STRATEGIC GAMES IN A COMPETITIVE MARKET: FEEDBACK FROM THE USERS’ ENVIRONMENT

Natalia Kudryashova
University of Cambridge
Wilberforce Road, Cambridge, CB30WA, UK

Abstract. We propose a model for the dynamics of a competitive market, in which strategic decision making of market players may be affected by the users’ switching behaviour. A novel concept, habitual attraction, is introduced to reflect the resistance of users against changing their routinely used provider. The model can be adopted for a particular market and allows for dynamic learning. We demonstrate applications of the model to the internet search market in the context of competition law and regulation, where a user centred description is essential, for instance, in the anti-trust proceedings.

1. Introduction. Strategic decision-making of players in a competitive market can benefit greatly from a proper understanding of the underlying dynamics of market. In addition such understanding can benefit regulators to distinguish effects of anti-competitive behavior from the inherent natural behavior as well as aid policy makers in devising efficient ways of regulation for these markets. We consider a market of a few providers competing on quality for the preferences of non-paying users and construct a model for its dynamics. The model mimics customer behavior in a market of intermediaries (platforms) providing matchmaking services between distinct groups of other market participants in which non-paying users are instrumental in bringing paying customers to the platform. The model thus differs fundamentally from the classical model of a two-sided market [13],[1], and lacks a monetary relationship between the platforms and the users, ruling out competition for user preferences on price, which is typically considered in literature in the context of competition, and does not assume that users are entirely rational.

An example of such market is given by the internet search market, which recently received considerable public and scholarly attention in conjunction with the anti-trust proceedings against Google, the major market player, holding 67.5% of the market in the USA and around 90% in the EU. Its major competitor in this markets is an alliance of Bing by Microsoft and Yahoo\(^1\). Concerns have been expressed regarding alleged anti-competitive practices of Google, resulting in a storm of litigation against that company, as well as a pending enquiry of the European Commission. The allegations are partly motivated by a disproportionately high market share of Google considering only the relative quality of the competing products, as user preferences in the market are not constrained by costs.

We will focus on the internet search market, and, by placing a strategic game of the market players (search providers) into an active user environment, explore consequences of behavioral aspects of the users, such as habitual attraction, for the dynamics of the market distribution. Though we will explicitly account for the specifics of the market in question in the formulation of the strategic game the conclusions regarding effects of user behavior

\(^1\)based on the data from http://www.comscore.com and http://statcounter.com, at the time of submission
on the market dynamics are not limited to the internet search market, while the model description can be re-adopted in a similar manner to the specifics of multi-sided markets dominated by unconstrained user preferences.

The internet search is often referred to as a gateway to the Web, in which a search platform acts as a matchmaker between users and providers of information on the net. In response to a key words query submitted by a user, the search platform displays two types of the search results: organic links, which are ideally the best match to the query, and sponsored links, which correspond to relevant paid advertisements. Both types of results are provided to the user for free. The platform’s profit is derived from selling the sponsored links to the advertisers, using payment per-click. The paid placements are auctioned in a generalised second price auction in which the advertisers’ bids are scaled by the platforms by some quality factors which allow the platform to control the quality and ensure a satisfactory click-through rate. The advertiser pays the platform only if the user clicks on the sponsored link. Since the user initiates both the action and the transaction, the financial success of the internet search provider in a competitive environment is bound to the popularity of the search platform with its users. The main service, however, which is essential in attracting the user to the search provider and in determining its market share, is an organic search, which by itself does not bring in any immediate revenue.

From the user’s perspective, free search of the internet has become an almost daily routine and an essential facility. The user choice between different search providers is not entirely rational, but reflects a variety of behavioral aspects. The search may be carried out using the same search provider, as long as their service is not unsatisfactory, even though switching to another provider is just "one click away". This may not change unless the perceived value for the user is significantly changed, for example, by a new experience, word of mouth or the media. Factors that affect decision making of a large proportion of users, such as sluggishness in changing the habits, may have serious consequences for the market dynamics and user switching between the platforms can significantly affect intended outcomes of the platforms strategies in a competitive environment. This sluggishness or resistance to change platform, even if the user is not entirely satisfied, is captured here in a parameter we refer to as habitual attraction.

Considerable attention in the literature has been devoted to the discussion of mechanisms of allocating sponsored links and strategies optimizing the revenue of a search provider or bidding of advertisers competing in on-line auctions ([15], [6], [5], [3], [2], [4], [17] and [9]). Yet, the dynamics of user preferences as well as the underlying behavioral aspects are typically left out in modeling the market, despite their importance and the vast amount of empirical data characterising user responses to the platforms adjustments (e.g. [7], [8], [12]).

We explicitly include users’ switching behavior, which may not be entirely rational, into strategic optimisation in the internet search market and consider its impact on the market performance in a competitive environment. In particular, we distinguish between bias-free users, whose preferences are based entirely on perception of the relative value of the offered service, and biased users, who, in addition, are habitually attracted to a particular platform.

Habitual attraction is key to understanding the distribution of the internet search market over the platforms and provides new insights to time evolution [10]. In light of this we revisit selected arguments arising in the context of anti-trust proceedings against Google. In particular, it turns out that habitual attraction modifies the notion of fair competition compared to the bias-free market, where the choice of the user is governed only by the relative perceived value of the provided service.

2. Results and discussion.

2.1. Model. We consider a repeated game in which $M$ platforms (indexed by $m = 1, \ldots, M$) optimize their revenue $\Pi^{(m)}$ for a period $T$ in an active user environment where preferences
for different platforms evolve in time. We assume that the market is collusion-free, and for the sake of simplicity, we restrict ourselves to the case of homogeneous goods. Though the search providers cannot influence the choices of users and advertisers directly, they may do so wittingly by promoting the desired behavior through appropriate strategies or, unwittingly, as a result of adverse factors beyond their control. We denote feasible strategies of platform \( m \) as \( x^{(m)} = (x^{(m)}_{\text{org}}, x^{(m)}_{\text{spons}}) \) and assume that they form a compact convex set \( X^{(m)} \) composed of closed subsets of strategies concerning the organic and the sponsored search: \( X^{(m)} = X^{(m)}_{\text{org}} \times X^{(m)}_{\text{spons}} \).

The strategies concerning organic search, \( x^{(m)}_{\text{org}} \) deal with the optimisation of the search algorithm and the organic display, resulting in a certain level of quality of the organic search. The strategies \( x^{(m)}_{\text{spons}} \) concern optimization of the bidding procedure, rating of advertisers and display of sponsored results, resulting in a certain level of quality of the displayed sponsored links. We measure the quality of the search by the average rate of user satisfaction \( \alpha^{(m)}_{\text{spons/org}} \in \mathcal{A}^{(m)}_{\text{spons/org}} \subset [0,1] \), where \( \mathcal{A}^{(m)}_{\text{spons/org}} \) denote the platform’s feasibility range. \( \alpha^{(m)}_{\text{org}} \) and \( \alpha^{(m)}_{\text{spons}} \) are parameters that can be verified in empirical studies of user responses to the platforms’ decisions, as, for instance, in [7], [8], [12]. We further assume that the search providers have a good idea on how their decisions affect the users, so that they have learned the relationship between feasible strategies and user satisfaction. Also some choice functions are available, for instance cost, that distinguish between the strategies delivering the same level of user satisfaction and select the preferable strategy.

The user switching feedback is expressed by the evolution of probabilities \( p^{(m)} \), \( m = 1, \ldots, M \) for choosing a platform for the next search, which, in turn, affect the objectives of the various platforms. We compare a market of unbiased users, whose preferences are entirely based on the relative quality of the competing services, with a market of biased users who are also habitually attracted to a particular platform.

2.2. Strategic optimization of the search providers.

2.2.1. Monopoly market. Strategic optimization of the search providers is typically concerned with optimisation of the ad-auction design, disregarding the presence of other platforms in the market (i.e. as if it were a monopoly) and is focused on selecting the optimal strategy from the subset \( X^{(m)}_{\text{spons}} \) (the superscript \( m \) is omitted):

\[
\tilde{x}_{\text{spons}} = \operatorname{argmax}_{x \in X_{\text{spons}}} \{ \Pi_k \},
\]

where \( \Pi_k = s_k \pi_k \) is a revenue from the search \( k \) in the event a feasible strategy \( x \) is adopted; \( \pi_k : X_{\text{spons}} \rightarrow \mathbb{R}^+ \) is a potential revenue resulting from bidding of advertisers and \( s_k \) is the probability that the user clicks on a sponsored link. It depends on the platform strategies only as long as they affect \( \alpha_{\text{spons}} \), i.e. \( s_k : \mathcal{A}_{\text{spons}} \rightarrow [0,1] \).

Since there is an "internal competition" between organic links, from which the platform cannot collect any revenue [14], and sponsored links, the strategy \( \tilde{x}_{\text{spons}} \) is not necessarily optimal for the case of monopoly. The "internal competition" can be straightforwardly accounted for by understanding \( s_k \) as a function of two parameters \( \alpha_{\text{org}} \) and \( \alpha_{\text{spons}} \), and by extending the trial set in eq. (1). The bidding behavior of the advertisers depends on various factors including \( \alpha_{\text{spons}} \). Typically, the dependence of \( \pi_k \) on \( \alpha_{\text{spons}} \) has an inverse U-shape. Assuming all factors except \( \alpha_{\text{spons}} \) are fixed near their optimal level, the optimization for a monopoly can be re-formulated as a two-step problem. First the optimal quality parameters that maximise the platform’s profit are determined:

\[
(\tilde{\alpha}_{\text{org}}, \tilde{\alpha}_{\text{spons}}) = \operatorname{argmax}_{(\alpha_{\text{org}}, \alpha_{\text{spons}}) \in \mathcal{A}_{\text{org}} \times \mathcal{A}_{\text{spons}}} \left[ s_k(\alpha_{\text{org}}, \alpha_{\text{spons}})\pi_k(\alpha_{\text{spons}}) \right]
\]

Subsequently the optimal strategies that deliver the target values on the basis of the learned relationships between the platforms actions and users response are determined. It is clear
that since \( s_k \) is a decreasing function of \( \alpha_{org} \) and, in case of monopoly, \( \pi_k \) is independent of \( \alpha_{org} \), it is optimal for a monopolist to deteriorate organic search.

2.2.2. Competitive market. In a competitive market, the revenue of each platform is constrained by the strategies of other platforms (denoted as \( x^{(-m)} \)) as well as by the finite size of the market. Then, the optimization problem for each platform reads:

\[
(\tilde{\mu}^{(m)}|x^{(-m)}) = \arg \max_{x^{(m)} \in X^{(m)}} \Pi^{(m)}
\]

where

\[
\Pi^{(m)} = \frac{1}{N} \sum_{k=1}^{N} p_k^{(m)} \pi_k^{(m)} s_k^{(m)}, \quad \sum_{m=1}^{M} \Pi^{(m)} \leq \mathcal{R}, \quad p_0^{(m)} = n^{(m)}(0),
\]

\( N \) is the number of searches during the period \( T \), \( p_k^{(m)} \) \((\sum_{m=1}^{M} p_k^{(m)} = 1)\) is the probability that platform \( m \) is chosen for the search \( k \) in the event platform \( m \) adopts a strategy \( x^{(m)} \) and other platforms adopts strategies \( x^{(-m)} \): \( p_k^{(m)} \) \( \{x^{(m)}|x^{(-m)}\} : X^{(m)} \times X^{(-m)} \rightarrow [0,1] \), and \( X^{(-m)} \) is the feasibility range of the strategies adopted by other platforms. The \( \{n^{(m)}(0)\}_{m=1,...,M} \) denote the distribution of the market between the platforms at the onset of the period \( T \) and \( \mathcal{R} \) the amount spent by the content providers in the ad-auctions.

The optimization problem (3) translates into a non-cooperative constant sum game \( \Gamma^{(1)} = \langle M, \{x^{(m)}\}_{m=1,...,M}, \{\Pi^{(m)}\}_{m=1,...,M} \rangle \), which by the Nash theorem, has an equilibrium in mixed strategies, so that the optimization problem (3) has at least one solution [16].

As previously \( s_k^{(m)} \) is a function of \( \alpha_{org}^{(m)} \) and \( \alpha_{spons}^{(m)} \), while the probabilities \( p_k^{(m)} \) depend on the strategies in so far as they influence the factors governing user choice of the platform. Since the popularity of the platform is determined mostly by the organic search, \( p_k^{(m)} \) are a function of \( \alpha_{org}^{(m)} \) and \( \alpha_{org}^{(-m)} \). Contrary to the monopoly case, \( \pi_k^{(m)} \) now also depends on \( \alpha_{org}^{(m)} \). Finally, the resource \( \mathcal{R} \) can be assumed to be distributed over different platforms according to their initial popularity. Of course in a learning game this can be readjusted at set times.

Again, one can re-formulate these optimization problems in terms of the quality parameters, so that one incorporate user dynamics directly into the strategic decision-making of the search provider and include other factors beside the quality of the search, such as habitual attraction as defined in the introduction. The effect of these factors will be considered explicitly in the section below.

3. Users dynamics. We will now assume that the platforms have chosen their the quality parameters for the period \( T \).

3.1. General model. We consider a large ensemble of representative users \((i = 1,...,I, I \rightarrow \infty)\) performing their search according to a Poisson process of some intensity \( \lambda \). User preferences are expressed by a probability \( p^{(m)}_{ik} \) to select a particular platform \( m \) for the search \( k \) at time \( t_{ik} \). Obviously the probability that the user \( i \) chooses platform \( m \) for his \((k+1)\)-th search is a sum of the probability that the user remains with the same platform after the search \( k \) and the probability that he or she switches from another platform:

\[
p^{(m)}_{ik+1} = Pr(stay)p^{(m)}_{ik} + Pr(select) \left(1 - p^{(m)}_{ik}\right).
\]

The probability to select a particular platform upon switching, \( Pr(select) \), is given by the transition matrix \( \{T^{ml}_{i}\} \), where \( T^{ml}_{i} \) is the probability that user \( i \) switches from platform \( l \) to platform \( m \) given his dissatisfaction with platform \( l \). \( Pr(stay) \), \( Pr(select) \) fully specify the model for user decision making. We assume that the evolution of the probabilities is governed by perceived user value of the organic
search and habitual attraction. In a bias-free market a user stays with the platform in the event he or she is satisfied with the previous search, i.e. with the probability \( \alpha^{(m)}_{i,k} \), and switches to another platform if he or she is dissatisfied, i.e. with the probability \( 1-\alpha^{(m)}_{i,k} \).

We assume that \( \alpha^{(m)}_{i,k} \) are iid random variables drawn from a distribution with mean \( \alpha_{org} \).

In a market with habitual attraction, a biased user stays with the platform not only when he or she is satisfied, but also, with some probability \( \gamma^{(m)}_{i,k} \) when he or she is dissatisfied.

The parameters \( \gamma^{(m)}_{i,k} \) characterize the “strength” of bias of user \( i \) to the platform \( m \). In a bias-free market, \( \gamma^{(m)}_{i,k} \) are all zero.

The above assumptions result in the following recursion:

\[
P^{(m)}_{i,k+1} = \alpha^{(m)}_{i,k} P^{(m)}_{i,k} + (1 - \alpha^{(m)}_{i,k}) \gamma^{(m)}_{i,k} P^{(m)}_{i,k} + \sum_{l=1, l \neq m}^{M} P^{(l)}_{i,k} \left(1 - \alpha^{(l)}_{i,k}\right) \left(1 - \gamma^{(l)}_{i,k}\right) T^{ml}_{i,k} \tag{6}
\]

The first term reflects the case that the user was satisfied with the platform \( i \) or she used previously, the second represents his unwillingness to switch even though he was not fully satisfied with the results of the previous search. The last term corresponds to the switch of the user from another platform when the previous search was unsatisfactory. It contains four factors. The first is the probability that the user was with platform \( l \) for the previous search. The second denotes his dissatisfaction and the third overcomes the habitual attraction to platform \( l \). The last factor gives the probability that he or she switches from platform \( l \) to platform \( m \) and is approximated here as:

\[
T^{ml}_{i,k} = \frac{\alpha^{m}_{i,k}}{\sum_{j \neq i} \alpha^{j}_{i,k}} \tag{7}
\]

Using the standard argument (e.g. [11]), it leads in the fluid limit to a differential equation:

\[
\frac{\partial p^{(m)}(t)}{\partial t} = -\left(1 - \alpha^{(m)}_{org}\right)(1 - \gamma^{(m)}) p^{(m)}(t) + \sum_{l=1}^{M} P^{(l)}(t) \left(1 - \alpha^{(l)}_{org}\right) \left(1 - \gamma^{(l)}\right) T^{ml} \tag{8}
\]

where \( \alpha^{(m)}_{org} \) and \( \gamma^{(m)} \) are mean values of the distribution of the corresponding iid random variables in the user ensemble and \( \sum_{m=1}^{M} p^{(m)}(t) = 1 \). Also \( T^{ml} \) represents an average of eq. (7) over all users. We assumed that the various terms are uncorrelated.

3.2. The market of two platforms. As an example we consider a market with two providers \( m = 1, 2 \). Each provider has a quality parameter \( \alpha^{(m)}_{org} \) and competes on the organic search.

For two providers \( T^{12} = T^{21} = 1 \). We denote \( p^{(1)}_{i,k} \) as \( p_{i,k} \). Then eq. (6) reduces to:

\[
p_{i,k+1} = \alpha^{(1)}_{i,k} p_{i,k} + (1 - \alpha^{(1)}_{i,k}) \gamma^{(1)}_{i,k} p_{i,k} + (1 - p_{ik})(1 - \alpha^{(2)}_{i,k})(1 - \gamma^{(2)}_{i,k}) \tag{9}
\]

By setting \( p_{i,k+1} = p_{i,k} \) we see that in the bias-free market the stationary distribution of the market is inversely proportional to the ratio of the probabilities that the average user is dissatisfied with the results of the search:

\[
\frac{n^{(1)}}{n^{(2)}} = \frac{1 - \alpha^{(2)}_{org}}{1 - \alpha^{(1)}_{org}} \tag{10}
\]

Thus each provider attains a market share proportional to the quality of its product, which is commonly regarded as a fair distribution. In Fig. 1A we compare the evolution for two cases. In the first case both have equal quality parameters \( \alpha \) and the market is equally shared eventually. In the second case the initially minor player has a much better product and eventually dominates the market, despite starting at a lower market share. When there
is habitual attraction and the two providers have the same quality parameters the initial market distribution propagates indefinitely, as shown in Fig. 1B. This clearly demonstrates the advantage of the first move on the market and shows that a distribution, regarded as unfair, can arise from natural market causes. Otherwise, the better product will (slowly) attain a monopoly position. The rate at which it attains the monopoly position depends on the strength of the habitual attraction. Let us now consider the case where a new provider enters the market. This is shown in Fig. 1C. Again we consider two cases, with initial
parameters specified in the figure legend. However, there is no habitual attraction to the new entrant, whereas the initial dominant provider enjoys habitual attraction. Note, that in this case, even when the service of the providers has the same quality, the new entrant eventually ends up with a vanishing market share. Only when the service of the new entrant is far superior than that of the incumbent provider gains market share, though at a slower rate than previously. In order to survive in a market with habitual attraction a new entrant is required to bring a superior product and last a lengthy initial period to overcome the habitual attraction towards the incumbent provider. Hence, after demonstrating the quality of its product, it may be advantageous for the new entrant to sell to an incumbent provider. However, this is not necessarily beneficial for the development of the service in general, especially for a highly concentrated market.

### 3.3. The Market of multiple platforms

Though account for multiple players in the market does not affect the major conclusions drawn for the two players regarding the steady state, it does affect the time scale and the manner in which the steady state is reached.

Comparison of the solutions for the market of two and three players shows that an increase in the number of players slows down equilibration for a bias-free market (Fig. 1D). However, in a market with habitual attraction equilibrium is speeded up (Fig. 1E). Then a larger number of players implies a faster growth of the market share for innovative entrants and better prospects for propagation of innovations (though also a smaller market share in the steady state as the market is shared by more players). Hence, the market share of the new entrant with a better product is smaller in the market with larger number of participants. Now consider the behaviour of the 2nd incumbent in a bias-free market for the case when the quality of the first incumbent is inferior to the quality of a new entrant (Fig. 1F). A novel feature is the maximum in the market share of the 2nd incumbent. As long as the quality of the 2nd incumbent is better than that of the first both the share of the new entrant and of the 2nd incumbent increase at the cost of the share of the first. After a transient period, the 2nd incumbent also looses market share to the new entrant to reach a steady state in accordance with their relative quality parameters. The maximum disappears as the quality of the 2nd incumbent approaches that of the first. Also it disappears when the quality parameters and the initial share of the 2nd incumbent and the new entrant are the same. Interestingly, when the quality parameters of the 2nd incumbent are better than that of the new entrant a maximum appears in the evolution of the preference for the new entrant rather than in the evolution of preference for the 2nd incumbent.

### 3.4. Determining quality parameters

**3.4.1. Monopoly market.** If the users do not leave the platform, the evolution of the average probability \( s_k \) due to the ‘competition’ between the sponsored and organic search discussed in 2.2.1 is described by eq. (8), in which \( \alpha^{(1)}_{org} \) and \( \alpha^{(2)}_{org} \) are replaced by \( \alpha_{spons} \) and \( \alpha_{org} \). Hence, similar conclusions may be drawn regarding the effect of possible user bias, positive towards the organic search and negative towards the paid advertisement. Clearly in the dynamic settings considered here it is optimal for the monopolist to entirely deteriorate organic search rather than optimize its quality. This is in contrast to optimal quality, \( \bar{\alpha}_{org} = \bar{\alpha}_{spons} \), arising from static considerations in which the user clicks on a sponsored link when he or she is either satisfied with the displayed sponsored links or is dissatisfied with the displayed organic results: \( s_k = \alpha_{spons} + (1 - \alpha_{org}) \).

**3.4.2. The market of two platforms.** We now assume that the platforms have determined the optimal \( \bar{\alpha}^{(m)}_{spons} \) by optimizing eq.(2) with respect to \( \alpha^{(m)}_{spons} \). We also assume that the quality parameters are all strictly less than 1, and that these parameters as well as the initial preferences \( p_0 \) and \( s_0 \) for the platform 1 are the same for all users. We therefore drop the
It is easy to see that the solution of eq. (8) reads:

\[ p_k = p_0(\alpha_{org}^{(1)} + \alpha_{org}^{(2)} - 1)^k + (1 - \alpha_{org}^{(1)}) \frac{1 - \alpha_{org}^{(1)} + \alpha_{org}^{(2)} - 1}{2 - \alpha_{org}^{(1)} - \alpha_{org}^{(2)}}. \]  

(11)

Similarly,

\[ s_k = s_0(\alpha_{org}^{(1)} + \alpha_{spons}^{(1)} - 1)^k + (1 - \alpha_{org}^{(1)}) \frac{1 - \alpha_{org}^{(1)} + \alpha_{spons}^{(1)} - 1}{2 - \alpha_{org}^{(1)} - \alpha_{spons}^{(1)}}. \]  

(12)

We substitute eqs. (11) and (12) into eq. (4) for the \( \Pi^{(1)} \) and further assume that the \( \pi_k^{(m)} \) do not depend on their \( \alpha_{org}^{(m)} \). It is easy to see that since \( N \) is a very large number, the revenue is maximised by \( \tilde{\alpha}_{org}^{(1)} \) maximising

\[ \frac{(1 - \alpha_{org}^{(1)})}{(2 - \alpha_{org}^{(1)} - \alpha_{spons}^{(1)})(2 - \alpha_{org}^{(1)} - \alpha_{spons}^{(2)})}, \]  

(13)
i.e. the optimal dissatisfaction with organic search of the 1st platform is a geometric average of the dissatisfaction with its own sponsored search and the organic search of the 2nd provider:

\[ 1 - \tilde{\alpha}_{org}^{(1)} = \sqrt{(1 - \alpha_{org}^{(2)})(1 - \alpha_{spons}^{(1)})}. \]  

(14)

When the 2nd platform also adopts the optimal strategy,

\[ 1 - \tilde{\alpha}_{org}^{(1)} = \left(1 - \tilde{\alpha}_{spons}^{(1)}\right)^2(1 - \tilde{\alpha}_{spons}^{(2)})^{1/3}. \]  

(15)

Clearly, the optimization of the providers own product weighs stronger than the quality of the competition.

3.5. Example of Applications. Evidently the current internet search market is not bias-free. This is obvious by considering the market share of the main players, Google and Bing+Yahoo!. Although initially the market may have been bias-free, the emergence of Google’s dominant design has led to a market with habitual attraction, in which Bing+ Yahoo!, despite having at present a similar quality of service, have problems in attaining a share in accordance with their relative quality. A mature market with habitual attraction may preserve the advantage of the first move. Furthermore a monopoly position of the product of higher quality is attained. Both results are often regarded as unfair, as they do not reflect the relative quality of the providers. In competition law a disproportionate share is often used to support allegations of anti-competitive behaviour. Clearly our model shows, that this evidence has to be regarded with caution, as natural causes may underly the resulting distribution, as in the present day internet search market. Similar arguments are used to support allegations of bundling, where a provider ties its new product a current successful product to attain a dominant position. As an example we mention the case of Streetmap v Google \(^2\), where Streetmap argued that Google’s market share in the market of online maps was disproportionately high compared to the relative quality of the product as a result of Google displaying Google maps at a prominent position. Again such a dominant position can be explained as a result of habitual attraction to the Google brand. However this is no guarantee of success, if the quality of the product is less than that of the competition, and even this may backfire. This is evidenced by introduction of products, such as Google+, which were not very successful.

\(^2\)Streetmap.eu Ltd v Google Inc, Case number 13-1013 at the High Court of Justice
4. Conclusions. We presented a dynamic model for a competitive collusion-free market, such as the internet search market, which is formulated in terms of parameters affecting users’ choices, such as their satisfaction. This makes it possible to account for user dynamics in optimizing the platforms’ strategy. A novel feature is the concept of habitual attraction, which reflects the users’ resistance against changing the platform he or she routinely uses. These features are usually absent in standard formulations based on ad-auction design and highlight the central role of the user. We illustrate the evolution of the market for certain model parameters. In addition, we optimize the revenue for the special case of two providers on the market with respect to the satisfaction of customers. The model demonstrates that behavioral factors of users should not be neglected when considering the dynamics of the market. The strong modification of the dynamics of the bias-free market has consequences for the market players and their strategies, particularly for new entrants, and may result in a disproportionately high market share which is thus not necessarily a result of unfair competition.

REFERENCES

[1] M. Armstrong, Competition in two-sided markets, *The RAND Journal of Economics*, 37 (2006), 668–691.
[2] S. Athey and G. Ellison, Position auctions with consumer search, *Quarterly Journal of Economics*, 126 (2011), 1213–1270.
[3] S. Athey and D. Nekipelov, A structural model of sponsored search advertising auctions, *Sixth ad auctions workshop*.
[4] J. Chen, D. Liu and A. B. Whinston, Auctioning keywords in online search, *Journal of Marketing*, 73 (2009), 125–141.
[5] Y. Chen and C. He, Paid placement: Advertising and search on the internet, *Economic Journal*, 121 (2011), F309–F328.
[6] M. O. Edelman B. and M. Schwarz, Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords, *American Economic Review*, 97 (2007), 242–259.
[7] D. G. Goldstein, R. P. McAfee and S. Suri, The cost of annoying ads, in *WWW2013*, 459–470.
[8] A. Hassan, R. Jones and K. L. Klinkner, Beyond dcg: user behavior as a predictor of a successful search, in *ACM WSDM 2010*, 221–230.
[9] K. Iyer, R. Johari and M. Sundararajan, Mean field equilibria of dynamic auctions with learning, *SIGecom Exch.*, 10 (2011), 10–14.
[10] N. Kudryashova, The market of internet sponsored links in the context of competition law: Can modeling help?, *WWW2014*, 331–332.
[11] T. G. Kurtz, Limit theorems for sequences of jump markov processes approximating ordinary differential processes, *Journal of Applied Probability*, 8 (1971), pp. 344–356.
[12] J. Li, S. Huffman and A. Tokuda, Good abandonment in mobile and pc internet search, in *ACM SIGIR 2009*, 43–50.
[13] J.-C. Rochet and J. Tirole, Platform competition in two-sided markets, *Journal of the European Economic Association*, 1 (2003), 990–1029.
[14] G. Taylor, Search quality and revenue cannibalization by competing search engines, *Journal of Economics Management Strategy*, 445–467.
[15] H. R. Varian, Position auctions, *Int. J. of Industrial Organization*, 25 (2007), 1163–1178.
[16] N. N. Vorobev, *Game theory*, Springer, 1977.
[17] L. Xu, J. Chen and A. Whinston, Effects of the presence of organic listing in search advertising, *Information Systems Research*, 23 (2012), 1284–1302.

Received September 2014; revised July 2015.

E-mail address: nk375@cam.ac.uk