Impact of Regulation and the Digital Markets Act on Competing Platforms

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Abstract. The regulation of platforms has been a hot topic, particularly in Europe with the Digital Markets Act (DMA) passed in 2022. The purpose of this paper is to design a mathematical model representing a game between long-term revenue-oriented platforms in competition playing with their ranking strategy of items. The objective of platforms is to apply a trade-off between short-term revenue from each visit by displaying most profitable items and long-term number of visits due to the satisfaction of users from the relevance of the displayed items. We analyze the output of the game and the impact of proposed regulation rules on platforms and users.

1 Introduction

Digital platforms have become a centerpiece of modern society, reshaping the way we live, work, and interact. By digital platforms, we typically mean and target here social media networks, e-commerce websites, and search engines. On the positive side, those platforms have democratized access to information and resources, empowering users to create, share, and participate in a global digital ecosystem. But the way they display items influences business, information and culture, among other things: an e-commerce web site incentivizes users to buy the first presented items, at the expense of others; similarly search engines guide people toward some content [6,7].

For that reason, the rise of digital platforms has raised several concerns about data privacy, misinformation and market concentration, leading to questions from governments and regulatory bodies about the impact and possible biases of those key actors. For example, the ranking methods applied by search engines have been questioned by the US Senate [9], the Federal Trade Commission [1], as well as the European Commission[3]. Recently, the European Commission has put under scrutiny a few big digital platforms labeled as “gatekeepers” and having an impact on the European Union’s digital economy. To address the issue,

[3] https://digital-strategy.ec.europa.eu/en/news/commission-sends-requests-information-17-very-large-online-platforms-and-search-engines-under

the *Digital Markets Act* (DMA) [3] was passed in 2022 with the objective of ensuring fair competition, stimulating innovation, and strengthening consumer protection in digital markets. The principle is to deal with the dominance of (mostly American) large tech companies and foster a more competitive and diverse digital ecosystem. Among obligations for (only) "big" platforms—where the notion of big is defined using thresholds on size and market share—are the obligation to provide interoperability and data portability, to grant fair access to data for competing businesses, and the interdiction of self-preferencing practices that could harm competition. Any non-compliance could lead to penalties reaching up to 10% of the company's global turnover.

The motivation for this paper regards the impact of regulation, particularly the DMA, on competing platforms, and the potential unintended consequences. Concretely, we aim at comparing the output from scenarios involving two competing platforms: one of free competition with no regulation or constraint, and the case where a platform (the "big" one) has to rank items neutrally (i.e., without taking into account any economic consideration). We will then see whether such an asymmetric regulation, which we label as the DMA scenario, is beneficial. We will also compare with a (third) fully-neutral case at almost no cost. It is to our knowledge the first contribution comparing such scenarios.

In order to model the behavior of strategic platforms, we extend the model in [4] where the optimal ranking strategy of a *single* platform is derived, taking care of the tradeoff between long-term and short-term revenues. Long-term revenues mean proposing the most relevant items, leading to users coming back and therefore more requests; it is considered a neutral behavior, that is, what is expected from the platform. Short-term revenues are based on presenting first items yielding the largest one-shot gains for the platform, not necessarily the most relevant for users; it can be considered a non-neutral behavior. To analyze the effect of DMA, the extension of the model in [4] consists in generalizing the work to two platforms in competition. This will allow us to see the impact on the two platforms of DMA compliance with respect to non-neutral and fully-neutral scenarios.

The remaining of the paper is organized as follows. Section 2 presents the baseline model and main results taken from [4] describing the optimal strategy for a (single) revenue-oriented platform. Section 3 then describes how the model can be extended to two platforms in competition and how the problem can be solved using the framework of non-cooperative game theory [8]. Section 4 analyzes the three following regulation scenarios: a "free" market where platforms can arbitrate their revenue tradeoff with no constraint, the DMA where a large platform is regulated but not a small one, and the fully-regulated case where platforms can only rank according to relevance. Section 5 numerically compares the three scenarios for a set of parameters, computing performance indicators for the outcomes regarding users and both platforms. Finally Section 6 concludes and gives directions for future research.

2 Model and results for a single platform

We recall the model in [4] that we will extend to multiple platforms in the next sections. Consider a platform, for example a search engine or a marketplace. We model the output of a (random) request as a random vector

$$Y = (M, R_1, G_1, \ldots, R_M, G_M)$$

where M is the number of relevant items (upper-bounded by m_0) for this query, R_i represents the relevance of the i-th item (that is, how much it aligns with a user's query and intent; upper bounded by 1), and G_i is the expected gain the platform will make if item i if clicked (upper bounded by K).

We assume the vector Y has a fixed probability distribution (discrete or continuous) over a compact (closed and bounded) subspace $\Omega \subseteq \cup_{m=0}^{m_0}(\{m\} \times ([0,1] \times [0,K])^m)$. For a given realization $y = (m, r_1, g_1, \ldots, r_m, g_m)$, the goal of the platform is to select a ranking of the m considered items, that is a permutation $\pi = (\pi(1), \ldots, \pi(m))$ of $\{1, \ldots, m\}$, such that item i will be displayed in position $\pi(i)$. The question is on the selection of *the (deterministic) stationary ranking policy* μ as a function of the possible realizations y, $\pi = \mu(y)$, that is, to select for each possible realization y the most "appropriate" permutation.

A parameter that has an important role for the ranking is the so-called *click-through-rate* (CTR), which represents the probability $c_{i,j}(y)$ that an item i at a position j is clicked, for query y. While its value may be complex in terms of y, it is often assumed that the click-through rate of item i at position j is separable into a position effect θ_j and a relevance effect $\psi_i(y)$, such that $c_{i,j}(y) = \theta_j \psi_i(y)$ [5]. (Without loss of generality we order the positions so that the higher the position in the ranking, the larger the position effect: $\theta_1 \geq \theta_2 \geq \cdots \geq \theta_m$.) One can interpret the position effect θ_j as the probability that an item i at position i is seen, while the relevance effect $\psi_i(y)$ is the (position-independent) probability that the item is clicked when seen. A less general but also rather understandable expression is to express the relevance effect as depending only on item i's relevance: $\psi_i(y) = \bar{\psi}_i(r_i)$.

From the specified model we can compute the average gain g and average relevance r for a given stationary ranking policy μ, as

$$g := g(\mu) = \mathbb{E}_Y \left[\sum_{i=1}^{M} \theta_{\mu(Y)(i)} \psi_i(Y) G_i \right] \tag{1}$$

$$r := r(\mu) = \mathbb{E}_Y \left[\sum_{i=1}^{M} \theta_{\mu(Y)(i)} \psi_i(Y) R_i \right]. \tag{2}$$

The platform wants to determine a stationary ranking policy μ maximizing a function ϕ which depends on the average gain *and* average relevance:

$$\max_{\mu} \phi(g, r), \tag{3}$$

where ϕ is an increasing function of both its arguments g and r with bounded second derivatives in the same arguments.

While one can keep a general form for the function ϕ, a practical case is when

$$\phi(g,r) = \lambda(r) \cdot (g + \beta)$$

where $\lambda(r)$ is the arrival rate of queries and $\beta > 0$ represents a(n average) revenue per visit to the platform apart from the potential gains stemming from ranking pages. Of course, λ is increasing in r: the more relevant you are, the more visits you get in the long term. Typically, the overall revenue of a platform is proportional to the rate of visits; the average direct gains then equal $\lambda(r) \cdot g$. There might also be a gain from each visit, whose average is denoted by β, leading to an additional revenue $\beta\lambda(r)$. The most relevant example is for a search engine where β corresponds to gains from ads displayed when a search is launched; for other marketplaces, β may also represent revenues from ads, or from other sales derived from a customer having reached the site.

A platform has therefore to find a ranking policy which is a trade-off between short-term revenue (based on the potential immediate gain from high-ranked items) and long-term revenue (based on the satisfaction of users due to the relevance of the ranking). This is what is analyzed in [4].

To simplify notations, define $\tilde{R}_i := \psi_i(Y)R_i$ and $\tilde{G}_i := \psi_i(Y)G_i$ the relevance and gain of item i weighed by the relevance-effect click probability (and define similarly their realizations $\tilde{r}_i$ and $\tilde{g}_i$). The following result then characterizes an optimal ranking policy.

Proposition 1 (L'Ecuyer *et al.* [4]) *Any optimal randomized policy must rank the pages by decreasing order of their value of $\tilde{r}_i + \rho\tilde{g}_i$ (except possibly on a subset of requests of probability 0), with the exception that the order at positions j, j' with the same position effect $\theta_j = \theta_{j'}$ does not matter.*

Such a policy is called a LO-ρ policy (Linear Ordering with weight ρ). That result remarkably simplifies the search for an optimal policy to just finding the optimal parameter ρ_*, which can be done easily by simple optimization techniques. To do so, the results derived in [4] when Y has a continuous distribution are helpful. For the gradient $\nabla\phi(g,r) = (\phi_g(g,r),\, \phi_r(g,r))$ of ϕ, define $h(g,r) := \phi_g(g,r)/\phi_r(g,r)$. Then the following result provides a method to compute an optimal ranking policy.

Proposition 2 *If the tuple (r_*, g_*) corresponds to the relevance and gain for an optimal LO-ρ policy, then the policy parameter satisfies $\rho = \rho_* = h(g_*, r_*)$. As (g_*, r_*) depends on ρ_*, one must have a fixed point $\rho_* = h(g(\mu(\rho_*)), r(\mu(\rho_*)))$.*

If h is bounded over its domain of definition, the fixed-point equation $\rho = \tilde{h}(\rho)$ (defining the function in terms of ρ) has at least one solution in $[0,\infty)$. If furthermore $\frac{\partial \tilde{h}}{\partial \rho}(\rho) < 1$ for all $\rho > 0$ (that is, $\tilde{h}$ is a contraction), then the solution is unique.

Determining ρ_* can be done by Monte Carlo simulation, Robbins-Monro type stochastic approximation, or successive iterations if $\rho \to \tilde{h}(\rho)$ is a contraction.

3 Model of platforms in competition

3.1 Mathematical formalization

We extend here the model to encompass the situation of two platforms, labeled by 0 and 1, in competition. For each platform $p \in \{0,1\}$, we index by p the output random vector of a query $Y^{(p)}$ as well as the number of relevant items $M^{(p)}$, and the relevance $R_i^{(p)}$ and expected gain $G_i^{(p)}$ of each of those items. Without loss of generality, those values are still upper-bounded by m_0, 1 and K, respectively. For each $p \in \{0,1\}$ the vector $Y^{(p)}$ has a fixed probability distribution (discrete or continuous) over a compact subspace $\Omega \subseteq \cup_{m=0}^{m_0}(\{m\} \times ([0,1] \times [0,K])^m)$.

The CTR $c_{i,j}^{(p)}(y^{(p)})$, quantifying the probability that an item i at a position j is clicked, for platform p and query $y^{(p)}$ is again assumed separable: $c_{i,j}^{(p)}(y^{(p)}) = \theta_j^{(p)} \psi_i^{(p)}(y^{(p)})$, with position and relevance effects being made dependent on p.

For the average gain $g^{(p)}$ and relevance $r^{(p)}$ at Platform p, the goal is to determine a ranking policy $\mu^{(p)}$ solution of

$$\max_{\mu^{(p)}} \phi^{(p)}(g^{(p)}, r^{(p)}, r^{(p')}) \tag{4}$$

where now the objective function $\phi^{(p)}$ depends not only on the parameters of p but on the relevance of the competing platform $p' = 1 - p$. Again, $\phi^{(p)}$ is increasing in both $g^{(p)}$ and $r^{(p)}$ with bounded second derivatives, and is here a decreasing function of $r^{(p')}$ to depict that a relevant competitor means less visits to the considered platform. We will use revenue expressions of the form

$$\phi^{(p)}(g^{(p)}, r^{(p)}, r^{(p')}) = \lambda^{(p)}(r^{(p)}, r^{(p')}) \cdot (g^{(p)} + \beta^{(p)}) \tag{5}$$

where $\lambda^{(p)}(r^{(p)}, r^{(p')})$ is the arrival rate of queries to platform p and $\beta^{(p)} > 0$ represents a(n average) revenue per visit to the platform. The function $\lambda^{(p)}$ is increasing in $r^{(p)}$ and decreasing in $r^{(p')}$.

For each visit/request, Platform p must select a ranking (permutation) of the $m^{(p)}$ considered items, $\pi^{(p)} = (\pi^{(p)}(1), \ldots, \pi^{(p)}(m^{(p)}))$ such that item i will be displayed in position $\pi^{(p)}(i)$. Following the results in [4], considering the policy of p' fixed, the optimal permutation is still to rank items in a decreasing order of $\tilde{R}_i^{(p)} + \rho \tilde{G}_i^{(p)}$ (with again $\tilde{R}_i^{(p)} = \psi_i{}^{(p)}(Y^{(p)}) R_i^{(p)}$ and $\tilde{G}_i^{(p)} = \psi_i{}^{(p)}(Y^{(p)}) G_i^{(p)}$).

We consider again $h^{(p)}(g,r,r') := \phi_g^{(p)}(g,r,r')/\phi_r^{(p)}(g,r,r')$, with $\phi_g^{(p)}$ (resp. $\phi_r^{(p)}$) the partial derivative of $\phi^{(p)}$ with respect to g (resp. r). Proposition 2 can be reformulated as:

Proposition 3 *For a fixed r', if the tuple $(r_*^{(p)}, g_*^{(p)})$ corresponds to the relevance and gain for an optimal policy, then it can be obtained from an LO-$\rho^{(p)}$ policy with $\rho^{(p)} = \rho_*^{(p)} = h^{(p)}(g_*^{(p)}, r_*^{(p)}, r')$. As $(g_*^{(p)}, r_*^{(p)})$ depends on $\rho_*^{(p)}$, one must have a fixed point $\rho_*^{(p)} = h^{(p)}(g^{(p)}(\mu^{(p)}(\rho_*^{(p)})), r^{(p)}(\mu^{(p)}(\rho_*^{(p)})), r')$.*

3.2 A game between platforms

In summary, the policy ranking choice of each platform p can be reduced to the choice of a single parameter $\rho^{(p)}$, that can be obtained by solving a fixed-point equation involving the average relevance r' of the competitor. Since that relevance r' depends on the parameter $\rho^{(p')}$, platforms impact each other through their ranking policies. The remainder of the paper analyzes that interaction using the framework of Game Theory [8], under different regulatory scenarios.

4 Analysis of three different regulation scenarios

The aim of this section is to introduce and analyze three different situations: i) the case without regulation when platforms can (and will) play the game trying to maximize their revenue; ii) the intermediate DMA situation when there is a regulation imposed to the big platform, considering one has a larger market size; iii) the fully-regulated case when platforms are ranking based on relevance only.

4.1 Game-theoretic analysis in the case of two platforms in competition

We consider here the situation when no regulatory constraint is imposed on either platform. From our competition model, the policy implemented by a platform is impacting the revenue, hence the optimal policy, of the competitor. Typically, a platform's policy is influenced by the choice of the opponent through the latter's impact on market shares (through its relevance). We therefore end up with a non-cooperative game where the utility of Platform $p \in \{0,1\}$ is $\phi^{(p)}(g^{(p)}, r^{(p)}, r^{(p')})$ and its decision variable is the stationary ranking policy $\mu^{(p)}$, and more specifically (due to the mathematical analysis presented before) the ranking parameter $\rho^{(p)}$ to apply to a LO-$\rho^{(p)}$ policy.

Subsection 3.1 defines the best-response of a platform p in response to a given policy of the competitor p': for a fixed policy of the competing Platform p', the best response of Platform p is derived in Proposition 3.

Formally, the best response of Platform p in response to the strategy $\rho^{(p')}$ of Platform p' is, from Proposition 1, among the LO-ρ policies:

$$\mathrm{BR}^{(p)}(\rho^{(p')}) = \mathrm{argmax}_{\rho} \phi^{(p)}(g^{(p)}(\rho), r^{(p)}(\rho), r^{(p')}(\rho^{(p')})),$$

where we here explicitly express the dependence on ρ and $\rho^{(p')}$ of $g^{(p)}$, $r^{(p)}$ and $r^{(p')}$ as computed in (1) and (2) for each platform.

The equilibrium concept in the competition between platforms is the so-called Nash equilibrium, which is a profile of policies $(\mu_*^{(0)}, \mu_*^{(1)})$, corresponding to a pair $(\rho_*^{(0)}, \rho_*^{(1)})$ from which no platform has an interest to deviate *unilaterally*: for each $p \in \{0,1\}$, ranking with $\rho_*^{(p)}$ is a best response of Platform p when Platform p' is ranking with LO-$\rho_*^{(p')}$.

The game in its most general form is played with both platforms maximizing their utility $\phi^{(p)}(g^{(p)}, r^{(p)}, r^{(p')})$, but we more specifically consider the case $\phi^{(p)}(g^{(p)}, r^{(p)}, r^{(p')}) = \lambda^{(p)}(r^{(p)}, r^{(p')}) \cdot (g^{(p)} + \beta^{(p)})$ of Equation (5).

A typical expression for $\lambda^{(p)}(r^{(p)}, r^{(p')})$, that we will use is

$$\lambda^{(p)}(r^{(p)}, r^{(p')}) = A^{(p)} \cdot e^{-(r^{(p')})^{\ell}/r^{(p)}} \tag{6}$$

for some parameters $A^{(p)} > 0$ and $\ell > 0$; note that this expression verifies the assumptions on the query rates in terms of relevances of both platforms.

In our numerical experiments, we will also use the (arbitrary and) default values $A^{(0)} = 10$, $A^{(1)} = 1$, $\ell = 2$ and $M^{(0)} = M^{(1)} = 20$, such that with equal relevance one platform (Platform 0) will have a much larger market share. The CTR values $\theta_i^{(p)}$ are displayed in Table 1 and are the same for both platforms. For simplicity, we also consider $\psi_i^{(p)} = 1$ for all i and p, i.e., the probability that a page is visited only depends on its ranking (and not in particular on its intrinsic relevance).

$\theta_1^{(p)}$	$\theta_2^{(p)}$	$\theta_3^{(p)}$	$\theta_4^{(p)}$	$\theta_5^{(p)}$	$\theta_6^{(p)}$	$\theta_7^{(p)}$	$\theta_8^{(p)}$	$\theta_9^{(p)}$	$\theta_{10}^{(p)}$	$\theta_{11}^{(p)}$	$\theta_{12}^{(p)}$	$\theta_{13}^{(p)}$	$\theta_{14}^{(p)}$
0.364	0.125	0.095	0.079	0.061	0.041	0.038	0.035	0.03	0.022	0020	0.015	0.013	0.011

Table 1. CTR values used in the paper, taken from [2]

The left panel of Figure 1 displays the revenue of a platform p in terms of ρ to illustrate that there is a maximum when the policy of the competitor is fixed, and the right panel shows the best responses of platforms with the previously

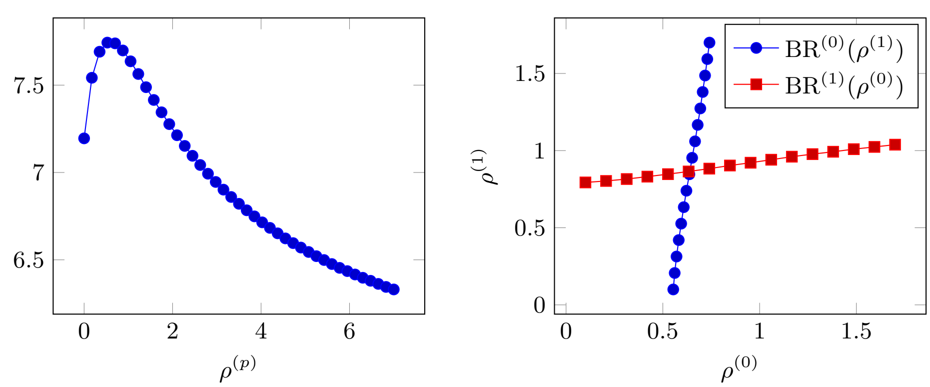

Fig. 1. *(Left)* Revenue of one platform when modifying its parameter ρ, when $\rho^{(p')} = 0.5$ and $\beta^{(p)} = 1$; *(Right)* Best responses of platforms.

described set of parameters. The existence and unicity of a Nash equilibrium, defined as an intersection point of the two best-response curves, can be readily checked from the unique intersection of best-response curves.

For this competitive scenario without regulation, we illustrate in Figure 2 the impact on the revenues, market shares, and average relevance of each platform at the Nash equilibrium of $\beta^{(0)}$, the average revenue per visit to Platform 0 outside of ranked items. The influence of the parameters $A^{(0)}$ and $A^{(1)}$ could also have been considered but is actually simple to analyze: as multiplicative constants in platforms' utilities, they have no impact on best-responses (and thus, equilibria), hence one can compute the equilibrium for one value of those parameters and deduce revenues (being proportional to $A^{(p)}$ for Platform p) and market shares for any value.

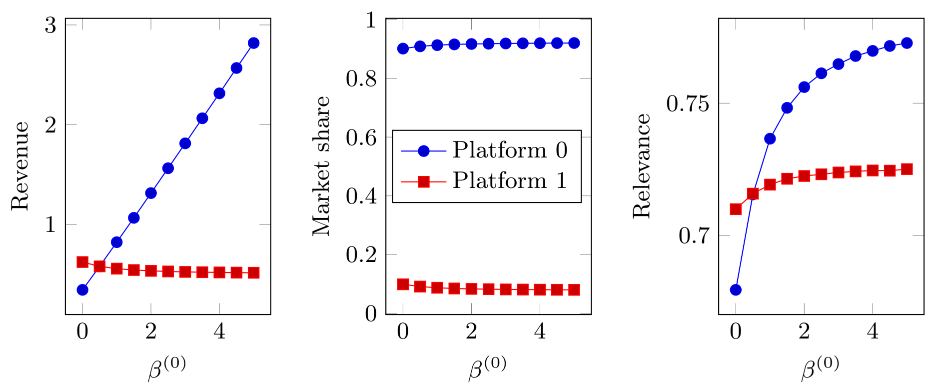

Fig. 2. Free competition. Revenues *(left)*, market shares *(middle)*, and average relevances *(right)* at equilibrium when $\beta^{(0)}$ varies.

From Figure 2, $\beta^{(0)}$ has a limited impact on the revenue of the "small" platform (Platform 1), but as could be expected a larger $\beta^{(0)}$ means more revenue for Platform 0. Note also that the impact on market shares remains limited. As regards relevance, the larger $\beta^{(0)}$, the higher the relevance for *both* platforms, meaning that an increasing revenue generated from visits (due to advertisement explicitly for example for a search engine) has a positive impact on the relevance of the competitor, which may seem surprising. That phenomenon can be explained as follows: a larger $\beta^{(0)}$ increases the importance of the number of visits $\lambda^{(0)}$ in the utility (5) with respect to the term $g^{(0)}$, i.e., incentivizes Platform 0 to increase its relevance $r^{(0)}$ by decreasing its ranking parameter $\rho^{(0)}$. Then to remain competitive, Platform 1 will also need to improve its relevance $r^{(1)}$, as is also illustrated by best-response functions being non-decreasing (see Figure 1).

4.2 A DMA-inspired regulation scenario

This subsection focuses on the situation that could correspond to what the DMA advocates, i.e., some regulation imposed on the biggest actors. For our context, such a regulation would prohibit the largest platform from ranking results based on something else than relevance. Hence, only the small platform, Platform 1, is allowed to play optimally. For Platform 0, ranking on relevance only implies $\rho_*^{(0)} = 0$. We then only need to compute the best-response $\rho_*^{(1)}$ of Platform 1 as in [4]. With this setting, the parameter $\beta^{(0)}$ has no impact on platforms' ranking strategies (as $\rho^{(0)} = 0$ and $\beta^{(0)}$ would affect Platform 1 only through $r^{(0)}$). As neither do $A^{(0)}$ and $A^{(1)}$, we refer to the curves comparing the three scenarios, in Section 5.

4.3 Fully neutral

Finally, consider now the last case with full neutrality where platforms can only rank based on relevance. In this case, $\rho_*^{(0)} = \rho_*^{(1)} = 0$: no game is played between platforms. Results are studied in the next section, comparing all three situations.

5 Quantitative comparisons of regulation scenarios

We now compare directly the output of the game for the three different regulation scenarios, for default values $\beta^{(0)} = 1$, $\beta^{(1)} = 0.5$, $A^{(0)} = 10$ and $A^{(1)} = 1$.

Figure 3 displays the revenues of the two platforms, their market shares, and relevance, for the three considered regulation regimes.

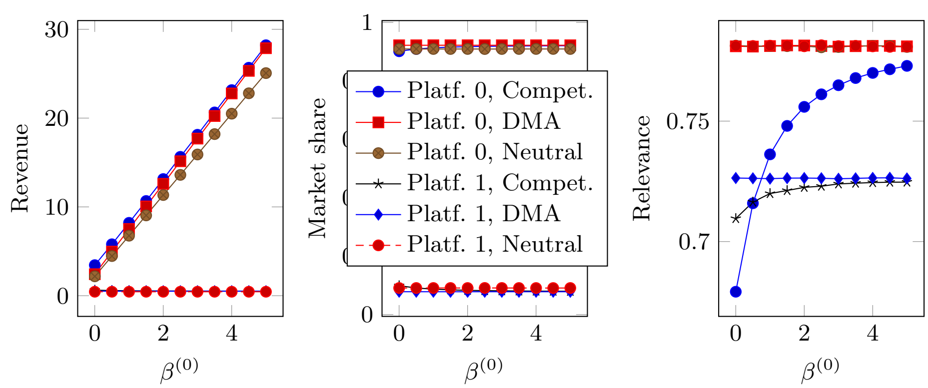

Fig. 3. Comparing regulation policies when $\beta^{(0)}$ varies.

One can check that the regulation procedure does not change much the revenue of the "small" platform whatever the value of $\beta^{(0)}$. There is a more perceptible effect on Platform 0, even if not that significant in terms of relative value.

In terms of market shares, the effect of the policy is insignificant, which shows that introducing regulation is useless if the goal is to reduce the importance of big platforms.

Of course, in the neutral case, relevances are maximal since it is on what the ranking is based. When $\beta^{(0)}$ gets larger (that is the proportion of gain of Platform 0 due to advertisements increases), the less interesting is the application of DMA on relevances with respect to competition.

6 Conclusions

We have presented a model with two platforms in competition, extending the monopoly situation of [4] where the optimal ranking strategy of items was computed and analyzed. Thanks to that extension, we have been able to analyze the impact of regulation procedures on platforms, in particular the Digital Markets Act (DMA) recently put in place in Europe. According to our model, DMA has a limited impact if talking about market shares or revenues of platforms.

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