Hybrid Platform Screening[*]

Clément Gras[†] and Guillaume Thébaudin[‡]

March 2023

Abstract

Online marketplaces commonly employ a hybrid business model, wherein they are vertically integrated and sell their own products competing with third-party sellers on their platform. Free entry of these sellers may lead to the presence of harmful and illegal products, which consumers are not able to differentiate from safe ones. We extend the model of Anderson and Bedre-Defolie (2021) allowing the platform to invest in screening of sellers to remove illegal third-party products. We find that seller screening has an ambiguous effect on entry on the platform, and a condition for a platform to engage in screening is that it accommodates entry. Also, we find that more integrated platforms tend to screen less. Moreover, a platform conducting seller screening sets higher commission fees, the level of which can decrease in platform's degree of vertical integration in contrast with previous literature. From a welfare perspective, platforms invest too little in screening as compared to social optimum, and a regulation mandating higher screening intensity has an ambiguous effect on consumers' surplus.

Keywords: Trade platform, Hybrid business model, Illegal products, Screening, Digital Services Act.

[*]We thank Marc Bourreau for his helpful comments. We also thank the audiences at internal seminars at Télécom Paris and Paris School of Economics.

[†]Paris School of Economics; e-mail: clement.gras@psemail.eu

[‡]Télécom Paris; e-mail: guillaume.thebaudin@telecom-paris.fr.

1 Introduction

In recent years, concerns have been raised about the proliferation of harmful products and content on online marketplaces. The emergence of e-commerce and globalisation of supply chains have enabled small sellers of potentially unsafe products to operate on a global scale, leveraging the platform's quasi-anonymity feature, and tap into a vast consumer base. According to an investigation conducted in 2019[1], the Wall Street Journal "found 4,152 items for sale on Amazon.com Inc.'s site that have been declared unsafe by federal agencies, are deceptively labeled or are banned by federal regulators—items that big-box retailers' policies would bar from their shelves." Yet, platforms operators are in a position to create and enforce rules for interactions on their marketplace, and have the ability to control and filter entry for sellers, to prevent bad actors from operating. For example, both Amazon[2] and Apple[3] publicly promote their use of advanced AI-powered algorithms designed to accurately detect bad actors and harmful content, to provide a safer and more trustworthy environment for consumers. The development of screening tools requires however significant investments, and platforms may lack incentives or resources to do so (see e.g. Jeon et al. (2021), Liu et al. (2021)).

To address these growing concerns, regulators have taken steps to establish rules that promote a safer digital space. The Digital Services Act[4] in Europe, for example, will reinforce obligations for online operators to remove illegal products as soon as they become aware of them on the platform. However, the Act does not mandate systematic screening of platforms. The UK Government also proposed in 2021 the Online Safety Bill[5], which imposes a duty of care and several obligations on large social media platforms to ensure the safety of their users.

Alternatively, consumers often have the option to buy products manufactured by platforms themselves, as many of them operate in a hybrid mode where they not only host third-party sellers but also sell their own products. These first-party goods differ from third-party ones in that the seller is known to be the platform itself. This potentially allows for higher quality and safer goods, given the platform's financial resources and control over the manufacturing and distribution processes. For instance, Amazon has developed its own brand called Amazon Basics, which offers a range of products such as cables, batteries, and kitchen appliances. Apple

[1] Amazon Has Ceded Control of Its Site. The Result: Thousands of Banned, Unsafe or Mislabeled Products, The Wall Street Journal

[2] Amazon and Product Safety, aboutamazon.eu

[3] Apple Platform Security, support.apple.com

[4] The Digital Services Act package, digital-strategy.ec.europa.eu

[5] A guide to the Online Safety Bill, gov.uk

also sells its own apps, such as Apple Music, competing with other sellers on their marketplace. This vertically integrated business model has called attention[6] with regard to possible conflicting interest with respect to third-party sellers. The existing literature on hybrid platforms indeed shows that the presence of a platform's own-retailer arm is likely to influence its decision-making regarding various instruments, such as commission fees, entry in specific markets and product ranking (see e.g. Anderson and Bedre-Defolie (2021), Hervas-Drane and Shelegia (2022), Zennyo (2022a))

In this paper, we investigate the impact of platform's vertical integration on the incentives of a platform to invest in a screening technology that detects and remove harmful third-party products. Notably, we also study the relationship between optimal screening choices and commission fees charged to sellers to operate on the marketplace.

To do so, we extend the hybrid platform model with free entry of monopolistic sellers as developed in Anderson and Bedre-Defolie (2021) by enabling the platform, in a "Gatekeeper" position, to screen third-party sellers at entry. The products sold on the marketplace can lead to consumer damage during product usage. Upon launching production by sourcing from overseas, sellers learn whether their product poses high risk to consumer (type-H), or low risk (type-L), before entering the marketplace. In line with current regulatory framework and liability regime in Europe, the platform is obliged to remove any detected type-H products, while letting rather safe ones operating on its marketplace. The level of investment in screening determines the probability that a type-H sellers is detected by the platform, and to the extent that this probability does not equal unity, both types of products are present on the marketplace. Consumers are not able to assess active third-party sellers' type, thus make their purchase decision based on their distribution given the level of screening conducted by the platform. They also have the possibility to purchase platform's own products which are relatively safe. The platform charges third-party sellers *ad-valorem* commission fees on all transactions they make on the marketplace.

We first show that screening investment has two opposite effects on the equilibrium marketplace size, determined by free entry of third-party sellers in a globalised supply-chain framework. On the one, it lowers incentives of sellers to enter the market because of the possibility of their products being of type-H and screened-out at entry. On the other hand, for sellers who managed to pass the screening process, higher screening intensity raises demand on the platform

[6]See for instance Europe's Digital Market Act

because of reduced consumers' anticipated damage risk of buying third-party products. We find that the platform will invest in seller screening at some cost to the extent that this positive effect on seller entry dominates. This occur in markets characterized by a high level of product differentiation and a large damage risk difference between the two types of seller.

Second, we find that investing in a positive level of screening leads the platform to charge higher commission fees to sellers. This strategic complementarity has important consequences when it comes to investigate the relationship between platforms combined choices and its degree of vertical integration, as measured by the mass of first-party products the platform is able to sell. Indeed, we find that a more integrated platform has lower incentives, for a given commission rate, to screen sellers because it suffers from a *business stealing* effect since screening accommodates entry. Combined with the fact that, for a given level of screening, a more vertically integrated platform sets higher commission fees, as shown in Anderson and Bedre-Defolie (2021), the overall effect of an increase in the mass of platform's products on both platform's choices is ambiguous. The ability of a platform to screen users indeed generates a new effect driving down commission fees as a result of more vertical integration, through lower screening intensity, which can dominate the positive effect found in Anderson and Bedre-Defolie (2021). We show through simulations that this is the case for some range of parameter values.

Finally, we find that, for every level of vertical integration, the platform invests too little in screening of sellers as compared to social optimum because it doesn't fully internalise consumers' surplus.

Our results have important policy implications. They highlight on the fact that, absent strict liability regime, platforms may spontaneously engage in screening of sellers. Moreover, they do so to the extent that screening accommodates entry, thus raising consumers' surplus through more variety on the platform. Attention should however be drawn towards highly integrated platforms for which incentives to screen sellers are lower. Finally, a regulation mandating platforms to raise screening induces them to raise commission fees, having an ambiguous effect on consumers' surplus.

Related literature

This paper contributes to two streams of literature: the governance of two-sided platforms, and more specifically hybrid marketplaces, and product liability in law and economics.

The first literature on platform governance first analyses optimal platform's pricing to leverage positive feedback loops associated with indirect network externalities and to solve the problem of coordination failures (Caillaud and Jullien (2003), Rochet and Tirole (2003), Rochet and Tirole (2006), Armstrong (2006)). Recent research on platform governance has examined digital platforms' incentives regarding various aspects. These include choosing the intensity of seller competition (Teh (2022)), introducing deceptive features (Johnen and Somogyi (2022)), biasing its innovation by trading off one side's surplus against that of the other side (Choi and Jeon (2022)), moderating content (Liu et al. (2021), Madio and Quinn (2021)), delisting low-quality sellers (Casner (2020), Eliaz and Spiegler (2011)), and ensuring privacy protection (Etro (2021a)). We contribute to this literature by studying platform's screening choices in a setting where, unlike previous studies (Casner (2020), Eliaz and Spiegler (2011)), there is free entry of monopolistic sellers and no search costs for consumers. We show that screening generates an ambiguous effect on seller entry, and we delineate market characteristics that induce the platform to invest in screening. Recent strand of this literature focuses on the effect of platform's vertical integration on pricing and commission fees (Hagiu et al. (2022), Etro (2022), Anderson and Bedre-Defolie (2021), Shopova (2021)), decision to enter a specific market (Etro (2021b), Hervas-Drane and Shelegia (2022), Madsen and Vellodi (2021), Lam and Liu (2022)) and to bias ranking (Zennyo (2022a), Hunold et al. (2022)). We first contribute to this literature by studying hybrid platforms' incentives to screen and de-list sellers, and show that a more integrated platform has lower incentives to invest in screening as a result of a *business stealing* effect. Second, we show that this can result in a negative relationship between vertical integration and commission fees, unlike previous studies (Anderson and Bedre-Defolie (2021)) using similar framework as ours. Etro (2022) highlighted the existence of an "extensive margin mechanism" pushing to lower commission rate as a result of vertical integration, in a setting with free entry of monopolistic sellers. They show that this effect can dominate the "demand substitution mechanism" as found in Anderson and Bedre-Defolie (2021), depending on consumer demand microfoundations considered. In our model, using Logit demand specification as in Anderson and Bedre-Defolie (2021), the mechanism leading to the finding is however different, and results from the ability of a platform to exert seller screening and to set commission fees in a combined manner. Hagiu et al. (2022) found that an hybrid platform tends to set similar commission rate than a pure marketplace because of the possibility of third-party sellers to showroom on the platform, which we do not consider in our study. Finally, Shopova (2021) studies the effect of the introduction of a low-quality version of a good by the platform in a vertically differentiated framework, and shows that it leads to lower commission fees. The intuition is that the platform internalises lower third-party sellers' demand and higher pass-through on their prices, effects which we do not capture in our monopolistic setting.

Second, this article contributes to law and economics in general and platform liability in particular. Recent papers build on the seminal literature on product liability (Spence (1977), Polinsky and Rogerson (1982)) and indirect liability (Hay and Spier (2005), Pitchford (1995), Mattiacci and Parisi (2003), Kraakman (1986)) to study the implications of different liability regimes on platforms' behavior and user welfare (Lefouili and Madio (2022), Jeon et al. (2021), Hua and Spier (2021)). Regarding this literature, we are expanding upon the findings of Jeon et al. (2021) by showing that the platform's spontaneous incentives to engage in screening are affected by its level of vertical integration when there is no strict liability regime in place. We further find that the platform's incentives to engage in screening are too little with respect to social optimum, and any regulation mandating higher screening levels has an ambiguous effect on consumer's surplus as the platform responds by an increase in commission rates.

Organisation of the paper

The rest of the paper is organized as follows. In the section 2, we describe the model set-up and motivate our main modeling assumptions. We study sellers' pricing and the process of free entry on the marketplace in section 3. We then investigate in section 4 platforms optimal choices of commission fees and screening intensity, and study how do they relate with respect to vertical integration. In section 5, we discuss platform's screening choices with respect to welfare maximisation and we conclude in section 6.

2 Model set-up

A platform, denoted A, enables transactions between buyers and sellers for a particular product category. The platform is in a "Gatekeeper" position, in a sense that it is a monopolist on its market and the unique gateway between sellers and buyers. In addition, it is able to sell its own versions of the product to consumers, which we refer as 'first-party' products. Independent sellers who use the platform so as to access consumers to sell their version of the product are referred as 'third-party' sellers. The products sold on the marketplace are risky and can lead to consumer damage D during product usage, occurring with some probability depending on seller identity. In the following, we introduce the three types of agents and their decisions.

Third-party sellers There is a large mass of infinitesimal potential independent sellers i. Before selling a product on the marketplace, a seller has to pay a fixed production cost k. This can be all type of expenses related to the design of the product and the launch of the production process by a manufacturer, in order to have the product available for sell. The product's marginal cost c is uniform across all sellers. Third-party sellers are however differentiated with respect to the probability of consumer damage D. After having paid the cost k, nature draws seller i's type in $\{L, H\}$, with probability λ of being a High-risk seller (type-H) and $(1 - \lambda)$ of being a Low-risk one (type-L). Sellers then learn their product's probability of damage occurrence, denoted s_i with $1 \geq s_H > s_L \geq 0$. We assume that type-H products are characterized as illegal *per se* by regulating agencies, due to their high level of danger.

Once on the platform, which he can enter at no (fixed) cost, seller i sets its price p_i. Types remain private information to each seller: they are unable to communicate this information to potential buyers. The platform can, however, infer it imprecisely through a seller screening technology at entry on the marketplace.

Moreover, we assume that primary liability is not enforceable such that consumers cannot obtain compensation for damages from sellers of illegal products.

The platform There is free entry of third-party sellers on the marketplace. The platform charges sellers an ad-valorem commission fee τ on each sales they make. As mentioned earlier, the platform is hybrid in a sense that it can also sell its own versions of the product directly to consumers on its marketplace. We denote by M the mass of first-party products, for which we will also refer as the degree of vertical integration of the platform, with the particular case of A being a pure marketplace at $M = 0$. In the model, we take M as given and we assume no fixed cost of production for the platform's products. The platform sets its price p_{Aj} for product j. All first-party products j have the same marginal cost c_A and probability of damage occurrence s_A, publicly known to everyone.

The platform can invest in a screening technology that detects at entry type-H products with probability $m \in [0, 1]$, at cost $K(m)$, with $K(0) = 0$, $K'(m) > 0$ and $K''(m) > 0$. We assume that this technology is the only way for the platform to detect harmful products. We refer to m as platform's 'screening intensity', which is perfectly observable by all agents. We assume that the platform is required to immediately de-list type-H products once they are detected. Moreover, we make the assumption that the technology does not make any type-2 errors.

Consumers There is a unit mass of consumers who can join the platform costlessly to buy one unit of product. Each consumer gets utility u_i from purchasing one unit from third-party seller i

$$u_i = v - p_i - s_i D + \mu\epsilon_i,$$

with ϵ_i is the idiosyncratic match value, and μ measuring product differentiation. Note that when she chooses to purchase from third-party seller i, a consumer is not able to assess sellers' type. The above utility is thus to be interpreted as *ex-post* utility of buying product i once the transaction has been made. As will be shown, *ex-ante* utilities are characterized by making expectations over the risk of buying from a third-party seller. In that regard, we assume that consumers are risk-neutral. Furthermore, we assume that consumers cannot communicate among each other, through a review system for instance, the type of product they have purchased.

They also have the possibility to purchase one of the M product versions j sold directly by the platform, of a known risk s_A, earning utility

$$u_{Aj} = v - p_{Aj} - s_A D + \mu\epsilon_{Aj}.$$

We allow for an exogenous mass one of outside options l granting consumer utility get $u_{0l} = \mu\epsilon_{0l}$.

We assume that match values ϵ_i, ϵ_{Aj} and ϵ_{0l} are independently and identically distributed with Gumbel (type I extreme value) distribution across products. After observing their match values, consumers buy the product which gives them the highest utility on board, or else nothing on the platform if the outside option is better. As shown in Anderson and Bedre-Defolie (2021), this yields product demand for third-party seller i

$$q_i = \exp\Big(\frac{v - p_i - s_i D}{\mu}\Big)A^{-1}. \tag{1}$$

Analogously, demand for first-party product j is given by

$$q_{Aj} = \exp\Big(\frac{v - p_{Aj} - s^A D}{\mu}\Big)A^{-1}, \tag{2}$$

with $A = \int_0^M \exp\Big(\frac{v-p_{Aj}-s^A D}{\mu}\Big)A^{-1}dj + \int_0^n \exp\Big(\frac{v-p_i-s_i D}{\mu}\Big)A^{-1}di + 1$ being the "Aggregate", a proxy for the market size which incorporates third-party and platform's products as well as the outside option which size is normalized to unity. Such consumer demand system is analogous to a Logit choice probability function among the three segments: first-party products, third-party products and the outside option.

Timing We consider the following timing. First, the platform decides its screening intensity m and the commission fees τ, which become publicly known. Second, third-party sellers make their entry decision by paying the fixed production cost k, and thereafter learn their type. Third, screening takes place and detected type-H products are removed from the platform with probability m. Fourth, active third-party sellers on the platform set their price p_i, and the platform do so for the mass M of its first-party products. Consumers then join the marketplace and discover their match values $\epsilon_i, \epsilon_{Aj}$ and ϵ_{0l} for each third-party product i, first-party product j and the outside option. They buy the product which gives them the highest utility on board, or else nothing on the platform if the outside option is better. Finally, harms occur to consumers of third-party product i with probability s_i, and to consumers of first-party product j with probability s_A.

We look for a Subgame Perfect Nash Equilibrium of this game using backward induction.

Discussion of modeling assumptions and motivating examples

Before solving the model, we offer context by discussing the main assumptions we have made and providing examples of market situations that align with our model.

Information advantage of the platform with respect to consumers We aim at modeling market situations in which platforms can have access at some cost to information about the type of products, but consumers do not. This is the case for instance in online marketplaces like Amazon or Walmart, where platforms can match products categorised as illegal by government agencies with those available on their marketplace. For example, the European customs services list information about dangerous and illegal products detected in the RAPEX (Rapid Exchange of Information System for dangerous products[7]) database. The database is not readily accessible and requires specialized knowledge and time to be comprehensible. Consumers may also not be aware about its existence. Moreover, sellers of dangerous products can employ strategies to avoid being categorized as such, which are known by platform operators given their experience and knowledge about sellers' behaviors. In this case, m would measure the effectiveness of platform's performed matching. Another market that fits our modeling assumptions is software

[7] See ec.europa.eu/safety-gate-alerts/screen/webReport

marketplaces, such as the Apple AppStore. Apple requires App developers to provide the code before listing them on the platform, and screens for known dangerous malware and any other malicious pieces of code that could harm users' privacy. Consumers, on the other hand, do not have access to the app's code and rely solely on the platform's screening process to ensure their safety.

Second, we make the important assumption that consumers do not have the ability to communicate with one another about products' type or potential damage they may have suffered. This means that we focus on products where damage occurs over a long period of time after the product has been launched and all consumers have made their purchase decision. An example of this could be the use of dangerous materials in a product which can cause illnesses in the long term. In the case of software platforms, privacy breaches are likely to affect all users of an app simultaneously, some time after release.

Timing of seller entry and knowledge about their type We also make the critical assumption that sellers only learn about their product type after the decisions to enter the market and the launch the production process have been made, at cost k. This assumption is based on the observation that many US or European Amazon sellers outsource their production process, mainly overseas, and do not have complete control over the manufacturing process, making it difficult to ascertain the quality of their contractors. According to a BusinessTechWeekly publication[8], "Most Amazon sellers prefer China because it is the hub for manufacturing a wide range of products" and "products that are sourced from there are cheaper." The article mentions that "the most crucial step is supplier selection," and that online marketplaces such as Alibaba or Alixpress are very popular platforms to find suppliers. However, these "marketplaces have different quality and safety standards. When you buy products from overseas suppliers, all these standards will not be met. You will have to ensure that the supplier adheres to local standards before product sourcing." Although Alibaba offers insurance services, known as "Trade Assurance[9]", which "protects the buyer in the event that the supplier fails to chip on time or the product quality varies from what have been agreed upon," suggestive evidence show that such protection protection is likely to be ineffective for importers. Indeed, many of them have raised concerns about the reliability of Alibaba's Trade Assurance service, stating that Alibaba mostly side with suppliers, on a Quora forum[10] titled "Can I blindly trust and trade with suppliers on

[8] How to find Wholesale Amazon Suppliers, businesstechweekly.com
[9] tradeassurance.alibaba.com
[10] Can I blindly trust and trade with suppliers on Alibaba with Trade Assurance?, quora.com

Alibaba with Trade Assurance?". One them, for instance, wrote "Do not trust Alibaba Trade Assurance. It's a scam. [...] When I finally received my orders, 15% were defective. [...] When I requested a refund for the defects Alibaba insisted that I pay for inspection service. After numerous videos and pictures they were still not satisfied with my evidence. I never received any refund."

Based on this suggestive evidence, we assume in our model a globalised supply chain, where all sellers source from overseas and are unable to assess the quality of wholesalers. There is a proportion λ of manufacturers of bad quality and dangerous products, and a pooling equilibrium exists in the wholesale market with price w. Sellers contract with manufacturers at cost k and any insurance offered by intermediaries in case of deception is ineffective. Once the merchandise is received, sellers can observe product quality and can sell them on the marketplace at no (fixed) cost. In this setting, all third-party sellers face the same marginal cost $c = w$.

In the context of software platforms, it is common for app developers to work with third-party companies that provide various services such as cloud computing, data management, analytics, and monetization. However, these third-party companies may be susceptible to malware infections that could compromise users' privacy and security.

Hence, we are modeling a situation where the supplier does not intend to harm consumers when entering the market, but can be victim of the malicious behavior of other participants in the value chain. Given that product differentiation is impossible on the marketplace with regards to consumers, they have incentives to start selling on the platform no matter their type. Note that this timing assumption ensures that both high- and low-quality sellers are present in the marketplace at equilibrium. If sellers were aware of their product quality before paying the sunk cost k, dangerous sellers would not find it profitable to enter the market because of lower expected profit resulting from platform's screening. Marketplaces would be full of high-quality and safe products, in contrast with what we observe on platform markets.

Regulatory framework and liability regime The regulatory framework used in our model is based on the proposed Digital Services Act that will fully apply in Europe by 2024. First, the Act states that platforms cannot be held liable for the presence of dangerous products on their marketplace, unless they are explicitly aware of their existence. Consequently, we assume that the platform immediately remove type-H products as soon as they are detected by the screening technology.

Furthermore, the DSA mandates algorithmic accountability and transparency reporting obligations for large platforms regarding illegal conducts of their users. We thus make the reasonable assumption that platform's screening intensity m can be observed by both consumers and third-party sellers.

Finally, we assume that sellers are judgement-proof, i.e. they are unable to compensate consumers for the harm caused by their products. Moreover, Zennyo (2022b) finds that platforms do not have incentives to take liability for third-party sellers, by offering compensation to consumers in case of damage. In Appendix, we show that this result holds in our setting, and therefore, we do not consider this possibility in our model.

3 Free entry of third-party sellers

In this section, we solve the subgame at Stage 2 where third-party sellers make their entry decision on the marketplace for given commission fee τ and screening intensity m. We first investigate sellers' demand and optimal pricing given that consumers have joined the platform and discovered their match values $\epsilon_i, \epsilon_{Aj}$ and ϵ_{0l}. We then study the process of free entry on the marketplace. Finally, we analyse how does the free entry market size is affected by platform's choices of screening intensity m and commission fees τ.

3.1 Demand and optimal pricing

Product demand Sellers of type L are preferred *ceteris paribus* but consumers are unable to differentiate these active sellers from those of type H. Since sellers are homogeneous in any other characteristics, it is impossible for them to credibly signal their type through their price. Indeed, any change in price by type-L sellers can be imitated by type-H sellers so that s_i and p_i are independent.

Thus, risk-neutral consumers form expectations on the average risk of damage occurrence solely based on the distribution of seller types active on the platform, given a level of screening m. Consequently, we have for all active sellers i

$$s_i = \frac{\lambda(1-m)s^H + (1-\lambda)s^L}{1-\lambda m} \equiv \tilde{s}^e(m), \tag{3}$$

with $\frac{d\tilde{s}^e}{dm}(m) = -\frac{\lambda(1-\lambda)(s^H-s^L)}{(1-\lambda m)^2} < 0$.

By investing more effort into screening, and *de facto* de-listing detected type-H sellers, the platform is able to influence consumers' expected net utility of buying third-party products.

Third-party seller i's demand thus depends on the level of screening m the following way:

$$q_i = \exp\Big(\frac{v - p_i - \tilde{s}^e(m)D}{\mu}\Big)A^{-1}. \tag{4}$$

For ease of exposition, we denote for the rest of the analysis $V(p,s) = \exp\Big(\frac{v-p-sD}{\mu}\Big)$ for a given price p and consumer damage risk s.

Optimal pricing Profit of third-party seller i active on the platform is given by

$$\pi_i(p_i, \tau, m, A) = (p_i(1-\tau) - c)\frac{V(p_i, \tilde{s}^e(m))}{A}. \tag{5}$$

Following Anderson and Bedre-Defolie (2021), we make the assumption that each third-party seller is infinitesimal in a sense that he takes the Aggregate as given when setting his price. As a result, maximisation of (5) yields:

$$p(\tau) = \frac{c}{1-\tau} + \mu. \tag{6}$$

Intuitively, each seller prices at marginal cost, adjusted by the level of commission fees τ, plus a mark-up determined by the level of differentiation μ. Given the symmetry of each seller, they all set the same price and earn profit $\pi(p(\tau), \tilde{s}^e(m), A)$.

3.2 Free entry process

Sellers make their decision to enter the marketplace and launch the production process at cost k by anticipating their profit on the platform. Given τ and m, the expected pay-off of doing so is given by

$$\pi^{prod} = (1-\lambda m)\cdot \pi(p(\tau), \tilde{s}^e(m), A) + \lambda m \cdot 0 - k. \tag{7}$$

There is a probability λm that sellers end up being of type-H after production launch and screened out of the platform at entry, thus earning zero profit. With the remaining probability, sellers will be able to enter the platform and earn $\pi(p(\tau), \tilde{s}^e(m), A)$. These are sellers of both types to the extent that $m < 1$. Free entry on the market thus determines the equilibrium value of the Aggregate, which we denote $\tilde{A}(\tau, m)$, determined by $\pi^{prod} = 0$:

$$\tilde{A}(\tau, m) = \frac{(1-\lambda m)\mu(1-\tau)}{k}V(p(\tau), \tilde{s}^e(m)). \tag{8}$$

Sellers enter the product market at cost k, which induces the Aggregate value to increase gradually, reducing each seller's individual demand and profit, up to the point $\tilde{A}(\tau, m)$ where sellers make zero expected profit at entry. Note that this free entry equilibrium Aggregate value is independent of the mass M and price p_A of platform's first-party products. The degree of platform's vertical integration thus does not affect the overall market size *ceteris paribus*.

The mass M of first-party products however affects the ratio between first- and third-party products available on the marketplace, with a fixed market size $\tilde{A}(\tau, m)$. If a mass n^{entry} of sellers found it profitable to enter the market, only a fraction $(1 - \lambda m)$ are able to operate after the screening process. For a given mass M and price p_A of first-party products, the equilibrium mass of active sellers $n^{active} = (1 - \lambda m)n^{entry}$, is thus determined by the equation $\tilde{A}(\tau, m) = \int_0^M V(p_{Aj}, s_A)dj + n^{active} \cdot V(p(\tau), \tilde{s}^e(m)) + 1$. Thus, given p_A, τ and m, a higher mass of platform's product M lowers the room for profitable third-party entry on the platform. Note also that any increase in $\tilde{A}(\tau, m)$ raises seller entry n^{entry} and consequently the mass of active sellers n^{active}.

3.3 Market size

We now turn to analyse how does the free entry market size $\tilde{A}(\tau, m)$, and analogously seller entry, is affected by platform's choices of screening intensity m and the commission fees τ.

Screening intensity Differentiating Equation (8) with respect to m leads to:

$$\frac{d\tilde{A}}{dm}(\tau, m) = \frac{\lambda(1-\tau)}{k}\Big(\underbrace{\frac{(1-\lambda)(s^H - s^L)}{1-\lambda m}D}_{\substack{\text{Increased attractiveness} \\ \text{due to reduced expected risk}}} \quad \underbrace{- \quad \mu}_{\substack{\text{Higher proba.} \\ \text{of being screened-out}}} \Big)V(p(\tau), \tilde{s}^e(m)) \tag{9}$$

An increase in screening intensity has two opposite effects on sellers' incentives to enter the market. On the one hand, it raises the probability of being screened-out of the platform at entry, if the seller end-up being of type H. On the other hand, for sellers who managed to pass the screening process of the platform, with a probability of 1 for type-L sellers and $(1 - m)$ for type-H, higher screening intensity lowers consumers' anticipated risk of buying from a third-party seller due to the lower chance of facing a seller of type-H. Platform's screening, by influencing consumer's expectations, thus acts as a positive demand shifter for active sellers. The first effect, negative, is proportional to the mark-up μ as a measure of their profit on the platform. The second effect, positive, is proportional to $(s^H - s^L)D$, i.e. the rate of decrease of consumers' risk expectation with respect to m. Thus, we have the following:

Lemma 1. *There exists a screening intensity threshold $\tilde{m} \in [0,1]$ such that the market size $\tilde{A}(\tau, m)$ increases with screening intensity m if $m > \tilde{m}$, and decreases otherwise.*

Proof. We have $\frac{d\tilde{A}}{dm}(\tau, m) > 0 \quad \text{if} \quad m > \frac{\mu-(1-\lambda)(s^H-s^L)D}{\lambda\mu}$.
We then define $\tilde{m} = \max\Big\{0, \min\big\{\frac{\mu-(1-\lambda)(s^H-s^L)D}{\lambda\mu}, 1\big\}\Big\}$. □

Commission fees Differentiating Equation (8) with respect to τ yields:

$$\frac{d\tilde{A}}{d\tau}(\tau, m) = -\frac{(1-\lambda m)p(\tau)}{k} V(p(\tau), \tilde{s}^e(m)) < 0. \tag{10}$$

As in Anderson and Bedre-Defolie (2021), an increase in the fees τ reduces the profitability of entry on the market, through more of sellers' profit extracted by the platform, in conjunction with higher prices set by sellers.

Moreover, by computing the cross derivative of $\tilde{A}(\tau, m)$, we have:

$$\frac{d^2\tilde{A}}{dmd\tau}(\tau, m) = -\frac{\lambda p(\tau)}{k\mu}\left(\frac{(1-\lambda)(s^H-s^L)}{1-\lambda m}D - \mu\right)V(p(\tau), \tilde{s}^e(m)) \tag{11}$$

It becomes apparent from equation (11) that if $m > \tilde{m}$, the shrink in market size induced by a marginal increase in τ is larger for higher levels of screening intensity. The decline is however lower in the region $m < \tilde{m}$. Intuitively, in the region $m > \tilde{m}$, higher screening intensity implies higher expected revenue on the market for a given τ. Given that the platform extracts a proportion τ of sellers' revenue, the marginal decrease in market size, and analogously in seller entry, is larger for higher levels of screening. The reverse is true for $m < \tilde{m}$. As a result, we have:

Lemma 2. *An increase in commission fees τ lowers entry on the platform. This market size reduction effect is stronger for higher levels of screening conducted by the platform if $m > \tilde{m}$.*

Therefore, both instruments available to the platform τ and m affect the profitability of entry on the marketplace; differently however. It increases in screening intensity if m is large enough ($m > \tilde{m}$) and decreases in commission fees τ. Moreover, the marginal decrease in market size induced by higher fees is more pronounced for high levels of screening intensity if $m > \tilde{m}$.

4 Platform's choices and vertical integration

In this section, we start by analysing platform's optimal pricing for its first-party products. We then study platform's optimal choices of commission fees and screening intensity, to further investigate how does these combined choices are affected by different degree of vertical integration of the platform as measured by the mass M of first-party products.

4.1 First-party products' pricing

After having set a given level of screening m and a commission fee τ, the platform's profit out of all sales made on the marketplace is given by:

$$\Pi^{sales} = \tau p(\tau)\frac{\tilde{A}(\tau,m) - \int_0^M V(p_{Aj}, s^A)dj - 1}{\tilde{A}(\tau,m)} + \int_0^M (p_{Aj} - c_A)\frac{V(p_{Aj}, s^A)}{\tilde{A}(\tau,m)}dj \tag{12}$$

The platform has two sources of revenue. It earns a margin $(p_{Aj} - c_A)$ out of sales of the mass M of first-party products j, with individual demand $V(p_{Aj}, s^A)/\tilde{A}(\tau,m)$. It also collects commission fees τ on the revenue $p(\tau)$ of every third-party transaction, of a total mass $(\tilde{A}(\tau,m) - \int_0^M V(p_{Aj}, s^A)dj - 1)/\tilde{A}(\tau,m)$. Given that the free entry aggregate value is independent of p_{Aj}, as in Anderson et al. (2020), the optimal platform's pricing formula is the same for all first-party products j and is given by:

$$p_{Aj}(\tau) = c_A + \mu + \tau p(\tau) \equiv p_A(\tau) \tag{13}$$

First-party products pricing rule is composed of marginal cost plus the mark-up μ, similar to third-party products, plus an additional component $\tau p(\tau)$. This last term represents the opportunity cost of lowering p_{Aj}, which implies a redirection of third-party demand towards its own product j, and thus leads to a loss in commission revenue.

4.2 Choice of commission fees

Given first-party products pricing rule, platform's profit at Stage 1, where it sets its screening intensity along with the commission fee, is:

$$\Pi(\tau,m) = \tau p(\tau)\frac{\tilde{A}(\tau,m) - MV(p_A(\tau), s^A) - 1}{\tilde{A}(\tau,m)} + (\mu + \tau p(\tau))\frac{MV(p_A(\tau), s^A)}{\tilde{A}(\tau,m)} - K(m) \tag{14}$$

Thus, as in Anderson and Bedre-Defolie (2021), optimal commission fees τ^* satisfies[11]:

$$(\tau^* p(\tau^*))'\left(\frac{\tilde{A}(\tau^*,m) - MV(p_A(\tau^*), s^A) - 1}{\tilde{A}(\tau^*,m)}\right) + \frac{\tau^* p(\tau^*) - \mu MV(p_A(\tau^*), s^A)}{\tilde{A}(\tau^*,m)^2}\frac{d\tilde{A}}{d\tau}(\tau^*,m) = 0 \tag{15}$$

[11]We refer to Anderson and Bedre-Defolie (2021) for the proof of the existence of an interior solution τ^* and the concavity of platform's profit with respect to τ.

The first term represents the increase in platform revenue induced by an increase in τ, keeping constant the market size. The second term represents the loss in profit from seller exit due to higher commission rate. The exit of a seller implies a decrease in commission revenue, but also a redirection of demand towards all active sellers, including platform's own products. The net profit loss induced by market size contraction is given by the term $(\tau^* p(\tau^*) - \mu M V(p_A(\tau^*), s^A))/\tilde{A}(\tau^*, m)^2$. To see why, consider the exit of a single third-party seller following an increase in τ. Denoting $V = V(p(\tau), \tilde{s}^e(m))$, and respectively $V_A = V(p_A(\tau), s^A)$, we have $d\tilde{A}/d\tau = -V$. The lost revenue on that single exit is $\tau p(\tau) \cdot V/\tilde{A}$. This exiting seller's previous consumers then redirect towards either platform's products, third party products or the outside options. The platform products demand increases by $V \cdot MV_A/\tilde{A}^2$, each carrying a mark up $\mu + \tau p(\tau)$, and third-party products' demand rises by $n \cdot V^2/\tilde{A}^2$ worth $\tau p(\tau)$ per unit to the platform. Adding up these gains and losses leads to a profit decrease of

$$\begin{aligned}
&\frac{V}{\tilde{A}}\left(\tau p(\tau)\left(1 - n\frac{V}{\tilde{A}}\right) - (\mu + \tau p(\tau))\frac{MV_A}{\tilde{A}(\tau, m)}\right) \\
=&\frac{V}{\tilde{A}^2}\left(\tau p(\tau)(\underbrace{\tilde{A} - nV - MV_A}_{=1}) - \mu M V_A\right)
\end{aligned}$$

It is clear that the higher the mass M of products the platform's first-party products, the more will the platform benefit from the redirection of exiting seller demand. This demand redirection effect towards first-party products is however always dominated by the loss in commission revenues from third-party seller exit at equilibrium, since we must have $\tau^* p(\tau^*) > \mu M V(p_A(\tau^*), s^A)$ for τ to satisfy the optimality condition given in Equation (15).

Regarding the overall effect of an increase in platform integration on commission fees, we have the following:

Lemma 3. *For a given level of screening intensity m, an increase in platform's vertical integration M leads to an increase in the commission fees. Moreover, at equilibrium, the equilibrium commission fee satisfies $\tau^* p(\tau^*) > \mu M V(p_A(\tau^*), s^A)$.*

Proof. Equation (15) can be written as: $\tau^* p(\tau^*))'\left(\frac{\tilde{A}-1}{\tilde{A}}\right) + \frac{\tau^* p(\tau^*)}{\tilde{A}^2}\frac{d\tilde{A}}{d\tau} + \frac{\mu\tau^*}{1-\tau^*}\frac{MV_A}{\tilde{A}} = 0$.

Differentiating this last equality leads to $\frac{d\tau^*}{dM} = -\frac{\frac{\mu\tau^*}{1-\tau^*}\frac{V_A}{\tilde{A}}}{\frac{d^2\Pi}{d\tau^2}} > 0$. □

Lemma 3 reflects one of the main insight present in Anderson and Bedre-Defolie (2021) regarding regarding platform's commission fees incentives with respect to their degree ofvertical integration. On the one hand, a higher mass of first-party products M implies a lower mass of third-party sales, i.e. $(\tilde{A}(\tau^*, m) - MV(p_A(\tau^*), s^A) - 1)$ is lower, which reduces the benefits of increasing τ for a given market size. On the other hand, as discussed earlier, the platform benefits from the exit of sellers induced by higher commission fee as demand is partly redirected towards its own products. This last effects however always dominates, which leads a highly vertically integrated platform to set a high level of commission fees. Note however that this result in our model is only partial, since it takes the level of screening intensity as given.

Regarding the effect of platform screening on optimal commission fees, we find that:

Proposition 1. *In the region $m > \tilde{m}$, an increase in screening intensity conducted by the platform leads to higher commission fees.*

Proof. By computing the cross derivative of platform's profit with respect to τ and m, we have: $\frac{d^2\Pi}{d\tau dm} = \frac{\lambda\left(\frac{(1-\lambda)(s^H - s^L)D}{1-\lambda m} - \mu\right)}{(1-\lambda m)\mu\tilde{A}}\left(\frac{c(1+\tau(2-\tau))}{(1-\tau)^2} + \frac{c^2\tau}{\mu(1-\tau)^3} + (1+\tau)\mu + \frac{\tau\left(\tau p(\tau) - \mu MV_A\right)}{1-\tau}\right)$. Given Lemma 3, it is positive whenever $m > \tilde{m}$ and negative otherwise. □

Screening intensity and commission fees are found to be strategic complements to the extent that market size is increased as a result of higher screening intensity ($m > \tilde{m}$). Intuitively, in that region, the additional mass of third-party sellers on the platform raises platform's marginal benefit of increasing commission fees for a given size of third-party segment (first term in equation (15)). The effect is more ambiguous regarding the marginal revenue loss of higher commission fees (second term in equation (15)). On the one hand, it makes market size to shrink more following a marginal increase in τ by lemma 2, but on the other hand, greater market size lowers the net profit loss induced by market size contraction $(\tau^* p(\tau^*) - \mu MV(p_A(\tau^*), s^A))/\tilde{A}(\tau^*, m)^2$. Overall, we find that the latter effect is dominated by the other two, leading the platform to set higher fees for higher levels of screening if $m > \tilde{m}$.

4.3 Choice of screening intensity

We now turn to investigate platform's optimal screening choices. Variations of platform's profit given by equation (14) with respect to m is

$$\left(\frac{\tau p(\tau) - \mu MV(p_A(\tau), s^A)}{\tilde{A}(\tau, m)^2}\right)\frac{d\tilde{A}}{dm}(\tau, m) - K'(m) \tag{16}$$

By lemma 3, which states that optimal fees always satisfy $\tau p(\tau) > \mu MV(p_A(\tau), s^A)$, platform's profit is decreasing in $m < \tilde{m}$. Platform's incentives to invest in screening are however driven by its positive effect on seller entry, which is the case if $m > \tilde{m}$. As a result, we have:

Lemma 4. *A necessary condition for the platform to invest in screening $m > 0$ is $\tilde{m} < 1$.*

The positive demand shifter which benefits all active third-party sellers needs to dominate the entry-dissuading effect of screening for the platform to engage in a positive level of screening. As result, the platform is more likely to screen sellers in market characterized by a high level of differentiation μ, a large risk difference between seller types $s^H - s^L$ and a large potential damage D which all concur to a low $\tilde{m}$. We assume that this is the case in our setting by making the following simplifying[12] assumption:

Assumption 1. $\tilde{m} \leq 0$.

Further assuming the existence of an interior solution m^* maximising platform's profit, m^* is determined by

$$\Big(\frac{\tau p(\tau) - \mu M V(p_A(\tau), s^A)}{\tilde{A}(\tau, m^*)^2}\Big)\frac{d\tilde{A}}{dm}(\tau, m^*) = K'(m^*). \tag{17}$$

The platform balances the marginal benefits of a higher level of screening, manifested by the marginal profitability of market expansion, with the marginal investment cost.

Regarding platform's incentives to screen sellers in relation with the degree of vertical integration, we have the following:

Proposition 2. *For a given commission fee, an increase in platform's vertical integration leads to lower investments in seller screening.*

Proof. Differentiating Equation (17) yields: $\frac{dm^*}{dM} = \frac{\mu V_A \frac{d\tilde{A}}{dm}}{\tilde{A}^2 \frac{d^2\Pi}{dm^2}} < 0$ □

Entry of new sellers induced by higher screening implies a business-stealing effect with regard to incumbent sellers. This negative effect is particularly strong for the platform if it is highly present in the marketplace, i.e. a high M. The platform is thus less willing to engage in screening the more products it sells, for a given level of commission fee.

Furthermore, note that given the strategic complementarity between τ and m as shown above, the platform will set a higher screening intensity following an increase in commission fees.

4.4 Vertical integration

We have shown that commission fees and screening intensity both affect market size, differently however, and are strategically used by the platform to control third-party entry, in particular

[12]Our analysis remain valid for the case where $0 < \tilde{m} < 1$ under the following condition. Denote τ_0^* the optimal commission fee if $m = 0$, and τ_i^* the one if the platform sets $m^* \in [\tilde{m}, 1]$ as defined in equation (17). Given that platform's profit is decreasing in $m \in [0, \tilde{m}]$, the platform will choose m^* if $\Pi(\tau_i^*, m^*) > \Pi(\tau_0^*, 0)$.

in relation with its degree of vertical integration M. We now turn to investigate the platform's optimal combined use of these tools following a change in M.

Commission fees Equation (15) defining the optimal commission fee, evaluated at optimal screening intensity $m^*(\tau^*, M)$, can be written as:

$$\frac{\partial \Pi}{\partial \tau}(\tau^*, m^*(\tau^*, M), M) = 0 \tag{18}$$

Total differentiating with respect to τ and M equation (18) yields:

$$\frac{\partial^2 \Pi}{\partial \tau^2} d\tau^* + \frac{\partial^2 \Pi}{\partial m \partial \tau}\Big(\frac{\partial m^*}{\partial \tau} d\tau^* + \frac{\partial m^*}{\partial M} dM\Big) + \frac{\partial^2 \Pi}{\partial \tau \partial M} dM = 0, \tag{19}$$

which further leads to:

$$\frac{d\tau^*}{dM} = -\frac{\overbrace{\frac{\partial^2 \Pi}{\partial m \partial \tau}\frac{\partial m^*}{\partial M}}^{-} + \overbrace{\frac{\partial^2 \Pi}{\partial \tau \partial M}}^{+}}{\underbrace{\frac{\partial^2 \Pi}{\partial m \partial \tau}\frac{\partial m^*}{\partial \tau}}_{+} + \underbrace{\frac{\partial^2 \Pi}{\partial \tau^2}}_{-}}. \tag{20}$$

One can see from the above equation that the positive term at the numerator and the negative one at the denominator together stand for the direct effect of an increase in M on optimal commission fees, keeping constant the level of screening. Considering only these two terms comes down to Anderson and Bedre-Defolie (2021), and lead to a monotonous positive relationship between commission fees and platform's vertical integration. Enabling the platform to adapt its optimal level of screening following a change in M introduces the two additional terms in equation (20), which are proportional to $\frac{\partial^2 \Pi}{\partial m \partial \tau}$. Given proposition 1, τ and m are found to be strategic complements at the optimal level of screening ($m^* > \tilde{m}$), which leads a platform engaging in screening to set higher commission fees as compared to one which does not, and makes the relationship between commission fees and vertical integration a priori ambiguous. Indeed, an increase in M lowers platform's incentives to invest in screening, which acts as a force driving down commission fees. This effect is represented by the negative term at the numerator in equation (20). Strategic complementarity is also at play for the positive term at the denominator, which accounts for the feedback variations in screening intensity following a change in commission fees. Note that if τ and m were strategic substitutes, i.e. $\frac{\partial^2 \Pi}{\partial m \partial \tau} < 0$, then an increase in M would unambiguously lead to a higher level of commission fees.

Due to computational complexity, we are unable to provide exact theoretical analysis of equation (20). We however show through simulations of the model that there exist parameter values such that the relationship between commission fees and vertical integration is negative, in sharp contrast with Anderson and Bedre-Defolie (2021).

Proposition 3. *If a platform invests in seller screening, it is possible to observe a negative relationship between its optimal level of commission fees and its degree of vertical integration.*

In this simulation example, we model the fixed cost of screening as quadratic: $K(m) = \gamma m^2$, with $\gamma > 0$, and we use parameter values as described in Table (1). With such values, the good is valued at $v = 1.5$ by consumers, and can lead to consumer damage $D = 2$. There is an initial proportion of 4% of type-H sellers, who have a probability of consumer damage of 0.6, and the remaining type-L sellers have a risk of damage occurrence of 0.01. First-party products have the same marginal cost than third-party ones ($c = c_A = 0.5$) and present the same risk as type-L products ($s_L = s_A = 0.01$). Moreover, we have $\tilde{m} = 0$, such that we have $\frac{d\tilde{A}}{dm}(\tau, m) > 0$ for all $m \in [0, 1]$.

Parameter	Value	Parameter	Value	Parameter	Value
λ	0.04	D	2	v	1.5
s_H	0.6	c, c_A	0.5	μ	0.1
s_L , s_A	0.01	k	0.02	γ	0.025

Table 1: Parameters values used for simulation results of Figures (1), (2) and (3).

In the left panel of Figure 1, we have have plotted the optimal $\tau^*(M)$, as defined in equation (15) at the optimal point $m^*(\tau^*(M), M)$ defined in equation (17). Analogously, we have plotted $m^*(M)$ in the right panel. We observe that the optimal screening curve is flat and equal to is maximum value ($m^*(M) = 1$) for $M \lesssim 1.1$, and then decreases in M. It reaches $m^* = 0$ at the point $M^{max} \approx 2.06$, which corresponds to the vertical integration value above which the platform no longer welcomes third-party sellers, as can be seen in the left panel of Figure 2 where we have plotted $n^*(\tau^*(M), m^*(M))$ implicitly defined in equation (8). At M^{max}, platform's presence in the market is such that it doesn't find it profitable to accommodate third-party sellers, and *de facto* becomes a pure reseller. As for the the variation of $\tau^*(M)$, we observe that it is increasing in M in the range where the platform sets a maximum level of screening ($M \lesssim 1.1$), and then decreasing up to M^{max}.

These results can be interpreted as follows. For low enough degree of vertical integration, i.e. $M \lesssim 1.1$, the platform optimally sets a maximum level of screening: $m^*(M) = 1$. The business-stealing effect is small enough, as compared to screening costs, such that the platform finds

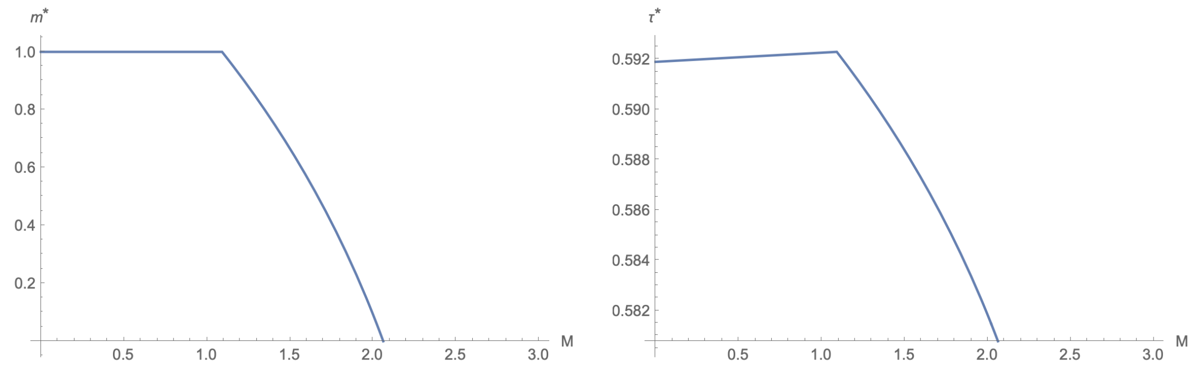

Figure 1: Variations of optimal screening intensity $m^*(M)$ (left panel) and commission fees $\tau^*(M)$ (right panel) with respect to M.

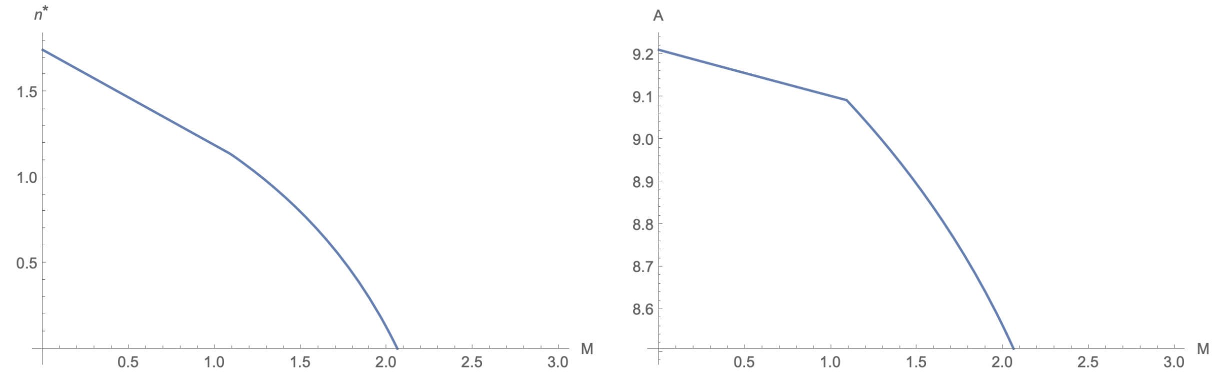

Figure 2: Variations of equilibrium mass of third-party seller $n^*(\tau^*(M), m^*(M))$ (left panel) and Aggregate value $\tilde{A}(\tau^*(M), m^*(M))$ (right panel) with respect to M.

it optimal to accommodate entry by a maximum level of screening to benefit from additional commission revenues. Given that $m^*(M) = 1$ on this range, strategic complementarity between the two instruments is not at play in the observed increase in commission fees on the same region. Instead, the mechanism described by lemma 3 is at play: as M increases, the platform benefits more from a redirection of demand of exiting sellers towards its own first-party products, which induces it to set higher τ.

For $M \gtrsim 1.1$, the marginal benefits of accommodating entry through maximum screening becomes lower than $K'(1)$ because of the larger business-stealing effect of new entrants. The platform thus invests less in screening in order to match these lower marginal benefits with the corresponding marginal cost $K'(m)$. It decreases up to $m^* = 0$ at the point $M = M^{max}$ where the platforms becomes a pure reseller where there is no benefits of screening investment. This drop in m^* causes the optimal commission fee to decrease given their strategic complementarity. Thus, in this range, the incentive of the platform to set higher commission fees, as shown in Anderson and Bedre-Defolie (2021), is dominated by the indirect effect through the decrease in screening intensity. We find the dominance of the strategic complementarity effect on optimal commission fees, along with a decreasing screening intensity in M, to be robust over a wide range of parameter values to the extent that the platform finds it profitable to welcome third-party sellers on its marketplace.

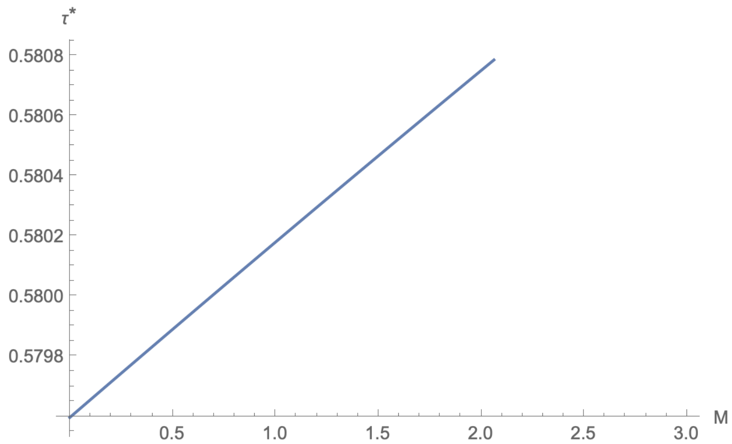

Figure 3: Variations of optimal commission fees $\tau^*(M)$ with respect to M restricted to $m = 0$.

Finally, for illustration purposes, we plotted in Figure 3 the optimal fee level $\tau^*_{m=0}(M)$ that would be set by a platform with no access to screening technology. In comparison with the right panel of Figure 1, we observe that $\tau^*_{m=0}(M)$ is increasing in M, and is such that $\tau^*_{m=0}(M) < \tau^*(M)$ for all $M < M^{max}$.

Screening intensity Using similar reasoning, variations of optimal screening intensity with respect to M are given by:

$$\frac{dm^*}{dM} = -\frac{\overbrace{\frac{\partial^2 \Pi}{\partial m \partial \tau}\frac{\partial \tau^*}{\partial M}}^{+} + \overbrace{\frac{\partial^2 \Pi}{\partial m \partial M}}^{-}}{\underbrace{\frac{\partial^2 \Pi}{\partial m \partial \tau}\frac{\partial \tau^*}{\partial m}}_{+} + \underbrace{\frac{\partial^2 \Pi}{\partial m^2}}_{-}}. \tag{21}$$

The two negative terms at the numerator and denominator of Equation (21) stand for the effect of an increase in M on optimal screening level, keeping constant the commission fees as in proposition 2. Enabling it to adapt to its optimal value for every level of vertical integration makes $m^*(M)$ *a priori* ambiguous. We were however not able to find any set of parameter values such that the indirect effects through commission fees dominates and makes screening intensity increasing in vertical integration, along with an increase in commission fees.

5 Welfare and platform's screening choice

In this section, we first assess the degree of divergence between the platform's screening decision and the one of a regulator aiming at maximising total welfare. We finally analyse the potential impact of a regulatory intervention that aims to minimize this discrepancy.

5.1 Welfare maximisation

We define total welfare $W(\tau, m)$ as the sum of platform's profit, third-party seller's profits and consumer's surplus. The sum of third-party sellers' profit is zero at equilibrium for all $m \in [0, 1]$: while active sellers earn strictly positive profits, free entry in the market ensures that the total loss incurred by sellers of type-H who end up being screened out by the platform is compensated for. As a result, we have:

$$W(\tau, m) = \Pi(\tau, m) + CS(\tau, m). \tag{22}$$

As shown in Anderson et al. (2020), consumer's surplus is given by $CS(\tau, m) = \ln \tilde{A}(\tau, m)$. Therefore, assuming the existence of an interior solution m^{W*} maximising total welfare, m^{W*} is determined by

$$\left(\frac{1}{\tilde{A}(\tau, m^{W*})} + \frac{\tau p(\tau) - \mu MV(p_A(\tau), s^A)}{\tilde{A}(\tau, m^{W*})^2} \right) \frac{d\tilde{A}}{dm}(\tau, m^{W*}) = K'(m^{W*}). \tag{23}$$

Comparison of equation (23) with platform's optimality condition given by equation (17) leads to the following:

Proposition 4. *For all degree of vertical integration, the platform under-invest in seller screening as compared to social optimum.*

Under-investment in screening conducted by the platform results from the fact that it doesn't fully internalise consumers' surplus. As consumer value the amount of variety available on the marketplace, the regulator sets a higher screening intensity than the platform so as to enhance third-party seller entry.

5.2 Screening regulation

We now turn to discuss the effect on consumers' surplus of a regulation mandating the platform to set higher screening intensity than its profit-maximising level m^*. To begin with, note that if the regulator observes $m^* = 0$, that is the platform doesn't engage in screening spontaneously, it is likely that market characteristics are such that screening lowers entry: $\tilde{m} > 1$.[13] In this case, mandating higher level of screening unambiguously lowers consumers' and total welfare.

Going back to market situations characterized by Assumption 1, an increase in screening intensity above m^*, letting the platform the ability to adapt the commission fees it charges to seller, yields:

$$\left.\frac{dCS}{dm}\right|_{\tau=\tau^*,m=m^*} = \frac{1}{\tilde{A}(\tau^*, m^*)}\left(\underbrace{\frac{\partial \tilde{A}}{\partial m}(\tau^*, m^*)}_{+} + \underbrace{\frac{\partial \tilde{A}}{\partial \tau}(\tau^*, m^*) \cdot \frac{d\tau^*}{dm}}_{-}\right). \tag{24}$$

Given the strategic complementarity between commission fees and screening intensity from the platform's view point, the platform will respond to a regulated increase in m by higher commission fees. A regulation mandating the platform to set higher screening intensity may thus lower consumer surplus depending on the size of the increase in commission fees.

6 Conclusions and policy implications

Theoretical contributions In this paper, we studied the incentives of a platform in a Gatekeeper position to screen third-party sellers who may sell harmful and illegal goods to consumers. These sellers operate in a globalised supply chain leading to uncertain product quality. We investigated to the relationship between platform's level of vertical integration and screening choices, along with its ability to charge commission fees to sellers. To do so, we extended the model of Anderson and Bedre-Defolie (2021) by enabling the hybrid platform, competing with monopolistic sellers, to invest in a technology that detects illegal products and remove them from the marketplace.

We find that platform's screening has an ambiguous effect on the entry on the marketplace of third-party sellers, and thus on product variety available to the platform. We show that a condition for the platform to engage in screening is that it accommodates entry, through lower consumer risk expectations of buying third-party products. This occur in markets characterised by a high level of product differentiation and a large damage risk difference between high- and low-risk sellers. Moreover, we find that a more integrated platform sets a lower screening intensity because it suffers from a greater *business stealing* effect, for a given level of commission fees.

[13] This can also be the case if $0 < \tilde{m} < 1$. The other possible reason to observe zero platform screening is too high screening costs $K(m)$, in such case a regulated increase in screening raises consumers' surplus and decrease platform's profit, having ambiguous impact on total welfare.

We further show that a platform investing in screening enables it to charge higher commission fees to sellers. This strategic complementarity between the two instruments available to the platform has important implications when it comes to investigate the relationship between platforms combined choices and its degree of vertical integration. Indeed, the ability of a platform to screen users generates a new effect driving down commission fees as a result of more vertical integration, through lower screening intensity, which can dominate the positive effect found in Anderson and Bedre-Defolie (2021). We show through simulations that this is the case for some range of parameter values.

Although the platform spontaneously engages in screening, it invests too little as compared to social optimum because it doesn't fully internalise consumers' surplus. Moreover, any regulation mandating a higher level of screening has an ambiguous effect on consumers' surplus, because the platform responds by an increase in commission fees leading to potentially less product variety on the marketplace.

Policy implications Our findings hold significant relevance in the implementation of the Digital Services Act in Europe, which aims to regulate platform conduct for a safer online environment. Specifically, we demonstrate that in the absence of strict regulations, platforms may voluntarily engage in product screening. However, we emphasize that the degree of vertical integration matters in these incentives, with highly integrated platforms investing less in screening. Moreover, our study highlights that screening results in higher commission fees set by the platform. Therefore, policymakers should consider this when mandating a certain level of screening, as it may negatively impact consumers' surplus.

References

Anderson, Simon P and Özlem Bedre-Defolie, "Hybrid platform model," *CEPR Discussion Paper No. DP16243*, 2021.

_ **, Nisvan Erkal, and Daniel Piccinin**, "Aggregative games and oligopoly theory: short-run and long-run analysis," *The RAND Journal of Economics*, 2020, *51* (2), 470–495.

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

Caillaud, Bernard and Bruno Jullien, "Chicken & egg: Competition among intermediation service providers," *RAND journal of Economics*, 2003, pp. 309–328.

Casner, Ben, "Seller curation in platforms," *International Journal of Industrial Organization, 72:102659*, 2020.

Choi, Jay Pil and Doh-Shin Jeon, "Platform design biases in two-sided markets," *The RAND Journal of Economics. Forthcoming.*, 2022.

Eliaz, Kfir and Ran Spiegler, "A simple model of search engine pricing," *The Economic Journal 121 (556): F329–F339*, 2011.

Etro, Federico, "Device-funded vs ad-funded platforms.," *International Journal of Industrial Organization, 75:102711*, 2021.

_ , "Product selection in online marketplaces," *Journal of Economics Management Strategy, Vol. 30, pp. 614–637*, 2021.

_ , "Hybrid Marketplaces with Free Entry of Sellers," 2022.

Hagiu, Andrei, Julian Wright, and Tat-How Teh, "Should platforms be allowed to sell on their own marketplaces?," *The RAND Journal of Economics*, 2022, *53*, 297–327.

Hay, Bruce and Kathryn E Spier, "Manufacturer liability for harms caused by consumers to others," *American Economic Review*, 2005, *95* (5), 1700–1711.

Hervas-Drane, Andres and Sandro Shelegia, "Retailer-led marketplaces," 2022.

Hua, Xinyu and Kathryn E Spier, "Holding platforms liable," *HKUST Business School Research Paper*, 2021, (2021-048).

Hunold, Matthias, Ulrich Laitenberger, and Guillaume Thébaudin, "Bye-box: An Analysis of Non-Promotion on the Amazon Marketplace," *CRED WORKING PAPER No 2022-4*, 2022.

Jeon, Doh-Shin, Yassine Lefouili, and Leonardo Madio, "Platform liability and innovation," *Available at SSRN 3945132*, 2021.

Johnen, Johannes and Robert Somogyi, "Deceptive Features on Platforms," *CEPR Discussion Paper No. DP16175*, 2022.

Kraakman, Reinier H, "Gatekeepers: the anatomy of a third-party enforcement strategy," *The Journal of Law, Economics, and Organization*, 1986, *2* (1), 53–104.

Lam, Wing Man Wynne and Xingyi Liu, "Dancing with rivals: How does platform's information usage benefit independent sellers?," *European Journal of Operational Research*, 2022.

Lefouili, Yassine and Leonardo Madio, "The economics of platform liability," *European Journal of Law and Economics*, 2022, *53* (3), 319–351.

Liu, Yi, Pinar Yildirim, and John Zhang, "Social Media, Content Moderation, and Technology," 2021.

Madio, Leonardo and Martin Quinn, "Platform design biases in two-sided markets," 2021.

Madsen, Erik and Nikhil Vellodi, "Insider imitation," 2021.

Mattiacci, Giuseppe Dari and Francesco Parisi, "The cost of delegated control: vicarious liability, secondary liability and mandatory insurance," *International Review of Law and Economics*, 2003, *23* (4), 453–475.

Pitchford, Rohan, "How liable should a lender be? The case of judgment-proof firms and environmental risk," *The American Economic Review*, 1995, pp. 1171–1186.

Polinsky, A Mitchell and William P Rogerson, "Products liability, consumer misperceptions, and market power," Technical Report, National Bureau of Economic Research 1982.

Rochet, Jean-Charles and Jean Tirole, "Platform competition in two-sided markets," *Journal of the european economic association*, 2003, *1* (4), 990–1029.

— **and** — , “Two-sided markets: a progress report,” *The RAND journal of economics*, 2006, *37* (3), 645–667.

Shopova, Radostina, “Private labels in marketplaces,” *Vienna Economics WP 2104*, 2021.

Spence, Michael, “Consumer misperceptions, product failure and producer liability,” *The Review of Economic Studies*, 1977, *44* (3), 561–572.

Teh, Tat-How, “Platform governance,” *American Economic Journal: Microeconomics*, 2022, *14* (3), 213–54.

Zennyo, Yusuke, “Platform encroachment and own-content bias,” *The Journal of Industrial Economics*, 2022, *70* (3), 684–710.

— , “Should Platforms be Held Liable for Defective Third-Party Goods?,” 2022.

Appendix

Incentives of the platform to take liability

Throughout the paper, we have assumed that the platform doesn't take liability for damages caused by judgement-proof sellers on consumers. In this section, we show that it never has incentives to do so at Stage 1 of the game, for both third-party products, as in Zennyo (2022b), and first-party ones.

Third-party liability Assume that the platform compensates consumers a share $\phi \in [0,1]$ of damage caused by third-party products bought on its marketplace.

Third-party seller i's demand becomes:

$$q_i = \exp\Big(\frac{v - p_i - (1-\phi)\tilde{s}^e(m)D}{\mu}\Big)A^{-1}, \tag{25}$$

leading to the same pricing formula as in equation (6), and the Aggregate value becomes:

$$\tilde{A}(\tau, m, \phi) = \frac{(1-\lambda m)\mu(1-\tau)}{k} V(p(\tau), (1-\phi)\tilde{s}^e(m)). \tag{26}$$

Platform's profit out of all sales made on the marketplace is given by:

$$\Pi^{sales} = (\tau p(\tau) - \phi \tilde{s}^e(m)D)\frac{\tilde{A}(\tau, m, \phi) - \int_0^M V(p_{Aj}, s^A)dj - 1}{\tilde{A}(\tau, m, \phi)} + \int_0^M (p_{Aj} - c_A)\frac{V(p_{Aj}, s^A)}{\tilde{A}(\tau, m, \phi)}dj, \tag{27}$$

leading to first-party products pricing formula

$$p_A = c_A + \mu + \tau p(\tau) - \phi \tilde{s}^e(m)D. \tag{28}$$

Taking liability decreases platform's net revenue of third-party sales and thus lowers opportunity cost of lowering first-party products' price.

Its profit at Stage 1 becomes:

$$\begin{aligned}\Pi(\tau, m, \phi) =& (\tau p(\tau) - \phi \tilde{s}^e(m)D)\frac{\tilde{A}(\tau, m, \phi) - MV(p_A(\tau), s^A) - 1}{\tilde{A}(\tau, m, \phi)} \\ &+ (\mu + \tau p(\tau) - \phi \tilde{s}^e(m)D)\frac{MV(p_A(\tau), s^A)}{\tilde{A}(\tau, m, \phi)} - K(m).\end{aligned}$$

Optimal commission fees τ^{l*} in this setting are determined by:

$$\left(\tau^{l*}p(\tau^{l*})\right)'\left(\frac{\tilde{A}(\tau^{l*},m,\phi)-MV(p_A(\tau^{l*}),s^A)-1}{\tilde{A}(\tau^{l*},m,\phi)}\right)+\frac{\tau^{l*}p(\tau^{l*})-\phi\tilde{s}^e(m)D-\mu MV(p_A(\tau^{l*}),s^A)}{\tilde{A}(\tau^{l*},m,\phi)^2}\frac{d\tilde{A}}{d\tau}(\tau^{l*},m,\phi)=0. \tag{29}$$

Moreover, we have:

$$\frac{\partial\Pi}{\partial\phi}(\tau,m,\phi)=-\,\tilde{s}^e(m)D\left(\frac{\tilde{A}(\tau,m,\phi)-MV(p_A(\tau),s^A)-1}{\tilde{A}(\tau,m,\phi)}\right)+\frac{\tau p(\tau)-\phi\tilde{s}^e(m)D-\mu MV(p_A(\tau),s^A)}{\tilde{A}(\tau,m,\phi)^2}\frac{d\tilde{A}}{d\phi}(\tau,m,\phi) \tag{30}$$

Using optimality condition (29), variations of platform's profit with respect to ϕ, given by equation (30), and evaluated at τ^{l*} and $m\in[0,1]$, simplifies to:

$$\frac{\partial\Pi}{\partial\phi}(\tau^{l*},m,\phi)=-\frac{\tau\mu\tilde{s}^e(m)D}{p(\tau)}\left(\frac{\tilde{A}(\tau^{l*},m,\phi)-MV(p_A(\tau^{l*}),s^A)-1}{\tilde{A}(\tau^{l*},m,\phi)}\right)<0 \tag{31}$$

As a result, the platform never has incentives to take liability for third-party products.

First-party liability We now turn to platform's incentives to take liability, of a share κ on damage caused by first-party products. Platform's profit out of product sales on its marketplace is:

$$\Pi^{sales}=\tau p(\tau)\frac{\tilde{A}(\tau,m)-\int_0^M V(p_{Aj},(1-\kappa)s^A)dj-1}{\tilde{A}(\tau,m)}+\int_0^M(p_{Aj}-c_A-\kappa s_A D)\frac{V(p_{Aj},(1-\kappa)s^A)}{\tilde{A}(\tau,m)}dj, \tag{32}$$

leading to first-party product price:

$$p_A=c_A+\kappa s_A D+\mu+\tau p(\tau) \tag{33}$$

First-party liability raises first-party products' marginal cost, which is fully passed on to consumers through higher price. As a result, consumers still pay the full damage cost, and the platform has no incentives to take first-party liability since its profit at Stage 1, given by

$$\Pi(\tau,m,\kappa)=\tau p(\tau)\frac{\tilde{A}(\tau,m)-MV(p_A(\tau),s^A)-1}{\tilde{A}(\tau,m)}+(\mu+\tau p(\tau))\frac{MV(p_A(\tau),s^A)}{\tilde{A}(\tau,m)}-K(m), \tag{34}$$

is independent on κ. Moreover, any regulation mandating platform to take liability on its own product $\kappa\in[0,1]$ would not change any of our results.