UNITE AND CONQUER:
Seller Collusion in Multi-Sided Markets

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Abstract

This paper aims to examine the relationship between marketplace design and seller competition on online platforms. Using a game-theoretic model, we investigate how various design choices, such as pricing strategies, may influence the likelihood of seller collusion and the incentives of platforms to either break or sustain cartels. Initial findings suggest that high transaction fees may reduce competition between sellers by increasing their incentives to collude, and platforms may also have the ability to manipulate the variety of products in each category. Our theoretical framework also allows for the examination of additional design features, such as information disclosure and the number of products, and their impact on seller competition. Overall, this research aims to contribute to the limited academic discussion on how the design of multi-sided markets affects competition on online platforms.

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.

It is no surprise that with online marketplaces' gain in economic relevance in recent years, the number of associated high-profile antitrust cases that feature anti-competitive behaviour of sellers has risen substantially [see, e.g., OECD, 2018].[1] And the further use of algorithmic pricing will likely amplify this number [Calvano et al., 2020; Ezrachi and Stucke, 2019; Competition and Markets Authority, 2021]. Despite the high complexity of marketplace design and its crucial effects on competition, the academic debate on anti-competitive behaviour among sellers within multi-sided markets, however, has been surprisingly limited.

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 delineate a platform's fee structure (i.e., its pricing model) from its remaining design choices about product variety and product transparency as well as its decisions to ration users. Based on these different channels of influence, we then probe sellers' incentives to coordinate on prices and study how such a platform can manipulate their' incentives to steer competition in its own favour. Ultimately, we provide conditions under which a platform is able to correct sellers' anti-competitive behaviour and when its incentives differ from that of a social planner whose goal is to maximize total welfare.

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 control the degree of perceived variety of goods sold within a product category, the platform 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

[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 [2022] for tacit price collusion. Similarly, the Italian 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 Competition and Markets Authority [2016] or the US Department of Justice [2015, 2016]. Moreover, the Competition and Markets Authority [2018] finds evidence for the "widespread use of algorithms to set prices, particularly on online platforms" [p.3].

in higher prices, which ultimately renders the platform less attractive to buyers. Hence, if sellers compete, the platform may ration buyers by raising usage fees since this decreases the size of the positive indirect network effects.

In addition, 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 the product category 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) sellers' profits 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. This creates motives 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.[2]

Alternatively, if buyer demand is very responsive to prices, the platform needs to leave some surplus to buyers, which will ultimately be captured by sellers and, hence, crowds out buyer demand. Since, in this case, neglecting to capture seller profits would be inefficient, the platform induces seller collusion to reap this extracted surplus once again from the sellers. Therefore, if buyers react strongly to price changes, the platform can make greater profits by inducing seller collusion.

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 within a product category on the platform. The platform can make design choices about its usage fees and other marketplace-relevant design features, such as the number of users and the degree of perceived product variation. The subsequent section studies platform governance choices through the lens of the previously described model. Potential policy implications are drawn in Section 5. Section 6 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,

[2] Examples include Amazon's 'Automate Pricing' and Aribnb's 'Smart Pricing' tools. The Competition and Markets Authority [2021] reports that other sharing economy platforms employ similar tools that allow sellers to delegate pricing to the platform or even require them to do so.

platform governance, platforms managing (seller) competition, and platform regulation as the literature studying the feasibility of seller coordination.

2.1 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 other design aspects of a platform beyond its pricing feature –such as user rationing, the degree of information disclosure, and limiting product variety– that have been so far neglected by this strand of the literature.

2.2 Platform Governance

While considering pricing aspects, we also contribute to the more recent literature stream 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].

However, most of these works study implications of innovation on platforms [Boudreau, 2010; Parker and Van Alstyne, 2018; Hagiu and Spulber, 2013; Edelman and Wright, 2015; Hagiu and Wright, 2019]. However, Teh's paper [2022] comes closest to ours, which we developed independently from him, by examining how a platform's fee structure affects seller competition. Different to Teh [2022] however, our framework takes the dynamics of seller competition into account, and platforms' pricing and design decisions are fully endogenous. 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 indirect network effects). Although exploring PPCs is not the primary goal of this paper, we propose a model where sellers' outside option is normalized to zero. Hence, one possible way of interpreting sellers' outside option in our model is that sellers expect to make the same profits across all available distribution channels.

In another paper, Johnen and Somogyi [2021] look at the role of *drip pricing* as a marketplace design tool. In their model, an online platform has the ability to reveal additional product attributes (such as shipping and return policies) either 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 features and seller competition.

2.3 *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.

2.4 *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]. 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.

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.

2.5 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).[3] 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,[4] *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 marketplace design features to encourage seller collusion. Namely, once collusion is established, the platform is able to extract all surplus from its users.

3 Model

This section outlines the model. We first describe competition on the platform level and then explain seller competition within a particular product category. 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 marketplace design features shape seller competition and how platforms 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 $n^S \in [0,1]$ sellers and $n^B \in [0,1]$ buyers on the platform.

[3] See, e.g., New York Times: https://www.nytimes.com/2020/07/30/technology/europe-new-phase-tech-amazon-apple-facebook-google.html. 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].

[4] See, e.g., Financial Times: https://www.ft.com/content/662c8e3f-4909-4bec-9131-c0237bb4897d.

Buyers interact with sellers via the platform in a given product category (or market segment), and sellers provide horizontally differentiated goods within each product category. Quality differences in goods can thus be seen as products of sellers who compete in different market segments, while sellers in the same category provide imperfect substitutes. For the sake of tractability, we assume that sellers' outside option is homogeneous and normalized to zero.[5] Buyers have an idiosyncratic stand-alone utility $u^B \in \mathbb{R}$ from joining the platform that follows some continuous distribution F with support $[0, 1]$.[6] Further, let $v \in \mathbb{R}_{++}$ be buyers' homogeneous valuation for goods within a given product category.[7] In each product category, 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 a product category:

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

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 between users: buyers benefit from the presence of a greater number of sellers and vice versa. 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 $t \in \mathbb{R}_+$. Without loss of generality, we further assume that the platform does not impose any transaction fee 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 t to sellers and has marginal costs

[5] The 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.

[6] Assuming $u^B \sim F[0, 1]$ captures the idea that each buyer has an individual outside option that is randomly distributed. Note that we do not impose any restrictions on the sign of u^B. It can therefore be either, positive (i.e., buyers enjoy being on the platform –perhaps for reputational or personal reasons– even though they might end up buying nothing in equilibrium), zero (i.e., buyers simply want to make the best deals, but they derive no stand-alone utility merely from being on the platform), or negative (i.e., buyers generally dislike the platform but use it to purchase goods since it provides the best value-for-money).

[7] We assume that buyers' valuation for goods within a product category is sufficiently large such that the market (segment) is covered (see Assumptions A1 and A2 below). Note, however, that together with the homogeneous valuation v for goods in the same product category, the specification of u^B allows for indirect network effects on the buyer side.

$w \in \mathbb{R}_+$. We assume that the platform cannot discriminate among sellers or buyers. Total platform profits can then be summarized as

$$\Pi_P(t) = (t - w) * n^S * n^B. \tag{3}$$

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

3.2 *Product Category Competition*

In each product category, sellers compete in a Salop [1979] fashion: there is a continuum of buyers and $N \in \mathbb{N}$ sellers who provide horizontally differentiated goods and are equally distributed across a circular city with perimeter equal to one. Let $\tau \in \mathbb{R}_+$ be the product-differentiation parameter within a given product category. With a slight abuse of notation, we also denote by N the set of all sellers in a given product category. Sellers are symmetric and have marginal costs $c \in \mathbb{R}_+$. Let $p_i \in \mathbb{R}_+$ be the price charged by seller $i \in N$ and $p_{-i} \in \mathbb{R}_+$ be the price charged by i's competitors $N \setminus \{i\}$. The total profits of seller i are then given by

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

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

Buyers, on the other hand, have for each product category a particular taste or idea about the product they want to purchase but face horizontally differentiated goods. Following the convention of the spatial economics literature, τ can alternatively be interpreted as the transportation cost that buyers incur in order to purchase the product of seller $i \in N$. For the sake of tractability, we assume linear transportation costs in each product category. As discussed above, buyers' willingness to pay is homogeneous and equal to $v \in \mathbb{R}_{++}$. Their outside option consists of not buying. 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].[8]

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. To see this, note that the number of sellers is given by

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

[8] One way of interpreting this assumption is that buyers first have to go to the sellers (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 a given buyer.

Since by assumption sellers' outside option is homogeneous and normalized to zero, they always join the platform as long as they can generate non-negative profits. Hence, in equilibrium either $n^S = 1$ (all sellers join) or $n^S = 0$ (no seller joins).

Buyers, on the other hand, prefer lower prices and a greater number 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 implies that buyers have a 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 (i.e., a transaction fee or a subscription-based model). Second, buyers and sellers decide whether to join the platform or not. Third, within each product category, 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 they highest price possible (i.e., the monopoly price).[9] Buyers then decide whether to purchase goods via the platform or not. We solve the model by using backward induction and study subgame perfect equilibria.

Finally, to rule out economically uninteresting cases, we state the following assumption:

A1. $v > c + w$

This assumption states that buyers' willingness to pay is sufficiently large. Precisely, it ensures that if both sellers and the platform operate at their respective marginal costs, there is volume in the marketplace such that buyers are inclined to purchase goods via the platform.

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

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 a product category. Before, however, we discuss possible product category equilibria.

4.1 Product Category Equilibria

In each product category 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. In the same, the platform generates profits from imposing a transaction fee, which increases the overall price in a product category.

Given this trade-off, we first describe equilibria within product categories 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 product category is either competitive or features local monopolies.

Lemma 1 (Product Category Equilibrium)**.** *There exists a unique Product Category Equilibrium. In particular, the product category is* competitive *if*

$$v > c + t + \tau/N. \tag{8}$$

Alternatively, the product category features local monopolies *if* $v < c + t + \tau/N$*. Moreover, both cases* coinincide *whenever* $v = c + t + \tau/N$*.*

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 $v < c + t + \tau/N$. Then, seller i's best response

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

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 $d_i = 1/N + (p_{-i} - p_i)/\tau$. Since sellers are symmetric, profit maximization reveals that the optimal price charged by all sellers satisfies

$$p^c \equiv p_i = c + t + \tau/N, \tag{10}$$

and they all obtain the same market share $d_i = 1/N$ for all $i \in N$ But, since buyers' participation constraint reads $v \leq c + t + \tau/N$, not all buyers along the Salop circle will purchase (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 $p^m \equiv v$, yielding $\pi^m = (v-c-t)/N$ 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 $v > c + t + \tau/N$. Then, if seller i sets a price $p_i > p^c$, this leads to a loss in market share (i.e., $d_i < 1/N$) and hence lower profits. Therefore, if $v > c + t + \tau/N$, sellers compete along the Salop circle with $p_i = p^c$ and $\pi^c \equiv \pi_i = \tau/N^2$ for all $i \in N$.

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

Lemma 1 shows that there are two 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 distances from each other. Then, the competitive outcome is equal to Bertrand competition with imperfect substitutes: charging a price higher than the competitive price p^c leads to a loss in demand, leading to lower profits. Hence, charging p^c 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 $p_i = p^m = v$ as long as $v > c$ 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 a product category when $v < c + t + \tau/N$.

Regardless of the product category 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^m and and p^c be the monopoly and competitive price in a product category, respectively. Then,*

i) if the product category is competitive, it holds that $p^m > p^c \iff \pi^m > \pi^c$.

ii) if the product category features local monopolies, it holds that $p^m < p^c \iff \pi^m < \pi^c$.

Proof. Take a competitive product category. Then $p^m = v > c + t + \tau/N = p^c$, where the inequality stems from Lemma 1 since sellers compete in that product cateogry. However, if seller i is the only seller in that product category, i's profits are maximized at $p_i = p^m$. Hence, $\pi^m > \pi^c$. Conversely, by a similar reasoning, if sellers act as local monopolies, then $p^m = v < c + t + \tau/N = p^c$ and $\pi^m < \pi^c$. □

Generally, Corollary 1 displays how prices and profits differ when comparing seller competition with local seller monopolies in a product category. 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 $p^m = v$.

As mentioned earlier, however, this differs starkly when buyers have a high willingness to pay: in competitive product categories, 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 provides scope for sellers to create a cartel. 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 when product categories are competitive, sellers have an incentive to collude since* $\pi^m > \pi^c$.

Proof. A necessary condition for collusion is that sellers can make greater profits when charging $p^{coll} > p^c$. The first statement of Corollary 1 shows that $\pi^m > \pi^c$ whenever sellers compete. Hence, only when product categories are competitive sellers have an incentive to collude. □

As a result, collusion can only arise in the competitive product category equilibrium. Therefore, for the remaining part of the paper, we thus assume that $p^m > p^c$ to rule out the economically uninteresting case of the monopolistic equilibrium:[10]

A2. $p^c < p^m$

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 No Seller Collusion

When sellers compete in the marketplace, they make profits equal to $\pi^c = \tau/N^2$ and charge prices $p^c = c + t + \tau/N$. The platform then maximizes profits with respect to the fees it imposes. Thus, the platform's problem formally reads

$$\begin{aligned} \max_t \Pi_P(t) &= (t-w) * n^B(p(t), n^S) * n^S(p(t), n^B) \\ \text{s.t. } p(t) &= c + t + \frac{\tau}{N} \end{aligned} \tag{11}$$

[10] Note that is assumption is equivalent to say that buyers prefer seller competition over collusion.

Based on this maximization problem, 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. Further, setting a transaction fee that is too high is inefficient since this would reduce buyer demand, which reduces the total volume in the platform's marketplace, and hence decreases profits.

Proposition 1 (Platform' best response – no collusion)**.** *Suppose Lemma 1 holds and that sellers compete. Then, the monopoly platform's best response to maximize profits is*

$$t^* \;=\; w\,\frac{\eta^B(p(t),n^S)}{\eta^B(p(t),n^S)-1} \quad \textit{with} \quad \eta^B(p(t),n^S) \;=\; \frac{t}{n^B(p(t),n^S)}\,\frac{\partial n^B(p(t),n^S)}{\partial t} \tag{12}$$

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.,

$$\max_t \Pi_P(t) \;=\; (t-w)*n^B(p(t),n^S)*n^S(p(t),n^B), \tag{13}$$

whose first order condition –while neglecting arguments for a moment– solves

$$n^B*n^S*(t-w)\left[\frac{dn^B}{dt}*n^S+n^B*\frac{dn^S}{dt}\right]=0. \tag{14}$$

Given that sellers charge $p^c = c+t+\tau/N$, they make profits $\pi^c = \tau/N^2 > 0$, so in equilibrium all sellers join the platform. Thus, in equilibrium $n^S(p(t),n^B) = n^S = 1$. Moreover, since seller profits are independent of t, also $dn^S/dt = 0$. This reduces the first order condition to

$$n^B(p(t),n^S)*(t-w)\frac{dn^B(p(t),n^S)}{dt}=0. \tag{15}$$

After rearranging terms and dividing by the optimal $t \equiv t^*$, we obtain the optimal pricing formula expressed in terms of the Lerner index:

$$\frac{t^*-w}{t^*} = -\frac{n^B(p(t),n^S)/t}{dn^B(p(t),n^S)/dt} \equiv -\frac{1}{\eta^B(p(t),n^S)}. \tag{16}$$

Alternatively, we can rearrange terms such that

$$t^* = w\,\frac{\eta^B(p(t),n^S)}{\eta^B(p(t),n^S)-1}, \tag{17}$$

which concludes the proof. □

Alternatively, to see that the platform can generate positive profits when sellers compete, we can rewrite the result of Proposition 1 in terms of a Lerner index as seen in the proof, i.e.

$$\frac{t^*-w}{t^*} \;=\; -\frac{1}{\eta^B(p(t),n^S)}. \tag{18}$$

Therefore, Proposition 1 tells us that in equilibrium, the platform charges a transaction fee t^* that is above its marginal costs w. Moreover, if sellers compete, they charge a price $p(t) = c + t + \tau/N$ and make profits equal to τ/N^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.

Proposition 1 also reveals further important comparative statics. For instance, a higher number of sellers per product category N allows the platform to charge a higher transaction fee. In fact, a greater number of sellers per product category 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. 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 since sellers pass the platform's transaction fees to buyers. Hence, also double marginalization becomes a more prevalent issue for the platform. To counteract, the platform's best response is to decrease its fees.

Additionally, improving product comparability (e.g., by decreasing τ) has two effects. First, sellers compete stronger by making products within a product category appear more similar to each other. 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 force the platform to set lower transaction fees. Intuitively, when buyer demand is responsive to prices, the platform must leave more surplus to buyers. Since sellers pass on the platform's fee to buyers, the platform thus has to reduce its fee to prevent buyers from leaving its marketplace. Alternatively, the platform can try to increase its stand-alone benefit to buyers u^B to counteract buyers' increased sensitivity to prices by, e.g., providing or improving add-on services.

4.3 *Seller Collusion*

This previous subsection looked at a product category equilibrium when sellers compete. In that case, sellers charge prices $p^c = c + t + \tau/N$ and make profits $\pi^c = \tau/N^2$. Given that sellers compete, Proposition 1 the platform's best response is to charge a fee of t^* to extract some surplus from the sellers while still allowing for cross-group externalities such that overall volume in the marketplace is maximized. However, since $\pi^c > 0$, the platform faces an issue of double marginalization that limits its ability to extract all surplus.

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 product category 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 compete in the above fashion. We then carve out the platform's best response to seller collusion.

Based on Corollary 2, a necessary condition for seller collusion is that if they coordinate on prices, they can obtain higher profits, i.e., $\pi^m > \pi^c$. Thus, given Assumption A2, we look at an infinitely-repeated game in discrete time with periods $k = 0, ..., \infty$ where sellers have a common discount factor $\delta(0, 1)$ and aim to maximize the discounted stream of (future) profits.

$$\sum_{k=0}^{\infty} \delta^k \pi(p). \tag{19}$$

Notably, the platform does not participate in the collusive agreement but may have a preferred conduct and might choose its transaction fee to influence how sellers act in its marketplace. Moreover, 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 within a product category. For ease of presentation, we assume sellers coordinate on the monopoly price p^m.[11]

We are now going to model seller collusion by looking at the grim trigger strategies [Friedman, 1971] – that is, once a seller deviates from the collusive scheme, all sellers play their competitive strategies and earn π^c profits.[12] Suppose now that sellers form a cartel that coordinates on prices that charges the monopoly price p^m. Hence, once the cartel is formed, each seller obtains $\pi^m > \pi^c$. If one seller decides to deviate from the collusive scheme, the deviator sets a price p_i^D to maximise deviation profits. The following lemma summarizes this result:

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

$$p^D = p^m - \frac{p^m - p^c}{2} \quad ; \quad d^D = \frac{1}{N} + \frac{p^m - p^c}{2\tau} \quad ; \quad \pi^D = \pi^m + \frac{(\pi^m - \pi^c)^2}{4\pi^c}. \tag{20}$$

Proof. Suppose $-i$ sellers play p^m and seller i deviates by playing p^D. Denote the i's profits, market share, and prices with superscript D. Then, i's best response p^D maximizes

$$\pi^D(p^D, p^m) = (p^D - c - t) * \left(\frac{1}{N} + \frac{p^m - p^D}{\tau}\right), \tag{21}$$

[11] In principle, colluding sellers could agree on any price between p^c and p^m. Hence, the is an infinite number of possible equilibria, as suggested by the Folk Theorem [Friedman, 1971]. In Appendix A, we relax this assumption and show that our results still hold when colluding sellers have the possibility to charge a price $p^{coll} \in [p^c, p^m]$.

[12] A careful reader might have noticed that if a seller deviates in one period, it does not necessarily imply that all sellers will play p^c directly after, given that sellers compete along the Salop circle. However, one deviation then leads to a cascade of sequential deviations that, over an infinite horizon, does not change results qualitatively. Hence, we can neglect these periods of "deviation cascades" without loss of generality.

where p^m is the price charged by the remaining $-i$ sellers, which yields p^D, d^D, and π^D as stated above. □

Proposition 2 shows that a deviating seller chooses a price below the cartel price p^m. By doing so, the deviator is able to gain a greater market share $d^D > 1/N$, which maximizes overall profits. Given that deviation is profitable, the participation constraint to collude is

$$\pi^m + \sum_{k=1}^{\infty} \delta^k \pi^m \;\geq\; \pi^D + \sum_{k=1}^{\infty} \delta^k \pi^c. \tag{22}$$

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 this participation constraint, we can rearrange terms of the above inequality to obtain a lower bound for the common discount factor:

$$\delta \;\geq\; \delta^* \equiv \frac{\pi^D - \pi^m}{\pi^D - \pi^c}. \tag{23}$$

Hence, collusion is only stable if $\delta \geq \delta^*$. Note further that since $\pi^m = \pi^m(t)$ and thus $\pi^D = \pi^D(t)$, also the critical discount factor $\delta^* = \delta^*(t)$, while π^c is independent of transaction fees t. To provide some further insights on the stability of seller collusion, we show in the next lemma how collusion stability relates to the transaction fee imposed by the platform:

Lemma 2 (Collusion incentives). *Denote δ^* the critical discount factor δ that enables collusion. For π^D and π^m as defined in Proposition 2 and Corollary 1, respectively, it holds that $\delta^*(t)$ is decreasing in t.*

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

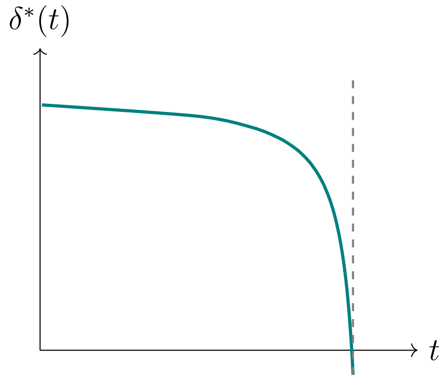
$$\delta \geq \delta^*(t) \equiv \frac{\pi^D(t) - \pi^m(t)}{\pi^D(t) - \pi^c}. \tag{24}$$

In combination with the result in Proposition 2, we can simplify the enumerator to $\pi^D(t) - \pi^m(t) = [\pi^m(t) - \pi^c]^2/(4\pi^c)$. Moreover, the denominator can be reduced to $\pi^D(t) - \pi^c = [\pi^m(t) - \pi^c]^3/(4\pi^c)$. Differentiating with respect to t then yields

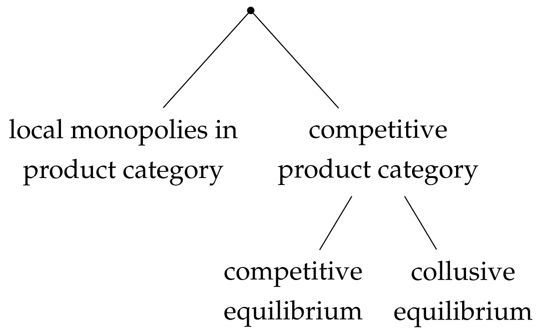
$$\frac{d\delta^*(t)}{dt} = -\frac{5}{N}\,\frac{\pi^m(t) - \pi^c}{4\pi^c} < 0. \tag{25}$$

□

Lemma 2 shows that if sellers collude, a higher transaction fee increases sellers' incentives to do so. In fact, higher transaction fees reduce both deviator profits as well as profits under collusion. Yet, deviator profits decrease faster than collusion profits. Taken



(a) Threshold value or the discount factor $\delta^*(t)$ depending on transaction fees t.



(b) Product category equilibria on the platform.

Figure 1: Collusion incentives and product category equilibria.

together, this renders collusion overall relatively more attractive. As a result, higher transaction fees can thus lead to stronger incentives for sellers to collude. Figure 1a depicts the relationship between collusion incentives and transaction fees imposed by the platform.

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

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

$$t^{coll} = v - c. \tag{26}$$

Proof. Suppose sellers charge $p^m = v$. Then, the platform's best response satisfies

$$\max_t \Pi_P(t) = (t - w) * n^B(p^m, n^S) * n^S(p^m, n^B). \tag{27}$$

Note that the first order condition implies that

$$n^B(v, n^S) * n^S(v, n^B) + (t - w)\left[\frac{dn^B(v, n^S)}{dt} * n^S(v, n^B) + n^B(v, n^S)\frac{dn^S(v, n^B)}{dt}\right] = 0. \tag{28}$$

Moreover, since sellers charge v, $dn^B(v, n^S)/dt = 0$ and in equilibrium all sellers join the platform. Therefore, also $n^S = 1$. The first order condition can thus be simplified to

$$0 = n^B(v, n^S)\left[1 + (t - w)\frac{dn^S(v, n^B)}{dt}\right], \tag{29}$$

which yields

$$(t - w)\,\frac{dn^S(v, n^B)}{dt} = (-1). \tag{30}$$

Hence, in equilibrium, neither $t - w = 0$ nor $dn^S(v, n^B)/dt = 0$. Moreover, $t < w$ can never be a best response since it is always dominated by $t = w$. Therefore, it must hold that

$t \geq w$, which in turn implies that $n^S(v, n^B)/dt < 0$. But when is $n^S(v, n^B)/dt < 0$? Note that sellers join the platform as long as they can make positive profits, or

$$n^S(v, n^S) = \Pr[\pi(v) * n^B \geq 0] \quad \text{with} \quad \pi(v) = \pi^m = \frac{v - c - t}{N}. \tag{31}$$

Therefore, $n^S(v, n^B)/dt < 0$ whenever $(v - c - t)/N = 0 \Leftrightarrow t = t^{coll} \equiv v - c$, which, by Assumption A1, is positive. This completes the proof. □

When sellers collude, buyer demand on the platform is minimized: sellers charge the monopoly price $p^m = v$ – making buyers indifferent between realizing their outside option and purchasing. Consequently, the colluding sellers act like a monopoly and can thus extract all buyer surplus. This also limits indirect network effects on the buyer side. Given that these indirect network effects are already limited, colluding sellers earn $\pi^m = (v - c - t)/N$ and the platform's best response is to extract this surplus once again by charging $t^{coll} = v - c$ irrespective of potential network effects. Therefore, by charging t^{coll}, the platform can eliminate potential issues of double marginalization. As a result, the monopoly platform can thus act as a vertically integrated firm when sellers collude.

4.4 *Collusion or Competition*

Suppose the monopoly platform can now decide whether sellers collude or compete, as depicted in the right branch in Figure 1b. In that case, which equilibrium will the platform prefer? As it turns out, the platform prefers seller collusion whenever buyers' have a very elastic demand or their willingness to pay is sufficiently large:

Proposition 4 (Equilibrium selection). *Let n^B_{coll} and n^B_c be the numbers of buyers in the collusive and the competitive equilibrium, respectively, and η^B_c the elasticity of buyer demand with respect to prices on the platform in the competitive equilibrium. The platform prefers seller collusion over seller competition iff*

$$\frac{t^{coll} - w}{t^*} * \frac{n^B_{coll}}{n^B_c} > -\frac{1}{\eta^B_c} \iff v > c + w\left[n^B_{coll} - \frac{1}{\eta^B_c - 1} n^B_c\right], \ \textit{where } \eta^B_c = \frac{t^*}{n^B_c} * \frac{\partial n^B_c}{\partial t}. \tag{32}$$

Proof. Denote the platform's profits in the competitive and the collusive equilibrium by Π^c_P and Π^{coll}_P, respectively. A monopoly platform prefers seller collusion whenever $\Pi^{coll}_P > \Pi^c_P$, or

$$(t^{coll} - w) * n^B_{coll} * n^S_{coll} > (t^* - w) * n^B_c * n^S_c. \tag{33}$$

Given that in both equilibria all sellers join, $n^S_{coll} = n^S_c = 1$. Therefore, we can rearrange terms and divide by t^* such that

$$\frac{t^{coll} - w}{t^*} * \frac{n^B_{coll}}{n^B_c} > \frac{t^* - w}{t^*} = -\frac{1}{\eta^B_c}, \tag{34}$$

which is equal to the statement on the left-hand side above.

Moreover, recall from Propositions 3 and 1 that $t^{coll} = v - c$ and $t^* = \eta^B/(\eta^B - 1)$, respectively. Hence, we can rearrange terms such that

$$v > c + w\left[n^B_{coll} - \frac{1}{\eta^B - 1} n^B_c\right], \tag{35}$$

which is equal to the right-hand side of the statement. □

Under seller competition, sellers pass on the transaction 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 under the optimal level of transaction fees t^* are lower than its profits by imposing t^{coll} when sellers compete. Therefore, when buyer demand is very elastic, the platform prefers seller collusion.

Moreover, Proposition 4 shows that a platform is inclined towards price coordination among sellers whenever buyers' willingness to pay is sufficiently large. This is also directly related to demand elasticity: when buyers have a large willingness to pay, reservation prices increase which makes buyer demand overall more inelastic. Thus, when demand is very inelastic, sellers could charge a higher price without crowding out much demand. But since extracting buyer surplus under competition is inefficient for the platform (because when sellers compete, they make positive profits), it prefers seller collusion. In this case, sellers capture all buyer surplus, which is then extracted once again by the platform. As a result, the platform also 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. Consequently, given the platform's ability to design and govern its marketplace, it can 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 should be held accountable for such practices. Following this result, we discuss potential consequences for policymakers in the next section.

5 Policy Implications

As the main result of this paper, Proposition 4 shows that a platform can indeed have incentives to establish consumer-harming practices while designing its marketplace. In this section, we discuss potential cases in which such behaviour is most likely to arise and carve out implications for competition authorities to tackle these practices.

5.1 Negative Buyer Demand Shocks

Negative shocks in buyer demand translate to a higher elasticity. Based on Proposition 4, and depending on the marginal elasticity change in buyer demand, the platform has 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 more attractive, but the critical discount factor also increases, as shown in Lemma 2, rendering 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 the demand shock is large enough such that buyer demand becomes sufficiently elastic, the platform's best response is 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 fees. Alternatively, if sellers do not collude despite their incentives, the platform may be able to coordinate sellers' pricing strategies centrally by providing them with suggestions or price recommendations or even by internalizing their pricing strategies. 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; Competition and Markets Authority, 2018]. Indeed, large online marketplaces like Amazon and Airbnb feature centralized pricing tools to give concrete price recommendations. In addition, the Competition and Markets Authority [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.

Competition authorities should thus be cautious when assessing cases of seller collusion on platforms whenever negative demand shocks occur. As our theory suggests, especially in such situations, online platforms might be motivated to exploit power over their marketplace design to encourage sellers to coordinate on prices.

5.2 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 Competition and Markets Authority [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.

6 Conclusion and Further Developments

Even though our current analysis is incomplete, our model establishes that online marketplaces do not necessarily act in favour of their users. In particular, when buyers are sensitive to price changes, the platform can have an incentive to foster sellers' coordination on prices. Moreover, the platform may want to internalize its pricing decisions entirely to avoid potential problems of double marginalization. Such instances should appear more frequently on product categories facing price sensitive demand or on a platform with a well-grounded user base.

In the next version, we plan to extend this paper in several ways. First and foremost, we intend to derive welfare implications as well as further implications for regulators with our model. So far, we have only looked at implications for seller competition. As one might suspect, seller collusion replicates the general welfare result of monopolies by minimizing overall welfare. However, the effects on welfare stemming from different ways of governing competition can be more nuanced, especially when the platform uses additional tools to design its marketplace.

Second, even though already derived, we plan to incorporate other pricing strategies of the platform into our paper. In particular, we will show that our results remain unchanged once the platform employs a pricing strategy featuring revenue-sharing. Moreover, we also plan to extend our results to the use of fixed membership fees and two-part tariffs.

Third, we intend to include the possibility that platforms can also charge buyers. Currently, our analysis is restricted to retail platforms or platforms where buyers cannot observe charged fees. However, to underline the "two-sidedness" of online marketplaces, including this possibility would make our results more general.

Fourth, we will augment our model to allow the platform to influence transportation costs as well as the stand-alone benefit for users. Including these tools opens novel channels for the platform to govern competition, and it will direct the focus of our paper closer to design features in the marketplace.

Fifth, we plan to derive implications when the timeline of the game is modified. In particular, we plan to alter the game's structure in such a way that the platform may choose what product category equilibrium will arise. This would reinforce our results and make the platform's incentives more explicit.

Finally, we also plan to relax our assumption about sellers' outside options. So far, their outside option is assumed to be normalized to zero for all sellers. However, similarly to the possibility for the platform to charge buyers, a non-homogeneous outside option for sellers would stress once more the nature of two-sided markets by making indirect network effects on the sellers' side more present. This can be done by either assuming that the sellers' outside option follows a similar distribution as for buyers, or by introducing a second platform. In general, one might suspect that the introduction of platform competition would limit the scope of our results; however, they should not vanish. Moreover, indirect network effects on the sellers' side provide the potential to stabilize seller cartels. In that, the effects of platform competition could be a priori ambiguous.

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.

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," *The 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.

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.

COMPETITION AND MARKETS AUTHORITY (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.

DEPARTMENT OF JUSTICE (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," *Nw. J. Tech. & Intell. Prop.*, 17, 217.

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

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?" *The 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: Supracompetitive 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," *The 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.

Nocke, V., M. Peitz, and K. Stahl (2007): "Platform ownership," *Journal of the European Economic Association*, 5, 1130–1160.

OECD (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," *The Journal of Industrial Economics*, 70, 371–395.

Parker, G. and M. Van Alstyne (2018): "Innovation, openness, and platform control," *Management Science*, 64, 3015–3032.

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," *The 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.

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

Generally, sellers can coordinate on any price $p^{coll} \in [p^c, p^m]$ 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^m, the following lemma establishes that the results of Proposition 2 can be generalized to hold under the Folk Theorem.

Lemma 3 (Folk Theorem)**.** *Suppose sellers can coordinate on prices $p^{coll} \in [p^c, p^m]$. Then there exists an $\alpha \in [0,1]$ such that collusive price and profits are given by*

$$p^{coll} = \alpha p^m + (1-\alpha)p^c \quad ; \quad d^{coll} = \frac{1}{N} \quad ; \quad \pi^{coll} = \alpha \pi^m + (1-\alpha)\pi^c. \tag{36}$$

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

$$p^D = p^c + \alpha \frac{p^m - p^c}{2} \quad ; \quad d^D = \frac{1}{N} + \alpha \frac{p^m - p^c}{2\tau} \quad ; \quad \pi^D = \pi^{coll} + \alpha^2 \frac{(\pi^m - \pi^c)^2}{4\pi^c}. \tag{37}$$

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

$$p^{coll} = \alpha p^m + (1-\alpha)p^c \quad ; \quad d^{coll} = \frac{1}{N} \quad ; \quad \pi^{coll} = \alpha \pi^m + (1-\alpha)\pi^c. \tag{38}$$

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

$$\pi^D = (p^D - c - t) * \left(\frac{1}{N} + \frac{p^{coll} - p^D}{\tau} \right), \tag{39}$$

which yields

$$p^D = p^c + \alpha \frac{p^m - p^c}{2} \quad ; \quad d^D = \frac{1}{N} + \alpha \frac{p^m - p^c}{2\tau} \quad ; \quad \pi^D = \pi^{coll} + \alpha^2 \frac{(\pi^m - \pi^c)^2}{4\pi^c}. \tag{40}$$

□