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Contents

Abstract

This thesis consists of three independent chapters and examines different antitrust issues related to gatekeeper platforms. Chapter I explores the vertical foreclosure problem in two-sided markets. In the context of Google's Accelerated Mobile Pages (AMP), Chapter 2 examines the issue of gatekeeper platforms' access to business users' data. Chapter 3 focuses on digital copyright and studies Google's behavior of using publishers' content to display short answers on search result pages.

The first chapter examines how the vertical integration of a monopolistic platform, which is characterized by bilateral cross-group network externalities, impacts its incentive to engage in downstream foreclosure. I focus on an environment where the platform and downstream sellers face uncertainty over the gains from trade at the contracting stage. As the random shock is non-contractible, contracting creates friction that distorts the platform's pricing structure. By contrast, vertical integration mitigates this problem by allowing the platform to incorporate the random shock in consumer pricing. Due to the interaction between transaction friction and cross-group network externalities, I find that vertical integration could reduce the platform's incentive of foreclosure.

The second chapter is joint work with Doh-Shin Jeon. We study how newspapers' adoption of AMP, a publishing format that enables instant loading of web pages in mobile browsers, changes data allocation and thereby newspapers' incentives to invest in quality journalism. The adoption of AMP allows Google to obtain consumer data from AMP articles and to combine it with other sources of consumer data to improve the targeting of the advertisements served by Google on other websites. Even if such data combination increases static efficiency, it can reduce dynamic efficiency when it lowers the ad revenue per newspaper traffic, thereby

reducing the quality of journalism. Newspapers face a collective action problem as a newspaper's adoption of AMP generates negative externalities to other newspapers through search ranking and data leakage. Google can leverage its market power in search and ad intermediation to induce newspapers to adopt AMP. We provide policy remedies.

The third chapter builds a theoretical model of divisible information goods to examine how a monopolistic search engine's use of snippets impacts content consumption and creation. By displaying snippets in the answer box on search result pages, the search engine unbundles the essential information and the supplemental information of articles. It, therefore, creates two opposite effects on publishers' incentive to invest in quality–the market size reduction effect and the elasticity variation effect. Its impact on social welfare is ambiguous. On the one hand, the answer box improves search efficiency by providing broader access to essential information and allowing inframarginal consumers to substitute essential information for the full article. On the other hand, it could cut down website traffic, lowering publishers' advertising revenue and incentive to invest in quality. I examine the impacts of different policies that enforce the search engine to pay for the use of snippets.

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Chapter 1

Vertical Integration and Foreclosure in Two-Sided Markets

1.1 Introduction

Two-sided platforms possess a special vertical relationship with their downstream sellers: on the one hand, like traditional upstream firms, they supply their service or infrastructure to downstream sellers who in turn meet with and sell final products to consumers; on the other hand, platforms also directly deal with consumers and charge them for access, a relationship absent under the traditional vertical structure. For example, Amazon supplies marketplace to third-party sellers at the same time collecting revenue from consumers via Prime; video game companies like Sony, Nintendo and Xbox supply API to developers while selling consoles to game players.

Furthermore, canonical two-sided market literature (Rochet and Tirole, 2003, 2006; Armstrong, 2006) argues that due to the cross-group network effect, it is crucial for platforms to optimize the pricing structure by taking into account how the change of price on one side will impact the participation of the other side. As platform's success hinges on getting both sides on board and its vertical structure differs from traditional upstream firms, one may presume that the economics of vertical integration and foreclosure in two-sided market could depart from traditional theories. I am thus concerned with following research questions: (1) what's the impact of vertical integration on a monopolistic platform's incentive to exclude a downstream seller? (2) how is the mechanism different from that in one-sided market?

These questions are particularly motivated by the heated debate around the recent vertical merger case between Time Warner and AT&T (US v. AT&T INC., 310 F. Supp. 3d 161, D.C. 2018). People worried that after the merger, AT&T as an Internet service provider (henceforth ISP) might favor the integrated content provider Time Warner over its downstream rivals such as YouTube and Netflix in online video streaming market by purposely degrading the connectivity to these rivals. For instance, the report from TechCrunch argues that [1]:

> "a slow degrading of the experience for YouTube or Netflix could be enough to move consumers to "preferred" content...While companies like Netflix and Alphabet have negotiated with the ISPs for years, the combination of these two news stories [merger between AT&T and Time Warner, and repeal of net neutrality] puts them in a significantly weaker negotiating position going forward."

Figure 1.1 depicts the competition relationship implied by the preceding arguments, which presents the special vertical structure of two-sided market. The fact that ISP is a two-sided platform connecting consumers and content providers casts doubts over TechCrunch's arguments. First, why would AT&T degrade connectivity to other independent streaming service providers? Due to positive cross-group network effect, the greater content variety consumers could enjoy the more they value the Internet. Not delivering the content consumers want to watch simply reduces the consumer's willingness-to-pay for Internet services. Second, even if there exists any incentive of foreclosure, why is it necessarily facilitated by vertical merger? And how the incentive of forelcosure will interact with cross-group network effects?

[1] https://techcrunch.com/2018/06/12/netflix-and-alphabet-will-need-to-become-isps-fast/ Also see the Economist: https://www.economist.com/leaders/2018/06/16/at-and-t-and-time-warner-are-cleared-to-merge

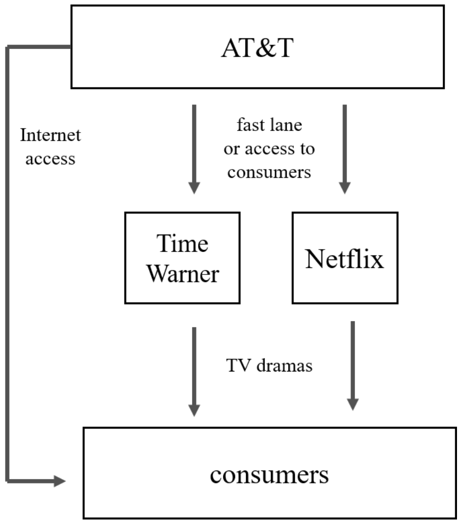


Figure 1.1: The Merger Case of AT&T and Time Warner

Building on these points, I extend the stylized two-sided market model developed by Rochet and Tirole (2003, 2006) and Armstrong (2006) to explore the implication of two-sidedness for a monopolistic platform's incentive to exclude a downstream seller. My objective is to show that the cross-group network effect brings a new efficiency channel of vertical integration that is unique to platforms and absent in counterparts of one-sided market.

The situation I have in mind is as follows: a monopolistic platform is an essential facility for interactions between a continuum of consumers and two sellers. The platform is characterized by bilateral cross-group network effects—the interaction between any consumer-seller pair generates benefits for both parties. Therefore the platform can extract surpluses from both sides through access charges. I assume the two sides arrive sequentially: the platform needs to contract with sellers over their entry to get established, and only after this it can price consumers.

The key assumption is that the platform and the two downstream sellers face uncertainty over the gains from trade at the contracting stage. Hence they decide terms based on expected profit. The realization of random shock to sellers' benefit per interaction is non-contractible which makes vertical integration relevant: when the platform supplies its facility to a seller through contracting, they need to agree upon a fixed royalty fee the seller pays for each of his interaction with consumers. By contrast, when integrated with a seller, the platform saves trouble of contracting by supplying its service internally. Then the platform could price consumers based on realized benefit the integrated seller obtains from interacting with a consumer, rather than a fixed royalty fee. In short, ownership structure determines the extent to which the consumer pricing responds to realizations of the random shock. My result shows that transaction friction will distort platform's pricing structure and this problem could be mitigated by vertical integration.

In such an environment, I assume the competition between sellers reduces the expected benefit they can obtain from interacting with a consumer, implying less surplus the platform can extract from sellers. This gives the platform an incentive to distort downstream competition by foreclosing a seller to prevent the seller-side surplus from being competed away. However, the platform faces a trade-off: although it might be profitable to engage in exclusion on the seller side, foreclosure will incur a revenue loss on consumer side as consumers have demands for both sellers' products. An immediate result is that for platforms exhibiting bilateral cross-group network externalities, the consumer side constitutes a constraint of curbing platform's tendency to engage in anti-competitive foreclosure on seller side.

Furthermore, in the main result of this paper, I show that vertical integration could change the monopolistic platform's incentive of foreclosure. Under vertical separation, because the platform prices consumers based on the fixed royalty fees paid by sellers, which in turn fixes the number of participating consumers, it only accounts for the first-order moment of the random shock at the contracting stage. By contrast, integrating with a seller allows the platform to partially internalize the random shock from seller side in consumer pricing. And the optimal participation rate of consumers will be increasing with the realization of random shock, which makes the contingent platform profit convex. This allows the integrated platform to additionally accounts for the second-order moment of random shock at the contracting stage, which is positive and proportional to the number of participating sellers. When the consumer demand is linear, contracting one additional seller amplifies the random shock's positive second-order effect, which in turn induces the integrated platform to engage in foreclosure less often than under vertical separation.

1.1.1 Related literature

The relationship between vertical integration and market foreclosure has been extensively studied by previous literature. Seminal papers include Hart and Tirole (1990), Ordover et al. (1990) and Segal (1999). Rey and Tirole (2007) and Fumagalli et al. (2018) provide excellent surveys on this research area. There are several recent applied work (Weeds, 2015; D'Annunzio, 2017; Crawford et al., 2018) examining content providers' exclusive provision of premium content to distributors in TV market, and they are related to this paper in terms of topic and the industry in question. All of these previous papers study vertical foreclosure issue under one-sided market structure.[2] So my paper contributes to this strand of literature by identifying a new mechanism behind the impact of vertical integration on foreclosure, which is unique to two-sided markets.

Nevertheless, Weeds (2015) and D'Annunzio (2017) provide useful benchmarks to understand the novelty of this paper's result. These two papers considered essentially identical situation in baseline models: a monopolistic programmer chooses whether to sell its premium content exclusively to two horizontally differentiated distributors located at the extremes of a Hotelling line. However, they obtained contrasting results: Weeds (2015) finds that in static case the vertically integrated programmer never refuses to supply the premium content to its downstream competitor, while D'Annunzio (2017) finds that the programmer always engages in exclusive dealing regardless of being independent or vertically integrated with a distributor. This is because D'Annunzio (2017) ruled out two-part tariff such that efficient allocation cannot be implemented. Up to this difference, both results show vertical integration doesn't impact the trade-off behind exclusive dealing decision in one-sided markets. By contrast, my model allows for two-part tariff, and the interaction between transaction friction and cross-group network effects makes vertical

[2]Weeds (2015) allows for two-sidedness of the downstream distributors by letting them partially financed by advertising, which only changes the intensity of downstream competition, So in her model the upstream firm is still one-sided and hence single monopoly profit theory holds. To the best of my knowledge, there are two papers explicitly addressing the problem that a network/platform strategically excludes its connected sellers: Chipty (2001) provides empirical evidence that a cable system is more inclined to foreclose rival cable networks after integration, without providing theoretical explanation; D'Annunzio and Russo (2015) considers a similar situation to this paper but has a different focus on how online advertising shapes Internet fragmentation.

integration impact the platform's incentive to engage in downstream foreclosure.

This paper also immediately connects to the pricing theories of two-sided market (Rochet and Tirole, 2003, 2006; Armstrong, 2006; Hagiu, 2006; Weyl, 2010) and the literature studying how platforms shape competition among sellers (see, e.g., Baye and Morgan, 2001; Karle et al., 2020). This paper contributes to this strand of literature by showing that the two-sidedness of platform not only complicates its pricing problem but also other strategic decisions such as vertical foreclosure.

The rest of the paper is organized as follows. In next section, I present the model setting. In Section 1.3, I derive the equilibrium results under different ownership structures and explain how incomplete contract under uncertainty creates transaction friction which distorts platform's pricing structure. In Section 1.4, I analyze the impact of partial vertical integration on the platform's incentive of foreclosure. And I explain why the mechanism behind the result is unique to two-sided market. Section 1.5 concludes.

1.2 Model Setting

1.2.1 Setup

The model is built upon the stylized two-sided market framework established by Rochet and Tirole (2003, 2006) and Armstrong (2006), and is characterized by bilateral cross-group externalities. It involves three groups of agents—a monopolistic platform, a continuum of heterogeneous consumers and two symmetric sellers $i = 1, 2$ who constitute *downstream market*.

Consider the platform an essential facility for consumers to enjoy sellers' goods. Each side's utility of joining the platform comes from interacting with the members on the other side. For consumers, they have unit demands for each seller's good. The unit valuation is identical across goods, while heterogeneous across consumers. Denote consumer utility per interaction β^c and assume it follows the distribution of $F(\cdot)$ over the interval $[l, h]$ with $-\infty \leq l < h \leq +\infty$. The corresponding density function is $f(\cdot)$, which is assumed to be continuous, twice-differentiable and log-concave to guarantee the platform's consumer pricing problem at stage 2 has a unique solution. On the other side, the seller $i \in \{1, 2\}$ obtains benefit β^s from interacting with a consumer, which could be interpreted as either product profit or ad revenue generated on a consumer to whom the seller can only assess through the platform. For simplicity, assume two sellers are symmetric such that their per interaction profits are identical. Denote the number of consumers and the number of sellers on the platform as n^c and n^s, then the gross utility of an agent joining the platform is $\beta^c \cdot n^s$ on the consumer side, and $\beta^s \cdot n^c$ on the seller side.

Uncertainty. Now we introduce uncertainty to seller benefit β^s. Assume $\beta^s = \bar{\beta}^s + \varepsilon$, where $\bar{\beta}^s$ is the expected seller benefit and ε is an exogenous random shock that is not realized yet when the two sellers contract with the platform over their entries. This random shock ε follows cumulative distribution function $G(\cdot)$ over an interval set $[-e, e]$ with $\mathbb{E}[\varepsilon] = 0$. [3] We impose the following assumptions on information structure:

1. $\bar{\beta}^s$ is common knowledge to the platform and sellers;
2. the random shock ε is non-contractible.

This transaction friction is essential for vertical integration to be relevant.

Competition. Next we introduce competition to the seller side by assuming the expected per-interaction seller benefit is decreasing in the number of participating sellers[4]: $\bar{\beta}^s = \begin{cases} \bar{\beta}^m & , n^s = 1 \\ \bar{\beta}^d & , n^s = 2 \end{cases}$, where $\bar{\beta}^m$ and $\bar{\beta}^d$ are respectively the expected per-interaction seller benefit when one seller and when both sellers active in the platform, and $\bar{\beta}^m > \bar{\beta}^d$. As a consequence, this gives the platform an incentive to exclude a seller to prevent profit in downstream market from being competed away. In addition, we assume $\bar{\beta}^s \geq e$ to make sure the realized seller benefit is always positive.

Timing. Like Hagiu (2006), we assume that two sides of the platform arrive in

[3]The results in this paper still hold even if we instead assume there are two separate random shocks to each seller. This is because once the platform and a seller agree upon a fixed royalty fee, the information regarding realization of the random shock to the seller in question will become irrelevant for platform to price consumers.

[4]In the case where $\bar{\beta}^s$ is interpreted as ad revenue per interaction, I apply the incremental pricing principle in Anderson et al. (2017) to provide a micro foundation in Appendix 1.6.1 to justify that competition between media platforms drives down advertising revenue. Similar results can be found in other literature on advertising with multi-homing viewers (Athey et al., 2016; Ambrus et al., 2016)

sequential order. That is, the platform needs to contract with sellers on entry first to be established. Formally, the timing is as follows:

Stage 1 Platform decides number of sellers to be accommodated and contracts with unintegrated sellers over entries. For integrated seller, there is no need for contracting and the platform just supplies its service internally at zero marginal cost.

Stage 2 The random shock ε is realized. Then platform sets *consumer access price* P^c. After observing the number of sellers and the access price, consumers join the platform if and only if:

$$\beta^c \cdot n^s - P^c \geq 0$$

with outside option normalized to 0.

1.2.2 Contracting at stage 1

We allow two-part tariff for the contract the platform offers to independent sellers, but rule out more complex contracting instruments. To focus on the role played by the transaction friction in the platform's foreclosure decision, we assume public contract to shut down friction resulting from lack of commitment power.

Following bilateral contracting literature (see,.e.g., Segal, 1999), we further assume the contracting process is a two-stage game: first, platform commits to a set of publicly observable bilateral contract offers to sellers; then, sellers simultaneously decide whether to accept or reject their respective offers. This contracting process guarantees that the platform could fully extract (expected) downstream market profit when there is no contracting externalities which is this model's case. By doing so, we could isolate the results from elimination of double marginalization.

If the platform wants to foreclose a seller, it could offer a contract in which the up-front lump-sum payment $K = +\infty$. For active sellers, it will offer a two-part tariff contract $T = K + p^s \cdot n^c$, where p^s is the royalty fee collected for each interaction ex post. The contract satisfies the active seller's participation constraint: $\mathbb{E}[(\beta^s - r) \cdot n^c] - K \geq 0$, where the outside option is normalized to 0. So at optimality $K = \mathbb{E}[(\beta^s - r) \cdot n^c]$.

1.2.3 Transformation of strategic variables

The platform is the only strategic player and its decisions include consumer access price P^c, number of sellers to deal with n^s, and the contract offers to seller 1 and 2—$\{T_1, T_2\}$. As participation constraint indicates $K = \mathbb{E}[(\beta^s - r) \cdot n^c]$, the platform's problem on seller side is reduced to choosing a royalty fee p^s to the active seller.

On consumer side, recall that their participation condition is $\beta^c \cdot n^s - P^c \geq 0$, which could be rearranged as $\beta^c \geq \frac{P^c}{n^s} \equiv p^c$. So for a given consumer indexed by β^c, her consideration is whether the utility β^c she derives from each interaction with a seller could compensate the price paid for it which is p^c. Therefore, the platform could just price consumers on per-interaction basis. Following the terminology of Rochet and Tirole (2003), we call p^c *consumer usage fee*. With this transformation, consumers' participation condition is not sensitive to number of sellers anymore,[5] which is in the same spirit of Rochet and Tirole (2003) and the insulating tariff in Weyl (2010). As such, we eliminate the multiple equilibria problem.

In short, the platform's initial action set $\{P^c, T_1, T_2\}$, where $T_i = K_i + p^s_i \cdot n^c$ and $i \in \{1, 2\}$ is now reduced to $\{n^s, p^s, p^c\}$. Balancing the usage fees p^s and p^c is a typical pricing problem of two-sided market, since platform's value comes from enabling interaction between different groups of agents. What departs from Rochet and Tirole (2003, 2006) is that p^s and p^c are determined sequentially and the platform could engage in exclusive dealing by choosing $n^s = 1$, which is the main focus of this paper.

1.3 Equilibrium Results

In this section, we derive equilibrium results under three different scenarios–complete contract (CC in shorthand), vertical separation (VS) and partial integration where the platform is merged with seller 1 (PVI). The complete contract case is a hypothetical scenario where we temporarily assume the platform could observe and contract

[5]It seems that network effect disappears since consumers don't care about the participation rate on the other side any more, which contradicts the two-sided market setting. But we will see in next section that the platform internalizes the per interaction seller benefit when pricing consumers. The necessity of balancing pricing structure is the defining characteristic of two-sided market as argued in Rochet and Tirole (2006).

over the realized random shock to establish a second-best benchmark[6]. Then we proceed to see the outcomes under vertical separation and partial integration respectively. In next section we compare these two vertical structure and see how vertical integration impacts platform's foreclosure incentive.

Consumer-side demand function. As consumers are indexed by $\beta^c \sim F(\cdot)$, and their participation condition is $\beta^c \geq p^c$, the demand function (i.e. the number of participating consumers) is $n^c(p^c) = 1 - F(p^c)$.

Extraction of seller surplus. To facilitate interpretation, we call r^s average seller surplus extracted by the platform per interaction at stage 2. Depending on ownership structure, r^s is respectively β^s, p^s and $\frac{\beta^s + p^s \cdot (n^s - 1)}{n^s}$ under complete contract, vertical separation and partial integration, where $\beta^s = \begin{cases} \beta^m & , n^s = 1 \\ \beta^d & , n^s = 2 \end{cases}$. The reason for introducing this notion will be clearer in the following subsections.

1.3.1 Benchmark: complete contract

Consider the hypothetical scenario where the platform could verify and contract over the realized random shock such that it sets $p^s = \beta^s$, implying the platform could perfectly extract the realized per-interaction seller benefit at stage 2, i.e. $r^s = \beta^s$.

Then the platform's problem is reduced to optimizing p^c by solving the following problem:

$$\max_{p^c} \; (p^c + \beta^s) n^c(p^c) n^s \qquad \text{(Program CC)}$$

For convenience of later use, we introduce the notion of contingent platform revenue (profit):

Definition 1. *We define **contingent platform revenue (profit)** as a function of the realized per-interaction seller benefit, given the number of active sellers n^s and consumer usage fee p^c, which formally is:*

$$\Pi(\beta^s; p^c, n^s) = (p^c + \beta^s) n^c(p^c) n^s$$

[6] It is not the first-best allocation because of uniform pricing on the consumer side

From the first-order condition, we can recover the Lerner formula of standard monopoly pricing problem:

$$\frac{p^c + \beta^s}{p^c} = \frac{1}{\eta}$$

where $\eta = -\frac{dn^c}{dp^c}\frac{p^c}{n^c}$ is the price elasticity of consumer demand. And we denote the optimal solution as $p^{c^*}(\beta^s)$. We call $p^{c^*}(\beta^s)$ second-best consumer pricing rule in the sense that it perfectly internalizes the realized seller benefit which could be viewed as "opportunity cost" per interaction of serving a consumer. Then substituting the second-best consumer price to the contingent platform revenue we obtain the value functions of platform profit under non-exclusion and exclusion:

$$\mathit{\Pi}^{NE}(\beta^d) \equiv \mathit{\Pi}(\beta^d; p^{c^*}(\beta^d), n^s = 2) = 2\big[p^{c^*}(\beta^d) + \beta^d\big]n^c(p^{c^*}(\beta^s)) \tag{1.1}$$

$$\mathit{\Pi}^{E}(\beta^m) \equiv \mathit{\Pi}(\beta^m; p^{c^*}(\beta^m), n^s = 1) = \big[p^{c^*}(\beta^m) + \beta^m\big]n^c(p^{c^*}(\beta^m)) \tag{1.2}$$

Back to stage 1, the platform decides whether it is profitable to exclude one of the two sellers, accounting for all possible realizations of random shock. So under complete contract, the exclusion condition is:

$$\mathbb{E}[\mathit{\Pi}^E(\beta^m)] > \mathbb{E}[\mathit{\Pi}^{NE}(\beta^d)] \tag{EC-CC}$$

Example: In this example, we impose specific distribution functions by assuming per-interaction consumer benefit $\beta^c \sim U[0,1]$ and and the random shock $\varepsilon \sim U[-0.5, 0.5]$. The second-best consumer pricing policy is:

$$p^{c^*}(\beta^s) = max\{\frac{1-\beta^s}{2}, 0\}$$

And the value functions of contingent platform revenue under exclusion and non-exclusion are respectively:

$$\mathit{\Pi}^{NE}(\beta^d) \equiv \mathit{\Pi}(\beta^s; p^{c^*}(\beta^d), n^s = 2) = \begin{cases} \frac{(1+\beta^d)^2}{2} & , \bar{\beta}^d - 0.5 \leq \beta^d < 1 \\ 2\beta^d & , 1 \leq \beta^d \leq \bar{\beta}^d + 0.5 \end{cases}$$

$$\mathit{\Pi}^{E}(\beta^m) \equiv \mathit{\Pi}(\beta^s; p^{c^*}(\beta^m), n^s = 1) = \begin{cases} \frac{(1+\beta^m)^2}{4} & , \bar{\beta}^m - 0.5 \leq \beta^m < 1 \\ \beta^m & , 1 \leq \beta^m \leq \bar{\beta}^m + 0.5 \end{cases}$$

As $\mathbb{E}[\mathit{\Pi}^E(\beta^m)]$ is increasing in $\bar{\beta}^m$, for any given $\bar{\beta}^d$, there exists an threshold of $\bar{\beta}^m$ above which exclusion condition EC-CC is satisfied. The collection of these thresholds forms the gray solid cutoff line in Figure 1.2 named "Benchmark". □

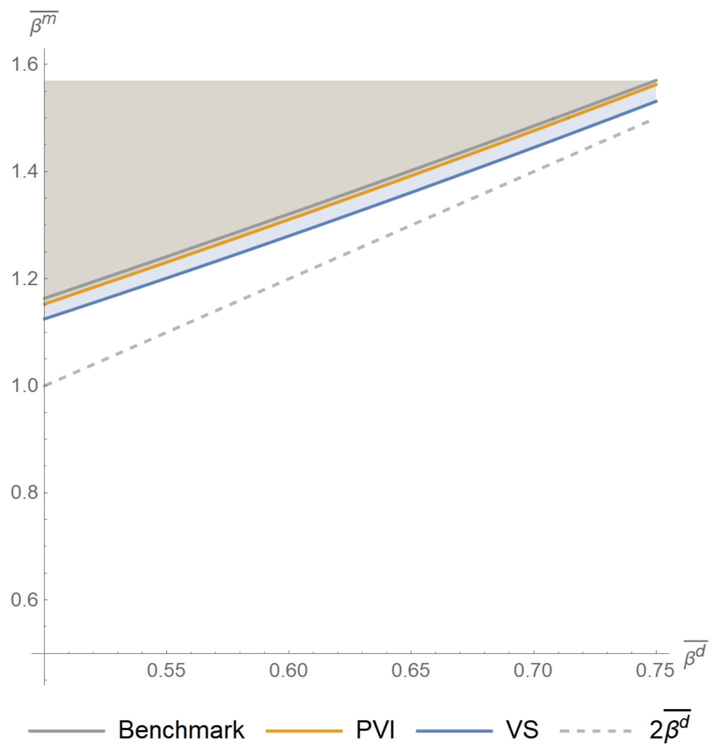


Figure 1.2: Exclusion Area

1.3.2 Vertical separation

From now on we go back to the normal setting where the random shock is non-contractible such that the platform needs to commit to a fixed royalty fee ex post when dealing with external sellers.

Although with two-part tariff the platform could fully extract expected seller surplus, the fixed royalty fee will make it leave some informational rent to the sellers ex post such that the average contingent seller surplus extracted by the platform is $r^s = p^s$.

At stage 2, given the number of sellers n^s the platform has accommodated, the platform's problem is to solve:

$$\max_{p^c} (p^c + p^s)n^c(p^c)n^s$$

Now the Lerner formula becomes: $\frac{p^c+p^s}{p^c} = \frac{1}{\eta}$ and we denote the consumer pricing policy function characterized by this formula as $p^c(p^s)$.

The stage 1's problem could be decomposed into two steps: the platform first determines the optimal royalty fee taking n^s as given; Then he compares the payoffs of the two regimes to decide the number of sellers to deal with. For the first step, the platform solves:

$$\begin{aligned} \max_{p^s} \ & \mathbb{E}[(P^c + p^s \cdot n^s)n^c(p^c)] + K \cdot n^s \\ \text{s.t. } \ & P^c = p^c \cdot n^s, \ p^c = p^c(p^s) \\ & K = \mathbb{E}[(\beta^s - p^s) \cdot n^c(p^s)] \end{aligned}$$

In the objective function, the first term is the expected payoff to the platform at stage 2, which is the aggregate usage fees paid by consumers plus the royalty revenue collected from sellers. The second term is the upfront lump-sum payments. The first constraint is the policy function from subgame starting at stage 2 and the second is the participation condition of sellers at stage 1.

The program could be simplified to

$$\begin{aligned} \max_{p^s} \ & \mathbb{E}[(p^c + \beta^s)n^c(p^c)n^s] = (p^c + \bar{\beta}^s)n^c(p^c)n^s \\ \text{s.t. } \ & p^c = p^c(p^s) \end{aligned} \tag{Program VS}$$

Now we compare programs CC and VS to see how incomplete contract causes friction. Under complete contract (program CC), as the platform could perfectly extract realized seller surplus, consumer pricing and henece their participation rate are risk-contingent.

In program VS, however, the platform cannot perfectly internalize the random shock anymore. This is because it needs to contract over the royalty fee first, which amounts to a commitment to certain level of ex-post surplus extraction and in turn imposes a constraint on consumer pricing at stage 2. It is straightforward that the optimal royalty would be $\bar{\beta}^s$, which is the expected seller benefit per interaction. In this case, the consumer usage fee and hence their participation rate is unresponsive to the random shock.

Then the expected platform profit at optimal tariffs under non-exclusion and exclusion respectively are:

$$\begin{aligned} 2\big[p^c(\bar{\beta}^d) + \bar{\beta}^d\big]n^c(p^c(\bar{\beta}^d)) &= \mathit{\Pi}^{NE}(\bar{\beta}^d) \\ \big[p^c(\bar{\beta}^m) + \bar{\beta}^m\big]n^c(p^c(\bar{\beta}^m)) &= \mathit{\Pi}^{E}(\bar{\beta}^m) \end{aligned}$$

These two equations follow from the fact that $p^{c^*}(\bar{\beta}^d) = p^c(\bar{\beta}^d)$ and $p^{c^*}(\bar{\beta}^m) = p^c(\bar{\beta}^m)$, as both consumer pricing policies are determined by the standard Lerner formula. Then, the platform's exclusion condition under separation could be expressed as:

$$\Pi^E(\bar{\beta}^m) > \Pi^{NE}(\bar{\beta}^d) \tag{EC-VS}$$

Example continued: Under vertical separation, the consumer pricing policy function at stage 2 becomes $p^c(p^s) = max\{\frac{1-p^s}{2}, 0\}$. And the platform's problem at stage 1 becomes:

$$\max_{p^s} \mathbb{E}[(p^c + \beta^s)n^c(p^c)n^s]$$
$$\text{s.t. } p^c = p^c(p^s) = \max\{\frac{1-p^s}{2}, 0\}$$

The constraint on consumer pricing implies that, in terms of maximizing contingent platform revenue $\Pi(\beta^s; p^c, n^s) = (p^c + \beta^s)n^c(p^c)n^s$, the optimal price under separation is biased from the second-best level. For instance, when $p^{c^*}(\beta^s) = \frac{1-\beta^s}{2}$ while $p^c(p^s) = \frac{1-p^s}{2}$, we can express the consumer pricing under vertical separation as the second-best price plus pricing distortion:

$$p^c(p^s) = \frac{1-p^s}{2} = \underbrace{\frac{1-\beta^s}{2}}_{\text{second-best pricing}} + \underbrace{\frac{\beta^s - p^s}{2}}_{\text{pricing distortion}}$$

And consequently the pricing distortion incurs a contingent profit loss to the platform relative to the second-best level:

$$\big[p^c(p^s) + \beta^s\big]n^c(p^c(p^s))n^s = \underbrace{\Pi(\beta^s; p^{c^*}, n^s)}_{\substack{\text{second-best contingent} \\ \text{platform profit}}} \underbrace{- (\frac{\beta^s - p^s}{2})^2 \cdot n^s}_{\text{profit loss}}$$

Imagine the realized seller benefit β^s is higher than p^s, then the consumer usage fee $p^c(p^s)$ under vertical separation is biased upwards such that the platform doesn't subsidize the consumer side enough and hence gets too few consumers on board comparing to the second-best level.

Therefore, the profit maximization problem VS could be transferred into a problem of choosing p^s that minimizes the expected profit loss due to pricing distortion on consumer side:

$$\min_{p^s} \mathbb{E}[\mathcal{L}(p^s; \beta^s) \cdot n^s]$$

where the contingent profit loss function is:

For $\bar{\beta}^s - 0.5 \leq \beta^s < 1,\ \mathcal{L}(p^s;\beta^s) = \begin{cases} (\frac{\beta^s - p^s}{2})^2 & , p^s < 1 \\ (\frac{1-\beta^s}{2})^2 - \beta^s & , p^s \geq 1 \end{cases}$

For $1 \leq \beta^s \leq \bar{\beta}^s + 0.5,\ \mathcal{L}(p^s;\beta^s) = \begin{cases} \frac{p^s - (2\beta^s - 1)}{2} \cdot \frac{p^s - 1}{2} & , p^s < 1 \\ 0, & , p^s \geq 1 \end{cases}$

Then solving the problem yields optimal royalty fee:

$$p^s(\bar{\beta}^s) = \begin{cases} \bar{\beta}^s & , 0.5 \leq \bar{\beta}^s < 1 \\ \forall p^s \text{ s.t. } \frac{1-p^s}{2} \leq 0 & , \bar{\beta}^s \geq 1 \end{cases}$$

When $\bar{\beta}^s \geq 1$, the expected seller surplus is sufficiently large such that platform stops charging consumers usage fee and only earns revenue from the seller side. In this case, there is a continuum of equivalently optimal two part tariff, one among which is $p^s = \bar{\beta}^s$. Therefore, setting $p^s = \bar{\beta}^s$ is always an equilibrium strategy.

The corresponding cutoff line of exclusion condition is represented by the blue line named "VS" in Figure 1.2. □

1.3.3 Partial integration

As two sellers are assumed to be symmetric, without loss of generality, suppose the platform is integrated with seller 1.

Built upon preceding analysis in the cases of complete contract and separation, it is straightforward to derive equilibrium outcome under partial integration which is an intermediate situation. For the subgame of exclusion, as the platform only deals with the integrated seller 1 and hence is able to perfectly price in realized random shock, the equilibrium outcome is identical to the second-best.

For the subgame of non-exclusion, the pivotal change from separation to partial integration is that the average seller surplus extracted by the platform per interaction is the average of β^s, which is the surplus extracted from the integrated seller, and p^s, the royalty fee paid by the independent seller. That is to say, $r^s = \frac{\beta^s + p^s}{2}$. The platform's problem at stage 2 becomes:

$$\max_{p^c} (p^c \cdot n^s + p^s + \beta^s) n^c(p^c)$$

which could be rewritten as:

$$\max_{p^c} (p^c + \frac{\beta^s + p^s}{2}) n^c(p^c) n^s$$

Now the consumer pricing policy $p^c(p^s, \beta^d)$ is characterized by the Lerner formula $\frac{p^c + \frac{p^s + \beta^d}{2}}{p^c} = \frac{1}{\eta}$. Therefore, under this regime, consumer usage fee p^c could partially react to the realized random shock, so does the number of participating consumers n^c. In short, partial integration mitigates transaction friction.

Then substituting the above policy function into contingent platform revenue function and denote it as $\mathit{\Pi}^{NE}_{PVI}(\beta^d; p^s)$

$$\mathit{\Pi}^{NE}_{PVI}(\beta^d; p^s) = 2\big[p^c(p^s, \beta^d) + \beta^d\big] n^c(p^c(p^s, \beta^d))$$

Back to stage 1, let

$$p^{s^*}_{PVI} = \operatorname*{argmax}_{p^s} \mathbb{E}[\mathit{\Pi}^{NE}_{PVI}(\beta^d; p^s] = \operatorname*{argmax}_{p^s} \mathbb{E}\Big[2\big(p^c(p^s, \beta^d) + \beta^d\big) n^c(p^c(p^s, \beta^d))\Big]$$

Denote the contingent platform profit under the optimal consumer pricing policy $p^c(p^{s^*}_{PVI}, \beta^d)$ as $\mathit{\Pi}^{NE}_{PVI}(\beta^d) \equiv \mathit{\Pi}^{NE}_{PVI}(\beta^d; p^{s^*}_{PVI})$. Then exclusion condition under partial integration can be expressed as:

$$\mathbb{E}[\mathit{\Pi}^E(\beta^m)] > \mathbb{E}[\mathit{\Pi}^{NE}_{PVI}(\beta^d)] \tag{EC-PVI}$$

Example continued: Under partial vertical integration, the consumer pricing policy function becomes $p^c(\beta^s, p^s) = \max\{\frac{1}{2}(1 - \frac{p^s + \beta^d}{2}), 0\}$. Because of imperfect internalization of random shock in consumer price, as separation case, the platform still needs to choose p^s that minimizes expected profit loss which is smaller thanks to the elimination of transaction friction in relation to seller 1.

The optimal royalty fee is:

$$p^{s^*} = \begin{cases} \bar{\beta}^d & , 0.5 \le \bar{\beta}^d < 0.75 \\ \frac{\bar{\beta}^d}{3} + \frac{1}{2} & , 0.75 \le \bar{\beta}^d < 1.5 \\ \forall p^s \text{ s.t. } \frac{p^s + \bar{\beta}^d - 0.5}{2} \ge 1 & , \bar{\beta}^d \ge 1.5 \end{cases}$$

Remark. When $0.75 \le \bar{\beta}^d < 1.5$, the optimal royalty fee is $p^{s^*} = \frac{\bar{\beta}^d}{3} + \frac{1}{2}$ which is smaller than $\bar{\beta}^d$. This is due to the asymmetry of contingent profit loss function on this segment. The source of asymmetry is from the fact that when the realized seller benefit is large enough the optimal consumer participation rate becomes constant at 1. Find a more detailed explanation in Appendix 1.6.2. When $\bar{\beta}^d \geq 1.5$, as before, there is a continuum of equivalently optimal two-part tariffs.

The orange line in between of gray and blue lines in Figure 1.2 is the collection of cutoffs of exclusion condition under partial integration.

1.4 The Impact of Vertical Integration on Foreclosure

In this section, we compare the exclusion conditions to examine how partial vertical integration impacts the platform's incentive to engage in downstream foreclosure. We start with the following lemma which gives a necessary condition on the existence of such incentive.

Lemma 1.1. *Regardless of vertical structure, a necessary condition for the platform having incentive to foreclose one of the two sellers is* $\bar{\beta}^m > 2\bar{\beta}^d$*, which means the expected aggregate seller surplus per consumer under a monopoly structure is higher than that under duopoly.*

Proof. This is equivalent to show that when $\bar{\beta}^m \leq 2\bar{\beta}^d$, it is always more profitable for the platform to accommodate both sellers than only one in equilibrium. Here we prove this result in the case of partial vertical integration. The result in the case of vertical separation can be proved analogously.

Suppose $n^s = 1$ is the optimal strategy when $\bar{\beta}^m \leq 2\bar{\beta}^d$. Under exclusion, the optimal consumer usage fee is $p^c(\beta^m)$ and the number of participating consumer is $n^c(\beta^m) \equiv n^c(p^c(\beta^m))$.Therefore, for any realized random shock $\varepsilon \in [-e, e]$, the platform's contingent revenue on consumer side is $p^c(\beta^m)n^c(\beta^m)$.

As each consumer has the same valuations towards both sellers' goods, the platform could earn another $p^c(\beta^m)n^c(\beta^m)$ by accommodating the second seller without changing the consumer usage fee $p^c(\beta^m)$, such that the number of participating consumers $n^c(\beta^m)$ also remains unchanged. On the other side, however, introducing another seller would change the per interaction seller benefit from β^m to β^d. So the expected change of seller-side revenue is $\mathbb{E}_\varepsilon[2\beta^d \cdot n^c(\beta^m)] - \mathbb{E}_\varepsilon[\beta^m \cdot n^c(\beta^m)] =$

$(2\bar{\beta}^d - \bar{\beta}^m)\mathbb{E}[n^c(\beta^m)] + \mathbb{E}_\varepsilon[\varepsilon \cdot n^c(\beta^m)] > 0$.[7] In aggregate of the two sides, accommodating the second seller is a profitable deviation.

Formally, $\mathbb{E}_\varepsilon[p^c(\beta^m)n^c(\beta^m) + (\bar{\beta}^m + \varepsilon) \cdot n^c(\beta^m)] < \mathbb{E}_\varepsilon[2 \cdot p^c(\beta^m)n^c(\beta^m) + 2(\bar{\beta}^d + \varepsilon) \cdot n^c(\beta^m)] \leq \mathbb{E}_\varepsilon[(p^c(\beta^d) + \beta^d)n^c(\beta^d) \cdot 2]$, where $p^c(\beta^d)$ is the optimal consumer usage fee when the platform chooses $n^s = 2$. □

In Figure 1.2. The necessary condition $\bar{\beta}^m > 2\bar{\beta}^d$ is represented by the gray dashed line called "$2\bar{\beta}^d$". Both exclusion cutoff lines of VS and VPI lie above the dashed line. This is intuitive: for a given realized random shock such that $\beta^m > 2\beta^d$, it is more profitable for the platform to accommodate only one seller than both of them, taking the number of participating consumers as fixed. However for any given consumer usage price, all participating consumers would pay for interacting with both sellers. So the gain of excluding a seller on seller side could be offset by the revenue loss on consumer side. Therefore, the threshold of exclusion is higher than that when only accounting for the gain from exclusion on seller side. The following proposition is an immediate result from the lemma.

Proposition 1.1. *For platforms exhibiting bilateral cross-group network effects, the consumer side constitutes a constraint of curbing platform's tendency to engage in anti-competitive foreclosure on seller side.*

1.4.1 Comparison of exclusion incentives

Recall the exclusion conditions under separation and partial integration are respectively:

$$\mathit{\Pi}^E(\mathbb{E}[\beta^m]) > \mathit{\Pi}^{NE}(\mathbb{E}[\beta^d]) \tag{EC-VS}$$

$$\mathbb{E}[\mathit{\Pi}^E(\beta^m)] > \mathbb{E}[\mathit{\Pi}^{NE}_{PVI}(\beta^d)] \tag{EC-PVI}$$

To examine the change in the platform's incentive to foreclose a downstream seller, we compare the payoff of exclusion under vertical separation $\mathit{\Pi}^E(\mathbb{E}[\beta^m] - \mathit{\Pi}^{NE}(\mathbb{E}[\beta^d])$ with that under partial integration $\mathbb{E}[\mathit{\Pi}^E(\beta^m)] - \mathbb{E}[\mathit{\Pi}^{NE}_{PVI}(\beta^d)]$. The following proposition gives a general result:

[7] $n^c(\beta^m)$ is weakly increasing in ε following from the pass-through result of standard monopoly pricing problem. So $\varepsilon \cdot n^c(\beta^m)$ is convex in ε. Then by Jensen's inequality, $\mathbb{E}_\varepsilon[\varepsilon \cdot n^c(\beta^m)] \geq 0$.

Proposition 1.2. *Vertical integration changes the platform's incentive of foreclosure by allowing the platform to account for the second-order effect of the random shock.*

Proof. By Taylor Expansion,

$$\begin{aligned}
\mathbb{E}[\Pi^E(\beta^m)] &= \mathbb{E}[\Pi^E(\bar{\beta}^m+\varepsilon)] \\
&= \mathbb{E}[\Pi^E(\bar{\beta}^m) + \Pi^{E'}(\bar{\beta}^m)\varepsilon + \frac{\Pi^{E''}(\bar{\beta}^m)}{2}\varepsilon^2] \\
&= \Pi^E(\bar{\beta}^m) + \frac{\mathbb{E}[\varepsilon^2]}{2}\Pi^{E''}(\bar{\beta}^m) \\
\mathbb{E}[\Pi^{NE}_{PVI}(\beta^d;\bar{\beta}^d)] &= \mathbb{E}[\Pi^{NE}_{PVI}(\bar{\beta}^d+\varepsilon;\bar{\beta}^d)] \\
&= \mathbb{E}[\Pi^{NE}_{PVI}(\bar{\beta}^d;\bar{\beta}^d) + \Pi^{NE'}_{PVI}(\bar{\beta}^d;\bar{\beta}^d)\varepsilon + \frac{\Pi^{NE''}_{PVI}(\bar{\beta}^d;\bar{\beta}^d)}{2}\varepsilon^2] \\
&= \Pi^{NE}_{PVI}(\bar{\beta}^d;\bar{\beta}^d) + \frac{\mathbb{E}[\varepsilon^2]}{2}\Pi^{NE''}_{PVI}(\bar{\beta}^d;\bar{\beta}^d) \\
&= \Pi^{NE}(\bar{\beta}^d) + \frac{\mathbb{E}[\varepsilon^2]}{2}\Pi^{NE''}_{PVI}(\bar{\beta}^d;\bar{\beta}^d)
\end{aligned}$$

So the difference in the incentives of foreclosure across the two regimes can be expressed as:

$$\begin{aligned}
&\big(\mathbb{E}[\Pi^E(\beta^m)] - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d)]\big) - \big(\Pi^E(\mathbb{E}[\beta^m]) - \Pi^{NE}(\mathbb{E}[\beta^d])\big) \\
=&\underbrace{\frac{\mathbb{E}[\varepsilon^2]}{2}\big[\Pi^{E''}(\bar{\beta}^m) - \Pi^{NE''}_{PVI}(\bar{\beta}^d;\bar{\beta}^d)\big]}_{\text{second-order effect of } \varepsilon} + \underbrace{\big(\mathbb{E}[\Pi^{NE}_{PVI}(\beta^d;\bar{\beta}^d) - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d;p^{s*}_{PVI})]\big)}_{\text{adjustment term due to the difference in } p^s}
\end{aligned}$$

□

The intuition of this result is as follows. Under vertical separation, the platform needs to contract over the royalty fees first. This is as if it commits to the amount of surplus it extracts from sellers for each interaction. So the consumer usage fee and hence the number of participating consumers are fixed: the random shock to the seller side cannot be transmitted to the consumer side. As a consequence, the platform only takes into account the direct first-order effect of the random shock on seller-side profit at the contracting stage. By contrast, when the platform is partially integrated, it avoids making the ex-ante commitment regarding surplus extraction from seller 1 and can learn realizations of the random shock. Therefore, at stage 2, the platform could partially incorporate the random shock into consumer usage fee, which makes the number of participating consumers also risk-contingent. The consumers' network externality will in turn creates second-order effect on seller-side revenue (i.e. $\beta^d \cdot n^c(p^c(\beta^d, p^s))$). In sum, vertical integration allows the platform to account for the second-order effect of the random shock on both sides.

How is the magnitude of second-order effect of ε determined? First, following from the results in last section, the platform's consumer pricing problem under different vertical structure can be generalized as:

$$\max_{p^c} (p^c + r^s) n^c(p^c) n^s$$

which is in the form of standard monopoly pricing problem. r^s can be interpreted as opportunity cost per interaction, which is a function of p^s and β^s depending on the vertical structure. Because the consumer distribution is log-concave, the optimal solution $p^c(r^s)$ is determined by the Lerner formula: $\frac{p^c+r^s}{p^c} = \frac{1}{\eta}$. Or equivalently, $p^c + r^s = \frac{1-F(p^c)}{f(p^c)}$. The standard monopoly pricing's pass-through is given by $\frac{dp^c}{dr^s} = -\frac{1}{2-\sigma(p^c)}$, where $\sigma(p^c) = -\frac{1-F(p^c)}{f(p^c)} \frac{f'(p^c)}{f(p^c)}$ is the curvature of consumer demand (the relative degree of convexity).

Therefore, the pass-through rate of the random shock from seller side to consumer side is $\frac{dp^c}{d\varepsilon} = \frac{dp^c}{dr^s} \frac{\partial r^s}{\partial \varepsilon}$, where the second factor is determined by the vertical structure and measures the extent to which the platform can internalize the random shock.

Then the contingent platform revenue at optimal consumer pricing $p^c(r^s)$ can be expressed as:

$$\mathit{\Pi}(\beta^s; p^c(r^s), n^s) = \big[p^c(r^s) + \beta^s\big] n^c(p^c(r^s)) n^s$$

Its second-order derivative with respect to ε is:

$$\begin{aligned} &\mathit{\Pi}''(\beta^s; p^c(r^s), n^s) \equiv \frac{d^2 \mathit{\Pi}(\beta^s; p^c(r^s), n^s)}{d\varepsilon^2} \\ =&2n^s(\frac{dp^c}{d\varepsilon} + 1)\frac{dn^c}{dp^c}\frac{dp^c}{d\varepsilon} + \frac{d^2p^c}{d\varepsilon^2} \cdot n^c \cdot n^s + (p^c + \beta^s)\Big[\frac{d^2n^c}{dp^{c2}} \cdot (\frac{dp^c}{d\varepsilon})^2 + \frac{dn^c}{dp^c} \cdot \frac{d^2p^c}{d\varepsilon^2}\Big] n^s \end{aligned}$$

In general, the second-order effect is determined by the number of participating sellers, the extent to which the platform responds to the random shock, and the curvature of the consumer demand.

Next we continue with the example to offer a more concrete analysis. The assumption of uniform distribution implies constant pass-through rate at $\frac{1}{2}$, such that the second and the third term in above expression disappear, which allows us to focus on the determinants of cross-group network externality and risk structure:

$$\Pi''(\beta^s; p^c(r^s), n^s) = 2n^s(\frac{dp^c}{d\varepsilon} + 1)\frac{dn^c}{dp^c}\frac{dp^c}{d\varepsilon} = n^s(-\frac{1}{2}\frac{\partial r^s}{\partial \varepsilon} + 1)\frac{\partial r^s}{\partial \varepsilon} > 0$$

Example continued. For the example where consumer benefit per interaction follows uniform distribution $\beta^c \sim U[0,1]$ and $\varepsilon \sim U[-0.5, 0.5]$, we obtain the following result regarding the impact of vertical integration on the platform's incentive of foreclosure:

Proposition 1.3. *$\forall(\bar{\beta}^d, \bar{\beta}^m)$ s.t. $\bar{\beta}^m > 2\bar{\beta}^d, \mathbb{E}[\Pi^E(\beta^m)] - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d)] \leq \Pi^E(\bar{\beta}^m) - \Pi^{NE}(\bar{\beta}^d)$, which implies that partial vertical integration reduces the platform's incentive to foreclose a seller comparing to separation.*

Proof. Firstly, by optimality of $p^{s^*}_{PVI}$, $\mathbb{E}[\Pi^{NE}_{PVI}(\beta^d)] \equiv \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d; p^{s^*}_{PVI})] \geq \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d; p^s = \bar{\beta}^d)]$. Therefore, $\mathbb{E}[\Pi^E(\beta^m)] - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d)] \leq \mathbb{E}[\Pi^E(\beta^m)] - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d; p^s = \bar{\beta}^d)]$.

As $\Pi^{E''}(\bar{\beta}^m) = \begin{cases} \frac{1}{2} & , 0.5 \leq \bar{\beta}^m < 1 \\ 0 & , \bar{\beta}^m \geq 1 \end{cases}$ and $\Pi^{NE''}_{PVI}(\bar{\beta}^d; \bar{\beta}^d) = \begin{cases} \frac{3}{4} & , 0.5 \leq \bar{\beta}^d < 1 \\ 0 & , \bar{\beta}^d \geq 1 \end{cases}$,

$$\begin{aligned}
\mathbb{E}[\Pi^E(\beta^m)] - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d)] &\leq \mathbb{E}[\Pi^E(\beta^m)] - \mathbb{E}[\Pi^{NE}_{PVI}(\beta^d; p^s = \bar{\beta}^d)] \\
&= \Pi^E(\bar{\beta}^m) + \frac{\mathbb{E}[\varepsilon^2]}{2}\Pi^{E''}(\bar{\beta}^m) - (\Pi^{NE}(\bar{\beta}^d) + \frac{\mathbb{E}[\varepsilon^2]}{2}\Pi^{NE''}_{PVI}(\bar{\beta}^d; \bar{\beta}^d)) \\
&= \Big(\Pi^E(\bar{\beta}^m) - \Pi^{NE}(\bar{\beta}^d)\Big) + \frac{\mathbb{E}[\varepsilon^2]}{2}\Big(\Pi^{E''}(\bar{\beta}^m) - \Pi^{NE''}_{PVI}(\bar{\beta}^d; \bar{\beta}^d)\Big) \\
&\leq \Pi^E(\bar{\beta}^m) - \Pi^{NE}(\bar{\beta}^d), \qquad \forall(\bar{\beta}^d, \bar{\beta}^m) \text{ s.t. } \bar{\beta}^m > 2\bar{\beta}^d \quad \square
\end{aligned}$$

The result that vertical integration reduces the platform's incentive to engage in exclusion can be seen in Figure 1.2: the shaded exclusion area is shrinking from separation to partial integration (even smaller if the contract is complete).

How do we interpret the result? The second-order effect of the random shock under partial integration is determined by two factors–the number of participating sellers n^s and the extent to which the platform internalizes the random shock which is measured by $\frac{\partial r^s}{\partial \varepsilon}$. Although the platform under exclusion internalizes the random shock more fully than in the case dealing with both sellers, contracting with an additional seller amplifies the positive second-order effect in a way that dominates the imperfect internalization of random shock. In short, accounting for second-order effect induces the integrated platform to engage in foreclosure less often than under vertical separation as the aggregate second-order effect is proportional to the number of participating sellers.

1.4.2 Discussion

Notice that the result of proposition 1.3 is specific to what I define below as "effective" two-sided market. In figure 1.2, although I didn't depict the cutoff lines in area $\bar{\beta}^d > 0.75$, it is not hard to see from those contingent platform revenue functions that as $\bar{\beta}^d$ grows even larger, the cutoff lines under partial vertical integration and separation will converge to the gray dashed line $\bar{\beta}^s = 2\bar{\beta}^d$, which is the exclusion condition when only seller-side exists, implying vertical integration's impact on incentive of foreclosure disappears. This is because the seller surplus generated by an interaction is so large that the platform provides its service to consumers for free to get all of them on board. Then the profit generated on consumer side becomes negligible such that the two-sided market degenerates into one-sided market, in which platform only considers seller side when making strategic decisions. In short, the multiplicative demand structure of the platform $n^c(p^c) \cdot n^s$ is the deterministic factor making vertical integration impact the platform's incentive of foreclosure, as under such structure the effect of random shock will be amplified by cross-group network externalities. So I call the platform *"effective"* two-sided market when the pricing on both sides are strictly positive.

This approach of defining two-sided market differs from the prevailing view that two-sided market are characterized by cross-group network effect. Some platforms widely recognized as two-sided market doesn't satisfy the "effective" criteria I propose here. Because of the nature of their products, platforms such as search engine and app stores don't charge consumers for access and therefore my findings cannot apply to these markets. By contrast, ISP market and video game companies falls within the scope of my analysis, as they charge positive prices to both consumers and business users.

1.5 Conclusion

This paper studies how vertical integration impacts a monopolistic platform's incentive to engage in downstream foreclosure. Particularly, I focus on an environment where the platform and sellers face uncertainty over gains from trade at the stage of contracting. Because the random shock to the seller side is non-contractible, contracting brings friction which distorts the platform's pricing on consumer side. Vertical integration mitigates this problem by allowing the platform to partially incorporate the random shock into consumer usage fee, enabling the number of participating consumers to be also risk-contingent. And cross-group network externalities make the contingent platform revenue convex in random shock. As a result, the platform under vertical integration internalizes the second-order effect of the random shock, which is absent under vertical separation. When consumer is uniformly distributed, as contracting an additional seller amplifies the positive second-order effect, the integrated platform engages in foreclosure less often than under vertical separation.

These results provide theoretical evidence that the two-sidedness of platform could not only complicates its pricing problem as suggested by canonical two-sided market literature, but also other strategic decisions such as vertical foreclosure. However, the precise impact of vertical integration on foreclosure needs to be empirically determined as the curvature of consumer demand could play a key role in the result as well. In terms of competition policy, the take-away message is that it is important for policymakers, who are concerned with potential anti-competitive consequences of vertical mergers, to notice there might be new efficiency channels arising in the two-sided platforms such that traditional theories might not apply.

Last, this paper shows that in monopolistic platform's pricing problem the pass-through interacts with cross-group network externalities. So future research could further explore the implication of pass-through mechanism in two-sided market and examine how it departs from traditional analysis.

1.6 Appendix

1.6.1 Micro-foundation for $\bar{\beta}^m > 2\bar{\beta}^d$

Here I provide a micro-foundation for $\bar{\beta}^m > 2\bar{\beta}^d$ when the seller benefit $\bar{\beta}^s$ is interpreted as ad revenue a seller earns from interacting with a consumer. $\bar{\beta}^m > 2\bar{\beta}^d$ means the competition between sellers for advertisers could drive down ad revenue per interaction.

When both sellers are purely financed by advertising, then $\bar{\beta}^s$ is the ad price per impression a seller charges advertisers. Assume that the transaction between sellers and advertisers is outside the platform, consumers are ad-neutral, and advertisers are homogeneous.

Here I brefly introduce the incremental pricing rule proposed by Anderson et al. (2017):

$$R^a = v \times N^E + (\delta \times v) \times N^S$$

where

- R^a: seller's advertising revenue per advertiser.
- v: WTP of advertiser for a successful unique contact with a consumer.
- N^E: the number of exclusive consumers.
- N^S: the number of consumers shared among publishers.
- δ: discount factor of the second impression.

The idea of this rule is that each seller can only charge advertisers the value of its exclusive consumers plus the incremental value associated with multi-homing consumers. When the second impression of an ad is less valuable and consumers are multi-homing across publishers, entry of new publisher will reduce the advertising price.

In my setting all participating consumers are multi-homing across the two sellers, by applying the incremental pricing rule, we get:

$$\bar{\beta}^m = v, \;\; \bar{\beta}^d = \delta v$$

When $\delta < \frac{1}{2}$, $\bar{\beta}^m > 2\bar{\beta}^d$.

1.6.2 Profit Loss Function under Partial Integration

When the platform is integrated with seller 1, the expression of the profit loss function under consumer pricing policy $p^c(p^s, \beta^d)$ in the case of non-exclusion is:

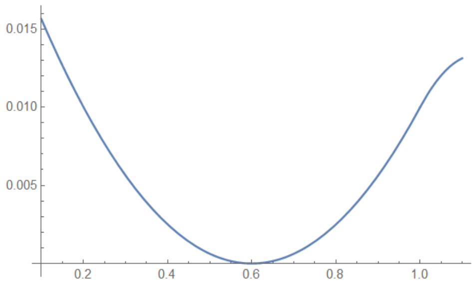
$$\mathcal{L}(\beta^d, p^s) = \begin{cases} 2(\frac{\beta^d - p^s}{4})^2 & ,\bar{\beta}^d - 0.5 \leq \beta^d < 1 \text{ and } \frac{p^s + \beta^d}{2} \leq 1 \\ 2(\frac{\beta^d - p^s}{4})^2 - 2(\frac{\beta^d - 1}{2})^2 & ,1 \leq \beta^d < 2 - p^s \\ 0 & ,1 \leq \beta^d \leq \bar{\beta}^d + 0.5 \text{ and } \frac{p^s + \beta^d}{2} > 1 \end{cases}$$

The first segment gives the contingent profit loss when the second-best usage fee $p^{c^*}(\beta^d) > 0$ and the platform charges $p^c = \frac{1}{2}(1 - \frac{\beta^d + p^s}{2}) > 0$ as well. On the second segment, it is the case when the random shock is relatively large such that the second-best usage fee becomes zero, but the platform still charges $p^c = \frac{1}{2}(1 - \frac{\beta^d + p^s}{2}) > 0$. On the third segment, the profit loss is zero if $p^{c^*}(\beta^d) = 0$ and the platform charges $p^c = 0$.

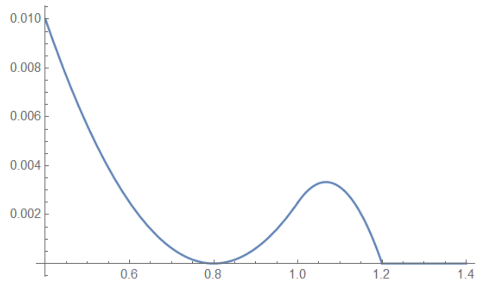
We use two specific cases to illustrate why the optimal fee is $\bar{\beta}^d$ when $0.5 \leq \bar{\beta}^d < 0.75$, while being $\frac{\bar{\beta}^d}{3} + \frac{1}{2} < \bar{\beta}^d$ when $0.75 \leq \bar{\beta}^d < 1.5$.

For instance, when $\bar{\beta}^d = 0.6$, the graph of the profit loss function at optimal $p^s = \bar{\beta}^d$ is in Figure 1.3a, which is roughly symmetric about $\beta^d = 0.6$.

By contrast, when $\bar{\beta}^d = 0.9$, the optimal royalty fee is $\frac{\bar{\beta}^d}{3} + \frac{1}{2} = 0.8$ and the graph of the contingent profit loss function under this optimal royalty fee is in Figure 1.3b, which is highly asymmetric. This is because when the expected seller benefit $\bar{\beta}^d$ is large enough, for positive or not too negative random shocks, the second-best consumer usage fee $p^c(\beta^d)$ would be close or equal to 0, which implies optimally the platform should get almost all consumers on board in these cases. Furthermore, because the optimal consumer participation rate becomes constant in random shock (i.e the cross-group network effects disappears), the profit loss due to consumer



(a) Profit loss function $\mathcal{L}(\beta^d, 0.6)$ when $\bar{\beta}^d = 0.6$



(b) Profit loss function $\mathcal{L}(\beta^d, 0.8)$ when $\bar{\beta}^d = 0.9$

Figure 1.3: Two Examples of Contingent Profit Loss Function

pricing distortion in $p^c(\beta^d, p^s)$ is relatively small, as illustrated by the fact that the contingent profit loss function on the second and third segments are smaller than that on first segment. In other words, the platform suffers more from contingent profit loss when the random shock is negative. To reduce the profit loss under highly negative shocks, it is rational for the platform to reduce the royalty fee below the expected seller benefit to avoid getting too many consumers on board in adverse situations.

Chapter 2

Data, Targeted Advertising, and Quality of Journalism: The Case of Accelerated Mobile Pages (AMP)*

2.1 Introduction

There is a general tendency by major gatekeeper platforms to use their power to channel consumer interactions with business users into their walled gardens. The development of Super Apps in China by the two major Chinese platforms (Alibaba and Tencent) is an extreme example of such a tendency: within each Super App, a consumer can carry out almost all her activities, including shopping, ride hailing, reading news, gaming, money transfer, and flight bookings, such that she barely needs to leave the Super App. Inspired by the Chinese Super Apps, Facebook and Uber have adopted a similar business strategy. Another example is Google's tendency to "swallow web", about which Shira Ovide, who writes the On Tech newsletter of the New York Times, expresses her concern as follows:

"One longstanding issue is Google's evolution from a website that pointed people to the best links online to one that's swallowing the web. ... Now, Google is more likely to prominently show information or advertisements from its own computer systems or scraped from other companies' websites — and keep you within

*This chapter is a join work with Doh-Shin Jeon.

Google's digital walls. Google isn't a front door to the internet anymore. It's the house. (New York Times, On Tech newsletter, September 24, 2020)"

A main reason for which major platforms expand their walled gardens instead of embracing an open Internet is that they want to collect as much data as possible about consumers' various online activities, which allows them to infer consumers' preferences and to predict their behaviors. This motive is particularly relevant to ad-financed platforms such as Google and Facebook, whose business model consists in harvesting consumer attention and data and monetizing them through targeted advertising (Zuboff, 2019). Platforms' access to business users' data raises a very important question: how does such data access affect the innovation of the platform ecosystem, in particular, the innovation incentives of business users?[1]

We explore this question in the specific context of newspapers' adoption of Google's Accelerated Mobile Pages (henceforth AMP), which is an open-source publishing format developed by Google to enable instant loading of web pages in mobile browsers. Both the CMA Report (2020) of the UK and the report of U.S. House of Representatives (2020) have expressed concerns about Google's anti-competitive practices in its implementation of AMP, especially about the so-called "data leakage" issue[2]. Specifically, Google hosts articles written in AMP format on its servers, thereby collecting consumers' browsing data on these articles. Then, Google can use this data for targeting ads to newspapers' readers on other websites, undermining the value of newspapers' ad inventories.

To provide a perspective on the importance of advertising revenue in the newspaper industry, we point out two worrying trends. According to Pew Research Center (2020),[3] the industry's advertising revenue fell sharply from 49 billion dollars in 2006 to 8 billion dollars in 2020, and as a consequence, the total number of newsroom employees declined from 74,410 in 2006 to 30,820 in 2020. During the same period, the newspaper industry has made a transition to the online world and

[1]For instance, the question arises regarding Amazon's use of business data of third-party sellers who sell on its marketplace, which is under investigation by the European Commission.

[2]There is another issue related to AMP, which we briefly describe in Section 2.8. For additional information regarding the AMP issues, see also Appendix S of the CMA Report (2020) (p.3 and p.17), Geradin and Katsifis (2019), Scott Morton and Dinielli (2020) and Srinivasan (2020)

[3]See Newspapers Fact Sheet at https://www.pewresearch.org/journalism/fact-sheet/newspapers/

has become increasingly dependent on Google, which monopolizes search and ad intermediation.[4] As quality journalism not only matters for consumer surplus but is also a pillar of democratic societies, it is vital to understand how Google's exercise of its market power influences the news industry and its implications for social welfare (Rolnik et al., 2019; OECD, 2021).

Against this background, we address the following questions regarding Google's AMP. How does newspapers' adoption of the AMP format change data allocation and thereby newspapers' incentives to invest in quality journalism? What is its impact on static and dynamic welfare? Does Google have any incentive to internalize the impact on the quality of journalism? How does Google leverage its market power in search and ad intermediation to induce newspapers to adopt AMP? What are policy remedies?

To answer these questions, we build a model that captures the online environment in which newspapers operate, involving consumers, a monopolistic search engine, competing providers of ad inventory, ad intermediaries, and advertisers. In particular, our model incorporates some main features of the open display advertising market in which the majority of publishers sell their display advertising inventory to a large number of advertisers through real-time auctions run by ad intermediaries. The ad intermediation market is dominated by Google.[5] We consider competition between Google and another ad tech intermediary T in this market.

In our model, consumers and advertisers interact in two different two-sided markets: the newspaper market and another market (called sector B) which is comprised of non-newspaper content providers. In other words, both consumers and advertisers multihome on these two markets. On the consumer side, newspapers compete among themselves for readership by choosing the quality of journalism. Each consumer chooses a single newspaper whose site she directly visits to read news. In addition, consumers also search for news by using the monopolistic search engine (SE) and read news from multiple newspapers depending on the search results. On the advertiser side, each newspaper faces competition from content

[4] According to CMA Report (2020), Google accounts for 25% of mobile website traffic for large publishers in the UK, is dominant in different layers of ad intermediation, and in particular has more than 90% share in the publisher ad server market.

[5] See the CMA Report (2020) and Jeon (2021) for detailed analysis of the ad intermediation market.

providers in sector B as each consumer multihomes on her favorite newspaper and her favorite content provider in sector B. We focus on strategic interactions between the search engine and newspapers.

The ad tech intermediaries collect consumer data for targeted advertising. The data allocation between SE and T is determined by the set of content providers each intermediary serves and their respective ability to track consumer activities. In the baseline model introduced in Section 2.2, we assume that all newspapers use T, which only collects consumer data from direct visit due to its imperfect tracking technology, while the SE serves the sector B and has perfect tracking technology. We assume the ad revenue generated from a consumer by an ad tech intermediary increases with the amount of data it has about the consumer but decreases with the extent of overlap with the data that the rival intermediary has about the consumer.

In this environment, AMP impacts newspapers through three different channels. First, AMP adoption generates the benefit of eliminating the loss of search referral traffic due to the slow loading of pages. Second, a newspaper's adoption decision affects the amount of its search-referral traffic as the SE promotes adopters' rankings and demotes non-adopters' rankings in search results. Third, because the SE hosts AMP articles and thereby collects browsing data on these pages, adopting AMP changes data allocation between the two ad intermediaries and thereby affects newspapers' ad revenues.

Section 2.3-2.5 study how AMP impacts news quality and social welfare. In Section 2.3, we study two benchmarks and show that if AMP does not involve any change in data allocation, it induces newspapers to invest more in the quality of journalism. In Section 2.4, we explain how AMP changes data allocation and perform a static analysis. We find that when newspapers' quality levels remain unchanged, AMP increases static welfare as the SE's access to AMP data improves ad targeting in sector B and thereby increases total surplus in the advertising market. Then, we endogenize newspapers' quality choices in Section 2.5 and find that the adoption of AMP leads to two opposite effects for newspapers: (i) the search traffic enhancing effect due to the fast-loading of articles, which is positive; and (ii) the data leakage effect, which reduces the ad revenue per direct traffic and is negative. As a result, when the data leakage effect dominates the search traffic enhancing effect, news quality is reduced, potentially leading to lower dynamic welfare. However, we find that the SE has no incentive to internalize the impact of its data combination on the quality of journalism.

In Section 2.6, we analyze newspapers' incentives to adopt AMP. Newspapers face a collective action problem as a newspaper's adoption of AMP generates two kinds of negative externalities to other newspapers—search ranking externality and data leakage externality. The first externality arises as the SE promotes adopters' articles in search results. Therefore, a newspaper's adoption will have negative impacts on other newspapers' search referral traffic. Second, a newspaper's adoption leaks to the SE data about other newspapers' direct readers when they are referred to its AMP articles by the SE. This reduces rival newspapers' advertising revenues from direct traffic. As an individual newspaper does not internalize these negative externalities on its competitors, we find that there always exists an equilibrium in which all newspapers adopt AMP. However, another equilibrium in which no newspaper adopts AMP can also exist when the loss in ad revenue from "data leakage" is strong enough.

In Section 2.7, we further examine the collective action problem by considering an extension where a fraction of newspapers is assumed to use the SE as their ad intermediary. We show that this creates a conflict of interest regarding data leakage between two groups of newspapers depending on whether they use ad tech T or ad tech SE, which Google can exploit to make the adoption equilibrium unique. This result implies that the SE can combine its market power in search and in ad intermediation through a divide-and-conquer strategy to gain control of newspapers' data.

In Section 2.8, we propose policy remedies which solve the collective action problem by eliminating the two sources of externalities and connect the remedies to the current regulatory interventions in the bargaining between Google and newspapers regarding the compensation Google should make for displaying newspapers' content.

In Section 2.9 we conclude. Appendix 2.10.2 contains omitted proofs. Readers may refer to Appendix 2.10.3 for an introduction to the open display advertising market, which provides stylized facts that guide our modeling choices.

2.1.1 Related literature

There is an emerging body of literature studying various data-driven (anti-)competitive strategies and exploring the implication of data combination (also known as data tying or data pooling) on competition(Ghosh et al., 2015; Condorelli and Padilla, 2020; de Cornière and Taylor, 2020; Bourreau et al., 2021). Our paper is more related to the papers studying online advertising. Ghosh et al. (2015) is an early paper studying the data leakage issue and explores conditions under which data-sharing enabled by cookie matching can improve one publisher's revenue while harming that of another. Bourreau et al. (2021) is more closely related to our paper, as they also use the AMP issue as one of the motivations and study a data-prominence trade-off faced by publishers. Namely, They consider a game where the dominant platform uses exclusive contract to offer prominent positions in exchange for publisher's data and are interested in its implication on data collection and ranking bias. We have very different focuses and mechanisms as we model the adoption of AMP as a voluntary opt-in game and study its consequence on newspapers' incentives to invest in news quality.

In addition, as we are concerned about a gatekeeper platform's access to business users' data, we contribute to the general discussion about regulation of data collection and usage by gatekeeper platforms. Existing literature explores different types of data-related issues than ours. For instance, Madsen and Vellodi (2021) considers whether vertically integrated marketplaces should be banned from using proprietary sales data of third-party sellers to develop competing product; Johnson et al. (2021) examines how policies for the ownership and control of consumer browsing data affect market outcomes in the online advertising industry.

As our objective is to show how Google, as a gatekeeper platform, affects the quality of journalism, our paper is related to numerous papers on news aggregators such as Dellarocas et al. (2013); Jeon and Nasr (2016); de Cornière and Sarvary (2022).[6] These papers examine different mechanisms through which a news aggregator (or a large digital platform like Facebook) affects competition among newspapers by influencing news sites' traffic, while taking the advertising revenue per traffic as given. By contrast, we account for Google's influence on newspapers' advertising business by making the ad revenue per traffic endogenous to data allocation, which in turn is influenced by Google's power in search market. In addition, our paper is related to the empirical paper of Calzada and Gil (2020), which examines the impact of Google News' opt-in policy on news publishers' traffic in Germany. A publisher's choice to opt out means shorter excerpts and no image for its articles indexed by Google News. Therefore, this policy generates a collective action problem similar to the one generated by search ranking externality in our model. They find that opting out reduced by 8% the number of visits to the outlets controlled by Axel Springer.

The two-sided market feature of our model makes our paper related to the canonical literature on media competition in two-sided markets (Anderson and Coate, 2005; Ambrus et al., 2016; Athey et al., 2018; Anderson et al., 2018; Anderson and Peitz, 2020) [7] and to its recent development accounting for the role of ad intermediaries (D'Annunzio and Russo, 2020, 2021).[8] We extend the stylized two-sided media market setup, where media firms compete both on the consumer side and on the advertising side, by introducing a gatekeeper platform that can act as

[6]See Jeon (2018) for a survey of the literature on news aggregators.

[7]This literature considers an environment in which publishers directly contract with advertisers to sell ad inventories. Anderson and Coate (2005) is the seminal paper that explicitly accounts for the cross-group externalities between consumers and advertisers in studying advertising market. Relaxing Anderson and Coate (2005)'s assumption that consumers are single-homing, Ambrus et al. (2016), Athey et al. (2018), and Anderson et al. (2018) examine how it affects the advertising market outcomes when a subset of consumers multi-home. Because all of these papers assume that publishers cannot perfectly track consumers, they focus on how repetitive impression affects ad price. By contrast, our paper assumes that all consumers generically multi-home on non-competing content providers and that Google has perfect tracking technology. Our model highlights the role consumer data plays in online targeted advertising.

[8]These two papers examine how the presence of different ad intermediaries affects media competition for advertisers. D'Annunzio and Russo (2020) explores the role of ad networks that track consumers across websites to cap the frequency of impressions. D'Annunzio and Russo (2021) considers ad intermediaries that use consumer browsing data on publishers' websites for targeted advertising and frequency capping. Both papers endogenize publishers' decision of outsourcing ad inventories to ad intermediaries.

an intermediary on both sides. We show that the gatekeeper platform can leverage its market power from the consumer side (i.e. the search market) to the advertising side for its benefit. We explicitly model consumers' generic multi-homing on different services to capture a main consequence of programmatic advertising: the boundary of the advertising market is much larger than that of each product (i.e. content) market.[9] Although the model of Krämer et al. (2019) also captures this situation, our paper is distinguished from theirs for the following reasons. First, they perform a static analysis, whereas we focus on dynamic efficiency in terms of quality choices. Second, they consider a setup of a representative advertiser in which each publisher chooses an ad price, while we consider the programmatic sale of display advertising. Last, they consider data sharing that improves ad targeting of both parties sharing the data; by contrast, we consider data leakage from newspapers to the SE, which is facilitated by the exercise of its market power in search and ad intermediation.

2.2 Baseline Model

In this section, we present the baseline model in which a group of consumers and a group of advertisers interact on two different two-sided markets—the newspaper market and sector B to be explained. On the consumer side, a monopolistic search engine (SE) mediates consumers' search for news. On the advertiser side, the SE acts as an ad tech intermediary and competes with another ad tech intermediary T to sell content providers' ad inventory to advertisers.

In our analysis, we focus on the strategic interaction between the SE and n number of ad-funded newspapers that compete on quality, although we also consider quality choice by content providers in sector B. The other market participants—consumers, advertisers, and ad tech intermediary T—are not strategic players. Figure 2.1 depicts the model's industry structure, which we explain below.

[9] A common assumption in these papers is that the boundary of the product (i.e. content) market coincides with that of the advertising market, which means that the same set of media that compete for readership also compete for advertising dollars.

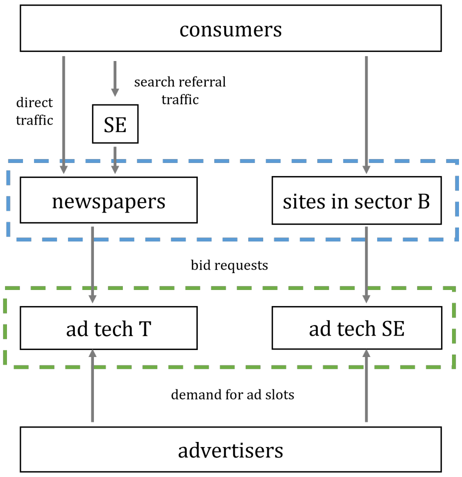


Figure 2.1: Industry Structure

Notes. The blue rectangle represents the content market in which newspapers compete in quality for both direct traffic and search referral traffic, but they do not compete with sites in sector B for traffic. The green rectangle represents the ad intermediation market where two ad intermediaries (SE and T) sell ad inventory to advertisers.

2.2.1 Newspaper market and Sector B

There are n online newspapers that are purely financed by advertising. Each newspaper i competes by investing in quality q_i at a cost $c(q_i)$, which is strictly increasing and strictly convex with $c(0) = 0$. Let $\mathbf{q} \equiv (q_1, ..., q_n)$ and $\mathbf{q}_{-i} \equiv (q_1, ..., q_{i-1}, q_{i+1}, ..., q_n)$.

The newspapers are horizontally differentiated, and their demands are determined by the quality vector $\mathbf{q}$. Each newspaper i's demand is composed of two sources—traffic from direct visit (direct traffic) $D^{d,i}(\mathbf{q}) = D^{d,i}(q_i, \mathbf{q}_{-i})$ and traffic referred by the monopolistic search engine (search referral traffic) $D^{s,i}(\mathbf{q}) = D^{s,i}(q_i, \mathbf{q}_{-i})$, $i \in \{1, 2, ..., n\}$. Regarding how these two traffic sources are formed, we have in mind a situation in which consumers have heterogeneous tastes for newspapers and each consumer has a single preferred newspaper whose site she visits directly and regularly. In addition, consumers also search for news by using the search engine (SE) and read news from multiple newspapers depending on the search results.

We make the following assumption about newspaper demand.

Assumption A1. *(i)* $D_i^{d,i} = \frac{\partial D^{d,i}}{\partial q_i} > 0,\ D_j^{d,i} = \frac{\partial D^{d,i}}{\partial q_j} < 0$ *for* $j \neq i$ *and the same for* $D^{s,i}(\mathbf{q})$*;*

(ii) $\sum_{j=1}^{n} D_j^{d,i} \geq 0$ *when* $q = q_1 = ... = q_n$ *and the same for* $D^{s,i}(\mathbf{q})$*;*

(iii) $D_{ii}^{d,i} = \frac{\partial^2 D^{d,i}}{\partial {q_i}^2} \leq 0,\ D_{ij}^{d,i} = \frac{\partial^2 D^{d,i}}{\partial q_j \partial q_i} \leq 0, j \neq i$ *and the same for* $D^{s,i}(\mathbf{q})$.

A1 (i) means that newspaper i's demand is increasing in its own quality q_i, while decreasing in any competitor j's quality q_j. A1 (ii) means that at symmetric quality, if all newspapers increase their quality, it at least weakly increases an individual newspaper's demand. This is the market expansion effect. In A1 (iii), $D_{ii}^{d,i} \leq 0$ guarantees that newspapers' profit maximization problems are concave; the property of cross-derivative $D_{ij}^{d,i} \leq 0, j \neq i$ implies that quality choices are strategic substitutes.

Regarding search referral traffic, it is convenient to think that the demand is determined by two stages. In the first stage, consumers visit the SE to search for news and, given the search result, decide which links to click through. The demand determined at this stage is captured by $D^{s,i}(\mathbf{q})$. In the second stage, the SE directs consumers to the news websites whose links are clicked. In this process, consumers may suffer from the slow loading of pages such that they decide not to read the news. We assume that the loss rate is $\delta \in [0, 1]$. As a result, the final search referral traffic is $(1 - \delta)D^{s,i}(\mathbf{q})$.

In addition to news consumption activity (considered activity A), we assume that each consumer also uses the Internet to visit other ad-financed content providers' applications or websites. For simplicity, we aggregate all other websites different from newspapers into a single sector called B. We make a reduced-form representation of sector B and assume that the demand of sector B, $D^B(q_B)$, is determined by its quality choice q_B as well, and $\frac{dD^B}{dq_B} > 0,\ \frac{d^2 D^B}{d{q_B}^2} < 0$. The cost of investing in quality is $c_B(q_B)$, which is strictly increasing and convex with $c_B(0) = 0$. The newspaper market and sector B constitute the content market, and we call players in these markets content providers.

2.2.2 Advertising market and data

Both newspapers and sites (or apps) in sector B are ad-financed and hence sell targeted ads. Every consumer multi-homes on her preferred news site and sector B. Although the sites in sector B do not compete with newspapers on the content side, consumers' multi-homing implies that they do compete with the latter on the advertiser side by offering ad inventory that targets the same consumers.

The sale of inventory for targeted advertising is mediated by ad tech intermediaries that organize real time auctions on behalf of advertisers and publishers. We consider a duopolistic ad tech market—an ad tech system operated by the SE and an alternative system T based on third-party ad intermediaries. We assume that the sites/apps in sector B use the ad tech service of the SE. Actually, we obtain qualitatively the same results if we assume that sector B represents the products of the SE whose advertising are sold by the SE.[10] In the baseline model, all newspapers are assumed to use the service of the ad tech intermediary T. We later extend the baseline model to a situation where an exogenous number of newspapers use the ad tech service of the SE.[11]

To describe targeted advertising revenues generated in the two ad tech systems, we start by describing data allocation. Let Ω^x be the complete data set generated by all of consumer x's online activities. In our model, we have $\Omega^x = \omega^{x,d} \cup \omega^{x,s} \cup \omega^{x,B}$, where $\omega^{x,k}$ represents the set of browsing data generated by consumer x's activity $k \in \{d, s, B\}$, that d stands for direct news reading, s search-referred news reading, and B activities in sector B. Then let $\Omega^{x,h} \subseteq \Omega^x$ be the set of data that ad intermediary $h \in \{SE, T\}$ has about consumer x. An ad tech system can collect and combine data on a consumer's various activities conducted on its customers' websites/apps across time only if it can identify the consumer. We assume that ad intermediary T can perfectly identify consumers in direct traffic but cannot identify consumers in search traffic. By contrast, the SE's tracking technology is superior such that it can combine any data sets it has access to. This assumption of asymmetric tracking technology between ad tech T and SE has a realistic foundation.[12] Together

[10]Google provides more than 53 consumer-facing services and products in the UK and gathers data through them (Appendix F of CMA Report (2020), p. F8)

[11]Studying a full-fledged competition between ad tech intermediaries in which they make offers to content providers is beyond the scope of this paper. To our knowledge, no paper provides yet a formal analysis of the competition in the ad tech market.

[12]Ad techs rely on cookies as identifiers when tracking consumers' activities in mobile browsers while using mobile advertising IDs (MAID) as identifiers for tracking in mobile apps. Due to technical limits, small ad techs may fail to match these two IDs from time to time, leading to the loss of consumer data. By contrast, due to the popularity of its consumer-facing services and Android operating system, Google could use first-party login to facilitate its matching (see detailed explanation in Appendix 2.10.3). So our model could be interpreted as consumers using apps to read news from

with the assumption on content providers' choices of ad tech intermediaries, this assumption on tracking ability implies that, in the benchmark without AMP, data allocation associated with a certain consumer x is $\Omega^{x,T} = \omega^{x,d}, \Omega^{x,SE} = \omega^{x,B}$.

Next, we use a reduced-form approach to let data allocation determine targeted advertising revenues, abstracting away from the details of real-time auction. When a content provider uses ad intermediary h, the overall advertising revenue generated by a unit of traffic associated with activity k is

$$\alpha_{k,h}(\Omega^{x,h}, \Omega^{x,h} \cap \Omega^{x,-h})$$

where $k \in \{d, s, B\}, h \in \{SE, T\}$ and $-h$ represents the rival ad tech system. Namely, we characterize the competition between the two ad tech systems by letting the advertising revenue in an ad tech system depend not only on the amount of data it owns but also on the extent of overlap between the two ad tech systems' data sets.

We impose the following assumption on this advertising revenue function:

Assumption B1. *$\forall k \in \{d, s, B\}$ and $\forall h \in \{SE, T\}$, $\alpha_{k,h}(\Omega^{x,h}, \Omega^{x,h} \cap \Omega^{x,-h})$ increases with $\Omega^{x,h}$ given $\Omega^{x,-h}$; and decreases with $\Omega^{x,h} \cap \Omega^{x,-h}$, given $\Omega^{x,h}$.*

We provide a microfoundation for this assumption in Appendix 2.10.1. The first part of the assumption means that the effect of increasing the amount of data held by ad tech system h on its advertising revenue is positive. Holding $\Omega^{x,h} \cap \Omega^{x,-h}$ constant, this is intuitive, as more data enables better targeting. Furthermore, this effect stays positive even if we take into account the effect through $\Omega^{x,h} \cap \Omega^{x,-h}$ (given $\Omega^{x,-h}$). To understand it, consider a data merger such that a subset of the rival's data, $\Omega^{x,-h} - \Omega^{x,h}$, is added to $\Omega^{x,h}$. This should increase the ad revenue of h even if the effect from better targeting is mitigated because this part of data is also possessed by the rival ad tech $-h$. The second part means that when the rival ad tech $-h$'s data set and hence its overlap with h's data set expand, ad tech h's data becomes less exclusive such that some ads that previously only h was able to target are now accessible to $-h$ as well. As a result, the inventory served by ad tech h becomes less unique, lowering its advertising revenue.

their single preferred news outlet while using mobile browsers to search for news from multiple newspapers, and ad tech T is unable to match consumers' cookie IDs with their MAIDs.

Note that the advertising revenue $\alpha_{k,h}(\Omega^{x,h}, \Omega^{x,h} \cap \Omega^{x,-h})$ also depends on the nature of ad inventories, i.e., which activity k the ad impression is associated with. First, even under symmetric data allocation, α_d and α_B could still be different. This is because the nature of the site on which an advert is displayed affects the willingness to pay of advertisers and thereby the advertising revenue. For instance, reputable advertisers do not want to show their ads besides hate/racism content. Second, $\alpha_{d,T}$ is different from $\alpha_{s,T}$. As we assumed above, ad tech system T is unable to identify consumers in newspaper's search-referral traffic, $\Omega^{x,T} = \varnothing$ for ad inventories associated with activity s. This means that newspapers can only use contextual advertising for search referral traffic, which only uses context data but not consumer behavioral data. Hence, we add a simplifying assumption:

Assumption B2. *All newspapers use contextual advertising for search-referral traffic such that ad revenue for search-referral traffic is constant and given by $\alpha_s \equiv \alpha_{s,T}(\varnothing, \varnothing)$ regardless of data allocation.*

B2 allows us to focus on the substitution between the ad revenue of newspapers' direct traffic and the ad revenue of sector B. It plays a role mainly in the extension in which we analyze a divide-and-conquer strategy by making the analysis tractable. Due to assumption B1, the contextual advertising revenue α_s is lower than the revenue generated from personalized ads that makes use of behavioral data.[13]

Last, we assume that an ad tech h's payoff is a fixed share τ^h of the advertising revenue it generates. τ^h is exogenously given and belongs to $(0, 1)$. We also call τ^h h's ad tech take.

2.2.3 The search engine and the roles of AMP

As introduced in the previous parts, the SE runs two businesses: it is a monopoly in the search market and faces competition from T in the ad intermediation market.

[13] For empirical evidence showing that advertisers bid more for impressions that enable identification of consumers than for those with only context information available, see Appendix F p. 29 of CMA Report (2020), Beales (2010) and Srinivasan (2020). For instance, according to CMA Report (2020)'s study of data generated by Google's Randomised Controlled Trial (RCT) of display advertising, UK publishers earned approximately 70 percent less revenue overall when they were unable to sell inventory using personalised advertising (i.e., when cookies were not available) but competed against others who could.

Due to its market power in the search market, the SE is able to influence newspapers' search referral traffic by altering their rankings in the search result. The search referral demand $D^{s,i}(\mathbf{q})$ represents the demand from an objective and non-distorted ranking of various news articles. When the ranking of a single newspaper, say newspaper i, is purposely promoted by the SE relative to the non-distorted search result, its search-referral traffic becomes $D^{s,i}(q_i, \mathbf{q}_{-i}; i+) \equiv D^{s|i+,i}(q_i, \mathbf{q}_{-i}) > D^{s,i}(q_i, \mathbf{q_{-i}}), \forall \mathbf{q}$. And when newspaper i's ranking is purposely demoted, its search referral traffic becomes $D^{s,i}(q_i, \mathbf{q}_{-i}; i-) \equiv D^{s|i-,i}(q_i, \mathbf{q}_{-i}) < D^{s,i}(q_i, \mathbf{q_{-i}}), \forall \mathbf{q}$.

The SE develops AMP technology, which overcomes the slow loading problem of web pages in mobile browsers. In addition, the SE will cache all web pages written in AMP format, allowing it to obtain consumers' browsing data regarding how they interact with these pages. As a result, if all newspapers adopt AMP for their traffic mediated by the search engine, the traffic loss δ will be eliminated but the SE collects the data $\omega^{x,s}$ on every consumer x and hence its data set expands to $\Omega^{x,SE} = \omega^{x,B} \cup \omega^{x,s}$.

2.2.4 Timing

Newspapers simultaneously decide whether to adopt the AMP and how much to invest in quality $q_i, i \in \{1, 2, ..., n\}$. At the same time, sector B chooses its quality q_B. Our equilibrium concept is Nash equilibrium, and we restrict our attention to the symmetric ones.

2.3 Two Benchmarks

In this section, we analyze two benchmarks for later use: one is the case without AMP, and the other one is a hypothetical situation where we assume SE cannot, through AMP, gain access to data set $\omega^{x,s}$ of consumers.

2.3.1 Benchmark of no AMP

Recall that when there is no AMP, the data allocation across the two ad techs is $\Omega^T = \omega^d$ and $\Omega^{SE} = \omega^B$. Therefore, in this case, a newspaper's advertising revenue per direct traffic and sector B's advertising revenue per traffic are as follows:

$$\alpha_d^N \equiv \alpha_{d,T}(\Omega^{x,T}, \Omega^{x,T} \cap \Omega^{x,SE}) = \alpha_{d,T}(\omega^{x,d}, \omega^{x,d} \cap \omega^{x,B})$$
$$\alpha_B^N \equiv \alpha_{B,SE}(\Omega^{x,SE}, \Omega^{x,SE} \cap \Omega^{x,T}) = \alpha_{B,SE}(\omega^{x,B}, \omega^{x,B} \cap \omega^{x,d})$$

where the superscript N refers to the regime of no AMP.

Taking other newspapers' quality choices $\mathbf{q_{-i}}$ as given, newspaper i solves the following profit maximization problem, which is concave due to Assumption A1:

$$\max_{q_i} (1 - \tau^T) \left[\alpha_d^N D^{d,i}(q_i, \mathbf{q_{-i}}) + \alpha_s(1 - \delta) D^{s,i}(q_i, \mathbf{q_{-i}})\right] - c(q_i)$$

where $\tau^T \in (0, 1)$ is the ad tech take of T. Hence, the best response is characterized by the first-order condition:

$$(1 - \tau^T) \left[\alpha_d^N D_i^{d,i}(q_i, \mathbf{q_{-i}}) + \alpha_s(1 - \delta) D_i^{s,i}(q_i, \mathbf{q_{-i}})\right] - c'(q_i) = 0.$$

The news quality at symmetric equilibrium is given by the following proposition:

Proposition 2.1. *In the benchmark without AMP, the news quality at the symmetric equilibrium, denoted by q^N, is characterized by*

$$(1 - \tau^T) \left[\alpha_d^N D_i^{d,i}(q^N, \ldots, q^N) + \alpha_s(1 - \delta) D_i^{s,i}(q^N, \ldots, q^N)\right] = c'(q^N) \text{ for all } i = 1, ..., n.$$

Sector B solves the problem of

$$\max_{q_B} (1 - \tau^{SE}) \alpha_B^N D^B(q_B) - c_B(q_B)$$

where $\tau^{SE} \in (0, 1)$ is the ad tech take of SE. Thus, the equilibrium quality q_B^N is determined by:

$$(1 - \tau^{SE}) \alpha_B^N D^{B'}(q_B^N) - c_B'(q_B^N) = 0.$$

2.3.2 Benchmark of AMP without changes in data allocation

In this second benchmark, we consider a hypothetical situation where the SE cannot access to the data sets ω^s through AMP. In other words, newspapers' adoption of AMP does not lead to any change in the allocation of data, and only has the direct effect of eliminating the friction δ in search referral traffic. The advertising revenues are still given by α_d^N and α_B^N. Therefore, it is immediate that:

Proposition 2.2. *Consider a benchmark in which AMP is adopted by all newspapers, but it does not affect the allocation of consumer data.*

(i) The news quality at the symmetric equilibrium, denoted by q^*, is characterized by

$$(1-\tau^T)\left[\alpha_d^N D_i^{d,i}(q^*,\dots,q^*)+\alpha_s D_i^{s,i}(q^*,\dots,q^*)\right]=c'(q^*)\textit{ for all } i=1,...,n.$$

(ii) Hence, AMP increases the quality of journalism: $q^*>q^N$.

This second benchmark establishes the result of one of the policy remedies we propose in Section 2.8.

2.4 AMP with Changes in Data Allocation: Static Analysis

From now on, we suppose that AMP changes the allocation of consumer data. In this section, we consider a static scenario in which we fix the quality levels in the two sectors at q^N and q_B^N and focus on the equilibrium in which all newspapers adopt the AMP format [14]. We analyze how AMP affects content providers' advertising revenues and the static welfare. The welfare result in this section will be contrasted with that in the next section where quality choices are endogenous.

2.4.1 The impact of AMP on data allocation and advertising revenue

When all newspapers adopt AMP, the data allocation between the two ad tech systems becomes: $\Omega^T=\omega^d,\Omega^{SE}=\omega^B\cup\omega^s$. Therefore, the ad revenue per unit of newspapers' direct traffic and the ad revenue per traffic in sector B respectively become:

$$\alpha_d^M\equiv\alpha_{d,T}(\Omega^{x,T},\Omega^{x,T}\cap\Omega^{x,SE})=\alpha_{d,T}(\omega^{x,d},\omega^{x,d}\cap\{\omega^{x,B}\cup\omega^{x,s}\})$$
$$\alpha_B^M\equiv\alpha_{B,SE}(\Omega^{x,SE},\Omega^{x,SE}\cap\Omega^{x,T})=\alpha_{B,SE}(\omega^{x,B}\cup\omega^{x,s},\{\omega^{x,B}\cup\omega^{x,s}\}\cap\omega^{x,d}).$$

where the superscript M refers to the regime of AMP. Because of Assumption B1, we have

[14]The existence of this equilibrium can be proven by following the logic of Proposition 2.11.

Lemma 2.1. *Suppose that all newspapers adopt the AMP format. This reduces the ad revenue for direct traffic to newspapers, while increases the ad revenue for traffic related to activity B:*

$$\alpha_d^N > \alpha_d^M, \alpha_B^N < \alpha_B^M.$$

To understand the result of $\alpha_d^N > \alpha_d^M$, consider consumer x who is a direct reader of newspaper 1. In the absence of AMP, $\Omega^{x,T} = \omega^{x,d}$ is the set of data that ad tech T has about this consumer and $\Omega^{x,SE} = \omega^{x,B}$ is the set of data that the SE obtains from her activity B. If the two activities are completely uncorrelated (i.e. $\omega^{x,d} \cap \omega^{x,B} = \varnothing$), the most appealing product to consumer x inferred from the data set $\omega^{x,d}$ will be different from the one inferred from $\omega^{x,B}$. If the quality of the data in $\omega^{x,d}$ is much better than that in $\omega^{x,B}$, the ad revenue newspaper 1 generates from x's direct visit would be much higher than what sector B generates. However, in the presence of AMP, if the SE gets access to the consumer x's data $\omega^{x,s}$, we have $\tilde{\Omega}^{x,SE} = \omega^{x,B} \cup \omega^{x,s}$. Then, if $\omega^{x,s}$ is correlated with $\omega^{x,d}$, this may allow the SE to infer sometimes the best match product that would be advertised by newspaper 1 alone in the absence of AMP. In such cases, the SE can engage in advertising arbitrage by targeting consumer x with the best match product in the ad space of sector B, reducing the ad revenue of newspaper 1.

2.4.2 Static welfare

We study how AMP changes static welfare given quality choices in both sectors. As each newspaper chooses quality q^N, their demands are given by $D^{d,1}(\mathbf{q}^N) = ... = D^{d,n}(\mathbf{q}^N) \equiv D^d(\mathbf{q}^N)$ for direct traffic and $D^{s,1}(\mathbf{q}^N) = ... = D^{s,n}(\mathbf{q}^N) \equiv D^s(\mathbf{q}^N)$ for search referral traffic, where $\mathbf{q}^N = (q^N, ..., q^N)$. And the demand in sector B is $D_B(q_B^N)$. We make the following assumption about advertisers' surplus:

Assumption B3. *(i) Given total advertising inventory (namely, traffic allocation), improving targeting in a subset of inventory increases total advertising surplus; (ii) Advertisers retain a constant share β of the total advertising surplus regardless of the presence of AMP.*

The second part of the assumption implies that we can express the total advertising surplus, which is defined as the sum of advertiser surplus and industry revenue, as $\frac{1}{1-\beta}$ times the joint advertising revenue of content providers and ad tech intermediaries. The advertising industry revenue in the absence of AMP is given as follows:

$$n(1-\tau^T+\tau^T)\underbrace{\left[\alpha_d^N D^d(\mathbf{q}^N)+\alpha_s(1-\delta)D^s(\mathbf{q}^N)\right]}_{\text{a single newspaper's ad revenue}}+(1-\tau^{SE}+\tau^{SE})\underbrace{\alpha_B^N D^B(q_B^N)}_{\substack{\text{total ad revenue}\\ \text{in sector B}}}$$

The welfare change induced by AMP comes from (i) the change in consumer welfare due to the elimination of traffic loss, which is positive; (ii) the change in the total surplus of the advertising sector, which is also positive:

$$\begin{aligned}
&\frac{1}{1-\beta}\left[n\alpha_d^M D^d(\mathbf{q}^N)+n\alpha_s D^s(\mathbf{q}^N)+\alpha_B^M D^B(q_B^N)\right]-\frac{1}{1-\beta}\left[n\alpha_d^N D^d(\mathbf{q}^N)+n\alpha_s(1-\delta)D^s(\mathbf{q}^N)+\alpha_B^N D^B(q_B^N)\right]\\
>&\frac{1}{1-\beta}\left[n\alpha_d^M D^d(\mathbf{q}^N)+n\alpha_s(1-\delta)D^s(\mathbf{q}^N)+\alpha_B^M D^B(q_B^N)\right]-\frac{1}{1-\beta}\left[n\alpha_d^N D^d(q^N)+n\alpha_s(1-\delta)D^s(\mathbf{q}^N)+\alpha_B^N D^B(q_B^N)\right]\\
>&0
\end{aligned}$$

The last inequality follows from Assumption B3 (i), which means that the increase in the advertising revenue from sector B due to better targeting more than compensates for the reduction in the advertising revenue from newspapers' direct traffic.

Proposition 2.3. *Suppose that all newspapers adopt the AMP format. Under B1-B3, AMP strictly increases static welfare.*

AMP improves static welfare even if AMP does not affect the loss rate of search-referral traffic (i.e., when the loss rate δ is close to zero). This is because AMP enables SE to use the data from search referral traffic to improve targeting efficiency in sector B, which in turn increases total surplus in the advertising industry.

2.5 AMP with Changes in Data Allocation: Dynamic Analysis

In this section, we consider the main scenario in which content providers' quality choices are endogenously determined and study how AMP affects dynamic welfare. We focus on the equilibrium in which all newspapers adopt AMP. The existence of such equilibrium is verified in the next section.

2.5.1 Quality choice

Expecting all other newspapers to adopt AMP and taking their quality choices $\mathbf{q_{-i}}$ as given, the newspaper i that also adopts AMP solves the following profit maximization problem:

$$\max_{q_i} (1-\tau^T) \left[\alpha_d^M D^{d,i}(q_i, \mathbf{q_{-i}}) + \alpha_s D^{s,i}(q_i, \mathbf{q_{-i}})\right] - c(q_i)$$

The best response is determined by the first-order condition:

$$(1-\tau^T) \left[\alpha_d^M D_i^{d,i}(q_i, \mathbf{q_{-i}}) + \alpha_s D_i^{s,i}(q_i, \mathbf{q_{-i}})\right] - c'(q_i) = 0.$$

Hence, the news quality in the symmetric equilibrium in which all newspapers adopt AMP is given by the following proposition:

Proposition 2.4. *When all newspapers adopt the AMP format, the news quality at the symmetric equilibrium, denoted by q^M, is characterized by*

$$(1-\tau^T) \left[\alpha_d^M D_i^{d,i}(q^M, ..., q^M) + \alpha_s D_i^{s,i}(q^M, ..., q^M)\right] = c'(q^M) \text{ for all } i = 1, ..., n.$$

Compared to the condition in Proposition 2.1 which characterizes the equilibrium news quality in the absence of AMP, newspapers' adoption of AMP has two opposite effects on their incentives to invest in quality. On the one hand, it increases the marginal benefit of investment by eliminating the loss δ in search referral traffic. On the other hand, it discourages investment as the data allocation reduces newspapers' advertising revenue in direct traffic. Therefore, we have the following result:

Proposition 2.5. *The effect of the AMP on news quality is ambiguous: news quality is reduced when the negative data allocation effect dominates. (e.g., $\delta = 0$, $\alpha_d^M << \alpha_d^N$), while the news quality is increased when the positive search traffic enhancing effect dominates. (e.g., $\delta >> 0, \alpha_d^M \simeq \alpha_d^N$)*

In the presence of AMP, sector B solves the problem of

$$\max_{q_B} (1-\tau^{SE})\alpha_B^M D^B(q_B) - c_B(q_B).$$

So the equilibrium quality q_B^M is determined by:

$$(1-\tau^{SE})\alpha_B^M D^{B'}(q_B^M) - c_B'(q_B^M) = 0.$$

q_B^M is higher than q_B^N as the increased advertising revenue per traffic increases the marginal benefit of investing in quality.

2.5.2 Welfare analysis

To facilitate welfare analysis, in this subsection, we impose a specific structure on demand functions. Regarding the demand in direct traffic, suppose that each consumer would read k^d number of news articles when she visits her favorite news outlet directly. Assume that q_i stands for the quality of a single article in newspaper i. Then newspaper i's overall quality is $k^d q_i$. As consumers single-home on one newspaper in terms of direct traffic, we apply the discrete-choice Logit model. Let consumer x's utility from direct visit to newspaper i be:

$$U_{x,i}^d = ln\big(v^d(k^d q_i)\big) + \varepsilon_{x,i}^d, \quad i = 0, 1, 2, ..., n,$$

where "0" stands for the outside option whose quality is q_0. In addition, $\varepsilon_{x,i}^d$ is i.i.d. according to the Type I Extreme Value distribution with scale parameter $\mu^d > 0$. Each consumer chooses the newspaper that delivers the highest utility.

This yields the following direct demand of newspaper i: $D^{d,i}(\mathbf{q}) = \frac{\tilde{v}^d(k^d q_i)}{\Sigma_{j=0}^n \tilde{v}^d(k^d q_j)}$, where $\tilde{v}^d(\cdot) = (v^d(\cdot))^{\frac{1}{\mu^d}}$. When we assume that $v^d(\cdot)$ is increasing and concave and that $\mu^d > 1$, this demand function satisfies the assumptions in A1. From this specification, we obtain the following consumer surplus from direct traffic: $CS^d = \mu^d ln(\sum_{i=0}^n \tilde{v}^d(k^d q_i))$.

In addition to direct demand, each consumer also has demand for k^s number of news articles via search. We assume that each consumer makes k^s independent search queries and that each query is associated with a separate discrete-choice problem. As a result, a consumer multihomes in terms of search-referral traffic in the sense that she reads articles from different newspapers in different searches. Let consumer x 's utility from reading an article of newspaper i discovered through the SE be $U_{x,i}^s = ln\big(v^s(q_i)\big) + \varepsilon_{x,i}^s, \quad i = 0, 1, 2, ..., n$ in which $\varepsilon_{x,i}^s$ is i.i.d. according to the Type I Extreme Value distribution with scale parameter $\mu^s > 0$. These preference shocks are independent across search queries and uncorrelated with those of direct traffic. Therefore, the search-referral demand of newspaper i without AMP is

$D^{s,i}(\mathbf{q}) = k^s(1-\delta)\frac{\tilde{v}^s(q_i)}{\Sigma_{j=0}^{n}\tilde{v}^s(q_j)}$, where $\tilde{v}^s(\cdot) = (v^s(\cdot))^{\frac{1}{\mu^s}}$.

Last, let consumer x's utility derived from activity B be $U_x^B = ln\big(v^B(q^B)\big) + \varepsilon_x^B$ and the utility derived from activity B's outside option be $U_{x,0}^B = ln\big(v^B(q_0^B)\big) + \varepsilon_{x,0}^B$, in which ε_x^B and $\varepsilon_{x,0}^B$ are as before i.i.d. according to the Type I Extreme Value distribution with scale parameter $\mu^B > 0$. And let $\tilde{v}^B(\cdot) = (v^B(\cdot))^{\frac{1}{\mu^B}}$ denote the normalized valuation of quality.

Furthermore, we introduce the following assumption:

Assumption A2. *Newspapers are sufficiently differentiated, namely μ^d and μ^s are sufficiently large.*

μ^d and μ^s are sufficiently large in the sense that it guarantees Lemma 2.3 and Lemma 2.5 that we introduce later on.

SE's profit

As the SE's profit is a constant share τ^{SE} of the advertising revenue generated in sector B for supplying ad tech service, it is immediate from the last subsection that SE always benefits from newspapers' adoptions of AMP—the data allocation effect of AMP not only increases the advertising revenue per traffic but also expands ad inventory in sector B:

$$\Pi^{SE,N} = \tau^{SE}\alpha_B^N D^B(q_B^N) < \Pi^{SE,M} = \tau^{SE}\alpha_B^M D^B(q_B^M)$$

Formally, we have the following result:

Proposition 2.6. *The SE always gains from newspapers' adoption of the AMP format. Therefore, even if the adoption of the AMP format reduces the quality of journalism, the SE has no incentive to internalize it.*

We assumed that the SE has no consumer-facing services related to activity B. In reality, Google owns many consumer-facing services, which will even strengthen our results, as Google will retain the whole benefit from having access to search-referral data instead of just having a fraction τ^{SE} of it.

Comparison of newspaper profit

When there is no AMP, the equilibrium newspaper profit is:

$$\pi^N(\alpha_d^N, \delta) = (1-\tau^T)[\alpha_d^N D^d(\mathbf{q}^N) + \alpha_s(1-\delta)D^s(\mathbf{q}^N)] - c(q^N).$$

We have the two following lemmas.

Lemma 2.2. *When there is no AMP, the news quality at the symmetric equilibrium q^N is decreasing in traffic friction δ.*

Lemma 2.3. *Under Assumption A2, a newspaper's profit π^N in the symmetric equilibrium without AMP satisfies $\frac{\partial \pi^N(\alpha_d^N,\delta)}{\partial \alpha_d^N} > 0$ and $\frac{\partial \pi^N(\alpha_d^N,\delta)}{\partial \delta} < 0$.*

The lemma means that the direct effect of a positive exogenous shock to the industry, such as increased ad price or reduced loss rate, dominates the negative effect of intensified competition on industry profit at symmetric equilibrium.

When there is AMP, the equilibrium newspaper profit becomes:

$$\pi^M(\alpha_d^M) = (1-\tau^T)[\alpha_d^M D^d(\mathbf{q}^M) + \alpha_s D^s(\mathbf{q}^M)] - c(q^M).$$

We obtain the following result about the comparison of newspapers' profit between the two regimes:

Proposition 2.7. *Under assumptions A1, A2, B1, and B2 we have:*

(1). the presence of AMP reduces the newspaper industry profit when δ is close to zero;

(2). When a_d^M is close enough to a_d^N, there exists a threshold $0 < \tilde{\delta} < 1$ determined by $\pi^N(\alpha_d^N, \tilde{\delta}) = \pi^M(\alpha_d^M)$, such that AMP increases the newspaper industry profit if δ belongs to $(\tilde{\delta}, 1)$.

Comparison of consumer surplus in content market

When there is no AMP, the equilibrium consumer surplus is:

$$CS^N(\delta) = \mu^d ln\big(\tilde{v}^d(k^d q_0) + n\tilde{v}^d(k^d q^N)\big) + k^s(1-\delta)\mu^s ln\big(\tilde{v}^s(q_0) + n\tilde{v}^s(q^N)\big) + \mu^B ln\big(\tilde{v}^B(q_0^B) + \tilde{v}^B(q_B^N)\big)$$

Note that only the first two terms in CS^N depend on δ.

Lemma 2.4. *When there is no AMP, consumer surplus CS^N is decreasing in δ.*

From Lemma 2.2, when there is no AMP, the equilibrium news quality is decreasing in the loss rate δ. And because consumer surplus is increasing in the news quality, it is immediate that CS^N is decreasing in δ.

When there is AMP, total consumer surplus is:

$$CS^M = \mu^d ln\big(\tilde{v}^d(k^d q_0)+n\tilde{v}^d(k^d q^M)\big)+k^s\mu^s ln\big(\tilde{v}^s(q_0)+n\tilde{v}^s(q^M)\big)+\mu^B ln\big(\tilde{v}^B(q_0^B)+\tilde{v}^B(q_B^M)\big)$$

Note that CS^M does not depend on δ.

Proposition 2.8. *Under assumptions A1, A2, B1, and B2, we have:*

(1) If $CS^N|_{\delta=0} \leq CS^M$, consumer surplus is always higher with AMP;

(2) If $CS^N|_{\delta=0} > CS^M$, there exists a threshold $\bar{\delta} > 0$ determined by $CS^N(\bar{\delta}) = CS^M$ such that when $0 \leq \delta \leq \min\{\bar{\delta}, 1\}$, consumer surplus is lower with AMP; when $\min\{\bar{\delta}, 1\} < \delta \leq 1$, consumer surplus is higher with AMP.

This proposition suggests that when AMP lowers the quality of journalism, AMP's impact on consumer surplus depends on the trade-off between the gain from higher content quality in sector B and the loss from lower quality of journalism. For instance, consider the case of $\delta \approx 0$, where AMP does not bring much efficiency but reduces the equilibrium quality of newspapers through data leakage. If AMP lowers consumer surplus in this case, then AMP reduces consumer surplus for any δ below a certain threshold.

Comparison of social welfare

Because newspapers and sites in sector B in our model are ad-financed, they create values by providing content to consumers as well as by selling advertising inventories to advertisers through ad intermediaries. Under Assumption B3, the aggregate social welfare without AMP is:

$$W^N = \underbrace{CS^N - nc(q^N) - c^B(q_B^N)}_{\text{social surplus in content industry}} + \underbrace{\frac{1}{1-\beta}\Big[n\alpha_d^N D^d(\mathbf{q}^N) + n\alpha_s(1-\delta)D^s(\mathbf{q}^N) + \alpha_B^N D^B(q_B^N)\Big]}_{\text{social surplus in advertising industry}}$$

And the aggregate social welfare with AMP is:

$$W^M = CS^M - nc(q^M) - c^B(q_B^M) + \frac{1}{1-\beta}\big\{n\alpha_d^M D^d(\mathbf{q}^M) + n\alpha_s D^s(\mathbf{q}^M) + \alpha_B^M D^B(q_B^M)\big\}$$

Lemma 2.5. *Under Assumption A2, newspapers always underinvest in quality relative to the quality level chosen by a social planner to maximize social welfare.*

Our model does not consider positive externalities to the society from high quality journalism such as improving voting outcomes by informing voters or making politicians accountable and so on. The lemma should hold a fortiori if we take into account such positive externalities.

In the following proposition, we provide a sufficient condition for the adoption of AMP to be socially efficient:

Proposition 2.9. *If $q^M > q^N$, then aggregate social welfare is higher with AMP (i.e., $W^M > W^N$).*

In this case, the effect of AMP on social welfare can be decomposed into three parts: (1) the adoption of AMP directly creates more surplus in both content market and advertising market by eliminating the loss of traffic due to slow loading; (2) a higher content quality in each sector improves consumer surplus and creates more advertising opportunities by expanding traffic to newspapers and sites in sector B; (3) data leakage to site B increases ad targeting, which further increases surplus in advertising market.

However, if the equilibrium quality of newspapers is lower with AMP, the effect of AMP on welfare is ambiguous, as it depends on:

(i) whether consumers are affected more by the decreased quality in journalism or by the increased quality in sector B;

(ii) whether the direct effect of eliminating the loss of search-referral traffic δ brought by AMP is large enough, which includes gains in both consumer surplus and advertising surplus;

(iii) whether the advertising surplus generated by increased ad inventory in sector B is high enough relative to the loss from the reduced inventory of newspapers;

(iv) to what degree data leakage improves matching efficiency of ad inventories in sector B.

Therefore, AMP is highly likely to reduce welfare when δ is close to zero, consumers value the quality of newspapers much more than that of sector B, and advertisers value the ad inventory of newspapers much more than that of sector B.

The next proposition provides a sufficient condition for AMP adoption to reduce welfare. In the proposition, we shut down both the effect on the traffic loss rate and the one on the quality in sector B to focus on the main trade-off, but by continuity the result carries over when the two effects are small.

Proposition 2.10. *Suppose $\delta = 0$, $q_B^M = q_B^N \equiv q_B$ and $q^M \ll q^N$. Then, if the positive effect of data leakage on advertising surplus is dominated by the negative effect of lower quality of journalism on welfare, aggregate social welfare is lower with AMP (i.e., $W^M < W^N$).*

2.6 Newspapers' Incentive to Adopt AMP

In this section, we study the incentives of newspapers to adopt AMP. As before, we focus on symmetric equilibria.

Newspapers face a collective action problem as one newspaper's adoption of AMP generates two kinds of negative externalities to the other newspapers: search ranking externality and data leakage externality. First, the search ranking externality arises as the SE promotes adopters' articles in search results. Therefore, a newspaper's adoption will have a negative impact on the search referral traffic of other newspapers. Second, a newspaper's adoption leaks data of other newspapers' direct readers to the SE, which reduces their advertising revenues from direct traffic.

To facilitate the exposition in this section, we refine the notation of the data set $\omega^{x,s}$ to be $\omega^{x,s}(l)$, where l is the number of newspapers adopting AMP. So in the previous sections we mean $\omega^{x,s}(n)$ by $\omega^{x,s}$. Then, when there are l newspapers adopting AMP, we denote the ad revenue per direct traffic of newspapers and the ad revenue per traffic of sector B as:

$$\alpha_d(l) \equiv \alpha_{d,T}(\omega^{x,d}, \omega^{x,d} \cap \{\omega^{x,B} \cup \omega^{x,s}(l)\})$$
$$\alpha_B(l) \equiv \alpha_{B,SE}(\{\omega^{x,B} \cup \omega^{x,s}(l)\}, \{\omega^{x,B} \cup \omega^{x,s}(l)\} \cap \omega^{x,d}),$$

where for simplicity, we assume that, given l, $\alpha_d(l)$ is the same for all newspapers, regardless of whether one has adopted AMP or not. Therefore, $\alpha_d^M \equiv \alpha_d(n)$, $\alpha_B^M \equiv \alpha_B(n)$ and $\alpha_d^N \equiv \alpha_d(0)$, $\alpha_B^N \equiv \alpha_B(0)$.

From Assumption B1, $\alpha_d(l)$ decreases and $\alpha_B(l)$ increases in l. This is because when there are more newspapers adopting AMP, the scale of data leakage is larger. This effect is in place in the absence of search distortion. In addition, the SE's promotion of AMP articles in search results further increases data leakage.

We first verify the existence of an equilibrium in which all newspapers adopt the AMP format. As explained in Section 2.2, the SE could leverage its market power in the search market to implement AMP by promoting adopters' rankings in the search result. When newspaper i is the only non-adopter, its articles are demoted in the search result, and hence, its search referral traffic becomes $D^{s,i}(q_i, \mathbf{q}_{-i}; i-) \equiv D^{s|i-,i}(q_i, \mathbf{q}_{-i}) < D^{s,i}(q_i, \mathbf{q_{-i}})$. When n is sufficiently large, the demotion of newspaper i in search ranking implies that its articles almost never appear in the first pages of search results and hence $D^{s|i-,i}(q_i, \mathbf{q}_{-i})$ is close to zero. Moreover, this implies $\alpha_d(n-1) \simeq \alpha_d(n)$. This is because when n is large, consumers are always directed to AMP articles such that the SE can perfectly track their search-referred news reading activities. Then, additional adoption of newspaper i has no impact on SE's data set.

Formally, we assume:

Assumption A3. *The number of competing newspapers n is sufficiently large such that the demotion of newspaper i in search rankings makes $D^{s|i-,i}(q_i, \mathbf{q}_{-i}^M)$ close to zero for any $(q_i, \mathbf{q}_{-i}^M)$ and $\mathbf{q}_{-i}^M = (q^M, \ldots, q^M)$, and that $\alpha_d(n-1) \simeq \alpha_d(n)$.*

Note that for the above assumption to hold, n does not need to be very large. For instance, if 5 articles per mobile page are shown in a search result and most consumers stop scrolling down from the fifth page, then $n > 21$ is enough.

Then we have:

Proposition 2.11. *Under assumptions A1, A3, B1, and B2, there exists an equilibrium in which all newspapers adopt the AMP format.*

We emphasize that when $\delta \approx 0$, the SE's leverage of its search monopoly power through demotion of non-adopters' positions is crucial in sustaining the all-adoption equilibrium. As we can see in the above inequality, without punishment in terms of ranking, non-adoption will not affect the search-referral traffic and remove the (small) negative impact of data leakage on the advertising revenue in direct traffic (i.e., $\alpha_d(n-1) > \alpha_d(n)$). This induces newspaper i not to adopt the AMP format.

Next, we examine when there exists another symmetric equilibrium in which no newspaper adopts the AMP format. Suppose newspaper i is the only adopter of AMP such that the SE promotes its AMP articles in search results. Hence its search referral traffic becomes $D^{s,i}(q_i, \mathbf{q}_{-i}; i+) \equiv D^{s|i+,i}(q_i, \mathbf{q}_{-i}) > D^{s,i}(q_i, \mathbf{q}_{-\mathbf{i}})$. Newspapers' ad revenue per direct traffic becomes $\alpha_d^M(1)$, satisfying $\alpha_d^M \equiv \alpha_d(n) < \alpha_d(1) < \alpha_d(0) \equiv \alpha_d^N$.

We provide a sufficient condition for the existence of the non-adoption equilibrium:

Proposition 2.12. *Under assumptions A1, B1 and B2, there exists an equilibrium in which no newspaper adopts the AMP format if the following condition is satisfied:*

$$\underbrace{(\alpha_d^N - \alpha_d(1))D^{d,i}(q^+, \mathbf{q}_{-i}^N)}_{\substack{\textit{reduction in ad revenue} \\ \textit{due to data leakage}}} > \underbrace{\alpha_s \left[D^{s|i+,i}(q^+, \mathbf{q}_{-i}^N) - (1-\delta)D^{s,i}(q^+, \mathbf{q}_{-i}^N)\right]}_{\substack{\textit{increase in search referral traffic} \\ \textit{due to promotion and higher speed}}}$$

where q^+ is the quality choice of newspaper i after its deviation:

$$q^+ = \arg\max_{q_i}(1-\tau^T)\left[\alpha_d(1)D^{d,i}(q_i, \mathbf{q}_{-i}^N) + \alpha_s D^{s|i+,i}(q_i, \mathbf{q}_{-i}^N)\right] - c(q_i).$$

In short, the all-adoption equilibrium always exists and the non-adoption equilibrium can also exist if the loss from data leakage is large enough relative to the expansion of search referral demand.

2.7 Extension: Divide-and-Conquer

This section relaxes the assumption in the baseline model that all newspapers use the ad tech system T by supposing that $m(< n)$ number of newspapers use the ad tech SE instead. We assume that search ranking of the SE is neutral with respect to whether a newspaper uses the ad tech T or SE.

In this case, there are two ways through which the SE collects consumers' browsing data on news pages directed by search. First, when the news page a consumer visits via search belongs to a newspaper using the ad tech SE, the SE collects her browsing data. Second, when the news page belongs to a newspaper that uses the ad tech T but has adopted AMP, the SE obtains her data by hosting the relevant page. We denote the amount of data the SE captures regarding a consumer x in search referral traffic as $\omega^{x,s}(m,l,g)$, where m is the number of newspapers using the ad tech SE, l is the number of newspapers adopting AMP among those who use the ad tech T, and g is the number of newspapers adopting AMP among those who use the ad tech SE . We impose the following assumption on $\omega^{x,s}(m,l,g)$:

Assumption B4. *The amount of data the SE obtains from search referral traffic on a consumer x, $\omega^{x,s}(m,l,g)$, has the following properties:*[15]
(1) Given l and g, it is increasing with the number of newspapers using its ad tech service: $\frac{\partial\omega^{x,s}(m,l,g)}{\partial m} \geq 0$.
(2) Given m, it is increasing with the number of newspapers adopting AMP: $\frac{\partial\omega^{x,s}(m,l,g)}{\partial l} \geq 0$ *and* $\frac{\partial\omega^{s}(m,l,g)}{\partial g} \geq 0$.

The properties of $\frac{\partial\omega^{x,s}(m,l,g)}{\partial m} \geq 0$ and $\frac{\partial\omega^{x,s}(m,l,g)}{\partial l} \geq 0$ are straightforward as the SE gains more access to data. The property of $\frac{\partial\omega^{x,s}(m,l,g)}{\partial g} \geq 0$ is because the SE promotes AMP articles in search results, which increases data leakage to the SE. For instance, more data is leaked to the SE when a consumer is diverted to an AMP article away from a non-AMP article of a newspaper using the ad tech T.

Now, the amount of data a newspaper has about its direct readers and hence the ad revenue per direct traffic will depend on which ad tech service it uses. For any newspaper using the ad tech T, the data allocation regarding its direct reader x is $\Omega^{x,T} = \omega^{x,d}$, $\Omega^{x,SE} = \omega^{x,s}(m,l,g) \cup \omega^{x,B}$. We denote the ad revenues generated from consumer x's direct visit to the newspaper and her visit to sector B as:

$$\alpha_d^T(m,l,g) = \alpha_{d,T}(\omega^{x,d}, \omega^{x,d} \cap \left\{\omega^{x,s}(m,l,g) \cup \omega^{x,B}\right\})$$
$$\alpha_B^T(m,l,g) = \alpha_{B,SE}(\left\{\omega^{x,s}(m,l,g) \cup \omega^{x,B}\right\}, \left\{\omega^{x,s}(m,l,g) \cup \omega^{x,B}\right\} \cap \omega^{x,d})$$

[15] *m,l,g are integers. In this assumption, we abuse the notation of partial derivative to simplify the expression.*

With some abuse of notation, the superscript T in $\alpha_B^T(m,l,g)$ denotes the advertising revenue of sector B from a consumer who is a direct reader of a newspaper that uses the ad tech T.

For any newspaper using the ad tech SE, given a direct consumer x', the SE tracks various online activities of the consumer and, therefore, collects the data set $\Omega^{x',SE} = \omega^{x',d} \cup \omega^{x',s}(m,l,g) \cup \omega^{x',B}$. Therefore, the ad revenues generated from her direct visit to the newspaper and from her visit to sector B are:

$$\begin{aligned}
\alpha_d^{SE}(m,l,g) &\equiv \alpha_{d,SE}(\Omega^{x',SE}, \Omega^{x',SE} \cap \Omega^{x',SE}) \\
&= \alpha_{d,SE}(\omega^{x',d} \cup \omega^{x',s}(m,l,g) \cup \omega^{x',B}, \omega^{x',d} \cup \omega^{x',s}(m,l,g) \cup \omega^{x',B}) \\
\alpha_B^{SE}(m,l,g) &\equiv \alpha_{B,SE}(\Omega^{x',SE}, \Omega^{x',SE} \cap \Omega^{x',SE}) \\
&= \alpha_{B,SE}(\omega^{x',d} \cup \omega^{x',s}(m,l,g) \cup \omega^{x',B}, \omega^{x',d} \cup \omega^{x',s}(m,l,g) \cup \omega^{x',B}).
\end{aligned}$$

In this case, both ad inventories associated with consumer x' are served by the same ad tech intermediary. We add the following assumption:

Assumption B5. *When both the ad inventory from direct traffic and the one from Sector B are served by the same ad tech intermediary, we assume $\alpha_{k,h}(\Omega^{x,h}, \Omega^{x,h})$ is increasing with $\Omega^{x,h}, \forall k \in \{d,s,B\}, h \in \{T, SE\}$.*

This assumption simply says that when an ad tech gains more data, it can improve ad targeting and thus increase each client's advertising revenue.

We point out the conflict of interest between two groups of newspapers. Whereas the ad revenue per direct traffic of a newspaper using the ad tech SE increases with the amount of search-referral data collected by the SE, the ad revenue of a newspaper using T decreases with the amount of search-referral data collected by the SE.

We first show that it is a dominant strategy for a newspaper using the ad tech service of the SE to adopt the AMP format. Consider newspaper i that uses the ad tech SE and takes as given the quality and the adoption choices of other newspapers. If newspaper i adopts the AMP, it improves its ranking and eliminates traffic loss δ, while the SE keeps having access to the browsing data from $m+l$ newspapers in search-referred news reading activities. So the only change in terms of data leakage is that i's adoption expands $\omega^{x,s}(m,l,g)$ to $\omega^{x,s}(m,l,g+1)$ as the SE promotes its AMP articles, which in turn increases the ad revenue per direct traffic from $\alpha_d^{SE}(m,l,g)$ to $\alpha_d^{SE}(m,l,g+1)$ according to B5. Therefore, we have:

Lemma 2.6. *Under A1, B1, B2, B4 and B5, it is a dominant strategy for a newspaper using the ad tech service of the SE to adopt the AMP format.*

From an argument analogous to the one used for Proposition 2.11, it is straightforward to see the existence of the adoption equilibrium in which all newspapers using the ad tech T also adopt AMP.

In what follows, we show that for m large enough, the adoption equilibrium is the unique equilibrium. We take it as given that the m newspapers using the ad tech SE adopt AMP. Consider an equilibrium candidate in which no newspaper using the ad tech T adopts the AMP format. Let $D^{s|-,i}(q_i, \mathbf{q}_{-i}; m)$ (respectively, $D^{s|+,i}(q_i, \mathbf{q}_{-i}; m)$) represent the search-referral traffic when newspaper i is a non-adopter (respectively, an adopter) when there are m number of adopters. Denote the quality vector in this equilibrium candidate $\mathbf{q} = (q^T, \ldots, q^T, q^{SE}, \ldots, q^{SE})$, where $q_i = q^T$ satisfies

$$(1-\tau^T)\left[\alpha_d^T(m,0,m)D_i^{d,i}(\mathbf{q}) + \alpha_s(1-\delta)D_i^{s|-,i}(\mathbf{q};m)\right] = c'(q^T);$$

and $q_i = q^{SE}$ satisfies

$$(1-\tau^{SE})\left[\alpha_d^{SE}(m,0,m)D_i^{d,i}(\mathbf{q}) + \alpha_s D_i^{s|+,i}(\mathbf{q};m)\right] = c'(q^{SE}).$$

A newspaper using the service of T has an incentive to deviate by adopting the AMP format if the following inequality holds:

$$\begin{aligned} & (1-\tau^T)\left[\alpha_d^T(m,0,m)D^{d,i}(\mathbf{q}) + \alpha_s(1-\delta)D^{s|-,i}(\mathbf{q};m)\right] - c(q^T) \\ \leq \; & (1-\tau^T)\left[\alpha_d^T(m,1,m)D^{d,i}(\widehat{q}, \mathbf{q}_{-i}) + \alpha_s D^{s|+,i}(\widehat{q}, \mathbf{q}_{-1}; m+1)\right] - c(\widehat{q}) \end{aligned}$$

where $\widehat{q}$ is determined by

$$\widehat{q} = \arg\max_{q_i}(1-\tau^T)\left[\alpha_d^T(m,1,m)D^{d,i}(q_i, \mathbf{q}_{-i}) + \alpha_s D^{s|+,i}(q_i, \mathbf{q}_{-1}; m+1)\right] - c(q_i).$$

A sufficient condition is that the inequality holds at $\widehat{q} = q^T$, which is equivalent to

$$\left[\alpha_d^T(m,1,m) - \alpha_d^T(m,0,m)\right] D^{d,i}(\mathbf{q}) + \alpha_s\left[D^{s|+,i}(\mathbf{q};m+1) - (1-\delta)D^{s|-,i}(\mathbf{q};m)\right] \geq 0.$$

When m is large enough (this is possible as n is large),[16] because of the SE's promotion of AMP articles, almost all the search traffic is directed to the AMP articles, implying that $D^{s|-,i}(\mathbf{q}; m)$ is close to zero. This in turn implies $\alpha_d^T(m, 1, m) \simeq \alpha_d^T(m, 0, m)$. Therefore, $\alpha_s D^{s|+,i}(\mathbf{q}; m+1)$ dominates all the other terms in the above inequality and, hence , the condition is satisfied. The same logic applies to any equilibrium candidate in which $l(< n-m)$ number of newspapers using the ad tech T adopt the AMP format in addition to the m number of newspapers using the ad tech SE. Therefore, we have the following result:

Proposition 2.13. *Under A1, A3, B1, B2, B4 and B5, there exists a threshold $\widehat{m}$ such that for $m > \widehat{m}$, all newspapers adopt the AMP format in the unique equilibrium.*

To conclude, we have shown in this section that the SE can combine its market power in search and ad intermediation to deploy a divide-and-conquer strategy to achieve the unique outcome in which all newspapers adopt AMP.

Last, we verify that the SE is indeed better off in an equilibrium where all newspapers adopt AMP relative to the benchmark without AMP. This is straightforward because all kinds of ad revenues generated by the ad tech SE are greater under AMP due to its larger data collection, i.e., $\omega^s(m, n-m, m) \geq \omega^s(m, n-m, 0) > \omega^s(m, 0, 0)$:

$$\alpha_B^T(m, n-m, m) > \alpha_B^T(m, 0, 0),$$
$$\alpha_d^{SE}(m, n-m, m) > \alpha_d^{SE}(m, 0, 0),$$
$$\alpha_B^{SE}(m, n-m, m) > \alpha_d^{SE}(m, 0, 0).$$

2.8 Policy Remedies and Discussion

2.8.1 Remedies

We propose two policy remedies to eliminate the two types of externalities, search ranking externality and data leakage externality, that generate the collective action problem among newspapers. First, in order to eliminate the search ranking externality, we propose that the SE use an objective criterion of loading speed and

[16]For the same reason given right after A3, m does not need to be very large

treat all articles meeting such criterion in a non-discriminatory way, regardless of whether the technology is developed by Google or not. This remedy can be interpreted as neutrality obligations. In particular, it allows the SE to demote articles that do not meet the speed criterion. Such exercise of search market power is socially desirable as long as newspapers' adoption of speed-enhancing technology improves welfare. If the SE does not discriminate articles at all, newspapers may not adopt the technology, for instance, when the adoption requires each newspaper to pay a high fixed cost. Second, in order to eliminate the data leakage externality, we propose to prohibit the SE from hosting articles on its server. If all newspapers adopt technologies meeting the speed criterion, the combination of the two policy remedies leads to the equilibrium we described in the benchmark of AMP without change in data allocation (characterized in Proposition 2.2), where adoption of AMP improves quality of journalism and social welfare.

The potential anti-competitive effect of gatekeeper platforms' collection and use of data has raised policy makers' concerns. Our remedy of prohibiting the dominant platform from unfairly gaining access to business user's data is echoed in the European Commission's Digital Markets Act (2020): "a gatekeeper shall...refrain from using, in competition with business users, any data not publicly available, which is generated through activities by those business users, including by the end users of these business users, of its core platform services or provided by those business users of its core platform services or by the end users of these business users".

One may argue that requiring gatekeeper platforms to share with news publishers data regarding how end users interact with the latter's content on the platform is a more efficient remedy for addressing the negative impact of AMP, as it preserves targeting efficiency in the advertising market. However, it is easy to show that this does not necessarily eliminate the negative impact of AMP on newspapers' ad revenues in direct traffic, particularly when the shared data is much more valuable to the platform than to the publishers. Then, it is more effective to forbid the platform from gaining access to the data in the first place.

2.8.2 Discussions

There are two additional channels through which Google leverages its market power in search and/or ad intermediation to impose anti-competitive rules on news publishers, which deserve discussion due to their close relationship with this paper.

The first channel is directly related to AMP and concerns the header bidding issue. Browser-side header bidding is a programming technique that enables a publisher to directly call multiple ad exchanges from the user's browser to collect bids. However, Google restricts the use of browser-side header bidding in AMP, which allows Google to leverage its monopoly power in the publisher ad server market to favor its own ad exchange over competitors.[17] We exclude this channel from our analysis, as it is about Google's leverage of its power in one layer of the ad intermediation market to favor its own business in another, and analyzing it requires us to model the complex chain of ad intermediation, which is beyond the scope of this paper. [18]

The second channel is the controversial news aggregator problem, which has been widely debated in the past decade. [19] This debate is about Google's practice of displaying snippets and images of news articles in its Search and Google News products without compensating news publishers for the use. Therefore, news publishers in different countries and continents, including those in the EU, the U.S. and Australia, have called for the reform of copyright laws to make news aggregators such as Google and Facebook pay for the use of their content.

This issue is closely related to our paper, as publishers' negotiations with Google over compensation features a similar coordination problem to that we have identified in Section 2.6. Specifically, Google's power to allocate newspapers' search-referral traffic by manipulating rankings in search results generates search ranking

[17]This is because to work around the AMP constraint on the use of JavaScript, the header bidding auctions have to take place in the publisher ad server, which is monopolized by Google. Google's publisher ad server disadvantages competing ad exchanges by imposing tighter latency restrictions on them. This will not only make it hard for bids collected by competing ad exchanges to arrive in time, but will also result in more cookie syncing failure and hence consumer data loss for these competitors.

[18]Interested readers could refer to Srinivasan (2020) and the complaint of the state of Texas, et al. against Google (2020) for more details on this specific aspect of AMP and refer to Jeon (2021) and the ACCC Final Report (2021) for the broader problem of Google's leveraging its power in different layers of ad tech value chain to promote its own services.

[19]See Jeon (2018) for a survey of the literature on news aggregators.

externalities among newspapers. For instance, Google can make only newspapers that have licensed their content eligible for the "Top Stories" carousel. To avoid being demoted in search results, newspapers would license their content to Google in exchange for a small amount of or zero compensation.

Policy markers in various jurisdictions are wary of this collective action issue. To address it, the Australian news media bargaining code[20]clearly requires that a digital platform, in its activities of crawling, indexing, making available and distributing news businesses' content, not discriminate by whether a news business is paid or not paid by the platform for making available the news business' covered news content.

In a similar vein, in the decision 21-D-17 of 12 July 2021[21], the French Authorité de la Concurrence fined Google for violating the neutrality obligation not to link the negotiation over related rights to the indexing, classification and presentation of protected content taken up by Google on its services. What Google did was to link the negotiation on the compensation to participation in the new Google News Showcase program. Because Showcase is initially embedded in the Google News and will be integrated into general Google search results, it is reasonable to expect that whether or not a news publisher participates in the Showcase program will greatly impact its search-referral traffic. As a consequence, "the strategy implemented by Google has thus strongly encouraged publishers to accept the contractual conditions of the Showcase service and to renounce negotiations relating specifically to the current uses of protected content...under the risk of seeing their exposure and their remuneration degraded compared to their competitors who would have accepted the proposed terms", says the decision.[22] Our policy remedy can be interpreted as neutrality obligations in search results as long as publishers' articles meet an objective criterion of loading speed.

The neutrality obligations can have even broader implications beyond the search

[20] https://www.accc.gov.au/focus-areas/digital-platforms/news-media-bargaining-code27

[21] https://www.autoritedelaconcurrence.fr/en/press-release/remuneration-related-rights-press-publishers-and-agencies-autorite-fines-google-500

[22] The German Bundeskartellamt also opened an investigation into the Google News Showcase issue, particularly regarding the announced integration of the Google News Showcase service into Google's general search function. See https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2021/04_06_2021_Google_Showcase.html

engine market for preventing digital platforms from using their ranking algorithm to induce business users into unfair contractual terms. For instance, in Italy, Amazon was fined for harming competitors by favoring third-party sellers that use the company's logistics services in the Amazon website's search results. As a remedy, the Italian regulator ordered Amazon to offer "fair and nondiscriminatory standards" for listings from third-party sellers, which it would monitor through an appointed trustee[23].

2.9 Conclusion

AMP allows Google to collect data from articles written in this format and to combine them with data from other sources in order to improve targeting of the ads served by Google on various websites. Even if such data combination improves static welfare, we found that it can reduce dynamic welfare by reducing newspapers' incentive to invest in the quality of journalism. In particular, we showed that Google has no incentive to internalize the impact of its conduct on news quality.

In this paper, we considered only Google's ad provision to third-party sites/apps. However, in reality, Google owns many consumer-facing products and serves ads in these products as well. Considering Google-owned ad inventory will strengthen the conflict between newspapers' investment in journalism and Google's data combination for ad targeting that we identified. In particular, given that a small fraction of valuable consumers explains most ad revenue of publishers,[24] Google has an incentive to engage in cream-skimming by showing ads to valuable consumers in its own products, which further exacerbates the conflict.

Our paper compared two particular data allocations and combinations that arise depending on whether AMP exists or not. In this simple environment, neutrality obligations in search results together with no hosting of news content by Google are desirable policy remedies. However, we consider our paper a call for future

[23] Eric Sylvers and Sam Schechner. "Amazon Fined $1.3 Billion in Italian Antitrust Case." The Wall Street Journal, Dec. 9, 2021, https://www.wsj.com/articles/amazon-fined-1-3-billion-in-italian-antitrust-case-11639043714

[24] See the complaint of the state of Texas, et al v. Google, LLC (2020) at https://www.texasattorneygeneral.gov/sites/default/files/images/admin/2020/Press/20201216%20COMPLAINT_REDACTED.pdf

research to address a more fundamental and general question: what is the optimal scope of data combination that takes into account both static and dynamic efficiency? If the optimal scope of data combination turns out to be narrower than Google's current practice, which combines a vast majority of data from third-party publishers with its own first-party data, then a policy intervention would be required to implement the optimal scope because a collective action problem would prevent publishers from maintaining a proper control of their data.

2.10 Appendix

2.10.1 Micro-foundation of B1

Suppose that there are $N > 0$ advertisers who are interested in showing ads to consumer x.

Suppose that a given set of data about consumer x, Ω^x, is available to the advertisers. They use the data to estimate their willingness to pay. Their estimations generate a vector of the willingness to pay

$$\mathbf{v}(\Omega^x) = (\widetilde{v}_1(\Omega^x), \widetilde{v}_2(\Omega^x), ..., \widetilde{v}_N(\Omega^x))$$

where $\widetilde{v}_k(\Omega^x)$ is the kth-highest willingness to pay and is a random variable. In one extreme of $\Omega^x = \varnothing$, we assume that $\widetilde{v}_1(\varnothing) = \widetilde{v}_2(\varnothing) = ..., = \widetilde{v}_N(\varnothing) = v^e$ where v^e is a positive constant. In the other extreme of perfect information $\Omega^x = \mathbf{\Omega}^x$, $\widetilde{v}_i(\mathbf{\Omega}^x) = v_i$ for $i = 1, ..., N$ with

$$v_1 > v_2 > ...(> v^e >)... > v_{N-1} > v_N.$$

As Ω^x increases from $\varnothing$ to $\mathbf{\Omega}^x$, the expected values of $\widetilde{v}_1(\Omega^x)$ and $\widetilde{v}_2(\Omega^x)$ increase to v_1 and $v_2(>> v^e)$ whereas the expected values of $\widetilde{v}_{N-1}(\Omega^x)$ and $\widetilde{v}_N(\Omega^x)$ decrease to $v_{N-1}(<< v^e)$ and v_N.

We assume that the expected values of the three highest valuations $\widetilde{v}_1(\Omega^x), \widetilde{v}_2(\Omega^x), \widetilde{v}_3(\Omega^x)$ are increasing in Ω^x.

Consider two sets $\Omega^{x,A}$ and $\Omega^{x,B}$ such that $\Omega^{x,A} \cap \Omega^{x,B} = \varnothing$. Consider two independent second-price auctions, each selling one spot: auction A uses data $\Omega^{x,A}$

and auction B uses data $\Omega^{x,B}$. Then, we assume that the probability that the highest bidder of one auction will be also the highest bidder or the second-highest bidder of the other auction is zero. This in turn implies that the outcomes of the two auctions do not depend on the sequential order of the auctions.

Consider now expanding $\Omega^{x,B}$ to $\Omega^{x,B\prime}$ such that $\Omega^{x,A} \cap \Omega^{x,B\prime} \neq \varnothing$. If auction A runs before auction B, the change in $\Omega^{x,B}$ does not affect the outcome of auction A: we here make a simplifying assumption that advertisers are myopic and hence the advertiser with valuation $\widetilde{v}_1(\Omega^{x,A})$ prefers participating in the first auction instead of giving up the first auction in order to participate in the second auction. If auction B runs before auction A, there is a probability $p(\Omega^{x,A} \cap \Omega^{x,B\prime})$, which increases with $\Omega^{x,A} \cap \Omega^{x,B\prime}$, that the winner of auction B has either $\widetilde{v}_1(\Omega^{x,A})$ or $\widetilde{v}_2(\Omega^{x,A})$. In this case, the ad revenue of auction A will be $\widetilde{v}_3(\Omega^{x,A})$ instead of $\widetilde{v}_2(\Omega^{x,A})$.

Finally, assume that consumer x is reader of newspaper i. She visits everyday the site of newspaper i and another site for activity B. But the order of her visit is random: with equal probability, she visits each site first and then visits the other site. Each site sells one ad spot per day. Then, the expected ad revenue of the newspaper from direct visit is

$$\begin{aligned} & \alpha_A(\Omega^{x,A}, \Omega^{x,A} \cap \Omega^{x,B'}) \\ = \; & (1 - \frac{1}{2} p(\Omega^{x,A} \cap \Omega^{x,B\prime}))\widetilde{v}^e_2(\Omega^{x,A}) + \frac{1}{2} p(\Omega^{x,A} \cap \Omega^{x,B\prime})\widetilde{v}^e_3(\Omega^{x,A}) \\ = \; & \widetilde{v}^e_2(\Omega^{x,A}) - \frac{1}{2} p(\Omega^{x,A} \cap \Omega^{x,B\prime}) \left[\widetilde{v}^e_2(\Omega^{x,A}) - \widetilde{v}^e_3(\Omega^{x,A})\right] \end{aligned}$$

where the superscript e represents expectation. $\widetilde{v}^e_2(\Omega^{x,A})$ increases with $\Omega^{x,A}$. $\frac{1}{2}p(\Omega^{x,A} \cap \Omega^{x,B\prime})$ increases with $\Omega^{x,A} \cap \Omega^{x,B\prime}$ for given $\Omega^{x,A}$, which satisfies the second part of B1. In order to satisfy the first part of B1, either the second component $\frac{p(\Omega^{x,A} \cap \Omega^{x,B\prime})}{2} \left[\widetilde{v}^e_2(\Omega^{x,A}) - \widetilde{v}^e_3(\Omega^{x,A})\right]$ is weakly decreasing in $\Omega^{x,A}$ or the effect from the first component $\widetilde{v}^e_2(\Omega^{x,A})$ should dominate the effect from the second component.

2.10.2 Omitted Proofs

Proof of Lemma 2.2. Differentiating the equilibrium condition in Proposition 2.1 with respect to δ on both sides, we get:

$$(1-\tau^T)\left[\alpha^N_d \Sigma^n_{j=1} D^{d,i}_{i,j}(\mathbf{q}^N) + \alpha_s(1-\delta)\Sigma^n_{j=1} D^{s,i}_{ij}(\mathbf{q}^N)\right] \frac{\partial q^N}{\partial \delta} - (1-\tau^T)\alpha_s D^{s,i}_i(\mathbf{q}^N) = c''(q^N)\frac{\partial q^N}{\partial \delta}$$

Solving for $\frac{\partial q^N}{\partial \delta}$, we obtain:

$$\frac{\partial q^N}{\partial \delta} = \frac{(1-\tau^T)\alpha_s D_i^{s,i}(\mathbf{q}^N)}{(1-\tau^T)\left[\alpha_d^N \Sigma_{j=1}^n D_{i,j}^{d,i}(\mathbf{q}^N) + \alpha_s(1-\delta)\Sigma_{j=1}^n D_{ij}^{s,i}(\mathbf{q}^N)\right] - c''(q^N)}$$

By Assumption A1, we have $D_i^{s,i} > 0$, $D_{ij}^{d,i} < 0$ and $D_{ij}^{s,i} < 0$ for $i, j = 1, 2, .., n$, and the cost function $c(q)$ is convex. Therefore, we have $\frac{\partial q^N}{\partial \delta} < 0$. $\square$

Proof of Lemma 2.3. We only prove $\frac{\partial \pi^N(\alpha_d^N, \delta)}{\partial \delta} < 0$, as $\frac{\partial \pi^N(\alpha_d^N, \delta)}{\partial \alpha_d^N} > 0$ can be proved analogously.

$$\begin{aligned}
-\frac{\partial \pi^N}{\partial \delta} &= -\Big[(1-\tau^T)[\alpha_d^N \Sigma_{j=1}^n D_j^{d,i}(\mathbf{q}^N) + \alpha_s(1-\delta)\Sigma_{j=1}^n D_j^{s,i}(\mathbf{q}^N)] - c'(q^N)\Big]\frac{\partial q^N}{\partial \delta} + (1-\tau^T)\alpha_s D^{s,i}(\mathbf{q}^N) \\
&= \underbrace{-(1-\tau^T)[\alpha_d^N \Sigma_{j\neq i} D_j^{d,i}(\mathbf{q}^N) + \alpha_s(1-\delta)\Sigma_{j\neq i} D_j^{s,i}(\mathbf{q}^N)]\frac{\partial q^N}{\partial \delta}}_{\text{the effect of intensified competition (-)}} + \underbrace{(1-\tau^T)\alpha_s D^{s,i}(\mathbf{q}^N)}_{\text{the direct effect of positive shock (+)}} \\
&> 0
\end{aligned}$$

The second equality follows from the optimality of q^N for newspaper i's profit maximization problem. When newspapers are sufficiently differentiated, the effect of intensified competition will be small such that the last inequality holds. $\square$

Proof of Proposition 2.7. (1) As $\frac{\partial \pi^N(\alpha_d^N, \delta)}{\partial \alpha_d^N} > 0$ from Lemma 2.3, when $\delta = 0$, we have $\pi^N(\alpha_d^N, 0) > \pi^N(\alpha_d^M, 0) = \pi^M(\alpha_d^M)$. This implies that the presence of AMP reduces the newspaper industry profit. (2) Taking the values of δ and α_d^N as given, we have $\lim_{\alpha_d^M \uparrow \alpha_d^N} \pi^M(\alpha_d^M) = \pi^N(\alpha_d^N, 0)$. This property together with $\frac{\partial \pi^N}{\partial \delta} < 0$ (from Lemma 2.3) guarantees the existence of the threshold $0 < \tilde{\delta} < 1$. $\square$

Proof of Proposition 2.8. (1) This is straightforward as consumer surplus CS^N is decreasing in δ from Lemma 2.4. (2) Recall from Proposition 2.5 that AMP raises news quality when the positive search traffic enhancing effect dominates the negative data allocation effect, and this condition holds particularly when $\delta >> 0$ and α_d^M is close to α_d^N. In this case, both the quality of newspapers and that of sector B are higher under AMP, implying $CS^M > CS^N(\delta)$. This result, together with the condition $CS^N|_{\delta=0} > CS^M$ and Lemma 2.4, implies that there is a threshold $\bar{\delta}$, below which $CS^N(\delta) > CS^M$ and above which $CS^N(\delta) < CS^M$. $\square$

Proof of Lemma 2.5. For instance, in the case without AMP, the newspapers' private incentive to invest in quality is given by the first-order condition in Proposition 2.1. By contrast, the first-order condition of the social planner's problem is:

$$\frac{\partial W^N}{\partial q^N} = \frac{\partial CS^N}{\partial q^N} - nc'(q^N) + \frac{1}{1-\beta}\Big[n\alpha_d^N\left[D_i^{d,i}(\mathbf{q}^N) + \Sigma_{j\neq i}^n D_j^{d,i}(\mathbf{q}^N)\right]$$

$$+ n\alpha_s(1-\delta)\big[D_i^{s,i}(\mathbf{q}^N) + \Sigma_{j\neq i}^n D_j^{s,i}(\mathbf{q}^N)\big]\Big]$$

$$=0$$

Therefore, the difference in their incentives to invest in quality can be expressed as::

$$\frac{1}{n}\frac{\partial W^N}{\partial q^N} - \frac{\partial \pi^N(\mathbf{q}^N)}{\partial q_i} = \underbrace{\frac{1}{n}\frac{\partial CS^N}{\partial q^N}}_{(+)} + \underbrace{(\frac{1}{1-\beta} - 1 + \tau^T)\big(\alpha_d^N D_i^{d,i} + \alpha_s(1-\delta)D_i^{s,i}\big)}_{(+)}$$
$$+ \underbrace{\frac{1}{1-\beta}\big(\alpha_d^N \Sigma_{j\neq i}^n D_j^{d,i} + \alpha_s(1-\delta)\Sigma_{j\neq i}^n D_j^{s,i}\big)}_{(-)}$$

When newspapers are sufficiently differentiated (as we assume in A2), the third term, which is the business stealing effect, is weak and dominated by the first two positive terms. As a result, the social planner has a greater incentive to improve newspapers' quality. □

Proof of Proposition 2.9. Recall that we assume newspapers are sufficiently differentiated such that q^M is lower than the quality chosen by the social planner. Similarly, sites in sector B also have a smaller incentive to invest in quality than the social planner. As the model's assumptions on demand and cost functions guarantee that the social surplus function is concave, we have $W^M(q^M, q_B^M) > W^M(q^N, q_B^N)$ when $q^M > q^N$. Under Assumption B3 (i), we have $n\alpha_d^M D^d(\mathbf{q}^N) + n\alpha_s D^s(\mathbf{q}^N) + \alpha_B^M D^B(q_B^N) > n\alpha_d^N D^d(\mathbf{q}^N) + n\alpha_s D^s(\mathbf{q}^N) + \alpha_B^N D^B(q_B^N)$. Therefore, $W^M(q^M, q_B^M) > W^M(q^N, q_B^N) > CS^M(\mathbf{q}^N, q_B^N) - nc(q^N) - c^B(q_B^N) + \frac{1}{1-\beta}\big[n\alpha_d^N D^d(\mathbf{q}^N) + n\alpha_s D^s(\mathbf{q}^N) + \alpha_B^N D^B(q_B^N)\big] > W^N$. □

Proof of Proposition 2.10. Under the condition $\delta = 0$ and $q_B^M = q_B^N$,

$$W^M(q^M) - W^N(q^N, \delta=0) = \underbrace{\big[W^M(q^M) - W^N(q^M, \delta=0)\big]}_{\text{efficiency effect of data leakage}} - \underbrace{\big[W^N(q^N, \delta=0) - W^N(q^M, \delta=0)\big]}_{\text{direct effect of lower quality}}$$

The main trade-off is captured by the above equation. By taking the quality of newspapers q^M as given, the first bracket represents the positive effect of data leakage, which leads to improved matching in targeted advertising, as captured in the static welfare analysis. The second captures the negative effect of lower quality on welfare. As assumptions on demand functions and cost functions guarantee that social surplus is concave in symmetric quality and q^N is assumed to be lower than the social optimum, any quality lower than q^N induces lower welfare. □

Proof of Proposition 2.11. Let q^- be the best response of newspaper i when it unilaterally deviates by not adopting AMP but expects all other newspapers to adopt AMP and to choose the equilibrium quality q^M:

$$q^- = \arg\max_{q_i}(1-\tau^T)\left[\alpha_d(n-1)D^{d,i}(q_i,\mathbf{q}_{-i}^M) + \alpha_s(1-\delta)D^{s|i-,i}(q_i,\mathbf{q}_{-i}^M)\right] - c(q_i).$$

Newspaper i has no incentive to deviate by not adopting the AMP format because:

$$\begin{aligned} & (1-\tau^T)\left[\alpha_d^M D^{d,i}(q^M,\mathbf{q}_{-i}^M) + \alpha_s D^{s,i}(q^M,\mathbf{q}_{-i}^M)\right] - c(q^M) \\ \geq\; & (1-\tau^T)\left[\alpha_d^M D^{d,i}(q^-,\mathbf{q}_{-i}^M) + \alpha_s D^{s,i}(q^-,\mathbf{q}_{-i}^M)\right] - c(q^-) \\ >\; & (1-\tau^T)\left[\alpha_d(n-1)D^{d,i}(q^-,\mathbf{q}_{-i}^M) + \alpha_s(1-\delta)D^{s|i-,i}(q^-,\mathbf{q}_{-i}^M)\right] - c(q^-) \end{aligned}$$

where the first inequality is from the optimality of q^M in newspaper i's profit maximization problem, and the second inequality holds under A3. □

Proof of Proposition 2.12.

$$\begin{aligned} & (1-\tau^T)\left[\alpha_d^N D^{d,i}(q^N,\mathbf{q}_{-i}^N) + \alpha_s(1-\delta)D^{s,i}(q^N,\mathbf{q}_{-i}^N)\right] - c(q^N) \\ \geq & (1-\tau^T)\left[\alpha_d^N D^{d,i}(q^+,\mathbf{q}_{-i}^N) + \alpha_s(1-\delta)D^{s,i}(q^+,\mathbf{q}_{-i}^N)\right] - c(q^+) \\ \geq & (1-\tau^T)\left[\alpha_d(1)D^{d,i}(q^+,\mathbf{q}_{-i}^N) + \alpha_s D^{s|i+,i}(q^+,\mathbf{q}_{-i}^N)\right] - c(q^+) \end{aligned}$$

The first inequality follows from the optimality of q^N for newspaper i's profit maximization problem when no newspaper adopts the AMP. The second inequality follows from the condition in the proposition. □

2.10.3 Industry Background on Open Display Market

In this section, we briefly introduce how the open programmatic display advertising market works to help readers get familiar with the context of our model and the motivation behind our modeling choices. For further references, see CMA Report (2020) and its online appendices for a detailed and comprehensive survey of digital advertising market. Also see Geradin and Katsifis (2019) and Srinivasan (2020) for their analysis of online display advertising issues from the angle of competition law.

The online display advertising market is composed of two segments, depending on whether or not ad inventories are sold through intermediaries. The first involves own-and-operated platforms such as Google Search and Facebook App, which sell a large amount of ad inventories from their consumer-facing services through their proprietary ad interfaces. The other segment, which is the focus of this paper, is the open display advertising market, in which a large number of publishers (such as newspapers, blogs, app owners and any other content/service providers) sell their ad inventory to a large number of advertisers through a complex chain of third-party ad intermediaries. These intermediaries, which are also called ad techs, organize and/or participate in real-time bidding auctions on behalf of publishers and advertisers. Examples of open display ads are the banner or video ads we frequently see on websites and apps.

How is consumer data used in personalized targeting? As display ads are usually targeted, consumer data plays an important role in determining what ads are relevant to a consumer and how much advertisers bid for ad impressions. To learn about consumers' purchasing intents, ad techs track consumers' online activities across websites and devices to infer what products might appeal to them. For instance, an ad intermediary can predict that a consumer may be interested in seeing the ad of the latest iPhone if she spends a lot of time reading tech news and reviews on smart phones. Based on the collected data, the essential work of ad techs is to build consumer profiles, each of which is a group of segments. Using the last example, the consumer profile could be {Female, France, Phone,...}, with each entry representing a segment. Accordingly, advertisers will create their audience by defining targeting criteria in terms of segments. For instance, a smart phone retailer can set her targeting audience as {location=France, monthly income > 1K, Phone}. Then, when a consumer visits a publisher's website, its ad server will send a bid request together with some data about the consumer (including user identifiers). This information is passed to ad intermediaries such as demand-side platforms (DSPs) which help advertisers to evaluate their willingness to pay and to make bids by matching the received information with consumer profiles that they built. An advertiser will bid on a consumer if she belongs to predefined audience. The winner finally displays an ad of her product on the page the consumer is browsing.

Tracking.[25] In such an environment, an ad tech's success largely depends on

[25] See a detailed explanation in Online Appendix G of CMA Report (2020)

how much consumer data it has, which in turn depends on the ability to track consumers across websites and devices. To compile a certain consumer's browsing activities conducted on different sites, the tracker needs to (i) learn that the consumer is visiting a web page when the event takes place; and (ii) identify the consumer in order to associate his different browsing events together.

The first point is done by embedding third-party codes on first-party websites. When a consumer visits a web page in which the code writes that it needs content input from third-party websites, her browser will send requests to both the first party (the website she is visiting) and the servers of the third-party websites. Information such as the referrer's URL, device info, IP addresses, etc can be passed along with the request. In this way, a third-party tracker learns that a consumer is visiting a website that contains its codes. The content fetched from a third-party tracker's server could be a banner/video ad if the tracker provides ad serving service to the first-party website or simply a 1x1 pixel transparent GIF that is invisible to visitors if the tracker provides analytic services to the first-party website. On the web, these third-party codes are called tags and pixels. Their counterparts in mobile apps are Third Party Libraries (TPLs) or Software Development Kits (SDKs). For a tracker to recognize that it is the same individual who visits a series of websites that embed its codes, the request sent to the tracker needs to contain a unique user identifier attached to the consumer or to her browser. This is mostly done via the best-known use of cookies. Cookies are small text files that a website's server drops in the browser when the server responds to the browser's request. Most importantly, it contains a randomly generated string of letters and numbers to serve as an identifier. For example, suppose that both the WSJ and the NYT use the ad service of Google's DoubleClick (which would be a third-party tracker in the example). When a consumer visits the WSJ for the first time, the browser will make requests to both WSJ and DoubleClick's servers, as the page needs both the news content and ads to fill spaces. When sending back those required contents, the WSJ and DoubleClick respectively set a cookie in the visitor's browser. The WSJ's cookie is called first-party cookie as it belongs to the domain the consumer is visiting, while the DoubleClick's is called third-party cookie.

Cookies are private to domains such that only the domain that sets the cookies can read them. However, cookies can be sent back whenever the browser requests content from their owners, as long as the user did not delete it. Continuing with the above example, suppose now that the consumer visits the NYT. As the NYT also requests ad input from DoubleClick, the cookie set earlier by DoubleClick will be sent back along with this request. By reading the cookie identifier, DoubleClick knows it is the same consumer who previously visited WSJ now being on NYT. As a result, DoubleClick can compile consumer activities on these two websites together.

One issue with cookies is that, as they are randomly generated, the identifiers in cookies set in a browser from different domains are different. As a consequence, when a publisher uses ad tech A to serve ads, whereas an advertiser uses ad tech B, the advertiser cannot identify the consumer of which the impression is on sale with the cookie ID set by ad tech A. Then, ad tech B engages in cookie matching (also called cookie syncing) during a real-time bidding process to identify the same consumer in its own database and to evaluate the advertiser's willingness to pay for the impression. This process of cookie matching is prone to failure, resulting in approximately 30 percent failed matching.

In addition to cookie IDs, trackers can also use email addresses, IP addresses, user account IDs, device info, or a combination of them to identify consumers. In particular, trackers in mobile apps use mobile advertising IDs (MAIDs) as user identifiers, which are unique to mobile devices and shared with all apps. Therefore, all tracking parties in mobile apps share a common identifier associated with each device, and they save the trouble of cookie matching, as in the web tracking case.

Finally, to build more complete user profiles, trackers need to perform cross-device tracking to link MAIDs with cookie IDs. This can be greatly facilitated by IP addresses, email addresses or first-party login details/internal IDs.

Stylized Facts on the Competition in the Ad Intermediation Market

The Ad intermediation market consists of several layers along its complex value chain from publishers to advertisers. On the supply side, there are publisher ad servers and supply side platforms (SSPs) and on the demand side, there are demand side platforms (DSPs) and advertiser ad servers.

Because of various acquisitions and the leverage of data, advertising inventories, and speed advantage, Google is currently the dominant player at each vertical layer of ad intermediation. Below, we report Google's market shares in the UK provided by CMA Report (2020). The publisher ad server market is monopolized by Google, as Google Ad Manager accounts for more than 90 percent of the display ads served in the UK. Google has a 50-60 percent share in the SSP market in the UK. Google's DSP DV360 has a 30-40 percent market share. Google operates a DSP through Google Ads, which has a 10-20 percent market share. Hence, the combined market share in DSP becomes 40-60 percent in the UK. The advertiser ad server market is highly concentrated, and Google accounts for approximately 80-90 percent of the ads served to UK users. We describe in detail how Google gains data advantage that can be leveraged in competition.

Sources of Google's Data Advantage:

- Google offers a wide range of leading consumer-facing services. For instance, Google provides more than 53 consumer-facing services and products in the UK, including Google Search, YouTube, and Gmail. (Appendix F of CMA Report (2020), 2020, p. F8). This allows it to collect a vast amount of first-party consumer data and to derive valuable insights about users. For instance, search data are very useful to advertisers as a source of learning purchase intent.

- Google can leverage the first-party data it has to attract publishers and advertisers to use its own ad intermediary by restricting access to those valuable first-party data to its proprietary platforms. To provide services, Google places its trackers on customers' websites and apps. According to CMA Report (2020), Google was found to be present as a third-party on approximately 85% of websites.

- Because consumers, especially Android users, log in to their Google account on each of their devices, Google has an advantage in cross-device tracking.

- Mainstream browsers are starting to ban the use of third-party cookies to protect consumer privacy. For instance, Apple's Safari and Mozilla's Firebox have blocked third party cookies by default and Google also plans to do so in Chrome in the coming years. This will hurt rival ad techs more than Google, as the former rely more heavily on the use of third-party cookies to collect information.

Implications for Competition Outcome. The lack of competition in ad intermediation translates into high ad tech fees, which is commonly referred to as "ad tech take". Ad tech take represents the difference between what advertisers pay and what publishers earn from digital advertising. The CMA report estimates that "on average publishers receive around 65% of initial advertising revenue that is paid by advertisers (i.e., the overall 'ad tech take' is around 35%)". Another estimate on the ad tech tax from the Wall Street Journal could be as high as 60%. [26].

[26]See https://www.wsj.com/articles/behavioral-ad-targeting-not-paying-off-for-publishers-study-suggests-11559167195

Chapter 3

Digital Copyright: Search Engine's Use of Snippets

3.1 Introduction

On Internet, search engines are the gatekeepers of millions of websites. As information intermediaries, they connect consumers with content providers through matching search queries with relevant articles or web pages. In 2004, Google's co-founder Larry Page said the search engine's mission is to get users "out of Google and to the right place as fast as possible." However, over these years, as a dominant player in the search market, Google has become a destination by directly answering search queries on results pages, rather than being a web index that directs consumers to other resources. This paper studies the impacts that a monopolistic search engine is a direct information provider has on the consumption and production of information goods in content markets.

Google implements the strategy of being an information provider through a couple of features placed on the top of its search results pages. "Featured snippet" contains, along with the hyperlink, information scraped from a content provider's website that Google thinks directly answers the search query in a brief way (see Figure 3.1 for an example). "Knowledge panel" compiles information from various resources to provide basic facts for queries such as people, places, or other things. News-related queries will trigger "top stories carousel" that displays photos and headlines of news articles selected into it. Throughout the paper, I will generally refer to these features as answer boxes and the information Google directly provides as snippets. According to a study commissioned by the Wall Street Journal in 2017, featured snippets appear on about 40% of results for searches formed as questions.[1]

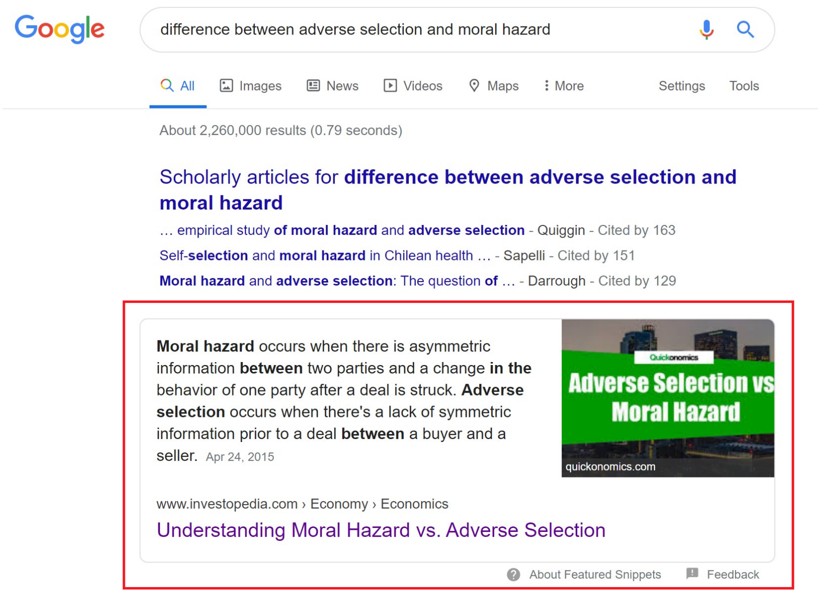


Figure 3.1: Example of Google's featured snippet

Although Google promotes the answer box as a way to improve user experience by helping them find useful information more quickly, this practice incurs various publishers' complaints that consumers will stop clicking through to their websites, preventing them from monetizing their contents. According to Jumpshot, about 62% of mobile and 35% of desktop searches on Google stopped at its search results pages (WSJ, June 2019). [2]. In 2017, the online review website Yelp charged Google for breaking the promise it made in the settlement of a 2012 FTC investigation not to use photos and reviews pulled from its website in Google's search results. In 2019, the lyrics website Genius filed a complaint against Google for displaying lyrics scrapped from its website. Genius claimed that when Google displayed lyrics in search results, the click-through rate to its website was between 5% and 20% as opposed to the 60%-80% rate absent the answer box. Across several jurisdictions,

[1] https://www.wsj.com/articles/googles-featured-answers-aim-to-distill-truthbut-often-get-it-wrong-1510847867

[2] https://www.wsj.com/articles/lyrics-site-genius-com-accuses-google-of-lifting-its-content-11560677400

news publishers seek being compensated by making the reform of copyright law. In the EU, European Parliament passed the digital copyright directive in 2019. The Article 15, which is commonly referred to as "Link Tax", reaffirms the news publishers' right to charge aggregators for the use of short snippets. In 2021, the Australian parliament passed the Australian News Media Bargaining Code, making it mandatory for digital platforms to negotiate with news publishers to compensate for the use of their content. As a response, Google denies its wrongdoings, arguing that features like "answer box" are popular among consumers, and if users do not like it, they can stop using its service. Besides, Google contends that publishers benefit from Google directing traffic to their websites.

From the economic point of view, the dispute between Google and publishers highlights a tension between enhancing search efficiency and preserving the incentives of content creation. To evaluate whether Google being a direct information provider constitutes anti-competitive behavior, we need to understand how this strategy impacts consumers' behavior of searching for information and, therefore, traffic to publishers' websites and how it, in turn, affects publishers' incentive to invest in quality. Moreover, Google Search is an information intermediary that relies on publishers to produce content, implying it should at least partially internalize the consequences of using snippets in content creation. Then, to what extent Google's private incentive of using the answer box is misaligned with the regulator?

I build a simple theoretical model of divisible information goods to answer these research questions. I have in mind a situation where consumers rely on the monopolistic search engine to find the information they need. The search process involves two stages. The first stage is to visit the search engine and enter the search query. The second stage is to click through, wait for the web page's loading, and read the article to find relevant information. Each stage incurs a cost of exerting effort. There are n ad-financed publishers whose articles are relevant for each search query. The key component of the model is to consider each article composed of two parts. *Essential information* is the part that directly answers the consumer's question in a very brief way, which could be a definition, central argument, or brief introduction.

Supplemental information is the remaining part of the article, such as background, explanation, or in-depth analysis, providing richer information. All articles contain essential information whose values are identical to all consumers. Publishers could invest in the quality of supplemental information, and consumers have heterogeneous tastes for quality and publishers. When the ranking algorithm is objective, it directs a consumer to the article that delivers the highest utility.

In the baseline model, I assume consumers can observe publishers' quality before searching. Hence their participation condition is that the expected utility of supplemental information in the best-match article is higher than the "opportunity cost" of searching, which is the two search costs less the value of essential information. As a consequence, the quality competition among publishers affects not only their market shares of infra-marginal consumers, which is determined by the ranking on search results pages, but also the market size, i.e., the number of consumers who actually search. After the search engine implements the answer box, which displays essential information from the best-match article on the search results page, consumers' opportunity cost of searching for supplemental information is higher than before. Therefore, the threshold of consumer who click through is higher, creating two opposite effects–market size reduction effect and elasticity variation effect–on publishers' incentive to invest in quality. The market size reduction effect is negative as fewer consumers click through due to the substitution between the snippet and the full article. The elasticity variation effect is determined by two factors: (1) high type consumers are more elastic to quality, which makes this effect tend to be positive; (2) the distribution of consumers' taste for quality. When the content market is monopolistic, although the equilibrium quality could be either higher or lower after the introduction of the answer box, the website traffic and publisher profit always go down.

The direct welfare effect of answer box can be decomposed into four components. The use of answer box enhances search efficiency by providing wider access to essential information to previously outside consumers and by allowing low type consumers to substitute the snippet for the full article. In addition, the search engine benefits from carrying more search queries. Therefore, taking quality of content as fixed, the direct effect of the answer box is always positive for consumer surplus. However, the answer box creates negative externality on publishers' websites and hence harms their advertising revenue. The overall social welfare effect is ambiguous. I also show there exit situations where the welfare effects on consumers and publishers are reversed after endogenizing the content quality.

To summarize, the core finding of this paper is that the mechanism of answer box is to unbundle the essential information and the supplemental information of an article, which attracts outside consumers to use the search engine, while creating direct negative externality on traffic to publishers' website. The equilibrium effect on publishers' profits and social welfare is ambiguous, depending on consumers' distribution of taste for quality and ability to observe publishers' quality before search.

3.1.1 Related Literature

The rise of digital platforms such as Google and Facebook has changed how information is distributed and thereby disrupted publishers' business models. This phenomenon leads to a strand of literature studying the impacts of news aggregators on the news industry. Jeon (2018) provides a comprehensive survey on this area. Dellarocas et al. (2013) and Jeon and Nasr (2016) are most closely related to this paper, and both of them model news aggregators, such as Google News, as competitors against newspapers' homepages for being consumers' starting point of news browsing activity. By contrast, this paper considers a gatekeeper search engine that consumers must pass to access content providers. This leads to the difference in our mechanisms: in their papers, the presence of aggregator has a market expansion effect on publishers in addition to the business stealing effect, while in this paper, the use of answer box only brings negative externality on website traffic that the expanded traffic to the search engine never flows into publishers. For other papers that also contribute to the discussion on the impact of digital platforms on content creators, Rutt (2011) uses Varian's search model to study how the importance of aggregators affects publishers' choice of business models between free access and paywall; de Cornière and Sarvary (2022) focuses on Facebook's strategy of bundling user-generated content and news articles and explores how this strategy impacts news quality.

This paper also contributes to the literature on search bias. As defined in FTC's statement of closing the investigation over Google's search practices (2013), search bias refers to the conduct of Google that it " unfairly preferences its own content on the Google search results page and selectively demotes its competitors' content from those results". In addition to the features mentioned in the introduction, in which the information contained in the answer box is usually scraped from third-party websites, Google also promotes and displays information from its own services such as Google Flights, Google Hotels, etc. De Corniere and Taylor (2014) explores how the vertical integration between a search engine and a publisher affects search bias when the search engine and two publishers compete in the advertising market.

The rest of the paper is organized as follows. Section 3.2 presents the baseline model. In Section 3.3, I first characterize equilibrium content quality in the regime without answer box and that with answer box. Then I compare the results to derive the effect of answer box on publishers' incentive to invest in quality. Last, I focus on two examples to study how the use of answer box impacts publisher profit. Section 3.4 provides welfare analysis. In Section 3.5, I study the impacts of different policies that make the search engine pay for the use of snippets. Section 3.6 concludes. The Appendix collects omitted proofs.

3.2 Baseline Model

We consider a representative search category in which there are N differentiated publishers providing the relevant information and their articles are imperfect substitutes. We use n to index the publishers. A continuum of consumers use the monopolistic search engine to look for information in this search category. Assume consumers have unit demands that they at most read the article that is displayed on the top of the search results page.

Search process. To obtain the information, consumers need to enter the query to the search engine first, which incurs a search cost c_1 and then the search engine directs them to the relevant publisher. To click on the link and read the article, consumers incur the second search cost c_2.

Information good. Consider each article provided by publishers as information good composed of two parts–essential information and supplemental information. *Essential information* is the part that directly answers the consumer's question in a very brief way, which could be a definition, central argument, factual description or brief introduction. *Supplemental information* is the remaining part of the article, such as in-depth analysis, background, explanation or reasoning, which gives richer and more detailed information.

For instance, for the search query "where is Toulouse", the essential part in the answer would be "Toulouse is located in the south-west of France". However, an article introducing Toulouse might include information like history, attractions and local food that consumers could also find useful as well.

In the model, we assume consumers homogeneously value the essential information as v. However, they have heterogeneous taste θ for the quality of supplemental information. Assume $\theta \sim F(\cdot)$, and the support is $[0,1]$. In addition, consumers have i.i.d preference shocks for different supplemental information provided by different publishers, which is denoted as $\varepsilon_{in} \sim G(\cdot)$ with $\mathbb{E}[\varepsilon_{in}] = 0$. Denote $\boldsymbol{\varepsilon}_i \equiv (\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{iN})$ as the vector of consumer i's preference shock. The preference shocks are independent of the taste for quality. When the quality of supplemental information provided by publisher n is q_n, the utility that consumer i with $(\theta_i, \varepsilon_{in})$ obtains from the whole content would be $v + \theta_i(q_n + \varepsilon_{in})$. Sometimes we drop the consumer index i to simplify notation.

Publishers. The value of v is exogenously given and common to all publishers. However, one can strategically invest in the quality q_n of supplemental information. The cost function of production is $C(v, q_n)$, which is convex in q_n and $C(v, 0) \geq 0$. If a publisher doesn't produce at all, the cost is zero. In addition, we assume that publishers are purely financed by display advertising and face competitive advertising market. As a result, we take the ad revenue per visit exogenous and denote it as α.

Search engine. For each search query, the search engine chooses one article's link to display on the top of the search results page. If it implements the answer box, then in addition to the link, it also displays the essential information. In the example of search query "where is Toulouse", consumers could directly learn "Toulouse is located in the southwest of France" on the search page without clicking the link and looking for the answer in the article themselves. Nevertheless, they can go on to the website and learn more about Toulouse.

We assume each search query carries a value of β to the search engine. This parameter can be interpreted either as search advertising revenue, or the shadow value created in the relationship, such as using consumer data for selling targeted ads on third-party websites and for developing new products.

Assumption 1. $c_1 < v < c_1 + c_2$

This assumption means that the value of essential information is high enough to cover the first stage search cost but not enough to cover both costs. In addition, $v > c_1$ guarantees that the answer box is efficient.

Timing and information structure. The game proceeds as follows:

Stage 1 The search engine decides whether to implement the answer box or not.

Stage 2 Observing search engine's choice, publishers decides the quality level of q_n.

Stage 3 After observing both the search engine and publishers' choices, consumers search for information.

In this baseline model, we assume consumers can observe publishers' quality before searching to capture the situation that consumers frequently search in the category such that they know what publishers are there and their quality levels. In the following sections, I will sometimes assume consumers cannot observe quality choices to simplify analysis.

In addition, we assume the search engine can observe publishers' quality choices, consumers' taste for quality and their preferences for each article. This implies that the search engine can perfectly infer consumers' valuation for each article. Consumers know their taste for quality, but only after reading an article can they learn the realization of the preference shock.

The equilibrium concept is subgame perfect Nash equilibrium and we focus on symmetric equilibrium for tractability.

3.3 Equilibrium Analysis

In this section, we assume the answer box can be unilaterally implemented by the search engine that the publishers cannot opt out from this scheme.

3.3.1 Benchmark: no answer box

Because the search engine's payoff is βD^{SE}, where D^{SE} is the number of received search queries, it is optimal for the search engine to use an objective ranking algorithm to maximize its traffic. Therefore, when a consumer with $(\theta, \boldsymbol{\varepsilon})$ enters the search query and then reaches the search results page, the search engine will place the link to the best match article on the top, which is determined by $\operatorname{argmax}_n v + \theta(q_n + \varepsilon_n)$.

Anticipating the search engine's ranking strategy, a consumer will come to use the search engine if and only if $\mathbb{E}[\max_n\{v + \theta(q_n + \varepsilon_n)\}] - c_1 - c_2 \geq 0$. Rearranging it, we obtain:

$$\theta\mathbb{E}[\max_n\{q_n + \varepsilon_n\}] \geq c_1 + c_2 - v$$

Therefore we can reinterpret consumers' participation condition in this way: the expected value of supplemental information in the best match article is greater than or equal to the "opportunity cost" of searching for it. Denote by $\bar{\theta}^N(\mathbf{q}) \equiv \frac{c_1+c_2-v}{\mathbb{E}[\max_n\{q_n+\varepsilon_n\}]}$ the location of marginal consumer that are indifferent between visiting the SE or not. The superscript N refers to the case of no answer box.

Given publishers' quality choices $\mathbf{q} = (q_1, q_2, \ldots, q_n)$, the outcome of stage 3 is that consumers with $\theta > \bar{\theta}^N(\mathbf{q})$ use the search engine to look for information and the search engine allocates traffic according to the rule of $\max_n q_n + \varepsilon_{in}$. As a result, the traffic received by publisher n would be $D_n^N(\mathbf{q}) = [1 - F\big(\bar{\theta}^N(\mathbf{q})\big)]\lambda_n(\mathbf{q})$, where $\lambda_n(\mathbf{q}) = Pr[q_n + \varepsilon_n \geq \max_{m\neq n}\{q_m + \varepsilon_m\}]$ is the market share the SE allocates to publisher n.

At stage 2, a publisher n solves the problem of

$$\max_{q_n} \pi_n^N(\mathbf{q}) \equiv \alpha D_n^N(\mathbf{q}) - C(v, q_n)$$

The best response is determined by the first-order condition:

$$\alpha\Big[-f(\bar{\theta}^N)\lambda_n(\mathbf{q})\frac{\partial\bar{\theta}^N(\mathbf{q})}{\partial q_n}+[1-F\big(\bar{\theta}^N(\mathbf{q})\big)]\frac{\partial\lambda_n}{\partial q_n}\Big]-\frac{\partial C(v,q_n)}{\partial q_n}=0 \tag{3.1}$$

We can see that a publisher increasing its quality creates two positive marginal effects on its traffic. First, it expands the overall market as higher content quality raises consumers' expected payoffs, which attracts outside consumers to use the search engine to search for information. Second, because publishers compete for infra-marginal consumers through investing in quality to obtain the top position on search results pages, higher quality gives a publisher higher market share.

Absent the answer box, the quality at symmetric equilibrium q^N is characterized by:

$$\alpha\Big[-f(\bar{\theta}^N)\frac{1}{N}\frac{\partial\bar{\theta}^N(\mathbf{q}^N)}{\partial q_n}+[1-F\big(\bar{\theta}^N(\mathbf{q}^N)\big)]\frac{\partial\lambda_n}{\partial q_n}\Big]-\frac{\partial C(v,q^N)}{\partial q_n}=0$$

where $\bar{\theta}^N \equiv \bar{\theta}^N(\mathbf{q}^N)=\frac{c_1+c_2-v}{q^N+\mathbb{E}[\max\boldsymbol{\varepsilon}]}$.

3.3.2 The case of answer box

Because $v>c_1$, all consumers incurs the first stage search and reads the snippet in answer box. Then only those with sufficiently high expected value for the supplemental information in the best match article will click through to websites to read the full article. The location of marginal consumer $\bar{\theta}^A(\mathbf{q})$ who is indifferent between clicking through or not is determined by:

$$\mathbb{E}[\max_n\bar{\theta}(q_n+\varepsilon_n)]=c_2 \Leftrightarrow \bar{\theta}^A(\mathbf{q})=\frac{c_2}{\mathbb{E}[\max_n\{q_n+\varepsilon_n\}]}$$

where the superscript A denotes the regime of answer box.

As a result, the search engine fully covers the market, while the traffic the publisher n receives becomes $D_n^A(\mathbf{q})=[1-F\big(\bar{\theta}^A(\mathbf{q})\big)]\lambda_n(\mathbf{q})$ and now its best response function is determined by

$$\alpha\Big[-f(\bar{\theta}^A)\lambda_n(\mathbf{q})\frac{\partial\bar{\theta}^A(\mathbf{q})}{\partial q_n}+[1-F\big(\bar{\theta}^A(\mathbf{q})\big)]\frac{\partial\lambda_n}{\partial q_n}\Big]-\frac{\partial C(v,q_n)}{\partial q_n}=0 \tag{3.2}$$

In the presence of answer box, the quality at symmetric equilibrium q^A is characterized by:

$$\alpha\Big[-f(\bar{\theta}^A)\frac{1}{N}\frac{\partial\bar{\theta}^A(\mathbf{q}^A)}{\partial q_n}+[1-F\big(\bar{\theta}^A(\mathbf{q}^A)\big)]\frac{\partial\lambda_n}{\partial q_n}\Big]-\frac{\partial C(v,q^A)}{\partial q_n}=0$$

where $\bar{\theta}^A=\frac{c_2}{q^A+\mathbb{E}[\max\boldsymbol{\epsilon}]}$.

3.3.3 The effects of answer box on publishers

Lemma 3.1. *Given any quality vector* $\mathbf{q}$*, we have the following properties on the comparison between marginal consumer locations* $\bar{\theta}^N(\mathbf{q}) \equiv \frac{c_1+c_2-v}{\mathbb{E}[\max_n\{q_n+\varepsilon_n\}]}$ *and* $\bar{\theta}^A(\mathbf{q}) \equiv \frac{c_2}{\mathbb{E}[\max_n\{q_n+\varepsilon_n\}]}$*: (1)* $\bar{\theta}^N(\mathbf{q}) < \bar{\theta}^A(\mathbf{q})$*; (2)* $\frac{\partial\bar{\theta}^A(\mathbf{q})}{\partial q_n} \leq \frac{\partial\bar{\theta}^N(\mathbf{q})}{\partial q_n} < 0, \forall n \in \{1,2,\ldots,N\}$.

Recall the assumption that $c_1 < v < c_1 + c_2$, the proof is straightforward.

This lemmas says that for any given quality choices of publishers, the introduction of answer box shifts marginal consumer's location rightward ($\bar{\theta}^N(\mathbf{q}) < \bar{\theta}^A(\mathbf{q})$). Comparing consumer participation conditions between the two regimes, the direct effect of implementing answer box on consumers is to increase their "opportunity cost" of searching for supplemental information, as the surplus from essential information $v - c_1$ is already realized on search results pages. In addition, shifting marginal consumer's location means that publishers now compete for higher end market segment where marginal consumers are more elastic to content quality ($|\frac{\partial\bar{\theta}^A(\mathbf{q})}{\partial q_n}| \geq |\frac{\partial\bar{\theta}^N(\mathbf{q})}{\partial q_n}|$).

Corollary 3.1. *Given quality choices, the introduction of the answer box expands the search engine's traffic but brings negative externality on traffic to publishers' websites.*

Figure 3.2 illustrates the direct effect of answer box on traffic allocation. The answer box enhances efficiency of searching for essential information, attracting previous outside consumers to use the search engine. However, the expanded traffic to the search engine doesn't flow to publishers. Moreover, inframarginal consumers located between $\bar{\theta}^N(\mathbf{q})$ and $\bar{\theta}^A(\mathbf{q})$ substitute the snippet for the full article, creating negative externality on website traffic.

To decompose the effect of the answer box on publishers' incentive to invest in quality, we take the difference in first-order conditions 3.1 and 3.2 and obtain:

$$\begin{aligned}
&\alpha\Big[-f(\bar{\theta}^A)\frac{\partial\bar{\theta}^A}{\partial q_n}\lambda_n(\mathbf{q}) + [1-F\big(\bar{\theta}^A(\mathbf{q})\big)]\frac{\partial\lambda_n}{\partial q_n}\Big] - \alpha\Big[-f(\bar{\theta}^N)\frac{\partial\bar{\theta}^N}{\partial q_n}\lambda_n(\mathbf{q}) + [1-F\big(\bar{\theta}^N(\mathbf{q})\big)]\frac{\partial\lambda_n}{\partial q_n}\Big] \\
=&\underbrace{\alpha\lambda_n(\mathbf{q})\Big[f(\bar{\theta}^N)\frac{\partial\bar{\theta}^N}{\partial q_n} - f(\bar{\theta}^A)\frac{\partial\bar{\theta}^A}{\partial q_n}\Big]}_{\text{elasticity effect}} + \underbrace{\alpha\Big[F\big(\bar{\theta}^N(\mathbf{q})\big) - F\big(\bar{\theta}^A(\mathbf{q})\big)\Big]\frac{\partial\lambda_n}{\partial q_n}}_{\text{market size effect}}
\end{aligned} \tag{3.3}$$

We define these two effects as follows.

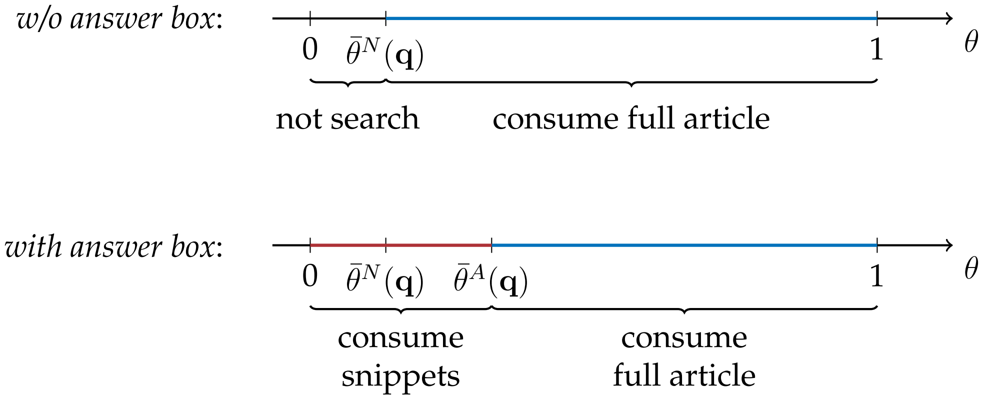


Figure 3.2: Direct effect of snippet on traffic allocation

Definition 2. *The introduction of the answer box creates two effects on publishers' incentives to invest in quality through shifting the marginal consumer's location in the second search stage:*

(1) ***Market size reduction effect****. The introduction of the answer box raises the threshold of consumers who click through, cutting down the traffic to publishers' websites.*

(2) ***Elasticity variation effect****. The use of the answer box makes publishers compete for higher-end market segment (i.e. consumers with higher θ), which changes the elasticity of demand.*

Market size reduction effect, captured through $F\big(\bar{\theta}^N(\mathbf{q})\big) - F\big(\bar{\theta}^A(\mathbf{q})\big)$, is always negative, as it lowers the marginal traffic a publisher obtains from winning the top position on search results pages through investing more in quality. The elasticity variation effect is ambiguous and determined by two factors. First, as higher type consumers are more sensitive to quality, $|\frac{\partial \bar{\theta}^A(\mathbf{q})}{\partial q_n}| \geq |\frac{\partial \bar{\theta}^N(\mathbf{q})}{\partial q_n}|$, this factor tends to encourages more investment. However, the marginal effect of investing in quality on market size also depends on the distribution of consumers' taste for quality. For instance, when the high type consumers are very scarce, the elasticity variation effect would be negative. By contrast, when consumers are uniformly distributed, this effect is positive. As a result, we have the following proposition.

Proposition 3.1. *The effect of the answer box on equilibrium content quality is ambiguous and determined by the relative magnitude of market size reduction effect and elasticity variation effect.*

To pin down the full equilibrium results and to understand how each effect drives the outcome, we consider two polar cases. The first example focuses on the monopolistic case where $N = 1$. Because there is no competition in content market, market size reduction effect disappears, which allows us to focus on the elasticity variation effect. In the second example, we use the Salop model to examine competitive content market with $N \geq 2$ and, for the sake of tractability, assume that consumers cannot observe publishers' quality choices before searching. In this situation, there only exists the market size reduction effect.

Monopolistic content market

Because the answer box allows the search engine to fully cover the market, it always has incentive to implement it as long as this doesn't discourage the monopolistic publisher from producing the relevant information. In the following proposition, we focus on the case that the publisher obtains non-negative equilibrium profit in both regimes.

Proposition 3.2. *When the content market is monopolistic, the publisher's traffic and profit always go down in equilibrium after the introduction of the answer box.*

Here I explain the rationale behind the result, and see the formal proof in Appendix. The mechanism of the answer box is to unbundle the consumption of essential information and supplemental information. Prior to the introduction of the answer box, the publisher could leverage the essential information v to attract the consumers $\{\theta : c_1 + c_2 - v < \theta \mathbb{E}[\max_n\{q_n + \varepsilon_n\}] < c_2\}$ to visit its website. The publisher cannot do this anymore after the introduction of the answer box and adjusts the investment in supplemental information either upward or downward, depending on the distribution of consumers' taste for quality. When the quality is decreased, the indirect effect of the answer box, $[1 - F(\bar{\theta}^A(q^N))] - [1 - F(\bar{\theta}^A(q^A))]$, is also negative such that the traffic goes down in equilibrium. When the quality is increased, although the indirect effect is positive, it is always dominated by the negative direct effect. This is because in the regime of answer box, the publisher must invest more heavily in supplemental information to attract the same number of consumers as before. For any consumer that was unprofitable to attract in the absence of answer box, it is even more so in the regime of answer box, as it is more costly to achieve the outcome.

Although in monopolistic content market only the elasticity variation effect changes the publisher's incentive to invest in quality, it is ambiguous whether the quality is increased or decreased as the effect depends on the distribution of consumers' taste for quality. The next proposition gives an sufficient condition for the use of answer box to enhance content quality.

Proposition 3.3. *When consumers are uniformly distributed $\theta \sim U[0, 1]$, the monopolistic publisher invests more in quality after the introduction of the anwser box.*

Competitive content market

In the preceding analysis, we find that a publisher's quality choice affects not only the ranking of their articles in results pages but also consumers' decision to search. This is driven by the assumption that consumers are able to observe publishers' quality. It particularly holds for the type of search queries that consumers frequently demand such that they know what publishers they will encounter.

To capture the case of random search queries where consumers cannot foresee the identities of publishers, consider there is a continuum of categories and each category has N publishers. A search query has a unique relevant category that is determined by the search engine. As a consumer does not know which category her search query belongs to, she forms a rational and symmetric expectation q^e over the qualities of publishers.

We use the Salop model to capture consumers' heterogeneous tastes for different supplemental information. Assume consumers are uniformly distributed around the circle of perimeter equal to 1, $x \sim U[0, 1]$. The search engine knows each consumer's location x, while herself not. As in the baseline model, we assume the search engine can perfectly predict consumers' valuations for each article and therefore match their search queries with the article offering highest utility $\text{argmax}_n\, v + \theta(q_n - t|x - x_n|)$. Assume the investment cost function is $c(v, q) = \frac{q^2}{2}$.

We solve for symmetric equilibrium. When there is no answer box, suppose all competitors of the publisher n choose quality q^N and consumers hold symmetric belief q^e over publishers' qualities. the utility of searching for information to the consumer x is:

$$v + \theta(q^e - 2N\int_0^{\frac{1}{2N}} txdx) - c_1 - c_2 = v + \theta(q^e - \frac{t}{4N}) - c_1 - c_2$$

Therefore, the marginal consumer's position is $\bar{\theta}^N = \frac{c_1+c_2-v}{q^e-\frac{t}{4N}}$.

When the publisher n's quality is q_n, for consumers reaching search result pages, its market share is $\lambda_n(q_n, \mathbf{q}_{-n}^N) = \frac{1}{N} + \frac{q_n - q^N}{t}$. Hence, publisher n solves the following problem:

$$\max_{q_n} \alpha(1 - \frac{c_1 + c_2 - v}{q^e - \frac{t}{4N}})(\frac{1}{N} + \frac{q_n - q^N}{t}) - \frac{q_n^2}{2}$$

The FOC is:

$$\alpha(1 - \frac{c_1 + c_2 - v}{q^e - \frac{t}{4N}})\frac{1}{t} - q_n = 0$$

Therefore, the symmetric equilibrium quality q^N is characterized by:

$$\alpha(1 - \frac{c_1 + c_2 - v}{q^N - \frac{t}{4N}})\frac{1}{t} - q^N = 0$$

There exists two solutions and we select the stable equilibrium which is the larger root.

When there is answer box, consumers' opportunity cost of searching for supplemental information becomes c_2. Accordingly, the symmetric equilibrium quality q^A is characterized by:

$$\alpha(1 - \frac{c_2}{q^A - \frac{t}{4N}})\frac{1}{t} - q^A = 0$$

Because consumers cannot observe publishers' quality choices before search, publishers' investment decision will only affect their market share among consumers who actually use the search engine, but not consumers' decision to search. Therefore, elasticity effect disappears and there only exists the negative market size effect, giving us the following result:

Proposition 3.4. *In competitive content market where $N \geq 2$ and consumers cannot observe publishers' quality choices before search, the answer box reduces content quality $q^A < q^N$ and website traffic. However, there exits a threshold $\bar{\alpha}$ on publishers' per-traffic ad revenue such that when $\alpha > \bar{\alpha}$ publisher profit is higher, and lower otherwise, in symmetric equilibrium.*

Due to the negative market size effect, the marginal benefit from investing in quality is reduced, leading to lower content quality in equilibrium. However, this also helps relax the quality competition among publishers, which saves their investment cost. When the per-traffic ad revenue is large enough, the negative effect on website traffic is dominated by the positive effect of relaxing quality competition so that publisher profit is higher.

3.4 Welfare Analysis

Define social welfare as the sum of consumer surplus, publisher profits and the search engine's profit. So when there is no answer box, it is expressed as

$$SW^N(\mathbf{q}) = \int_{\bar\theta^N(\mathbf{q})}^{+\infty}\int_{\boldsymbol{\varepsilon}\in\mathbb{R}^{\mathbb{N}}} v+\theta(\max_n\{q_n+\varepsilon_n\})-c_1-c_2\, d\mathcal{G}(\boldsymbol{\varepsilon})dF(\theta)+\Sigma_{n=1}^N\Big((\beta+\alpha)D_n^N(\mathbf{q})-c(v,q,q_n)\Big)$$

where $\mathcal{G}(\boldsymbol{\varepsilon}) = G(\varepsilon_1)G(\varepsilon_2)\cdots G(\varepsilon_N)$. And when there is the answer box, the social welfare is:

$$SW^A(\mathbf{q}) = \int_{-\infty}^{\bar\theta^A(\mathbf{q})} v-c_1\, dF(\theta) + \int_{\bar\theta^A(\mathbf{q})}^{+\infty}\int_{\boldsymbol{\varepsilon}\in\mathbb{R}^{\mathbb{N}}} v+\theta(\max_n\{q_n+\varepsilon_n\})-c_1-c_2\, d\mathcal{G}(\boldsymbol{\varepsilon})dF(\theta)+$$
$$\beta+\Sigma_{j=1}^n\Big(\alpha D_n^A(\mathbf{q})-c(v,q_n)\Big)$$

Taking the difference in social welfare between $SW^N(\mathbf{q}^N)$ and $SW^A(\mathbf{q}^N)$, we obtain the direct effect of the answer box on social welfare

$$SW^A(\mathbf{q}^N)-SW^N(\mathbf{q}^N) = \underbrace{F(\bar\theta^N(\mathbf{q}^N))(v-c_1)}_{(1)} + \underbrace{\int_{\bar\theta^N(\mathbf{q}^N)}^{\bar\theta^A(\mathbf{q}^N)} c_2-\theta(q^N+\mathbb{E}[\max\boldsymbol{\varepsilon}])\, dF(\theta)}_{(2)}$$
$$+\underbrace{\beta F(\bar\theta^N(\mathbf{q}^N))}_{(3)} - \underbrace{\alpha N\big(D^N(\mathbf{q}^N)-D^A(\mathbf{q}^N)\big)}_{(4)}$$

where $D^N(\mathbf{q}^N) \equiv D_1^N(\mathbf{q}^N) = D_2^N(\mathbf{q}^N) = \cdots = D_N^N(\mathbf{q}^N)$ and $D^A(\mathbf{q}^N) \equiv D_1^A(\mathbf{q}^N) = D_2^A(\mathbf{q}^N) = \cdots = D_N^A(\mathbf{q}^N)$.

The decomposition has four components: (1) is the increase in consumer surplus due to broader access to essential information; (2) is the increase in consumer surplus due to higher search efficiency, as consumers whose average valuation of supplemental information is smaller than the second-stage search cost could just consume the snippet in answer box; (3) comes from the search engine's higher shadow revenue; (4) is the reduction in publishers' advertising revenue.

The unbundling effect of the answer box brings search efficiency not only by attracting previously outside consumers to consume essential information, but also by allowing infra-marginal consumers to save search cost by substituting the snippet for the full article. However, this creates negative externality on website traffic. Therefore, we have the following result on the direct welfare effect of the answer box.

Proposition 3.5. *Taking content quality $\mathbf{q}^{\mathbf{N}} = (q^N, \dots, q^N)$ as fixed, the answer box increases consumer surplus while harms publisher profit. The impact on social welfare is ambiguous.*

When $q^A > q^N$, the indirect effect of the answer box on social welfare is as follows:

$$\begin{aligned} SW^A(\mathbf{q}^A) - SW^A(\mathbf{q}^N) = &\int_{\bar{\theta}^A(\mathbf{q}^A)}^{\bar{\theta}^A(\mathbf{q}^N)} \theta(q^A + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2 \, dF(\theta) + \int_{\bar{\theta}^A(\mathbf{q}^N)}^{+\infty} \theta(q^A - q^N) \, dF(\theta) \\ &+ N[\alpha(D^A(\mathbf{q}^A) - D^A(\mathbf{q}^N)) - (c(v, q^A) - c(v, q^N))] \end{aligned}$$

The case $q^A \leq q^N$ can be obtained by switching the superscripts of N and A on q and $\mathbf{q}$.

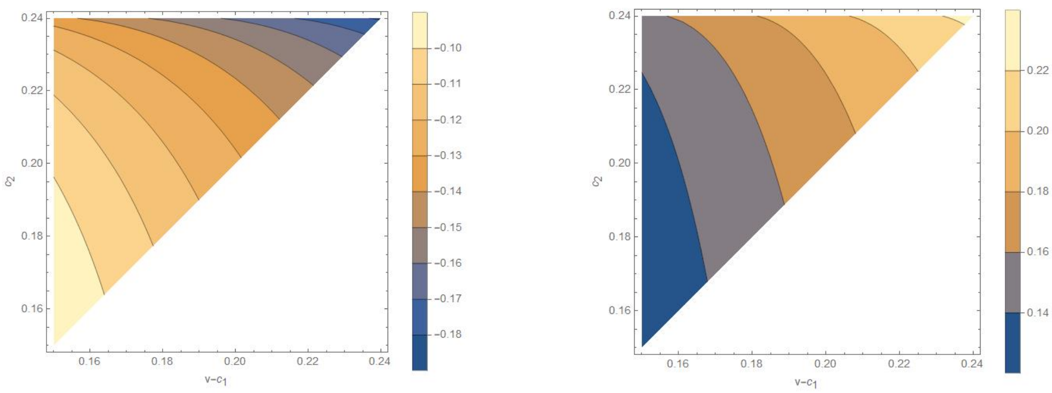
Proposition 3.6. *When $v - c_1$ is sufficiently close to zero, the introduction of the answer box increases social welfare and its impacts on consumer surplus and publisher profit are negligible.*

When $v - c_1$ is close to zero, i.e., the essential information does not create much surplus, it is always the demand for supplemental information that drives consumers to search. Therefore, the answer box barely changes the marginal consumer's location, which in turn has negligible effect on publishers' incentive to invest in quality. As a result, the use of the answer box does not impact consumer surplus and publisher profit. Moreover, because the search engine benefits from carrying more search queries, social welfare is increased after the introduction of the answer box.

Following the results in Section 3.3.3, we know that when the content market is monopolistic, $\theta \sim U[0, 1]$, and consumers can observe the content quality before search, the answer box remains to benefit consumers while harm the publisher after endogenizing its impact on quality choice. In the next proposition, we use a parametrization of the competitive content market example in Section 3.3.3 to show there exit situations where the direct welfare effects on consumers and publishers are reversed.

Proposition 3.7. *Under the competitive content market model and taking* $n = 2, t = 1, \alpha = 1.2$ *as fixed, when* $0.15 \leq v - c_1 \leq 0.24$ *and* $v - c_1 \leq c_2 \leq 0.24$*, there exits symmetric equilibrium and in this parameter region, the use of the answer box is always to raise publisher profit while reduce consumer surplus.*

This is proven by the numerical results. Figure 3.3a and 3.3b respectively draws the contour of difference in consumer surpluses $CS^A - CS^N$, and the contour of difference in publisher profit $\pi_n^A - \pi_n^N$.



(a) Difference in consumer surplus

(b) Difference in publisher profit

Figure 3.3: Welfare Effects of the Answer Box in Competitive Content Market

3.5 The Snippet Licensing Game

In this section, we examine the effects of different policies that enforcing the search engine to pay for the use of snippets. We focus on symmetric quality choices and take them as fixed at the level of q.

3.5.1 Take-it-or-leave-it Contract

In the first case, the regulator simply mandates the SE to pay publishers for the use of snippets. The licensing game will proceed as follows. First, the search engine makes take-it-or-leave it offers $T \geq 0$ to publishers. That is to say, by paying a publisher the amount of money T, the SE obtains the copyright of the snippet and it can display the snippet as it likes. Next, the SE designs its search results pages, deciding whether to implement the answer box and the ranking of articles for each consumer. Last, consumers make search decisions.

Because the search engine only cares about the number of consumers who use its search service and all consumers have $v > c_1$, as long as the SE obtains at least once license, it will display the snippet in the answer box for every consumer. However, this will incur distortion in second-stage search process, as the publisher who gets displayed in the answer box does not necessarily provide the supplemental information with highest match value.

Conditional on that the SE obtains license from at least one publisher and thus is able to implement the answer box, there would be multiple equilibria regarding its ranking strategy. To address this problem, we select the Pareto-dominant equilibrium. That is to way, when there are more than one publishers licensing their content, the search engine will select the one offer highest $v + \theta(q_n + \varepsilon_n)$ into the answer box.

Proposition 3.8. *When N is sufficiently large, all publishers license their content to the search engine at the price of $T = 0$ in equilibrium.*

Proof. Whenever there is at least one rival publisher licensing their content, it is profitable for a certain publisher n to license hers for free as well, because otherwise she never gets placed on the top of search result pages and thereby receives zero website traffic.

From last section, when no one licenses content, the traffic received by a publisher is $\frac{1-F(\bar{\theta}^N)}{N}$, where $\bar{\theta}^N(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) = c_1 + c_2 - v$. Then if publisher n deviates to licensing her content to the SE, the traffic she receives would be $1 - F(\bar{\theta}^A)$, where $\bar{\theta}^A(q + \mathbb{E}[\varepsilon_n]) = c_2$. Because $\lim_{N\to+\infty} \frac{1-F(\bar{\theta}^N)}{N} = 0$, when N is large enough, $1 - F(\bar{\theta}^A) > \frac{1-F(\bar{\theta}^N)}{N}$.

Therefore, the unique equilibrium is that all publishers license their content for free. $\square$

3.5.2 Neutrality Obligation (Incomplete)

Suppose now the regulator imposes neutrality obligation on the SE, requiring it not to condition the rankings on search results pages on the contracting outcome. In our model, this means that at the stage of designing search results pages, the search engine does not implement the answer box if the best match publisher didn't license its content. Denote the set of publishers who have reached agreement with the search engine as $\mathcal{C}$. $C = |\mathcal{C}|$ is the number of publishers licensing their content.

Knowing under neutrality obligation the SE always places the link to the best match article on the top regardless of the use of answer box, a consumer who has read the snippet will click through to the publisher's website if and only if $\theta(q + \mathbb{E}[\max_n \boldsymbol{\varepsilon}]) \geq c_2$. Therefore, consumers with $\theta \geq \bar{\theta}^A$ always consume the full article.

For consumers with $\theta < \bar{\theta}^A$, their expected net utility of engaging in search is:

$$v - c_1 + Pr\{\max_{n \in N/\mathcal{C}}\{\varepsilon_n\} > \max_{n \in \mathcal{C}}\{\varepsilon_n\}\}[\theta(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2]$$

where $Pr\{\max_{n \in N/\mathcal{C}}\{\varepsilon_n\} > \max_{n \in \mathcal{C}}\{\varepsilon_n\}\} = \frac{N-C}{N}$. Denote the cutoff at which the expected net utility of searching is equal to zero as $\hat{\theta}(C)$.

Lemma 3.2. *We take $\mathcal{C}$ as given. (1).$\hat{\theta} < \bar{\theta}^N$, where $\bar{\theta}^N(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) = c_1 + c_2 - v$. (2).Define $\bar{\bar{\theta}}$ by $v + \bar{\bar{\theta}}(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2 = 0$. If $\frac{C}{N}v - c_1 > 0, \hat{\theta} < \bar{\bar{\theta}}$; otherwise, $\hat{\theta} \geq \bar{\bar{\theta}}$*

When there are C publishers licensing their content, consumer search behavior is characterized as follows. Consumers with $\theta < \hat{\theta}$ don't search; those in $\hat{\theta} \leq \theta < \max\{\hat{\theta}, \bar{\bar{\theta}}\}$ will use the SE to search for information, and they only consume snippets in answer box if there is one in the search results page, and quit the searching otherwise; those with $\max\{\hat{\theta}, \bar{\bar{\theta}}\} \leq \theta < \bar{\theta}^A$ will only consume snippets in answer box if there is one in the search result page, and consume the full article otherwise; consumers with $\theta > \bar{\theta}^A$ always click through to read the full article.

Therefore, the traffic received by a publisher $n \in \mathcal{C}$ is $\frac{1-F(\bar{\theta}^A)}{n}$, and by a publisher $n \in N/\mathcal{C}$ is $\frac{1-F(\max\{\hat{\theta}(C), \bar{\bar{\theta}}\})}{n}$.

For the SE, if it wants to induce C publishers to accept its offer, the market clearing price should be:

$$T(C) = \begin{cases} \alpha[\frac{1-F(\hat{\theta}(C-1))}{N} - \frac{1-F(\bar{\theta}^A)}{N}] = \frac{\alpha[F(\bar{\theta}^A)-F(\hat{\theta}(C-1))]}{N}, & \frac{C}{N}v - c_1 \leq 0 \\ \alpha[\frac{1-F(\bar{\bar{\theta}})}{N} - \frac{1-F(\bar{\theta}^A)}{N}] = \frac{\alpha[F(\bar{\theta}^A)-F(\bar{\bar{\theta}})]}{N}, & \frac{C-1}{N}v - c_1 > 0 \end{cases}$$

Therefore, the SE solves the following problem:

$$\max_C \beta[1 - F(\hat{\theta}(C))] - C \cdot T(C)$$

Case 1: $\bar{\bar{\theta}} < 0 \Leftrightarrow v > c_2$.

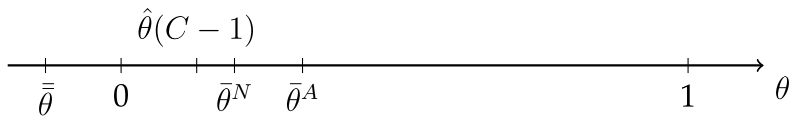


Figure 3.4: Traffic allocation when $\bar{\bar{\theta}} < 0$

In this case, there doesn't exist consumers who drop the search process without consuming any information. When the SE wants to obtain C licenses, it not only needs to compensate the publishers for the negative externality on their website traffic $\theta \in [\bar{\theta}, \tilde{\theta}]$, but also pay for the expanded traffic $\theta \in [\hat{\theta}(C-1), \bar{\theta}]$ stemming from rival publishers' license of snippets.

3.6 Conclusion

This paper studies the impact that a gatekeeper search engine becomes a direct information provider has on the consumption and the production of information goods. I find that the use of answer box unbundles the consumption of essential information and supplemental information of an article. The direct effect is to expand traffic to the search engine while creating negative externality on traffic to publishers' websites. Its impact on publishers' incentive to invest in content quality is ambiguous, depending on the relative strength of the market size effect and the elasticity effect. When the content market is monopolistic, the website traffic and publisher profit always go down after the introduction of answer box. When the content market is competitive, consumers are uniformly distributed and they cannot observe quality choice before search, the use of answer box relaxes quality competition in content market such that quality is decreased while publisher profit is higher in equilibrium. The welfare effect is even more ambiguous, as on the one hand, the use of answer box enhances search efficiency by providing broader access to essential information and by allowing inframarginal consumers to substitute the snippet for the full article; while on the hand, it can harm publishers' advertising revenue and content quality.

These results suggest that it is not clear a priori whether Google'practice of using the answer box constitutes an anti-competitive behavior, as the effect can vary with different search categories. They are also in line with the rationale behind the decision FTC made in 2013 to settle with Google over the investigation of its search practice, which states that "Google adopted the design changes that the Commission investigated to improve the quality of its search results, and that any negative impact on actual or potential competitors was incidental to that purpose."

3.7 Appendix

Proof of Proposition 3.2: To prove the publishers' traffic goes down, it is to show that $\bar{\theta}^A(q^A) \geq \bar{\theta}^N(q^N)$.

First, if it is the case that equilibrium quality is reduced $q^A < q^N$, because $\frac{\partial \bar{\theta}^A}{\partial q_n} < 0$, then $\bar{\theta}^A(q^A) \geq \bar{\theta}^A(q^N) > \bar{\theta}^N(q^N)$.

Then, consider the case that $q^A \geq q^N$ and we prove the result by contradiction. Suppose it is the opposite of the proposition so that $\bar{\theta}^A(q^A) < \bar{\theta}^N(q^N)$, i.e. publishers' traffic goes up after they adjust their quality upward in response to the introduction of answer box.

Let $\hat{q}^A$ be the quality level such that the publisher's traffic in the regime of answer box is equal to the traffic induced by quality q^N in the absence of answer box, i.e., $\bar{\theta}^A(\hat{q}^A) = \bar{\theta}^N(q^N)$. Because $\bar{\theta}^N(q^N) = \frac{c_1+c_2-v}{q^N}$ and $\bar{\theta}^A(\hat{q}^A) = \frac{c_2}{\hat{q}^A}$, $\hat{q}^A = \frac{c_2}{\bar{\theta}^A(\hat{q}^A)} = \frac{c_2}{\bar{\theta}^N(q^N)} > q^N = \frac{c_1+c_2-v}{\bar{\theta}^N(q^N)}$. This is intuitive—because the introduction of answer box disables publishers to leverage the essential information to attract consumers to click through to their websites, they must invest more heavily in supplemental information to obtain the same amount of traffic as that when there is no answer box.

Similarly, let $\hat{q}^N$ be the quality level such that the publisher's traffic in absence of answer box is equal to the traffic induced by quality q^A in the regime of answer box, $\bar{\theta}^N(\hat{q}^N) = \bar{\theta}^A(q^A)$. Then we have $\hat{q}^N = \frac{c_1+c_2-v}{\bar{\theta}^A(q^A)} < q^A = \frac{c_2}{\bar{\theta}^A(q^A)}$.

Furthermore, we have $q^A - \hat{q}^A = \frac{c_2}{\bar{\theta}^A(q^A)} - \frac{c_2}{\bar{\theta}^N(q^N)} > \hat{q}^N - q^N = \frac{c_1+c_2-v}{\bar{\theta}^A(q^A)} - \frac{c_1+c_2-v}{\bar{\theta}^A(q^A)}$, which means that to enhance traffic from $1 - F(\bar{\theta}^N(q^N))$ to $1 - F(\bar{\theta}^A(q^A))$, the quality increment needed in the regime of answer box is higher than that in the regime of no answer box.

By the optimality of q^A under the regime of answer box, $\pi^A(q^A) = \alpha D^A(q^A) - C(v, q^A) > \pi^A(\hat{q}^A) = \alpha D^A(\hat{q}^A) - C(v, \hat{q}^A)$. Rewriting this inequality, we obtain $\alpha[F(\bar{\theta}^N(q^N)) - F(\bar{\theta}^A(q^A))] > C(v, q^A) - C(v, \hat{q}^A)$.

If it is profitable to recruit consumers with $\bar{\theta}^A(q^A) \le \theta \le \bar{\theta}^N(q^N)$ in the regime of answer box, so is it in the absence of answer box, as the latter case requires less investment in supplemental information:

$$
\begin{aligned}
\pi^N(\hat{q}^N) - \pi^N(q^N) =& \alpha\Big[[1 - F(\bar{\theta}^N(\hat{q}^N))] - [1 - F(\bar{\theta}^N(q^N))]\Big] - \Big[C(v, \hat{q}^N) - C(v, q^N)\Big] \\
=& \alpha\Big[F(\bar{\theta}^N(q^N)) - F(\bar{\theta}^A(q^A))\Big] - \Big[C(v, \hat{q}^N) - C(v, q^N)\Big] \\
>& \Big[C(v, q^A) - C(v, \hat{q}^A)\Big] - \Big[C(v, \hat{q}^N) - C(v, q^N)\Big] \\
=& \int_{\hat{q}^A}^{q^A} \frac{\partial C(v,q)}{\partial q} dq - \int_{q^N}^{\hat{q}^N} \frac{\partial C(v,q)}{\partial q} dq \\
=& \int_{\hat{q}^A + (\hat{q}^N - q^N)}^{q^A} \frac{\partial C(v,q)}{\partial q} dq + \int_{\hat{q}^A}^{\hat{q}^A + (\hat{q}^N - q^N)} \frac{\partial C(v,q)}{\partial q} dq \\
& - \int_{\hat{q}^A}^{\hat{q}^A + (\hat{q}^N - q^N)} \frac{\partial C(v, q - (\hat{q}^A - q^N))}{\partial q} dq \\
=& \int_{\hat{q}^A + (\hat{q}^N - q^N)}^{q^A} \frac{\partial C(v,q)}{\partial q} dq + \int_{\hat{q}^A}^{\hat{q}^A + (\hat{q}^N - q^N)} \frac{\partial C(v,q)}{\partial q} - \frac{\partial C(v, q - (\hat{q}^A - q^N))}{\partial q} dq \\
>& 0
\end{aligned}
$$

The last inequality is by the fact that $\frac{\partial^2 C(v,q)}{\partial q^2} \ge 0$ and hence $\forall q, \frac{\partial C(v,q)}{\partial q} > \frac{\partial C(v, q-(\hat{q}^A - q^N))}{\partial q}$ as we have proved that $\hat{q}^A > q^N$. However, $\pi^N(\hat{q}^N) - \pi^N(q^N) > 0$ contradicts the optimality of q^N in the absence of answer box. Therefore, it must that $\bar{\theta}^A(q^A) \ge \bar{\theta}^N(q^N)$.

When the equilibrium quality is increased, it is straightforward that the profit goes down, as the publisher has lower traffic and higher investment cost. When the equilibrium quality is decreased, the profit is also smaller because:

$$\pi^N(q^N) = \alpha D^N(q^N) - c(v, q^N) > \alpha D^N(q^A) - c(v, q^A) > \alpha D^A(q^A) - c(v, q^A) = \pi^A(q^A)$$

The first inequality is by the optimality of q^N in the case of no answer box. $\square$

Proof of Proposition 3.3: When the content market is monopolistic and $\theta \sim U[0,1]$, equation 3.3 becomes $\alpha(\frac{d\bar{\theta}^N}{dq} - \frac{d\bar{\theta}^A}{dq}) = \alpha(\frac{c_2}{q^2} - \frac{c_1+c_2-v}{q^2}) > 0$. In this case, only the elasticity variation effect is at play. Moreover, when consumers are uniformly distributed, the fact that higher type consumers are more sensitive to quality enhances the marginal return. Therefore, the monopolist publishers invests more in quality after the introduction of the answer box as long as it obtains non-negative profit. $\square$

Proof of Proposition 3.4: Denote consumers' opportunity cost of searching for supplemental information by K. When there is no answer box, $K = c_1 + c_2 - v$; otherwise, $A = c_2$. At a given K, the symmetric equilibrium quality q^* is the larger root of $\alpha(1 - \frac{K}{q - \frac{t}{4N}})\frac{1}{t} - q = 0$, which is $q^* = \frac{t^2+4N\alpha+\sqrt{t^4-64KN^2t\alpha-8Nt^2\alpha+16N^2\alpha^2}}{8Nt}$. Because $c_1 + c_2 - v > c_2$ and q^* is decreasing in K, $q^N > q^A$.

For q^* to constitute a symmetric equilibrium, it needs to satisfy the following conditions:

$$t^4 - 64KN^2t\alpha - 8Nt^2\alpha + 16N^2\alpha^2 \geq 0$$
$$\pi(\mathbf{q}^*) = \frac{\alpha}{N}(1 - \frac{K}{q^* - \frac{t}{4N}}) - \frac{q^{*2}}{2} \geq 0$$

Taking the difference in equilibrium publisher profit across the two regimes,

$$\begin{aligned}
&\pi^A(\mathbf{q}^A) - \pi^N(\mathbf{q}^N) \\
=&\frac{\alpha}{N}(1 - \frac{c_2}{q^A - \frac{t}{4N}}) - \frac{{q^A}^2}{2} - \Big(\frac{\alpha}{N}(1 - \frac{c_1 + c_2 - v}{q^N - \frac{t}{4N}}) - \frac{{q^N}^2}{2}\Big) \\
=&\frac{t}{N}(q^A - q^N) - \frac{(q^A + q^N)(q^A - q^N)}{2} \\
=&(\frac{t}{N} - \frac{q^A + q^N}{2})(q^A - q^N)
\end{aligned}$$

Because $q^A < q^N$, $\pi^A(\mathbf{q}^A) - \pi^N(\mathbf{q}^N) \geq 0$ is equivalent to $\frac{q^A+q^N}{2} \geq \frac{t}{N}$. As q^* is increasing with α in the parameter region where q^* constitutes symmetric equilibrium, there exits a threshold $\bar{\alpha}$ such that when $\alpha > \bar{\alpha}$, $\frac{q^A+q^N}{2} \geq \frac{t}{N}$. $\square$

***Proof of Lemma 3.2**:* (1). We first prove that $\hat{\theta} < \bar{\theta}^N$. Because $\bar{\theta}^N < \bar{\theta}^A$, where $\bar{\theta}^A(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) = c_2$, we have $\bar{\theta}^N(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) < c_2$. Therefore,

$$v - c_1 + \frac{N-C}{N}[\bar{\theta}^N(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2] \geq v - c_1 + \bar{\theta}^N(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2 = 0$$

As $v - c_1 + \frac{N-C}{N}[\theta(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2]$ is increasing in θ, $\hat{\theta} < \bar{\theta}^N$.

(2). At $\theta = \bar{\bar{\theta}}$,

$$v - c_1 + \frac{N-C}{N}[\bar{\bar{\theta}}(q + \mathbb{E}[\max \boldsymbol{\varepsilon}]) - c_2] = \frac{C}{N}v - c_1$$

Therefore, if $\frac{C}{N}v - c_1 > 0, \hat{\theta} < \bar{\bar{\theta}}$; otherwise, $\hat{\theta} \geq \bar{\bar{\theta}}$. $\square$

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