag{61}$$

so taking the first order condition is proportional to

$$\frac{d\delta^*}{df} \propto \pi_{NE}^{coll} + \pi_{NE'}^{com} - 2\pi_{NE}^{com}. \tag{62}$$

Hence, the sign of the derivative depends on sign$(\pi_{NE}^{coll} + \pi_{NE'}^{com} - 2\pi_{NE}^{com})$. □

Proposition 21 (NE – Platform Pricing (Seller Collusion))**.** *When sellers collude, the platform's profit maximizing fee is equal*

$$f_{NE}^{coll} \;=\; -\frac{N_{coll}^S * N_{coll}^B}{N_{coll}^B \frac{dN_{coll}^S}{df} + N_{coll}^S \frac{dN_{coll}^B}{df}}. \tag{63}$$

Proof. The platform's maximization problem reads

$$\begin{aligned} \max_f \Pi_P \;&= f * N_{coll}^S * N_{coll}^B \\ \text{s.t.} \quad p^{coll} &= v \quad \text{and} \quad N^S = \frac{v-f}{F}. \end{aligned} \tag{64}$$

We divide this proof into two part. We first show that $f < v$, followed by the derivation of f_{NE}^{coll}.

First, notice that $f < v$. To see this, recall that by Assumption A1 $p^{coll} > p^{com} \iff v > f + \tau/(N_{com}^S)^2$. And together with $N_{coll}^S = (v-f)/F$, this implies that $v > f + \sqrt{\tau F}$. Hence, also $f_{NE}^{coll} < v$.

Finally, setting the first order condition of the maximization problem above to zero yields,

$$N_{coll}^S * N_{coll}^B + f\left(N_{coll}^S \frac{dN_{coll}^B}{dN^S} + N_{coll}^B\right)\frac{dN_{coll}^S}{df} \;=\; 0, \tag{65}$$

which, since $(dN_{coll}^B/dN^S) * (dN^S coll/df) = dN_{coll}^B)/df$, can be rearranged into the expression of the above proposition. ☐

Proposition 22 (NE – Preferred Conduct (IC))**.** *In the presence of indirect network effects on both sides of the market, the platform's preferred conduct is seller competition.*

Proof. We first show that the platform's profit maximizer f_{NE}^{coll} satisfies the incentive compatibility constraint. We then proof this proposition formally by contraposition. First, notice that the incentive compatibility constraint is satisfied whenever $\pi^{coll} > \pi^{com} \iff (v-f)/N_{coll}^S > \tau/(N_{com}^S)^2 * N_{com}^B$, which can be rearranged into $v > f + \tau/([N_{com}^S)^2 * N_{com}^B * N_{coll}^S$. Hence, the upper bound of f is even more strict than in Proposition 21, but always satisfied. To see this, recall firs that Assumption A1 is $p^{coll} > p^{com} \iff v > f + \tau/N_{com}^S * N_{com}^B$. Therefore, if Assumption 1 is less restrictive then the incentive compatibility constraint, then

$$f + \tau/N_{com}^S * N_{com}^B \;<\; f + \tau/N_{com}^S * N_{com}^B \;\iff\; N_{com}^S \;<\; N_{coll}^S, \tag{66}$$

which is impossible. Thus, the platform's profit maximizer f_{NE}^{coll} satisfies also the incentive compatibility constraint.

As a second step, suppose the preferred conduct is collusion. Then, preferring collusion implies that $\Pi_P^{coll} > \Pi_P^{com}$, which is equivalent to

$$f_{NE}^{coll} * N_{coll}^S * N_{coll}^B \;>\; f_{NE}^{com} * N_{com}^S * N_{coll}^B \tag{67}$$

and can be expressed as relative mark-ups such that

$$\frac{N^S_{coll} * N^B_{coll}}{\eta^S_{coll} + \eta^B_{coll}} > \frac{N^S_{com} * N^B_{com}}{\eta^S_{com} + \eta^B_{com}}. \tag{68}$$

Then, rearranging terms yields

$$\frac{\eta^S_{com} + \eta^B_{com}}{\eta^S_{coll} + \eta^B_{coll}} > \frac{N^S_{com} * N^B_{com}}{N^S_{coll} * N^B_{coll}}, \tag{69}$$

where the left-hand side is equal to one since the platform faces no marginal costs. However, notice that the right-hand side is greater to one due to the presence indirect network effects. But this is a contradiction. Hence, in the presence of indirect network effects on both sides of the market, the platform's preferred conduct is competition. □