

Seller Curation in Platforms*

Ben Casner[†]

August 21, 2020

Abstract

This article explores why market platforms do not expel low-quality sellers when screening costs are minimal. I model a platform market with consumer search. The presence of low-quality sellers reduces search intensity, softening competition between sellers and increasing the equilibrium market price. The platform admits some low-quality sellers if competition between sellers is intense. Recommending a high-quality seller and this form of search obfuscation are complementary strategies. The low-quality sellers enable the recommended seller to attract many consumers at a high price and the effect of the recommendation is strengthened as low-quality sellers become more adept at imitating high-quality sellers.

Keywords: Search Obfuscation, Two-sided Markets, Platforms, Screening, Recommendations

JEL Codes: D21, D83, L22, L15

*I wish to thank Jim Peck, Huanxing Yang, PJ Healy, Yaron Azrieli, Jinsoo Bae, Adam Dearing, Laura Doval, Kirby Nielsen, Teddy Kim, Soyoung Lee, Volcker Nocke, Gustavo Saraiva, Lucy Xiaolu Wang, Parker Wheatley, Jidong Zhou and many others for their helpful comments. All mistakes are my own.

[†]The Ohio State University. Mailing address: 410 Arps Hall, 1945 N. High St. Columbus OH, 43210. Email: casner.15@osu.edu.

1 Introduction

Platforms which connect buyers and sellers suffer a loss of reputation if they host too many low-quality sellers. Reputational effects can have a significant impact on customer retention (Nosko and Tadelis 2015). However, many platforms seem unwilling to curate the quality of sellers on their marketplace. For example, many sellers of low-quality exercise nutritional supplements on Amazon use fake reviews to imitate high-quality sellers. Amazon seems reluctant to respond to this problem even though many of these fake reviews are easy to detect algorithmically.¹ While the cost of screening could potentially explain some of this behavior, costs cannot explain why this reluctance appears even in cases when simple measures could significantly increase the average quality of products on offer. The computer game platform Steam has notoriously low barriers to entry, with one notable example where users found that software they had purchased was just an empty folder. It would be a relatively simple matter to ensure that a game must at least run before the platform allows it to be sold.² It therefore seems likely that these platforms have an incentive to not screen out low-quality sellers.

To address the question of why a platform might want a lax screening policy I present a model where a monopoly market platform hosts sellers in exchange for a percentage of their revenue.³ Sellers can either be low- or high-quality, and the platform sets the proportion of low-quality sellers on its market. Consumers participating in the platform's market must search before they can purchase from a seller. The presence of the low-quality sellers creates two countervailing effects: The *obfuscation effect*

1. See <https://www.npr.org/sections/money/2018/06/27/623990036/episode-850-the-fake-review-hunter>.

2. See <https://www.gamerevolution.com/news/373453-steam-poorly-moderated-selling-empty-game-folder>

3. I discuss a model with competition between platforms in [Appendix B](#)

reduces consumer search intensity, softening competition between sellers and raising equilibrium market prices. The *lemon effect* reduces consumer confidence in the quality of goods on the market which reduces their willingness to pay. The platform will admit a positive proportion of low-quality sellers if the obfuscation effect is stronger than the lemon effect. If the platform is able to recommend a high quality seller, then that seller will benefit from obfuscation without being subject to the lemon effect which further increases platform profits and increases the likelihood that it will adopt a lax screening policy.

The obfuscation effect is so named because I show that the low-quality sellers can act as a search obfuscation mechanism (Ellison and Ellison 2009). Consumers never knowingly purchase from a low-quality seller, so if a consumer searches and encounters a low-quality seller then they will pay the search cost to visit another seller, and they will continue searching until they encounter a seller they believe to be high-quality. The possibility of encountering a low-quality seller upon searching decreases the value of searching as the proportion of low-quality sellers increases, which in turn leads to higher equilibrium prices.⁴ Although decreasing the value of search drives some consumers away from the market, the platform increases seller profits, and consequently its own revenue per consumer, by softening competition between sellers.

The low-quality sellers in my model attempt to fool consumers into believing that they are high-quality sellers. Consumers know the probability that low-quality sellers successfully imitate high-quality sellers, but cannot distinguish between a high-quality seller and a low-quality seller who is successful in their deception. The lemon effect reflects the fact that the presence of low-quality sellers reduces consumers' confidence in the quality of any prospect they are considering because it is possible that it is a

4. One could equivalently think of this as an increase in the effective search cost.

low-quality seller in disguise. Consumers will have diminished willingness to pay for sellers' products and are less eager to participate in the platform's market because of the possibility that they may be scammed. The lemon effect is harmful to the platform, so if it is significantly stronger than the search obfuscation effect then the platform does not admit any low-quality sellers.

In independent work, Barach, Golden, and Horton (2019) show that highlighting recommended sellers can be a powerful tool for platforms. At first glance this practice might initially seem to be contradictory to the obfuscation effect in my model. In fact, by combining the literatures on search obfuscation and seller recommendations, we can see that recommending a high-quality seller and obfuscating search via low-quality sellers are *complementary strategies* for the platform.⁵ It is profit maximizing for the platform to recommend a high quality seller, so the recommendation is credible and the recommended product is not subject to the lemon effect. Consumers are therefore willing to pay a higher price for the recommended seller's product than the product of a random seller of uncertain quality. Consumers, the recommended seller, and the platform are better off with the recommendation for any fixed proportion of low-quality sellers. However, by mitigating the lemon effect the recommended seller reduces the platform's incentive to screen. The ability to recommend a seller can even cause the platform to allow low-quality sellers under parameter sets where it would not absent the ability to recommend. Consumer gains from the recommendation may thus be diminished or even eliminated by an increase in the proportion of low-quality sellers.

5. An example of this kind of highlighting on Amazon includes "Amazon's choice" products. On Steam, new software is often highlighted in a "top new releases" section on the front page.

2 Related Literature

The idea behind search obfuscation starts with the observation that increasing search costs often lead to higher prices and larger profits, with the extreme case being Diamond’s (1971) result that firms will price as local monopolies if consumers can be completely prevented from searching. Ellison and Ellison (2009) and Ellison and Wolitzky (2012) demonstrate that coordination on increasing search costs can survive even with sophisticated consumers. Although as Ellison and Wolitzky discuss, it is not clear why firms would not simply coordinate on price if they can coordinate on increasing search costs.⁶ Armstrong and Zhou (2015) explain the phenomenon of “exploding offers” in both labor and consumer search markets as an attempt by firms to deter search.

These models all rely on individual firm actions affecting the market as a whole. Most of the previous papers which have considered obfuscation by monopolists (e.g. Petrikaitė (2018) or Gamp (2019)) have done so in the context of multi-product firms which also have control over prices. The obfuscation in my model is more akin to the wholesaler recommended prices in Lubensky (2017) in that it is a way for the platform to regain some of the price control it sacrifices by not selling directly to consumers.⁷ This control comes from softening competition between sellers, meaning that I also contribute to the literature on within group effects in platforms (Weyl 2010; Belleflamme and Peitz 2019).

The search obfuscation in my model is mechanically similar to the noisy search in Yang (2013) or the relevance of sellers in Eliaz and Spiegel (2011) and Chen

6. de Roos (2018) shows that limited product comparability can aid price collusion. Therefore, price collusion and obfuscation together may be easier to justify than either alone.

7. I do not address the question of why the business chooses to operate as a platform instead of selling directly. See Hagiu and Wright (2015) for a discussion of the tradeoffs between selling as a platform and direct sales.

and Zhang (2018). In all three models higher search quality is represented by a reduced probability of encountering a product in which the consumer is uninterested (i.e. 0 match utility). Encountering a low-quality seller in my model is equivalent to an irrelevant search in those models, which means that reducing the proportion of low-quality sellers is similarly equivalent to increasing the precision of search.

Eliaz and Spiegler (2011) is one of the most similar papers to mine in that it focuses on a platform obfuscating search by controlling the average quality of sellers. However, their platform receives a payment per search so it is thus a much more direct conclusion in their case that the platform benefits from extending the search process. By specifying a model in which the platform benefits directly from higher seller revenue rather than indirectly via additional searches, I am able to connect obfuscation to the seller recommendation and search prominence literature. My results on recommended sellers depend in part on the recommended seller holding a prominent search position. All consumers who buy from the recommended seller search only once, but because the platform in my model is skimming a portion of seller profits rather than charging a price per search, its profits increase.

Chen and Zhang (2018) find similar effects in terms of the effects of including low-quality sellers on search persistence and pricing, but their main focus is on the trade-off between increasing the variety of products available and allowing more low-quality sellers to enter the market. They do not derive analytical results for the effects of including low-quality sellers on industry profit when sellers are horizontally differentiated, nor do they consider the impact of average seller quality on consumer participation.

Importantly, neither Eliaz and Spiegler (2011) nor Chen and Zhang (2018) include deceptive sellers, whereas the imperfectly observable quality in my model drives the pricing advantage held by the recommended seller. There is a significant literature

looking at false advertising and deceptive sellers (e.g. Corts (2014) Piccolo, Tedeschi, and Ursino (2015), Rhodes and Wilson (2018)) but these papers focus on determining when the socially optimal policy allows some false advertising instead of platform profit. Gamp and Kraehmer (2018) come closer in that they examine the interaction between deceptive sellers and competition in a search environment. But again they are not interested in platform design, instead focusing on seller incentives to provide high or low-quality products.

Athey and Ellison (2011) and Chen and He (2011) examine prominence in the context of sponsored search auctions, whereby a seller pays for prominence in a search engine's results. The primary interest of both papers is their respective auction mechanisms and showing that higher quality sellers will bid for more prominent positions. The platforms in these models are largely passive, primarily interacting with consumers and sellers by modifying the auctions (i.e. setting a reserve price) rather than the search environment itself. Mamadehussene (2019) considers obfuscation in the context of a price comparison platform which is selling prominence, but the obfuscation comes from sellers rather than the platform, which combined with his platform's revenue model does not allow for the complementarity I find between obfuscation and the seller recommendation.

Unlike these previous papers, the benefit of the recommendation to the platform in my model does not come from selling prominence. Prominence is important because it directs consumers to the recommended seller, but it does not drive the seller's pricing behavior. The recommended seller's higher price comes instead from the credibility of the platform's recommendation allowing the recommended seller to raise its price without driving away consumers. This result differs significantly from Yea's (2018) cheap talk model where a platform's recommendation is only credible if all of its messages are revenue equivalent in equilibrium.

My finding that the recommendation can improve consumer welfare has empirical support from Chen and Yao’s (2016) finding that following platform recommended search order significantly reduces search costs with little loss in expected match utility. Additionally, I provide an explanation for the effectiveness of “cheap talk” recommendations in Barach, Golden, and Horton’s (2019) field experiment. Finally, while not explicitly modeled as such, one could think of a platform’s first party content as a form of recommendation, so this paper is also relevant to the literature on platform “coopetition” (Zhu and Liu 2018; Zhu 2019).

Hagiu and Jullien (2011) and White (2013) examine motivations for market platforms to reduce search quality via mechanisms other than search obfuscation. The “search diversion” described by these papers is similar to my model in that garbling search drives away some consumers, but the benefit to the platform takes the form of increased trading volume for high margin products. In my model the benefit instead arises from higher market prices for all products.

Search design is an important consideration for market platforms, Dinerstein et al. (2018) show that search design has a significant impact on seller pricing decisions in platform markets. They describe how a change in eBay’s search design which lowered search costs reduced price dispersion and equilibrium prices. Teh (2019) independently derives some platform search design results similar to those I show in Section 4, although his paper examines questions of platform governance more generally and does not consider deceptive sellers.

3 The Model

The agents in the basic model consist of a monopoly platform, a unit mass of consumers, each with unit demand, a continuum of high-quality sellers, and a continuum of low-

quality sellers, both with strictly positive total mass.⁸

Consumers decide whether to shop on the platform, those who do not participate in the platform's market have access to an outside option. The population distribution of utility for this outside option follows the continuous and concave CDF $Q(\cdot)$. Let α be the proportion of low quality sellers in the platform's market, and $V(\alpha)$ the expected value to a consumer of participating in the platform's market given α . Consumers will participate in the platform's market if $V(\alpha)$ is greater than their value for the outside option, so the mass of participating consumers is $Q(V(\alpha))$.⁹

Those consumers who do decide to participate face an environment similar to Wolinsky (1986) or Anderson and Renault (1999). Consumer i 's utility when purchasing from seller j charging price p_j is

$$\epsilon_{ij} - p_j \tag{1}$$

ϵ_{ij} is a consumer-seller specific match utility term. Consumers cannot observe p or ϵ before visiting a seller and can only purchase from sellers they have visited. For high-quality sellers ϵ is distributed according to the log-concave distribution function $f(\epsilon)$ with corresponding CDF $F(\epsilon)$, and support $[\underline{\epsilon}, \bar{\epsilon}]$ where $\underline{\epsilon} \geq 0$ and $\bar{\epsilon} \in (\underline{\epsilon}, \infty)$.¹⁰

8. In equilibrium all sellers charge the same price, so the platform only cares about the mass of transactions. Unit demand implies that consumers only consider the proportion of high vs. low-quality sellers on the platform and its effect on the search process. The model does not include an entry or operating cost, so the scaling effect from relative mass of sellers to consumers on seller profits does not change any seller decisions. For all of these reasons, the exact mass of sellers in the game or on the platform does not matter, but for the sake of notational simplicity I assume that the total mass of sellers on the platform is 1.

9. For the purposes of this model I will be assuming that a positive proportion of consumers participate in the platform's market. This is a fairly trivial assumption as the platform makes 0 profit with no consumers and a positive profit otherwise, but it allows me to ignore uninteresting equilibria where the sellers charge unreasonably high prices because they are indifferent over all prices with no consumers.

10. Strictly speaking the assumption that $\underline{\epsilon} \geq 0$ is not necessary for my results, but I include it to prevent confusion regarding the distinction between low- and high-quality sellers.

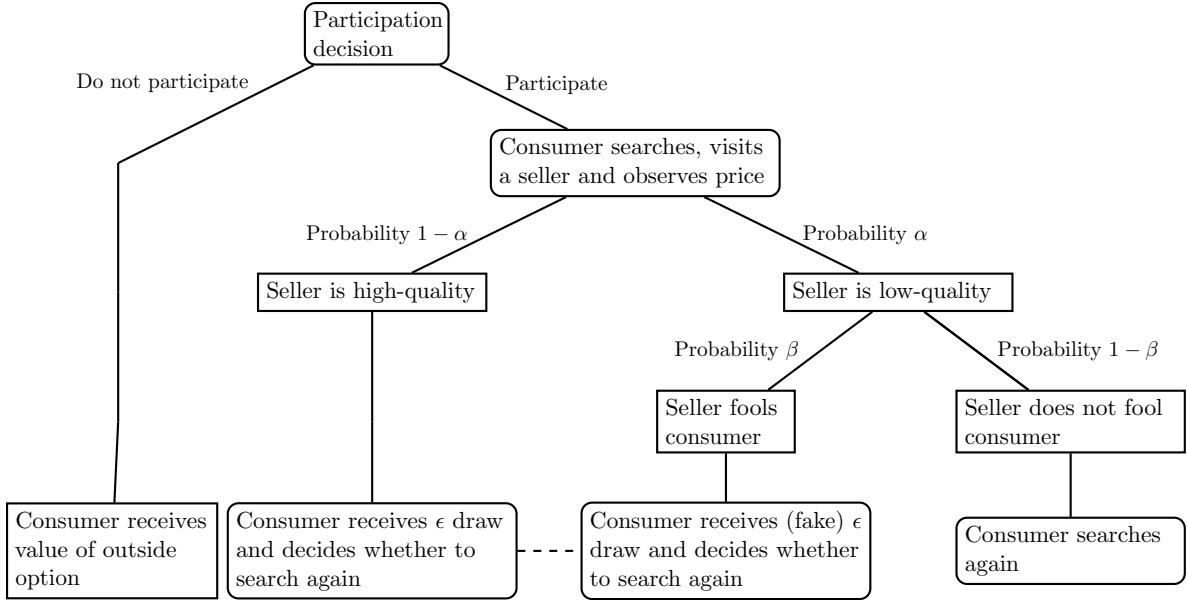


Figure 1: The process by which consumers learn about seller quality and their match value. Rounded corners indicate consumer actions, right angled corners indicate random events. The dashed line connects two nodes within an information set.

For low-quality sellers $\epsilon = 0$, so consumers never purchase from a seller they know to be of low-quality. Low-quality sellers attempt to imitate high-quality sellers and successfully fool a visiting consumer with exogenous probability $\beta > 0$.¹¹ Thus, upon visiting a low-quality seller, consumers do not purchase with probability $1 - \beta$ and with probability β the consumer incorrectly believes the low-quality seller to be a high-quality seller. Upon successfully deceiving a consumer, the low-quality seller is indistinguishable from a high-quality seller, but this does not necessarily mean that the consumer will purchase from that seller. A consumer who is fooled by a low-quality seller receives a fake match utility signal which follows $f(\epsilon)$ and represents the extent to which the sales tactics which successfully deceive a consumer appeal to that consumer. Consumers cannot distinguish between a true match utility draw

11. I use this reduced form process here because endogenous deception would likely make the model intractable. See Smirnov and Starkov (2018) for a detailed model of low-quality sellers imitating high quality sellers. I discuss comparative statics on β in Section 4 and the possibility of the platform influencing β in Section 5

from a high-quality seller and a fake match utility signal from a successful low-quality seller. The consumer purchases from a low-quality seller only if that low-quality seller successfully fools the consumer *and* the perceived match utility is sufficiently high. This process is shown as a flowchart in [Figure 1](#).

The platform receives an exogenous proportion of sellers' revenue and sets the proportion of low-quality sellers α to maximize profit. While the obfuscation in this model is essentially a story about failing to screen, I assume that the platform can perfectly and costlessly determine seller quality and so does not face any sort of screening cost when directly deciding the proportion of low-quality sellers. This assumption allows me to focus on the primary mechanisms behind my results, see [Section 6](#) for a discussion of screening costs and their implications. I assume that this proportion of low-quality sellers is publicly observable.¹² Sellers' only decision is what price to charge given the proportion α of low-quality sellers.

3.1 Equilibrium of the Market Subgame

As is standard in the search literature I use symmetric weak perfect Bayesian equilibrium for my solution concept and assume that searchers' beliefs about other sellers' prices are not affected by observing one seller deviate from equilibrium. The timing of the model proceeds as follows:

1. The platform sets the proportion of high-quality and low-quality sellers.
2. Consumers commit to either participating in the platform's market or remaining with the outside option.¹³

12. Public observability here represents the reputation costs to the platform of allowing low quality sellers.

13. Commitment is not a binding assumption in the benchmark model since the search environment is stationary, so if consumers find participation initially worthwhile they will always find it worthwhile.

3. Sellers admitted by the platform set prices simultaneously.
4. Consumers participating in the platform's market search among sellers and make purchasing decisions.

Consumer Search Behavior

Consumers are aware of the presence of low-quality sellers, so if the proportion of low-quality sellers on the platform is α , then a consumer who has searched and found a prospect $-p_j + \epsilon_{ij}$ will evaluate the value X_b of this current option as

$$\Psi \epsilon_{ij} - p_j \equiv X_b \tag{2}$$

where

$$\Psi = \frac{1 - \alpha}{\beta\alpha + 1 - \alpha} \tag{3}$$

The term Ψ is the mathematical representation of the lemon effect, so I call it the *lemon coefficient*. It represents the fact that, conditional on a consumer evaluating a product as high-quality, the probability that the product they are observing is actually high quality is the probability $1 - \alpha$ that they encountered a high-quality seller, divided by the probability $\beta\alpha + 1 - \alpha$ of the event that they evaluate a product as high quality. This coefficient is decreasing in β because the more able low-quality sellers are to successfully imitate high-quality sellers, the less the consumer will believe that the product they are considering is actually high-quality.

Search is undirected, so a searching consumer will randomly select a new seller to

The intuition behind the main results should still hold if search is not stationary. See Burdett and Vishwanath (1988), Choi and Smith (2016), or Casner (2020) for a discussion of the effects of a non-stationary search environment.

visit.¹⁴ If a consumer chooses to search for another prospect, they find a low-quality seller with probability α , and conditional on visiting a low-quality seller they correctly determine that this seller is low-quality with probability $1 - \beta$, so with probability $\alpha(1 - \beta)$ the consumer must search at least once more. Those consumers who search twice need to search a third time with probability $\alpha(1 - \beta)$ and so on. Let c denote the (strictly positive) cost of searching, the expected cost of finding an additional prospect is then

$$\begin{aligned} \sum_{k=0}^{\infty} [\alpha(1 - \beta)]^k c &= \frac{c}{1 - \alpha(1 - \beta)} \\ &= \frac{c}{\beta\alpha + 1 - \alpha} \end{aligned} \quad (4)$$

Denote by p the price that sellers set in a symmetric equilibrium and ϵ' the hypothetical match utility draw at a new prospect. Consumers expect that all unobserved sellers set price p so the expected payoff X_s from finding another prospect is

$$X_s \equiv \int_{\underline{\epsilon}}^{\bar{\epsilon}} \max[\Psi\epsilon_{ij} - p_j, \Psi\epsilon' - p] f(\epsilon') d\epsilon' - \frac{c}{\beta\alpha + 1 - \alpha} \quad (5)$$

A searcher can recall past prospects freely, so the new prospect is preferred only if $\epsilon' > \epsilon_{ij} + \frac{p-p_j}{\Psi}$.¹⁵ Setting the utility of searching (X_s) equal to the utility of staying with the current prospect (X_b), consumers are indifferent between staying with the current prospect and searching again if

$$\Psi\epsilon_{ij} - p_j = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \max[\Psi\epsilon_{ij} - p_j, \Psi\epsilon' - p] f(\epsilon') d\epsilon' - \frac{c}{\beta\alpha + 1 - \alpha} \quad (6)$$

14. High-quality sellers in this environment face a symmetric problem and will hence set symmetric prices. Low-quality sellers only make a profit if they successfully imitate a high-quality seller, so they must set the same price as the high quality sellers. Since all sellers are ex ante identical, consumers have no incentive to engage in ordered search if doing so requires even the slightest effort.

15. I use this assumption of free recall because it matches the previous literature and it slightly eases derivation. In equilibrium no consumer exercises recall so there are no qualitative differences between allowing recall vs. no recall for this model.

Combining terms and simplifying

$$c = (1 - \alpha) \int_{\epsilon_{ij} + \frac{p-p_j}{\Psi}}^{\bar{\epsilon}} \left[\epsilon' - \epsilon_{ij} - \frac{p-p_j}{\Psi} \right] f(\epsilon') d\epsilon' \quad (7)$$

Define U as the ϵ_{ij} which solves [Equation \(7\)](#). In equilibrium all sellers set the same price, so the stopping rule is given by

$$c = (1 - \alpha) \int_U^{\bar{\epsilon}} (\epsilon' - U) f(\epsilon') d\epsilon' \quad (8)$$

and consumers will stop at a seller if they draw $\epsilon > U$. U is consumers' reservation match value and depends on α only through the latter's effect on [Equation \(8\)](#).

Proposition 1. *In a symmetric equilibrium the reservation match value U is decreasing in the proportion of low quality sellers α .*

Proof. All proofs are provided in [Appendix A](#). ■

The right hand side of [Equation \(8\)](#) is decreasing in U . From the assumption of symmetry in prices, U does not change with α except through its effect on the stopping rule, so the RHS of [Equation \(8\)](#) is also decreasing in α . If α increases, then U must decrease in order to maintain equality. Intuitively, as the cost of searching increases relative to the marginal value, consumers are willing to stop after observing a lower match value. The possibility of encountering a low-quality seller and having to search again increases the effective search cost and hence reduces consumer search intensity. This decrease in search persistence as the proportion of low-quality sellers increases is the mathematical expression of the search obfuscation effect defined in [Section 1](#).

It is worth noting that β has no effect on search behavior once a consumer is

participating in the platform’s market. This is because the probability that the consumer is being scammed is the same across all prospects. Thus, while the lemon effect reduces the consumers’ perceived valuation of each prospect, it reduces their valuation *equally* across all prospects. It does not influence the relative valuation of an additional search relative to c because an increase in the probability of being fooled reduces the expected search cost to find an additional prospect as well as reducing consumers’ confidence in that prospect. These factors exactly cancel out and so β does not influence search behavior in equilibrium. This result relies on ex-ante symmetry across sellers and does not hold for the recommended seller in [Section 5](#).

Seller pricing

Sellers’ only decision once they join a platform is what price to charge. Since consumers’ beliefs about other sellers’ prices are not affected by observing deviations, they use the stopping rule derived above. It is easy to show that an equivalent definition of U is the ϵ which solves $\Psi\epsilon - p = \int_{\epsilon}^{\bar{\epsilon}} \max[\Psi\epsilon - p, \Psi\epsilon' - p] f(\epsilon') d\epsilon' - \frac{c}{\beta\alpha+1-\alpha}$ ($= X_s$ in equilibrium). U is the critical match value determining whether a consumer stops or continues to search after visiting seller j only if $p_j = p$. The precise implication of this stopping rule is that consumers purchase any observed prospect whose net expected utility exceeds the difference $\Psi U - p$.¹⁶ Consumers stop at a seller charging price p_j if ϵ_{ij} makes value of consumption greater than value of an additional search or:

$$\Psi\epsilon_{ij} - p_j > \Psi U - p \tag{9}$$

16. While it might be more intuitive to derive equilibrium prices if the stopping rule were expressed in terms of this net expected utility (e.g. Bar-Isaac, Caruana, and Cuñat (2012) do so), the gains from ease of intuition would be more than offset by unwieldy expressions later on.

A consumer will stop at a seller who sets $p_j > p$ only if the match utility draw is high enough so that the net expected utility from purchasing exceeds this cutoff. Solving Equation (9) for ϵ_{ij} , the probability that a given consumer who visits a seemingly high-quality seller j charging price p_j buys from that seller is the probability that $\epsilon_{ij} > U + \frac{p-p_j}{\Psi}$, or more directly: $1 - F\left(U + \frac{p-p_j}{\Psi}\right)$.

Let γ denote the probability that a consumer stops after visiting an arbitrary seller. In equilibrium this probability is $\gamma = (\alpha\beta + 1 - \alpha)(1 - F(U))$, but since that probability is based on other sellers' prices I introduce γ here to emphasize that seller j 's price is disciplined only by the proportion of consumers who stop after visiting j . Given participation $Q(V(\alpha))$, a total mass $Q(V(\alpha))\gamma$ consumers will search once and then purchase. With probability $1 - \gamma$ consumers leave after visiting a seller they visit and so a mass $Q(V(\alpha))(1 - \gamma)$ will evaluate at least two prospects, $Q(V(\alpha))(1 - \gamma)^2$ three prospects and so on. Taking this to the limit, each seller will receive $\frac{Q(V(\alpha))}{\gamma}$ consumer visits and this mass will not be affected by an individual seller's deviation since each seller is infinitesimal compared to the size of the market.¹⁷ The platform takes an exogenous percentage ξ of seller revenue, and the marginal cost of production

17. Technically the mass should be this fraction divided by the total mass of sellers, but as mentioned in Footnote 8 I assume this latter mass to be 1 since the ratio of buyers to sellers is irrelevant for all agents' decisions.

is 0.¹⁸ high-quality seller profit is then

$$\pi = \underbrace{(1 - \xi)}_{\text{Seller's revenue share}} \underbrace{\frac{Q(V(\alpha))}{\gamma}}_{\text{Number of consumer visits}} \underbrace{p_j \left[1 - F \left(U + \frac{p_j - p}{\Psi} \right) \right]}_{\text{Price*purchase probability}} \quad (10)$$

and low-quality seller profit is $\beta\pi$. It is a matter of simple calculus to find that the profit maximizing price for both high- and low-quality sellers is determined implicitly by

$$p_j = \Psi \frac{1 - F \left(U + \frac{p - p_j}{\Psi} \right)}{f \left(U + \frac{p - p_j}{\Psi} \right)} \quad (11)$$

Symmetry then implies $p_j = p$ so

$$p = \Psi \frac{1 - F(U)}{f(U)} \quad (12)$$

Log concavity of $f(\cdot)$ ensures sufficiency of the first order condition (Bagnoli and Bergstrom 2005).¹⁹ The lemon coefficient appears in the price as well as consumers'

18. An exogenous platform commission is both realistic and not essential for my results. Both Steam and Amazon set the same commission across many product categories with heterogeneous competitive environments, suggesting that factors exogenous to the market do play an important role in determining their pricing. If I were to endogenize the commission then I could follow Teh (2019) and introduce a positive marginal cost of production for sellers. In which case the commission would affect seller pricing, but my environment is sufficiently close to his that adapting his result that the platform will allow low-quality sellers if their marginal costs are sufficiently low would not be overly difficult, although it would come at the cost of significant added complexity. Given that much of my motivation comes from software platforms, it would arguably be more sensible to assume no marginal cost and instead endogenize the commission by assuming it is set using Nash bargaining. In this case ξ would continue to be an independent multiplier on profits and would not affect pricing, curation, or participation decisions.

19. Note that while symmetric costs mean that the profit maximizing prices are identical, this does not allow for the possibility that high-quality sellers might want to signal their quality via prices. However, even if I were to allow for different marginal costs, the cost of the low-quality sellers would surely be lower, meaning that the low-quality sellers could imitate any strategy the high-quality sellers might adopt which allows for positive profits. Given that consumers never knowingly purchase from a low-quality seller, the result would always be pooling on the high-quality sellers' price.

evaluation of their match utility. As consumers' faith in the product they are purchasing decreases, sellers must lower their prices to compensate. On the other hand, the search obfuscation effect reduces the appeal of moving on to a different seller, which reduces U and pushes equilibrium prices upward. If the obfuscation effect dominates the lemon effect, which happens when low-quality sellers are not too adept at imitating high-quality sellers (β small), then softened competition causes prices to increase with the proportion of low-quality sellers α . This logic is formalized in [Proposition 2](#)

Proposition 2. *Equilibrium prices are increasing in the proportion of low-quality sellers if their probability of fooling any given consumer is sufficiently low. Formally: For any α , $\frac{\partial p}{\partial \alpha} > 0$ if β is sufficiently small.*

3.2 Consumer Surplus

A consumer who participates on the market will stop after observing $\epsilon > U$. With probability Ψ this observation comes from a high-quality seller, so the expected match utility is $\Psi \int_U^{\bar{\epsilon}} \epsilon \frac{f(\epsilon)}{1-F(U)} d\epsilon$. The expected number of prospects observed is $\frac{1}{1-F(U)}$, with an average of $\frac{1}{\beta\alpha+1-\alpha}$ searches required to find each prospect, so the expected search cost is $\frac{c}{(1-F(U))(\beta\alpha+1-\alpha)}$. Finally, all sellers will charge the same price p , so

$$V(\alpha) = \Psi \int_U^{\bar{\epsilon}} \epsilon \frac{f(\epsilon)}{1-F(U)} d\epsilon - \frac{c}{(1-F(U))(\beta\alpha+1-\alpha)} - p \quad (13)$$

Using [Equation \(8\)](#) and [Equation \(11\)](#), then simplifying

$$V(\alpha) = \Psi \left(U - \frac{1-F(U)}{f(U)} \right) \quad (14)$$

Both the lemon effect and search obfuscation reduce $V(\alpha)$.²⁰ The term $U - \frac{1-F(U)}{f(U)}$ is the consumer surplus retained by consumers who purchase from high-quality sellers. Conditional on purchasing from a high-quality seller, this surplus is not influenced by the lemon effect. However, search obfuscation reduces U so consumers will receive less surplus as a result of reduced search intensity if the proportion of low-quality sellers increases. Because receiving positive surplus is conditional on purchasing from a high-quality seller, the expected value of participating in the platform’s market is scaled down by the lemon coefficient. The more likely consumers are to be ripped off by a low-quality seller, the lower their expected payoff.

This clearly illustrates the difference between the obfuscation and lemon effects. The obfuscation effect allows the sellers to capture more of the expected surplus available in the market. This reduces participation but can be beneficial to the platform because it receives a share of the increase in sellers’ profits. On the other hand, the lemon effect reduces the total amount of expected surplus, which benefits no one.

4 Search Obfuscation Via Low Quality Sellers

Every consumer who shops on the platform will purchase at the symmetric equilibrium price p . The platform operates costlessly, so its profit is

$$\Pi = \xi p Q(V(\alpha)) \tag{15}$$

20. This implies that unlike Rhodes and Wilson’s (2018) “price effect”, the lemon effect’s impact on price is never sufficient to create a net benefit to consumers from the presence of these low-quality sellers. The main differences that lead to these divergent results are: 1. the seller in their model is a monopolist, whereas I am considering a competitive setting and 2. Their price effect comes from a change in deception probability (equivalent to changing β in my model) whereas my model focuses on changes in the proportion of low-quality sellers. I discuss comparative statics on β after [Proposition 4](#).

Because ξ is an exogenous scalar, maximizing Π is equivalent to maximizing $\frac{\Pi}{\xi} = pQ(V(\alpha))$, so to simplify notation I suppress ξ unless it is relevant.

Proposition 3. *The platform admits a positive proportion of low-quality sellers if the search cost is sufficiently low, and low-quality sellers are not too adept at imitating high-quality sellers: $\alpha > 0$ in equilibrium if both conditions 1 and 2 hold.*

1. β is sufficiently small

2. c is sufficiently small and $f(\bar{\epsilon}) > 0$ or $\frac{Q'(V(0))}{Q(V(0))} \in o\left(\frac{\frac{\partial p}{\partial U}}{1 + \frac{\partial p}{\partial U}}\right)$ as $U \rightarrow \bar{\epsilon}$

Lower search costs create more intense competition between sellers, so intuitively [Proposition 3](#) says that the platform will admit low-quality sellers if the competition between sellers on the platform is sufficiently intense in their absence (so that the increased prices from softening competition compensate for the reduction in consumer participation from search obfuscation) but only if the loss in consumer confidence stemming from the possibility of being fooled by the low-quality sellers is not too large (so that the the reduction in consumer participation from the lemon effect does not eliminate the benefits to the platform from search obfuscation).

Requiring positive $f(\bar{\epsilon})$ or highly concave $Q(\cdot)$ ensures that the marginal reduction in demand from search obfuscation is negligible relative to the marginal revenue increase when the proportion of low-quality sellers $\alpha = 0$. When $Q(\cdot)$ is highly concave, the slope of participation function will be extremely shallow for high $V(\alpha)$. $V(\alpha)$ is maximized in terms of endogenous parameters at $\alpha = 0$, and is increasing as c decreases. Thus this assumption is equivalent to assuming there are few consumers who are indifferent about participating when the platform admits no low-quality sellers and the search cost is sufficiently low. Alternatively, requiring $f(\bar{\epsilon}) > 0$ ensures that the marginal increase in price from obfuscation at $\alpha = 0$ is bounded away from 0 as c

decreases. Meanwhile the marginal revenue loss from consumers leaving the platform becomes arbitrarily small for sufficiently small c .²¹

Example

Because analytic solutions for price, reservation match value, and participation are not generically available, the proof of [Proposition 3](#) relies on limiting arguments. The reader might then quite reasonably wonder whether the platform only admits low-quality sellers in a small portion of the relevant parameter space. I introduce a numerical example here to demonstrate that this not the case. Suppose $\epsilon \sim U[0, 1]$ for the high-quality sellers and $Q(V(\alpha)) = V(\alpha)$ (equivalent to assuming that the platform is a monopoly at one end of a Hotelling line with transport cost 1).

It is then relatively straightforward—although algebraically tedious—to use $\frac{\partial \Pi}{\partial \alpha}$ ([Equation \(30\)](#) in the proof of [Proposition 3](#)) to find that the platform will admit low quality sellers when $c < \frac{1}{16}$, and $\beta < \frac{\sqrt{c}-2c}{2(\sqrt{c}-2c)}$. [Figure 2](#) shows the region where derivative of platform profit with regard to the proportion of low-quality sellers at $\alpha = 0$ is positive.

For $c \geq 0.25$ no consumers would participate in the platform’s market even at $\alpha = 0$, and market platforms tend to have search costs that are quite low relative to the purchase price. The prices in this example tend to be in the region of 0.2 (see [Figure 3](#) in the discussion of comparative statics below). Hong and Shum ([2006](#)), Blake, Nosko, and Tadelis ([2016](#)), and Ursu ([2018](#)), all find price to search cost ratios below 10% in online search, so search costs above 0.05 seem unrealistic in this example. Depending on how tightly one narrows the search cost, the platform is admitting low-quality sellers in 10% – 20% of the relevant parameter space, which is not the majority but hardly a special case. This is reinforced further when one considers that β close to 1

21. These conditions are sufficient, but not necessary. See the proof of [Proposition 3](#) for more detail.

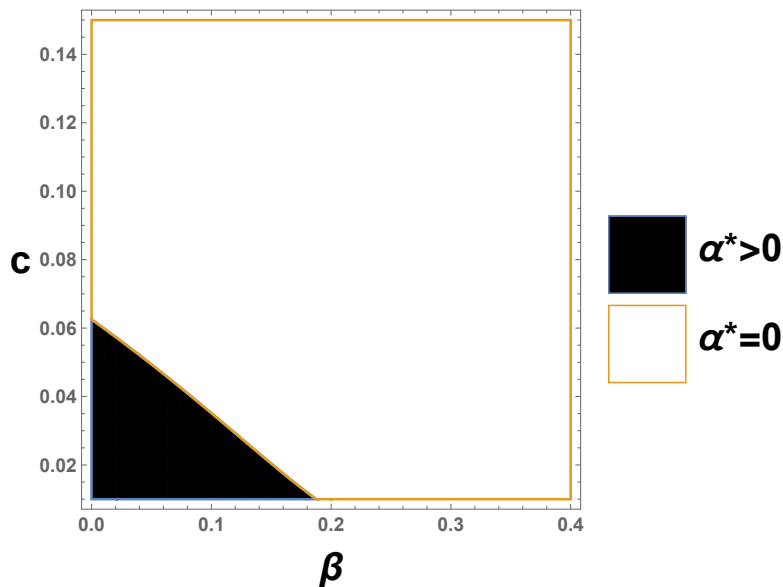


Figure 2: A parameter space showing the values where the platform will admit a positive proportion of low-quality sellers in this numerical example. When parameters lie in the shaded region the platform sets $\alpha > 0$ in equilibrium, but it admits no low-quality sellers in the white region.

is probably unreasonable. This result is robust to various distributions, and becomes even stronger with the introduction of recommended sellers (see [Section 5](#)).

4.1 Equilibrium Curation Decision

Assuming that conditions 1 and 2 of [Proposition 3](#) are satisfied is equivalent to assuming that the platform will set $\alpha \in (0, 1)$, because if the platform sets $\alpha = 1$ then no consumer will participate in the platform's market, so the only possible corner solution is at $\alpha = 0$, which is precluded by [Proposition 3](#). Define an *interior equilibrium* as any equilibrium with $\alpha \in (0, 1)$. The following first order condition for

the platform's curation decision is a necessary condition in any interior equilibrium.

$$\underbrace{p \left(1 + \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2} \right) - \beta B(\alpha)}_{\text{Net marginal impact of low-quality sellers on price}} = \underbrace{\frac{Q'(V(\alpha))}{Q(V(\alpha))}}_{\text{Consumers leaving the platform}} \quad (16)$$

Where $B(\alpha)$ is an algebraic construct introduced to reduce unnecessary mathematical clutter. The definition of $B(\alpha)$ can be found in the proof of [Lemma 1](#).

Roughly speaking, the first term on the left hand side of [Equation \(16\)](#) represents the elasticity of market prices with regard to the proportion of low-quality sellers, and $\beta B(\alpha)$ is a mitigation in this price increase caused by the lemon effect. It is the result of β and consumers' expectations about β . The right hand side is the elasticity of consumers' participation in the platform. The following condition is stronger than needed to give sufficiency of the first order condition, but is nevertheless not terribly restrictive²²:

Assumption 1. *The variance of $f(\cdot)$ is large*

Let α^* denote the proportion of low-quality sellers in equilibrium.

Lemma 1. *Under [Assumption 1](#), α^* is determined uniquely by [Equation \(16\)](#) for any interior equilibrium.*

[Lemma 1](#) allows me to use [Equation \(16\)](#) to evaluate the comparative statics of α^* .

Proposition 4. *Under [Assumption 1](#), for any interior equilibrium*

1. *The proportion of low-quality sellers decreases in search cost: α^* is decreasing in c .*

²². See the proof of [Lemma 1](#) for details of why this assumption is sufficient for single peakedness of platform profit in the curation decision.

2. If $Q(V(\alpha))$ is linear, then the proportion of low-quality sellers decreases in the deception probability: α^* is decreasing in β for linear $Q(V(\alpha))$.

The obfuscation effect from the low-quality sellers effectively increases the search cost, but comes at the cost of lost consumer participation and lower consumer confidence. Increasing c does not contribute to the lemon effect, but does increase prices, so if the search cost increases, then the platform has less incentive to increase the effective cost further via low quality sellers. Increasing the search cost does not contribute to the lemon effect so directly increasing this cost seems to be a preferable option for the platform rather than obfuscating search via low-quality sellers. However, as Eliaz and Spiegel (2011) note, an action which is so hostile to consumers would likely incite a strong negative reaction from consumers and potentially even regulatory scrutiny.

Even if consumers and regulators were to remain complacent about an increase in search costs, many platforms have a number of different markets which share a common search environment. For example, the market for high-end headphones on Amazon is likely much less competitive than the market for exercise supplements. Thus, allowing more low-quality sellers in the supplement market would allow Amazon to increase the search cost in that market without also increasing search costs in the headphone market. Additionally, if screening costs are a factor (see Section 6) then obfuscation via low-quality sellers may be more cost effective than direct obfuscation via increased search costs.²³

Potential low-quality sellers who do not get to participate in the platform are worse off with a higher search cost, but the platform and all sellers (both low- and high-quality) participating in the platform are better off. Sellers are able to charge a

23. While the platform in this model is choosing the proportion of low-quality sellers, this is abstracting away from the idea that there would be some base rate of α and the platform would need to screen sellers in order raise or lower it. Increasing c would require an active and visible change in platform design, but increasing α only involves reducing screening effort.

higher price because the proportion of low-quality sellers is lower which reduces the lemon effect and increases total profits. Interestingly, the consumers can be better off with a higher search cost as well. Because α^* is decreasing in c , an increase in search costs reduces the probability that they encounter and then trade with a low-quality seller, and the effect of this increased confidence relative to an equilibrium with lower search cost increases market participation.²⁴

As β increases, the lemon effect becomes stronger compared to the search obfuscation effect, so the marginal cost of admitting additional low-quality sellers increases and α^* decreases. Linearity of $Q(\cdot)$ ensures that the effects of consumers' decreased willingness to pay are outweighed by their decreased market participation. If $Q(\cdot)$ is highly concave, then $Q'(\cdot)$ might be small enough relative to $Q(\cdot)$ that the price reduction from an increase in β can be stronger than the effect on demand and an increase in β could *increase* α^* because the platform would rather serve fewer consumers at a higher market price. However, no matter what the effect on α^* , both the platform and sellers are worse off as β increases because it causes consumers' confidence to decrease more quickly as α increases. As with c , the effect of β on consumer welfare is ambiguous. Directly, an increase in β reduces welfare by making consumers more vulnerable to the low-quality sellers, but if it reduces α^* sufficiently then consumers can be made better off in equilibrium because the number of low-quality sellers they encounter decreases.

Figure 3 shows comparative statics from the uniform example above. Increasing the deception probability makes consumers better off as a result of increased screening, and the platform's profit decreases slightly. Increasing search costs makes consumers

24. Using the numerical solution above, holding β constant at 0.15, $\alpha^* \approx 0.19$ when $c = 0.01$, giving $V(0.19) \approx 0.85$. When $c = 0.018$ $\alpha^* = 0$ and $V(0) = 0.86$. It is worth noting that while the range of c where increasing search costs benefit consumers is narrow in this example, the reduction in α means that even when consumers are worse off with the increased search cost, it is often not a significant loss. When $c = 0.03$ (tripling search costs compared to the base case) $V(0) = 0.82$.

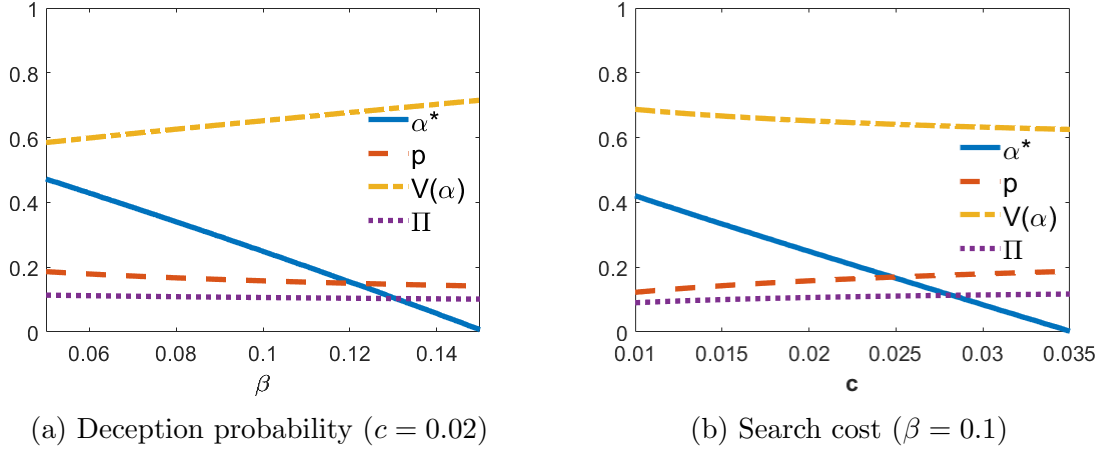


Figure 3: Comparative statics using the uniform numerical example.

worse off and increases platform profit.

5 Recommending a Seller

At face value, recommending certain sellers to consumers seems like behavior contradictory to increasing search costs by admitting low-quality sellers. Why make it easier for consumers to distinguish high quality sellers when the point of obfuscation is to reduce comparison shopping? However, if the platform can credibly recommend a high-quality seller to consumers then this behavior is in fact a *complementary* strategy to admitting low-quality sellers. The low-quality sellers strengthen the effect of the recommendation, allowing the recommended seller to charge a higher price, and the recommendation mitigates the impact of the lemon effect which increases consumers' participation on the platform. Consequently platform profits are always higher with a recommended seller when $\alpha > 0$, and the set of parameters where the platform will admit a positive proportion of low-quality sellers is wider with a recommended seller.

I model the recommendation process by having the platform choose a high-quality seller to be *prominent* in the sense of Armstrong, Vickers, and Zhou (2009). All

consumers visit the recommended seller first at no search cost, but if they choose to move on and visit other sellers then their search process is undirected sequential search as in the previous section. As will become apparent later, the platform is better off recommending a high-quality seller than a low-quality seller, so consumers view this recommendation as credible and believe with probability 1 that the recommended seller is high-quality. Denote the recommended seller by R , in this case consumer i 's evaluation of the utility from the recommended seller given match value draw ϵ_{iR} and price p_R is simply

$$-p_R + \epsilon_{iR} \tag{17}$$

The value of searching for another prospect is quite similar to the basic monopoly model

$$\int_{\underline{\epsilon}}^{\bar{\epsilon}} \max[-p_R + \epsilon_{iR}, \Psi\epsilon' - p] f(\epsilon') d\epsilon' - \frac{c}{\beta\alpha + 1 - \alpha} \tag{18}$$

Where p is the equilibrium price of the non-recommended sellers. The new prospect is preferable if

$$\epsilon' > \frac{\epsilon_{iR} + p - p_R}{\Psi} \tag{19}$$

By logic almost identical to that in the basic model, the stopping rule is then given by

$$c = (1 - \alpha) \int_{\frac{U_R + p - p_R}{\Psi}}^{\bar{\epsilon}} \left[\epsilon' - \frac{U_R + p - p_R}{\Psi} \right] f(\epsilon') d\epsilon' \tag{20}$$

Where U_R is the ϵ_{iR} which solves [Equation \(20\)](#). As in [Section 3](#), U_R as derived above

is based on the recommended seller charging the expected price p_R . Equation (20) implies that consumers will stop at the recommended seller if the net utility they receive from doing so exceeds $U_R - p_R$. Suppose the recommended seller deviates to price p'_R , then consumers stop at the recommended seller if $\epsilon_{iR} - p'_R > U_R - p_R$ and the probability that these consumers stay after visiting is $1 - F(U_R + p'_R - p_R)$. The mass of consumers participating in the platform's market is $Q(V(\alpha))$, so the recommended seller's profit is given by

$$\pi_R = p'_R(1 - \xi)Q(V(\alpha))(1 - F(U_R + p'_R - p_R)) \quad (21)$$

Consumers have rational expectations over firm prices and do not observe deviations, so the recommended seller takes consumer participation as given.²⁵ The profit maximizing price is thus given by

$$p'_R = \frac{1 - F(U_R + p'_R - p_R)}{f(U_R + p'_R - p_R)} \quad (22)$$

In equilibrium consumers' expectations about the price are correct so

$$p_R = \frac{1 - F(U_R)}{f(U_R)} \quad (23)$$

Note the absence of the lemon coefficient. Consumers believe with certainty that the recommended seller is high-quality, so α influences the recommended seller's price only through U_R . Consumers who draw $\epsilon_{iR} < U_R$ and visit other sellers never return

25. The commitment assumption has more effect than in the baseline because the search environment is no longer completely stationary. Relaxing this assumption would mean that all consumers visit the recommended seller, but a subset of consumers would then leave the platform after finding that both the recommended seller's product and the value of continuing to search are less appealing than the outside option. This creates broadly similar results as I present here with almost identical intuition at the cost of greatly increasing the difficulty of the analysis. Further details are available upon request.

to the recommended seller, so the other sellers are only competing with each other and price as in the previous section; This leads consumers who do not purchase from the recommended seller to use the stopping rule defined by [Equation \(8\)](#). Consumers' greater confidence in the recommended seller's product gives the recommended seller a competitive advantage which is formalized in [Proposition 5](#).

Proposition 5. *In the equilibrium with a recommended seller*

1. *Consumers visiting sellers after the recommended seller have the same reservation match value U as in [Section 3](#) and these other sellers charge the same price p .*
2. *The net expected utility above which the consumer stops searching is the same at the recommended seller and the other sellers: $U_R - p_R = \Psi U - p$.*
3. *The recommended seller sets a higher price than the other sellers if the proportion of low-quality sellers is positive: $p_R > p$ if $\alpha > 0$.*
4. *The recommended seller sets an identical price to the other sellers and the reservation match values are identical if there are no low-quality sellers: $U_R = U$ and $p_R = p$ if $\alpha = 0$.*

One of the less obvious implications of part 2 in [Proposition 5](#) is that the benefit the recommended seller accrues from search obfuscation is exactly the same as the benefit gained by the other sellers. Its pricing advantage comes entirely from the lemon effect. If we were to set $\beta = 0$ then the recommended seller and the other sellers would all set the exact same price. The recommended seller's profit actually *increases* as the lemon effect gets stronger as long as consumer participation doesn't decrease too much.

Define $V^R(\alpha)$ as the expected value to consumers of participating in the platform's market when there is a recommended seller. Solving explicitly for this value

$$V^R(\alpha) = (1 - F(U_R)) \left[\int_{U_R}^{\bar{\epsilon}} \epsilon \frac{f(\epsilon)}{1 - F(U_R)} d(\epsilon) - p_R \right] + F(U_R) \Psi \left(U - \frac{1 - F(U)}{f(U)} \right) \quad (24)$$

Corollary 1. *Consumers' value of participation in the market is greater with a recommended seller than in the equilibrium where all sellers are symmetric: $V^R(\alpha) > V(\alpha)$ for all $\alpha > 0$.*

The consumer value increases with the recommendation for two reasons: First, the consumers observe the recommended seller with no search cost.²⁶ Second, while the recommended seller's price is higher than the symmetric equilibrium price, the recommended seller does not capture all of the surplus gained from mitigating the lemon effect, with the remainder going to consumers.

An immediate consequence of [Corollary 1](#) is that consumers ex ante utility is higher at the recommended seller despite its higher price, so visiting the recommended seller first is incentive compatible. If consumers never visit the recommended seller then the search problem is stationary. If consumers do not wish to visit the recommended seller in the first search, then visiting it cannot be more appealing than visiting a random seller in any subsequent search, implying that consumers would never visit the recommended seller. In that case, the value of participation would be exactly equal to participation in the equilibrium with no recommended seller, but by [Corollary 1](#) they can do better by visiting the recommended seller in the first search. Therefore $(1 - F(U_R))$ of the consumers who visit the platform will stop at the recommended seller and pay p_R , the rest will purchase from one of the other sellers and pay p . The

26. The assumption that the prominent seller is observed at no cost can be significantly relaxed and the result will still hold. However it seems natural that search costs would be significantly reduced when seeing the recommended seller and imposing this assumption drastically simplifies the analysis.

platform’s profit with a recommended seller is thus

$$\Pi^R = \xi Q(V^R(\alpha)) [(1 - F(U_R))p_R + F(U_R)p] \quad (25)$$

From [Proposition 5](#) $p_R > p$, so $(1 - F(U_R))p_R + F(U_R)p > p$, and from [Corollary 1](#) $Q(V^R(\alpha)) > Q(V(\alpha))$ for any proportion of low-quality sellers. The platform’s profits must be strictly higher with the recommended seller at any fixed $\alpha > 0$, and at least weakly higher when $\alpha = 0$. Given that the platform can still pick any $\alpha \in [0, 1]$ with the recommended seller, its profit must be greater with the ability to recommend. This proves [Proposition 6](#).

Proposition 6. *The platform’s profits are higher in the equilibrium of the model where it can recommend a seller than in the model with no recommended seller. This inequality is strict whenever the platform-profit maximizing proportion of low-quality sellers is positive in the model with the recommended seller.*

Also note that if the platform recommends a low quality seller, then the share of the platform’s profits coming from the recommended seller are scaled down by at least β even if consumers’ ex ante beliefs do not change, so the platform is strictly better off recommending a high quality seller.²⁷

Unlike in the previous section, the platform’s profit is not necessarily decreasing in β . Because a stronger lemon effect increases the strength of the recommendation, the additional profit from a stronger recommended seller can more than compensate for the lost profit of the other sellers and reduced participation. Therefore, while a platform which is able to exert influence over β (e.g. by monitoring sellers or providing

²⁷. As is common with this sort of recommendation model (e.g. Athey and Ellison (2011)) there is an alternate equilibrium where consumers don’t believe the platform’s recommendation, in which case the platform is indifferent over which type of seller to recommend. However, given that recommending a high-quality seller is always at least weakly incentive compatible, it seems sensible to focus on the more interesting equilibrium.

stronger review/certification systems) would always reduce it in the base model, this is not necessarily the case when recommendations are available.²⁸

The positive effect of β on platform profits, and the profitability of the recommendation in general, would be further strengthened if the platform were to auction the recommendation using a second price auction. The recommendation is more profitable for a high-quality seller, so it would maintain credibility and capture all of the supply-side benefits of the recommendation. I leave detailed consideration of this process for future work.

Proposition 7 summarizes comparisons of the marginal effect of the low-quality sellers between the symmetric monopoly model and the model with the recommended seller. Let α^{R*} denote the equilibrium proportion of low-quality sellers in the model with the recommended seller.

Proposition 7. *For any interior equilibrium:*

1. *If the proportion of low-quality sellers is sufficiently small, then the reservation match value at the recommended seller is smaller than at the other sellers and it is also more responsive to changes in the proportion of low-quality sellers: $\frac{\partial U_R}{\partial \alpha} < \frac{\partial U}{\partial \alpha}$ for small α and $U_R < U$ for small $\alpha > 0$.*
2. *The equilibrium proportion of low-quality sellers is higher with the recommended seller if participation is less sensitive to the curation decision than price: $\alpha^{R*} > \alpha^*$ if $Q(\cdot)$ is sufficiently concave.*

Part 1 implies that if the equilibrium proportion of low quality sellers is small without a recommended seller, then it will be weakly higher with a recommended

28. Using the uniform example from before, $\frac{\partial \Pi}{\partial \beta} > 0$ with a recommended seller at $c = 0.05, \beta = 0.2$ and consequent choice of $\alpha = 0.27$. While the necessity of solving for α at every parameter point investigated makes numerical search fairly slow, it appears that the parameter regions where the platform finds β beneficial are narrow, but extant. I thank an anonymous referee for suggesting this avenue of inquiry.

seller. The most interesting case being the parameter ranges where the platform would fully screen with no recommended seller but admits a small proportion of low quality sellers if it can make a recommendation. [Corollary 2](#) formalizes this intuition.

Corollary 2. *The set of parameters where the platform admits a positive proportion of low-quality sellers is larger when it can recommend a seller than when it cannot. If the equilibrium proportion is small but positive in the baseline model, then the platform admits more low-quality sellers when it can make a recommendation:*

1. *The set of β and c such that $\alpha^* > 0$ is strictly contained in the set where $\alpha^{R*} > 0$.*
2. *The set of β and c such that $\alpha^{R*} > \alpha^*$ strictly contains the set such that $\alpha^* = 0$ and $\alpha^{R*} > 0$*

The recommendation increases the marginal benefit and reduces the marginal cost of admitting low-quality sellers when α is small. From [Proposition 4](#) α^* will be small but positive when β and/or c are large but not *too* large. So $\alpha^{R*} > \alpha^* > 0$ in a band of parameters contained within the set where $\alpha^* > 0$ but near the border with the set where $\alpha^* = 0$ and $\alpha^{R*} > 0$. If either parameter is very large then the equilibrium proportion of low-quality sellers is 0 in both models.

α^{R*} can be smaller than α^* when c and β are small so in general the comparison between α^{R*} and α^* is ambiguous in this case. Price is more responsive to α with the recommended seller, but because the average price paid by consumers is higher when a recommendation is possible, the revenue lost from consumers moving to the outside option is also greater. Part 2 of [Proposition 7](#) says that for $Q(\cdot)$ sufficiently concave the increased ability to raise prices has more effect than the revenue loss from consumers leaving the platform, in which case $\alpha^{R*} \geq \alpha^*$ under all parameter sets. [Figure 4](#) summarizes these conclusions visually.

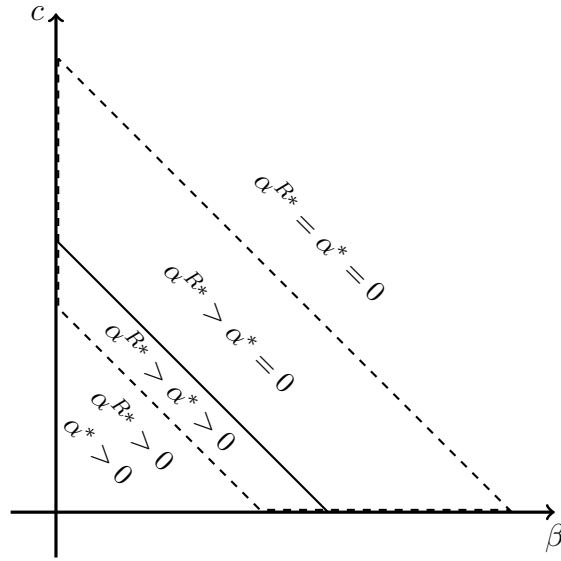


Figure 4: A diagram showing the comparison between α^* and α^{R^*} as a function of the parameters.

The fact that the recommendation increases the willingness of the platform to admit low-quality sellers also speaks to the complementary nature of the recommendation and obfuscation when it comes to the platform's profits. [Proposition 6](#) shows that adding the recommendation on top of admitting low-quality sellers is more profitable than admitting low-quality sellers alone. The platform is free to set $\alpha = 0$ in the model with a recommendation, so the fact that it does not means the two strategies together must be more profitable than just the recommendation. The previous literature (e.g. Armstrong and Zhou ([2011](#))) on prominence has assumed that the benefit to the platform from providing a recommendation comes from the fee sellers pay to the platform in exchange for a prominent position. My platform is not charging such a fee, and the increase in profits from the recommendation is a result of the presence of the low-quality sellers. Indeed, if the platform were to recommend a seller without admitting low-quality sellers then this would have almost no impact on the platform's profits. Participation would increase slightly given that I assume the recommended

seller is observed at no cost, but my model would otherwise be equivalent to that of Armstrong, Vickers, and Zhou (2009). In that paper, a prominent seller charges an identical price to all other sellers when there are a continuum of sellers. The price difference for the recommended seller in my model comes from the lemon effect, which is not present when $\alpha = 0$.

Example

Continuing the example from the symmetric equilibrium, we can use [Proposition 5](#) to find

$$U_R - p_R = \Psi \left(1 - \sqrt{\frac{c}{1 - \alpha}} \right) - p \quad (26)$$

Using p from the symmetric equilibrium example and the fact that $p_R = \frac{1 - F(U_R)}{f(U_R)} = 1 - U_R$ we can solve this equation to find

$$U_R = \frac{1}{2} \Psi \left(\frac{\beta\alpha + 2(1 - \alpha)}{1 - \alpha} - 2\sqrt{\frac{c}{1 - \alpha}} \right) \quad (27)$$

Plugging these solutions into [Equations \(24\)](#) and [\(25\)](#), I again compute the derivative of platform profits at $\alpha = 0$. The results are displayed in [Figure 5](#), and they show that admitting low-quality sellers is much more profitable for the platform in the model with the recommended seller than in the model without.

Comparing these results to [Figure 2](#), the set of parameters where the platform admits low-quality sellers in equilibrium is roughly quadrupled with a recommended seller. For example: at $c = 0.07$ and $\beta = 0.1$ the platform would not admit any low-quality sellers without a recommended seller, but the marginal profit from the initial low-quality sellers is comfortably positive when a recommendation is possible.

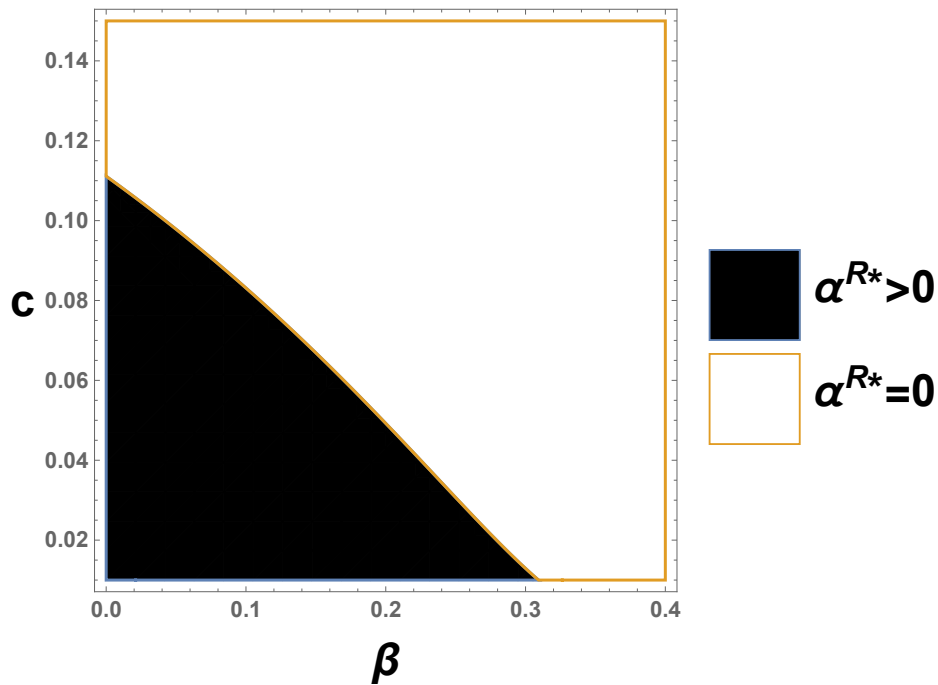


Figure 5: A parameter space showing when the platform will admit a positive proportion of low-quality sellers when it has the ability to recommend a high-quality seller in this numerical example. When parameters lie in the shaded region the platform sets $\alpha > 0$ in equilibrium, but it admits no low-quality sellers in the white region.

6 Discussion

In this section I discuss several topics which do not merit a full extension of the model but which nevertheless have potentially important implications for my results.

Screening Costs

In the model I assume that the platform can freely set the proportion of low-quality sellers in order to demonstrate the search obfuscation mechanism. This is obviously not the case for real world platforms and so the reader might reasonably question how to interpret this model. To answer that question, consider a situation where there is a base rate of low-quality sellers and that the platform must pay a cost to find and expel low quality sellers.

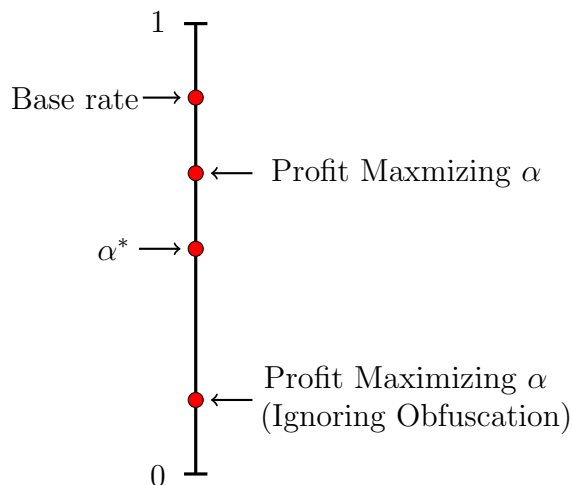


Figure 6: The proportion of low-quality sellers with no screening, at the profit maximizing level, if there were 0 screening cost, and if the platform treated prices as independent of the proportion of low quality sellers.

In [Figure 6](#) I show an example of a situation that could then occur. The base rate of low quality sellers if the platform does not screen is approximately $\frac{5}{6}$.²⁹ If

²⁹. These numbers are chosen to optimize readability of the figure rather than coming from any data.

the platform had no screening costs then it would set $\alpha^* = \frac{1}{2}$, but because screening out the low-quality sellers is costly, its profit maximizing proportion is $\frac{2}{3}$. However, if the platform ignored the search obfuscating effect of the low-quality sellers (i.e. if it assumed that getting rid of these sellers would have no effect on price) then it would instead screen to a proportion of $\frac{1}{6}$. An outside observer who fails to take obfuscation into account might then wonder why the platform sets $\alpha = \frac{2}{3}$ instead of $\frac{1}{6}$. If instead α^* were greater than the base rate then we might not see any screening at all, as screening out high-quality sellers might incite a significant negative reaction by consumers or even legal action against the platform.

This example illustrates the point that the phenomena I demonstrate would show up in real world behavior as inaction on the part of the platform. An empirical use for this model could be to explain gaps between predicted optimal levels of screening and actual screening in platform markets.

Alternative Platform Revenue Structures

Platforms could extract revenue by other means. For example: introducing a fixed fee per transaction paid by the sellers would directly raise the market price without impacting consumer confidence. In cases where a platform is charging such a fee we would expect to see more intensive curation, but as pointed out above, the impact on competition in the platform would still act as an additional screening cost for the platform. Therefore we would still expect to see α above the level which would be implied by a naive screening policy which ignored competitive effects.

On the other hand if the platform were to charge an entrance fee to consumers, it would instead have an incentive to maximize the value of consumers' participation in the market and then extract this value via the entrance fee. We can see evidence of this pattern in the fact that Apple (which makes a great deal of money from the sale

of iPhones) screens the apps on its platform much more intensively than Google does for the Google Play store.

Cost of Returns

I do not model the possibility that unsatisfied consumers might wish to return the products they have purchased. Assuming that returns are costly to the platform, then the main effect of adding returns would be to magnify the negative impact of β on platform profits. Consumers who purchase a product only to later return it not only do not contribute to profits, but increase costs. However, if β is sufficiently low then the volume of returns should be low enough that the increased profits from search obfuscation would still overcome the combined negative effects of the lemon effect and return costs. Although the equilibrium proportion of low-quality sellers would be lower than if returns were not a factor.³⁰

The impact of returns on platform profit may be mitigated or even positive if consumers engage in the search process again after returning a low-quality product. While even a return policy that fully reimbursed the purchase price could not eliminate the negative impact of being scammed on consumers as they will still have expended search costs on purchasing a dud product, it would mitigate their welfare loss. Consequently, consumers value of participation $V(\alpha)$ and therefore $Q(V(\alpha))$ would increase at any α with the introduction of a return policy. See Hinnosaar and Kawai (2018) for a more thorough discussion of sellers' optimal behavior when returns are a factor.

30. Customers often complain that Amazon makes return products unnecessarily difficult, either by making the process obtuse or requiring them to visit one of Amazon's physical locations. It may be the case that this is an intentional strategy intended to mitigate the costs of accepting returns.

7 Conclusion

This project explores the effects of low-quality sellers in platform markets and why platforms might be reluctant to curate the selection of sellers who list in their markets. In this model, platforms choose the proportion of high and low quality sellers on their markets with no screening cost. Sellers and consumers then participate in a market search game similar to Wolinsky (1986).

The impact of low-quality sellers can be broken down into a search obfuscation effect and a lemon effect. The search-obfuscation effect reduces consumers' willingness to search and so softens competition between sellers on the platform. The lemon effect reflects consumers' belief that the product they are purchasing might be a low-quality product successfully imitating a high-quality product, which reduces their willingness to pay. Both effects reduce consumers' participation in the market, but only the former is beneficial to the platform, so if the low-quality sellers are too adept at fooling consumers then the platform would prefer to admit no low-quality consumers. However, if the obfuscation effect dominates the lemon effect and the market is sufficiently competitive then the platform-profit maximizing proportion of low-quality consumers is positive *despite the lack of screening cost*.

If the platform can recommend a high-quality seller, then that seller will not be subject to the lemon effect and so charges a higher price. Recommending a high-quality seller is more profitable for the platform than simply obfuscating search as in the baseline model. The ability to recommend may cause the platform to admit low-quality sellers when it would not without a recommended seller. This recommended seller does not capture all of the benefits of the recommendation, so consumer welfare is higher with a recommended seller at any proportion of low-quality sellers. However, the net effect of recommendation may be negative for consumers if the ability to

recommend causes the platform to admit more low-quality sellers.

References

- Anderson, Simon P, Andre De Palma, and Yurii Nesterov. 1995. Oligopolistic competition and the optimal provision of products. *Econometrica: Journal of the Econometric Society*, 1281–1301.
- Anderson, Simon P., and Regis Renault. 1999. Pricing, Product Diversity, and Search Costs: A Bertrand-Chamberlin-Diamond Model. *RAND Journal of Economics* 30 (4): 719–735.
- Armstrong, Mark, John Vickers, and Jidong Zhou. 2009. Prominence and consumer search. *The RAND Journal of Economics* 40 (2): 209–233.
- Armstrong, Mark, and Jidong Zhou. 2011. Paying for prominence. *The Economic Journal* 121 (556): F368–F395.
- . 2015. Search deterrence. *The Review of Economic Studies* 83 (1): 26–57.
- Athey, Susan, and Glenn Ellison. 2011. Position auctions with consumer search. *The Quarterly Journal of Economics* 126 (3): 1213–1270.
- Bagnoli, Mark, and Ted Bergstrom. 2005. Log-concave probability and its applications. *Economic Theory* 26 (2): 445–469.
- Bar-Isaac, Heski, Guillermo Caruana, and Vicente Cuñat. 2012. Search, design, and market structure. *American Economic Review* 102 (2): 1140–60.

- Barach, Moshe A, Joseph M Golden, and John J Horton. 2019. *Steering in online markets: the role of platform incentives and credibility*. Working Paper, Working Paper Series 25917. National Bureau of Economic Research, June.
- Belleflamme, Paul, and Martin Peitz. 2019. Managing competition on a two-sided platform. *Journal of Economics & Management Strategy* 28 (1): 5–22.
- Blake, Thomas, Chris Nosko, and Steven Tadelis. 2016. Returns to consumer search: evidence from ebay. In *Proceedings of the 2016 acm conference on economics and computation*, 531–545. ACM.
- Burdett, Kenneth, and Tara Vishwanath. 1988. Declining reservation wages and learning. *The Review of Economic Studies* 55 (4): 655–665.
- Casner, Ben. 2020. Learning while shopping: an experimental investigation into the effect of learning on consumer search. *Experimental Economics*.
- Chen, Yongmin, and Chuan He. 2011. Paid placement: advertising and search on the internet. *The Economic Journal* 121 (556): F309–F328.
- Chen, Yongmin, and Tianle Zhang. 2018. Entry and welfare in search markets. *The Economic Journal* 128 (608): 55–80.
- Chen, Yuxin, and Song Yao. 2016. Sequential search with refinement: model and application with click-stream data. *Management Science* 63 (12): 4345–4365.
- Choi, Michael, and Lones Smith. 2016. Optimal sequential search among alternatives. *Available at SSRN 2858097*.

- Corts, Kenneth S. 2014. Finite optimal penalties for false advertising. *The Journal of Industrial Economics* 62 (4): 661–681.
- de Roos, Nicolas. 2018. Collusion with limited product comparability. *The RAND Journal of Economics* 49 (3): 481–503.
- Diamond, Peter. 1971. A model of price adjustment. *Journal of Economic Theory* 3 (2): 156–168.
- Dinerstein, Michael, Liran Einav, Jonathan Levin, and Neel Sundaresan. 2018. Consumer price search and platform design in internet commerce. *American Economic Review* 108 (7): 1820–59.
- Eliaz, Kfir, and Ran Spiegler. 2011. A simple model of search engine pricing. *The Economic Journal* 121 (556): F329–F339.
- Ellison, Glenn, and Sara Fisher Ellison. 2009. Search, obfuscation, and price elasticities on the internet. *Econometrica* 77 (2): 427–452.
- Ellison, Glenn, and Alexander Wolitzky. 2012. A search cost model of obfuscation. *The RAND Journal of Economics* 43 (3): 417–441.
- Fudenberg, Drew, and Jean Tirole. 1991. *Game theory*. Cambridge, MA: MIT Press.
- Gamp, Tobias. 2019. Guided search. Working paper.
- Gamp, Tobias, and Daniel Kraehmer. 2018. Deception and competition in search markets. Working Paper.
- Hagiu, Andrei, and Bruno Jullien. 2011. Why do intermediaries divert search? *The RAND Journal of Economics* 42 (2): 337–362.

- Hagiu, Andrei, and Julian Wright. 2015. Multi-sided platforms. *International Journal of Industrial Organization* 43:162–174.
- Hinnosaar, Toomas, and Keiichi Kawai. 2018. Robust pricing with refunds. Working Paper.
- Hong, Han, and Matthew Shum. 2006. Using price distributions to estimate search costs. *RAND Journal of Economics* 37 (2): 257–275.
- Lubensky, Dmitry. 2017. A model of recommended retail prices. *The RAND Journal of Economics* 48 (2): 358–386.
- Mamadehussene, Samir. 2019. The interplay between obfuscation and prominence in price comparison platforms. *Management Science*.
- Nosko, Chris, and Steven Tadelis. 2015. The limits of reputation in platform markets: an empirical analysis and field experiment. Working Paper.
- Petrikaitė, Vaiva. 2018. Consumer obfuscation by a multiproduct firm. *The RAND Journal of Economics* 49 (1): 206–223.
- Piccolo, Salvatore, Piero Tedeschi, and Giovanni Ursino. 2015. How limiting deceptive practices harms consumers. *The RAND Journal of Economics* 46 (3): 611–624.
- Rhodes, Andrew, and Chris M Wilson. 2018. False advertising. *The RAND Journal of Economics* 49 (2): 348–369.
- Smirnov, Aleksei, and Egor Starkov. 2018. Bad news turned good: reversal under censorship. Working Paper.
- Teh, Tat-How. 2019. Platform governance. Working Paper.

- Ursu, Raluca M. 2018. The power of rankings: quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Science* 37 (4): 530–552.
- Weyl, E Glen. 2010. A price theory of multi-sided platforms. *American Economic Review* 100 (4): 1642–72.
- White, Alexander. 2013. Search engines: left side quality versus right side profits. *International Journal of Industrial Organization* 31 (6): 690–701.
- Wolinsky, Asher. 1986. True monopolistic competition as a result of imperfect information. *The Quarterly Journal of Economics* 101 (3): 493–511.
- Yang, Huanxing. 2013. Targeted search and the long tail effect. *RAND Journal of Economics* 44 (4): 733–756.
- Yea, Sangjun. 2018. Quality disclosure in online marketplaces. Working Paper.
- Zhu, Feng. 2019. Friends or foes? examining platform owners' entry into complementors' spaces. *Journal of Economics & Management Strategy* 28 (1): 23–28.
- Zhu, Feng, and Qihong Liu. 2018. Competing with complementors: an empirical look at amazon. com. *Strategic Management Journal* 39 (10): 2618–2642.

A Omitted Proofs

Proof of Proposition 1

Because U is determined by Equation (8), the derivatives of both sides with regard to α must be equal.

$$\begin{aligned} 0 &= - \int_U^{\bar{\epsilon}} (\epsilon' - U) f(\epsilon') d\epsilon' - (1 - \alpha) \frac{\partial U}{\partial \alpha} \int_U^{\bar{\epsilon}} f(\epsilon') d\epsilon' \\ \implies \frac{\partial U}{\partial \alpha} &= - \frac{\int_U^{\bar{\epsilon}} (\epsilon' - U) f(\epsilon') d\epsilon'}{(1 - \alpha)(1 - F(U))} \end{aligned} \quad (28)$$

since $\int_U^{\bar{\epsilon}} f(\epsilon') d\epsilon' = (1 - F(U))$. All of the elements of the fraction on the right hand side are positive, so the negative of the fraction must be negative and $\frac{\partial U}{\partial \alpha} < 0$. ■

Proof of Proposition 2

Directly taking the derivative of Equation (11)

$$\begin{aligned} \frac{\partial p}{\partial \alpha} &= \frac{-(\beta\alpha + 1 - \alpha) + (1 - \beta)(1 - \alpha)}{(\beta\alpha + 1 - \alpha)^2} \frac{1 - F(U)}{f(U)} + \frac{\partial U}{\partial \alpha} \Psi \frac{-f(U)^2 - f'(U)(1 - F(U))}{f(U)^2} \\ &= \frac{-\beta}{(\beta\alpha + 1 - \alpha)^2} \frac{1 - F(U)}{f(U)} + \frac{\partial U}{\partial \alpha} \Psi \frac{-f(U)^2 - f'(U)(1 - F(U))}{f(U)^2} \end{aligned} \quad (29)$$

In a symmetric equilibrium, U does not depend on β , so as $\beta \rightarrow 0$ the first term in the parentheses on the right hand side approaches 0 and the second term approaches $\frac{\partial U}{\partial \alpha} \frac{-f(U)^2 - f'(U)(1 - F(U))}{f(U)^2}$. From Proposition 1 $\frac{\partial U}{\partial \alpha} < 0$, and Anderson, De Palma, and Nesterov (1995) demonstrate that $\frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} > 0$ for a log concave distribution, so $\frac{\partial U}{\partial \alpha} \frac{-f(U)^2 - f'(U)(1 - F(U))}{f(U)^2} > 0$. Therefore $\lim_{\beta \rightarrow 0} \frac{\partial p}{\partial \alpha} > 0$ and by inspection $\frac{\partial p}{\partial \alpha}$ is continuous in β , so it must be the case that $\frac{\partial p}{\partial \alpha} > 0$ for β sufficiently small. ■

Proof of Proposition 3

Taking the derivative of Π with regard to α

$$\begin{aligned}
\frac{\partial \Pi}{\partial \alpha} &= \frac{\partial p}{\partial \alpha} Q(V(\alpha)) + pQ'(V(\alpha))V'(\alpha) \\
&= \left(\frac{-\beta}{(\beta\alpha + 1 - \alpha)^2} \frac{1 - F(U)}{f(U)} + \frac{\partial U}{\partial \alpha} \Psi \frac{-f(U)^2 - f'(U)(1 - F(U))}{f(U)^2} \right) Q(V(\alpha)) \\
&\quad + pQ'(V(\alpha)) \left(\frac{-\beta}{(\beta\alpha + 1 - \alpha)^2} \left(U - \frac{1 - F(U)}{f(U)} \right) + \Psi \frac{\partial U}{\partial \alpha} \left(1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right) \right) \quad (30) \\
&= \frac{-\beta}{(\beta\alpha + 1 - \alpha)^2} \left(Q(V(\alpha)) \frac{1 - F(U)}{f(U)} + pQ'(V(\alpha)) \left(U - \frac{1 - F(U)}{f(U)} \right) \right) \\
&\quad + \Psi \frac{\partial U}{\partial \alpha} \left(pQ'(V(\alpha)) \left[1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right] - Q(V(\alpha)) \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right)
\end{aligned}$$

The first term in the brackets represents the change in profits due to the lemon effect. The lemon effect pushes prices down and drives consumers away from platform, so this term is always negative. The second term represents the change in profits resulting from search obfuscation; this effect can be either positive or negative depending on whether the increased prices make up for reduced participation. When $\alpha = 0$ the second term does not depend on β at all. If this second term is positive then for β sufficiently small the entire derivative must be positive and platform profit is increasing in α at $\alpha = 0$, this gives condition 1.

The second term is positive at $\alpha = 0$ if

$$pQ'(V(0)) \left[1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right] < Q(V(0)) \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \quad (31)$$

In other words, admitting low-quality sellers is profitable if the revenue loss from consumers leaving the platform (the left hand side) is less than the increase in revenue from the obfuscation effect. As $c \rightarrow 0$, p will approach 0, and $Q'(V(0))$ will be decreasing. From Anderson, De Palma, and Nesterov (1995), $\frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} > 0$, so the left hand side will go to 0 as the search cost decreases. However, it is theoretically

possible that in the limit $\frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2}$ could tend to 0 sufficiently quickly that the revenue loss from reduced participation is greater than the revenue increase from obfuscation for all values of c . If $f(\bar{\epsilon}) > 0$, then $\lim_{c \rightarrow 0} \frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2} > 0$, which eliminates this concern. Alternatively we can rearrange the inequality to be

$$\frac{Q'(V(0))}{Q(V(0))} \left(1 + \frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2} \right) < \frac{1}{p} \quad (32)$$

If $\frac{Q'(V(0))}{Q(V(0))} \in o\left(\frac{\frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2}}{1+\frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2}}\right)$ —equivalent to highly concave $Q(\cdot)$ —then the density of marginal consumers will become so thin as search costs decrease that the revenue increase from obfuscation must overcome the change in participation for c sufficiently small.

■

Proof of Lemma 1

Sufficiency of the first order condition follows immediately if Π is single peaked in α .

Π is single-peaked in α if

$$\frac{\frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2}}{p \left(1 + \frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2} \right)} - \frac{Q'(V(\alpha))}{Q(V(\alpha))} - \beta B(\alpha) \quad (33)$$

Where

$$B(\alpha) = \frac{(1-F(U))}{(1-\alpha) \int_U^{\bar{\epsilon}} (\epsilon - U) f(\epsilon) d\epsilon} \frac{Q(V(\alpha))^{\frac{1-F(U)}{f(U)}} + pQ'(V(\alpha)) \left(U - \frac{1-F(U)}{f(U)} \right)}{Q(V(\alpha))^{\frac{1-F(U)}{f(U)}} \left(1 + \frac{f(U)^2+f'(U)(1-F(U))}{f(U)^2} \right)} \quad (34)$$

is decreasing in α . Because $Q(\cdot)$ is concave and $V(\alpha)$ is decreasing in α , $\frac{Q'(V(\alpha))}{Q(V(\alpha))}$ must be increasing in α . β must be small enough under for Proposition 2 to apply, otherwise

the platform would not admit any low-quality sellers since Π is strictly decreasing in α if p is not increasing. Therefore $\frac{1}{p}$ must decrease in α , so the only possible sources of multiple maxima are $\frac{\frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2}}{\left(1 + \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2}\right)}$ and $\beta B(\alpha)$. If the variance of $f(\cdot)$ is sufficiently large (so that $f(\cdot)$ is small) then the effect of $\frac{1}{1-\alpha}$ in the first term of $B(\alpha)$ dominates and $B(\alpha)$ is increasing in α . Finally,

$$\frac{\frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2}}{\left(1 + \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2}\right)} = \frac{1 + \frac{f'(U)(1-F(U))}{f(U)^2}}{2 + \frac{f'(U)(1-F(U))}{f(U)^2}} \quad (35)$$

is the ratio of the change in price as U decreases to the change in $V(\alpha)$ as U decreases. This ratio can increase or decrease in U , but if $f'(U)$ is sufficiently close to 0 (e.g. with a uniform distribution or high variance distribution) then the effects of $\frac{1}{p}$ and $\frac{Q'(V(\alpha))}{Q(V(\alpha))}$ dominate the other terms and profit is single-peaked in α .

■

Proof of Proposition 4

Proof of part 1: First note that Π is increasing in α if the left hand side of Equation (16) minus the right hand side is positive.

As c increases, U decreases and p increases, meaning that $V(\alpha)$ decreases. Since the direct effect of α on p decreases prices via the lemon coefficient, Assumption 1 implies that

$$\frac{\frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2}}{p \left(1 + \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2}\right)} - \frac{Q'(V(\alpha))}{Q(V(\alpha))} - \beta B(\alpha) \quad (36)$$

is increasing in U , so if c decreases then marginal profits in α decrease for all values of α . Concavity of the objective function then further implies that the α which solves

Equation (16) must decrease, so α^* decreases.

Proof of part 2 If $Q(V(\alpha)) = \frac{V(\alpha)}{t} t > 0$, then from Equation (30)

$$\begin{aligned}
\frac{\partial \Pi}{\partial \alpha} &= \frac{1}{t} \left[\frac{-2\beta(1-\alpha)}{(\beta\alpha+1-\alpha)^3} \left(\frac{1-F(U)}{f(U)} \left(U - \frac{1-F(U)}{f(U)} \right) \right) \right. \\
&\quad \left. + (\Psi)^2 \frac{\partial U}{\partial \alpha} \left(\frac{1-F(U)}{f(U)} \left[1 + \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2} \right] - \left(U - \frac{1-F(U)}{f(U)} \right) \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2} \right) \right] \\
&= \frac{(1-\alpha)}{t(\beta\alpha+1-\alpha)^2} \left[\frac{-2\beta}{\beta\alpha+1-\alpha} \left(\frac{1-F(U)}{f(U)} \left(U - \frac{1-F(U)}{f(U)} \right) \right) \right. \\
&\quad \left. + (1-\alpha) \frac{\partial U}{\partial \alpha} \left(\frac{1-F(U)}{f(U)} \left[1 + \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2} \right] - \left(U - \frac{1-F(U)}{f(U)} \right) \frac{f(U)^2 + f'(U)(1-F(U))}{f(U)^2} \right) \right] \tag{37}
\end{aligned}$$

The terms outside of the square brackets do not matter for determining the effect of β on α^* . The first term in brackets is negative and decreasing in β , the second term in the brackets is positive in any interior equilibrium and does not vary with β . From Assumption 1 the sum inside the brackets must be decreasing in α , so if the first term becomes more negative then α^* must decrease.

■

Proof of Proposition 5

Consumers only move on from the recommended seller if ϵ_{iR} is low, which means that any consumer who visits a different seller will never go back to the recommended seller. Deriving the stopping rule for these consumers then follows precisely the same steps as in Section 3. Because consumers are using the Section 3 stopping rule, the non-recommended sellers will charge the Section 3 price.

For the rest of the lemma, begin by comparing Equation (8) and Equation (20), it must be the case that

$$\begin{aligned} \frac{U_R + p - p_R}{\Psi} &= U \\ \implies U_R &= \Psi U + p_R - p \end{aligned} \tag{38}$$

This equation can be rearranged to give part 2. Suppose $p_R \leq p$, then $p_R - p \leq 0$ and $U_R < U$ as $\Psi < 1$ when $\alpha > 0$. But $f(\cdot)$ is log concave so $\frac{1-F(x)}{f(x)}$ is decreasing in x and

$$p_R = \frac{1 - F(U_R)}{f(U_R)} > \frac{1 - F(U)}{f(U)} > \Psi \frac{1 - F(U)}{f(U)} = p \tag{39}$$

Which contradicts the assumption that $p_R \leq p$ and proves part 3. The proof of part 4 uses nearly identical logic to show that an inequality in either direction produces a contradiction, noting that $\Psi = 1$ when $\alpha = 0$.

■

Proof of Corollary 1

With probability $1 - F(U_R)$ consumers purchase from the recommended seller and receive expected utility $\int_{U_R}^{\bar{\epsilon}} \epsilon \frac{f(\epsilon)}{1-F(U_R)} d(\epsilon) - p_R$. With probability $F(U_R)$, consumers move on from the recommended seller, in which case their search problem is identical to the equilibrium without a recommended seller and their expected payoff is $\Psi \left(U - \frac{1-F(U)}{f(U)} \right)$, so

$$V(\alpha) = \left[\int_{U_R}^{\bar{\epsilon}} \epsilon \frac{f(\epsilon)}{1-F(U_R)} d(\epsilon) - p_R \right] (1 - F(U_R)) + F(U_R) \Psi \left(U - \frac{1-F(U)}{f(U)} \right) \tag{40}$$

Focusing on the first term

$$\begin{aligned}
\int_{U_R}^{\bar{\epsilon}} \epsilon \frac{f(\epsilon)}{1 - F(U_R)} d(\epsilon) - p_R &= \int_{U_R}^{\bar{\epsilon}} (\epsilon - p_R) \frac{f(\epsilon)}{1 - F(U_R)} d(\epsilon) \\
&> \int_{U_R}^{\bar{\epsilon}} (U_R - p_R) \frac{f(\epsilon)}{1 - F(U_R)} d(\epsilon) \\
&= U_R - p_R \\
&= \Psi \left(U - \frac{1 - F(U)}{f(U)} \right)
\end{aligned} \tag{41}$$

Where the last equality comes from [Proposition 5](#). Plugging this inequality into the value function

$$\begin{aligned}
V(\alpha) &> ((1 - F(U_R)) + F(U_R)) \Psi \left(U - \frac{1 - F(U)}{f(U)} \right) \\
&= \Psi \left(U - \frac{1 - F(U)}{f(U)} \right)
\end{aligned} \tag{42}$$

Since U is identical to the reservation utility from the equilibrium without the recommended seller, [Equation \(42\)](#) implies that consumers must be strictly better off with the recommended seller. ■

Proof of [Proposition 7](#)

Part 1: Since part 2 of [Proposition 5](#) holds for all α , the derivatives of both sides of the equation must be equal

$$\frac{\partial U_R}{\partial \alpha} \left(1 + \frac{f(U_R)^2 + f'(U_R)(1 - F(U_R))}{f(U_R)^2} \right) = \Psi \frac{\partial U}{\partial \alpha} \left(1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right) - \frac{\beta}{(\beta\alpha + 1 - \alpha)^2} \left(U - \frac{1 - F(U)}{f(U)} \right) \tag{43}$$

Rearranging

$$\frac{\partial U_R}{\partial \alpha} = \Psi \frac{\partial U}{\partial \alpha} \frac{\left(1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right)}{\left(1 + \frac{f(U_R)^2 + f'(U_R)(1 - F(U_R))}{f(U_R)^2} \right)} - \frac{\beta}{(\beta\alpha + 1 - \alpha)^2} \frac{\left(U - \frac{1 - F(U)}{f(U)} \right)}{\left(1 + \frac{f(U_R)^2 + f'(U_R)(1 - F(U_R))}{f(U_R)^2} \right)} \tag{44}$$

Since $U_R = U$ and $\Psi = 1$ for $\alpha = 0$, this then implies that $\frac{\partial U_R}{\partial \alpha} < \frac{\partial U}{\partial \alpha}$ for α sufficiently close to 0, which in turn implies that $U_R < U$ for α positive but near 0.

Part 2: Taking the derivative of platform profit

$$\begin{aligned} \frac{\partial \Pi_R}{\partial \alpha} = & Q'(V(\alpha))V'(\alpha) [(1 - F(U_R))p_R + F(U_R)p] \\ & + Q(V(\alpha)) \left[(1 - F(U_R))\frac{\partial p_R}{\partial \alpha} + F(U_R)\frac{\partial p}{\partial \alpha} - \frac{\partial U_R}{\partial \alpha}f(U_R)(p_R - p) \right] \end{aligned} \quad (45)$$

Evaluating the derivative of the recommended seller's profit

$$\frac{\partial p_R}{\partial \alpha} = -\frac{\frac{\partial U_R}{\partial \alpha}f(U_R)^2 + f'(U_R)(1 - F(U_R))}{f(U_R)^2} \quad (46)$$

From [Equation \(44\)](#) this derivative must be positive. From [part 1](#) of this proposition for small α it is larger than the change in p with α , but the comparison is ambiguous for large α . Additionally, because $p_R > p$ for $\alpha > 0$, the marginal costs of increasing α (the first term on the right hand side of [Equation \(45\)](#)) of can potentially be larger when the platform recommends a seller as well. However, from [Corollary 1](#), $Q'(V(\alpha))$ must be closer to 0 in the equilibrium with the recommended seller because $V(\alpha)$ is larger. For $Q(\cdot)$ sufficiently concave, this effect dominates and $\frac{\partial \Pi_R}{\partial \alpha} > \frac{\partial \Pi}{\partial \alpha}$ for all α , so from [Assumption 1](#), we must have $\alpha^{R*} > \alpha^*$. ■

Proof of [Corollary 2](#)

From [Proposition 3](#) and [Proposition 4](#), for β or c sufficiently large, α^* is close to 0. But then from [Proposition 7](#) and [Corollary 1](#) a change in α must result in a larger increase in seller profits must and a smaller decrease in participation when the platform can recommend a seller. It follows immediately that $\alpha^{R*} > \alpha^*$ for any β and c pair in

this set such that α^* is positive but small. Further, comparing Equation (45) and Equation (30), it follows from inspection and part 4 of Proposition 5 that that the former will be strictly greater at $\alpha = 0$ when $\frac{\partial p_R}{\partial \alpha} > \frac{\partial p}{\partial \alpha}$. Part 1 of Proposition 7 implies that this last condition will hold at any c and β pair such that the optimal α^* is exactly 0. Thus $\alpha^{R*} > 0$ at those pairs, and as Equation (45) will changes smoothly with β and c there must be parameters outside the set where α^* is positive such that $\alpha^{R*} > 0$.

■

B Duopoly platforms

Suppose that instead of a single monopoly platform, two platforms (denoted 1 and 2) compete in a duopoly setting with single homing consumers and multi-homing sellers. I use the subscript 1 to denote the variables relevant to platform 1 and 2 to those on platform 2. For this section I focus on symmetric equilibrium where all sellers on platform i set the same price given α_i , and where $\alpha_1 = \alpha_2$. With the additional platform, the timing of the model changes slightly:

1. The platforms set α_1 and α_2 simultaneously.
2. Consumers commit to participating in one of the platforms' markets or remaining with the outside option.
3. Sellers set prices simultaneously on each platform.
4. Consumers participating a platform's market search among sellers and make purchasing decisions.

Prices are not observable to consumers so multi-homing sellers set the prices independently on each platform by best responding to consumer search behavior. Similarly, as consumers commit to a platform before searching, the proportion of low-quality sellers on the other platform does not influence their search behavior. For $i = 1, 2$ the derivations from the monopoly model apply:

$$\begin{aligned}
 p_i &= \frac{(1 - \alpha_i)}{\beta\alpha_i + 1 - \alpha_i} \frac{1 - F(U_i)}{f(U_i)} \\
 V(\alpha_i) &= \frac{(1 - \alpha_i)}{\beta\alpha_i + 1 - \alpha_i} \left(U_i - \frac{1 - F(U_i)}{f(U_i)} \right)
 \end{aligned} \tag{47}$$

Where U_i is determined by [Equation \(8\)](#), substituting α_i for α . The mass of consumers who commit to platform i is given by the continuous and differentiable function $Q_i(V(\alpha_1), V(\alpha_2))$, where $Q_i(V(\alpha_i), V(\alpha_{-i}))$ is increasing and concave in $V(\alpha_i)$ and decreasing in $V(\alpha_{-i})$. Furthermore, I assume that

$$\frac{dQ_i(x, x)}{dx} = \frac{dQ_{-i}(x, x)}{dx} \geq 0 \text{ for } i = 1, 2 \tag{48}$$

This assumption implies that neither platform has an inherent competitive advantage. If both platforms provide the same expected value, and this value increases while remaining symmetric, then any change in demand must come from the outside option. Behavior is identical to the monopoly once consumers have committed to a platform, so the major implication of introducing platform competition is that consumer participation in a platform's market will depend on both platforms' curation decisions.

Lemma 2. *In the symmetric duopoly model, for β and c sufficiently small and if $\max f'(\cdot)$ sufficiently small then $\alpha_i = \alpha_{-i} = 0$ cannot be an equilibrium.*

Proof. Following the same derivation steps as in the proof of [Proposition 3](#), a platform's

profit is increasing if β is sufficiently small and at $\alpha_i = \alpha_{-i} = 0$

$$\frac{\frac{\partial Q_i(V(0), V(0))}{\partial V(\alpha_i)}}{Q_i(V(0), V(0))} \frac{\left(1 + \frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}\right)}{\frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}} < \frac{1}{p_i} \quad (49)$$

By precisely the same logic as in the proof of [Proposition 3](#), if

$$\lim_{U_i \rightarrow \bar{c}} \frac{\frac{\partial Q_i(V(0), V(0))}{\partial V(\alpha_i)}}{Q_i(V(0), V(0))} \frac{\left(1 + \frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}\right)}{\frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}} < \infty \quad (50)$$

then the above inequality must hold for c sufficiently small. ■

The logic of the proof of [Lemma 2](#) is similar to that of [Proposition 3](#), and the intuition is similar as well. If the the platform markets are sufficiently competitive, and the lemon effect not too strong, then each platform will have an incentive to obfuscate search even if the other platform has no low-quality sellers.

Assumption 2. β and c are sufficiently small so that $\alpha_i = \alpha_{-i} = 0$ is not an equilibrium.

By nearly the same reasoning as in the monopoly model, platform profit is guaranteed to be concave for $f(\cdot)$ sufficiently small across its range, so [Assumption 3](#) gives sufficiency of the first order condition for platform i 's curation decision.

Assumption 3. The variance of $f(\cdot)$ is sufficiently large so that $\frac{\frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}}{p_i \left(1 + \frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}\right)} - \frac{\frac{\partial Q_i(V(\alpha_i), V(\alpha_{-i}))}{\partial V(\alpha_i)}}{Q_i(V(\alpha_i), V(\alpha_{-i}))} - \beta B_i(\alpha_i, \alpha_{-i})$ is decreasing in α_i

[Lemma 2](#) describes equilibrium curation levels in this environment. Let α_D^* denote the symmetric equilibrium curation decision in the duopoly model, then

Lemma 3. Under *Assumption 2* and *Assumption 3*, if $Q_i(V(\alpha_i), V(\alpha_{-i}))$ is continuously differentiable then an equilibrium with symmetric $\alpha > 0$ exists and for $i = 1, 2$, α_D^* is determined implicitly by

$$\frac{\frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2}}{p_i \left(1 + \frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2} \right)} = \frac{\frac{\partial Q_i(V(\alpha_D^*), V(\alpha_D^*))}{\partial V(\alpha_i)}}{Q_i(V(\alpha_D^*), V(\alpha_D^*))} + \beta B_i(\alpha_D^*, \alpha_D^*) \quad (51)$$

Where

$$B_i(\alpha_D^*, \alpha_D^*) = \frac{(1-F(U_i))}{(1-\alpha) \int_{U_i}^{\epsilon} (\epsilon - U_i) f(\epsilon) d\epsilon} \frac{Q_i(V(\alpha_D^*), V(\alpha_D^*)) \frac{1-F(U_i)}{f(U_i)} + p_i \frac{\partial Q_i(V(\alpha_D^*), V(\alpha_D^*))}{\partial V(\alpha_i)} \left(U_i - \frac{1-F(U_i)}{f(U_i)} \right)}{Q_i(V(\alpha_D^*), V(\alpha_D^*)) \frac{1-F(U_i)}{f(U_i)} \left(1 + \frac{f(U_i)^2 + f'(U_i)(1-F(U_i))}{f(U_i)^2} \right)} \quad (52)$$

Proof. $B_i(\alpha_i, \alpha_D^*)$ approaches ∞ as α_i approaches 1, so no platform will ever set $\alpha_i = 1$. *Assumption 2* ensures that $\alpha_i = \alpha_{-i} = 0$ is never an equilibrium. *Assumption 3*, *Assumption 2* and continuous differentiability of $Q_i(V(\alpha_i), V(\alpha_{-i}))$ together ensure that a solution to [Equation \(51\)](#) in α_i exists for some range of $\alpha_{-i} > 0$ and that this solution is both necessary and sufficient for profit maximization if the optimal response to α_{-i} is positive. Since $V(\alpha)$ is continuous in α and $\alpha_i, \alpha_{-i} \in [0, 1]$, the payoff functions are continuous and (by assumption) single-peaked in the platform's own strategies, and the strategy spaces are compact. Therefore by theorem 1.2 in Fudenberg and Tirole (1991) an equilibrium in pure strategies exists and by *Assumption 2* it must have at least one $\alpha > 0$.

Furthermore, there must be an equilibrium which has symmetric $\alpha > 0$. Define $\alpha(\alpha_{-i})$ as platform i 's reaction function. Since $Q_i(V(\alpha_i), V(\alpha_{-i}))$ is continuously differentiable, the solution to [Equation \(51\)](#) must vary with α_{-i} continuously. $\alpha(\alpha_{-i})$ is the solution to [Equation \(51\)](#) if this solution is non-negative or 0 if it is not, so $\alpha(\alpha_{-i})$ must be a continuous function. As the domain of $\alpha(\cdot)$ is $[0, 1]$, and the range is contained in this compact, convex set, Brouwer's fixed point theorem implies that

there exists α_{-i} such that $\alpha(\alpha_{-i}) = \alpha_{-i}$. Furthermore, from [Assumption 2](#) this α_{-i} must be positive, and so the symmetric solution is determined by [Equation \(51\)](#). ■

[Lemma 2](#) states that under relatively mild conditions a symmetric equilibrium exists where both platforms admit a positive number of low-quality sellers if their retail markets would be highly competitive without them. This does not rule out the possibility of an asymmetric equilibrium, but I leave analysis of such equilibria for future work. [Proposition 8](#) compares α^* , the equilibrium curation decision in the monopoly model, to α_D^* , the equilibrium decision in the duopoly.

Proposition 8. *Under Assumptions 1 to 3, if the equilibrium in the multi-platform model is symmetric then $\alpha_D^* > \alpha^*$ if and only if*

$$\frac{\frac{\partial Q_i(V(\alpha^*), V(\alpha^*))}{\partial V(\alpha_i)}}{Q_i(V(\alpha^*), V(\alpha^*))} < \frac{Q'(V(\alpha^*))}{Q(V(\alpha^*))} \quad (53)$$

That is, the equilibrium proportion of low-quality sellers increases with the addition of a second platform if and only if demand is less elastic in the duopoly platform case.

Proof. Assumptions 1 to 3 ensure sufficiency and necessity of the first order conditions. The conclusion comes directly from comparing [Equation \(51\)](#) to [Equation \(16\)](#) and the assumption of concavity in both cases. The presence of $B_i(\alpha_D^*, \alpha_D^*)$ and $B(\alpha^*)$ means that the comparison is not immediately obvious. However, it is easy to show that

$$\begin{aligned} B_i(\alpha_D^*, \alpha_D^*) = & \frac{(1 - F(U_i))}{(1 - \alpha) \int_{U_i}^{\bar{\epsilon}} (\epsilon - U_i) f(\epsilon) d\epsilon} \left(\frac{1}{1 + \frac{f(U_i)^2 + f'(U_i)(1 - F(U_i))}{f(U_i)^2}} \right. \\ & \left. + \frac{\frac{\partial Q_i(V(\alpha_D^*), V(\alpha_D^*))}{\partial V(\alpha_i)}}{Q_i(V(\alpha_D^*), V(\alpha_D^*))} \frac{p_i \left(U_i - \frac{1 - F(U_i)}{f(U_i)} \right)}{\frac{1 - F(U_i)}{f(U_i)} \left(1 + \frac{f(U_i)^2 + f'(U_i)(1 - F(U_i))}{f(U_i)^2} \right)} \right) \end{aligned} \quad (54)$$

and

$$\begin{aligned}
B(\alpha^*) = & \frac{(1 - F(U))}{(1 - \alpha) \int_U^{\bar{\epsilon}} (\epsilon - U) f(\epsilon) d\epsilon} \left(\frac{1}{1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2}} \right. \\
& \left. + \frac{Q'(V(\alpha^*))}{Q(V(\alpha^*))} \frac{p \left(U - \frac{1 - F(U)}{f(U)} \right)}{\frac{1 - F(U)}{f(U)} \left(1 + \frac{f(U)^2 + f'(U)(1 - F(U))}{f(U)^2} \right)} \right)
\end{aligned} \tag{55}$$

Given that both $B(\alpha^*)$ and $B_i(\alpha_D^*, \alpha_D^*)$ are positive, the only difference between the two first order conditions is the comparison of $\frac{Q'(V(\alpha^*))}{Q(V(\alpha^*))}$ to $\frac{\frac{\partial Q_i(V(\alpha_i), V(\alpha_{-i}))}{\partial V(\alpha_i)}}{Q_i(V(\alpha_i), V(\alpha_{-i}))}$. If the latter is smaller at $\alpha_i = \alpha_{-i} = \alpha^*$, then by [Assumption 3](#) α_D^* must be larger than α^* for [Equation \(51\)](#) to hold. ■

Because the effects of α on price are identical in the two models, any differences in the curation decision must come from differences in the elasticity of the participation function. It would be unreasonable to expect $Q(V(\alpha^*)) < Q_i(V(\alpha^*), V(\alpha^*))$, however it is entirely possible that consumer participation might be less elastic in the equilibrium of a competitive market. The larger set of choices available to consumers in a duopoly environment means that consumers are more likely to have a strong preference for the platform they choose in equilibrium, (or a strong aversion to both options if they choose the outside option) so a consumer will attract fewer new consumers if it lowers α . This effect is strengthened if $\frac{\partial^2 Q_i(V(\alpha_D^*), V(\alpha_D^*))}{\partial V(\alpha_i) \partial V(\alpha_{-i})} > 0$ because this implies that as platform $-i$ allows more low-quality sellers, platform i loses fewer consumers when it increases α_i .