A Competitive Model of Ranking Agencies

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Abstract

This paper investigates the discrepancy among the multiple ranking lists of the same performers. It treats ranking lists as some well-positioned information products rather than the repetitive measures of performance. Hence, discrepancy stems from the differentiation rather than the measure errors. In the model, two ranking agencies have each compiled a list that ranks a set of performers for an audience. The audience weighs the two ranking lists by how much each list is promoted aggregately by the performers, and formulates a perceived ranking for each performer. In order to boost their perceived rankings, performers decide which ranking list to promote, and how much to promote. Each agency decides on the rankings to maximize the aggregate promotion devoted to its own list. In equilibrium, both ranking agencies will choose the top-bottom approach, i.e., ranking the top-ranked performer on the competing list at the bottom of its own list, to maximize the biggest ranking difference for some performers. In response, only those performers enjoying the biggest ranking difference will promote the corresponding list, while the other performers will free ride their promotion.

Keywords: ranking, competition

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1. Introduction

When buying a car, numerous buyers often turn to J.D. Power & Associates or Edmunds.com. When purchasing a big-screen TV, many people check *Consumer Reports* or CNET.com. When picking which movie to watch, countless movie-goers visit IMDB or Metacritic.com. And, when considering which college to go, a vast number of parents read *Princeton Review* or *US News & World Report*. In a market with so many comparable products, it is helpful for consumers to refer to third-party agencies that rank them [1] (e.g., Senecal and Nantel 2004; Reinstein and Snyder 2005; Smith, Menon and Sivakumar 2005; Zhang, et al. 2010) . By doing so consumers not only improve the quality of their decisions but also avoid making difficult trade-offs on multiple products. A seemingly plausible practice until discrepancies turn up among the multiple ranking lists in many categories.

For example, in the category of antivirus software, all top-ranked products on the ranking lists by six major agencies (*PC World*, *PC Magazine*, PC Antivirus Reviews, AV Comparatives, and AV Test Lab) were either ranked at the bottom or not ranked at all. Similar observations can be made in the automotive industry. For the rank of the 2013 Best Midsize Sedan, top picks from each of the four agencies (*Consumer Reports*, *Motor Trend*, AOL, and *US News & World Report*) were either not picked or ranked very low by other agencies. Even rankings based on simple objective factors, such as fuel economy, yielded unexpected contradictions. For example, VW's Passat was ranked No.1 in its segment by *Kelly Bluebook*, but ended up as No. 5 on Edmund's list (the last spot).

[1] Numerical rating bears the inherent ordinal information of ranking, and categorical rating is a special ranking with lots of ties on each rank.

Honda Accord was ranked No. 2 by Autobytel, but was down to No. 6 (second to bottom) by Automedia. In the category of education, the rankings of business schools, by five of the foremost agencies, were persistently inconsistent. Questions raised by Professor Ronald Yeaple, such as, "Why is Stanford ranked No. 5 by *Businessweek* but No.1 by U.S. News?" and "Why does MIT show up only in one publication's Top Five?" attract media attention and readers' debates (Forbes.com 2012).

One apparent source of discrepancies is the different criteria used by different agencies when compiling their ranking lists. Some of the criteria are subjective rather than objective, and the weights are often arbitrary (e.g., Policano 2007). Since many products rarely preserve the ranking of their performance across different criteria, it is unlikely that the different ranking agencies generate identical or close to identical lists.

Yet, the fact that agencies use different criteria may not provide the full answer as to the question of ranking discrepancy. In most cases, performance measures spawn across multiple independent dimensions, and a single numerical score needs to be computed for comparison. Consequently, objective ordinal rankings rarely exist among non-dominant performers. (Which car is better? One has a good reliability but scores poorly in fuel economy, and the other is the opposite, others being equal.) Using different weights, agencies can subjectively achieve different or even opposite ranking outcomes based on objective performance measures. (In the car example above, either car can be ranked better than the other.) Therefore, a ranking list is not only a subjective measure of quality, but also a well positioned information product. The discrepancy among multiple ranking lists may result from the differentiation of those information products, as each agency chooses to align with some performers but alienate others.

In this paper, we study the possible explanation for the ranking discrepancy across different lists by treating ranking lists as information products. Specifically, we model two agencies that each compiles a list that ranks a cohort of performers to an audience. The audience weighs the two ranking lists by how much each list is promoted aggregately by the performers, and formulates a perceived ranking for each performer. In order to boost their perceived rankings from the audience, performers decide which ranking list to promote, and how much to spend. Anticipating the performers' promotion decisions, the two agencies decide on the rankings to maximize the aggregate promotion of their lists, respectively.

We find that, in order to maximize the aggregate promotion for their lists, the two agencies adopt a top-bottom approach, namely, ranking the top-ranked performer on the competing list at the bottom of its own list. This approach is an equilibrium outcome, and creates maximum discrepancy in terms of the ranking difference between the two lists. Consequently, only performers that enjoy the biggest ranking difference promote the pertinent list; other performers free ride on their promotional efforts.

Using data of recent business school rankings from five major agencies, we find that within the same tiers of business schools, the five ranking lists bear little correlation among each other. We further find that, a ranking agency is more likely to rank a business school favorably if that school is ranked unfavorably and with greater discrepancy by other agencies.

The extant literature has long identified the influence of third-party agencies on consumer decision-making (Senecal and Nantel 2004; Reinstein and Snyder 2005; Smith, et al. 2005; Zhang, et al. 2010), and has examined firms' strategic decisions under such an influence (Chen and Xie 2005; Martins 2005). Some researchers investigate how performers play the ranking game—to improve their rankings in the short run and at a lower cost (Corley and Gioia 2000)—and the implications of such a practice on ranking agencies (Free, Salterio and Shearer 2009). Yet, research on how agencies play their ranking game is sparse. This paper sheds light on the interactions between multiple third-party agencies, and offers an explanation on the ranking discrepancy in different lists.

2. Model

A naïve audience wants to know how a set of N performers differ from each other in terms of overall performance, and would like to form a perceived ranking list r for them. Two ranking agencies, Agency 1 and Agency 2, provide a ranking list of the N performers to the audience, denoted as R_1 and R_2, respectively. The audience factors in R_1 and R_2 to form r based on the influence of each list, which is measured by the aggregate promotion of each list by the performers. The performers want to improve their standing on r; to do so each performer decides which ranking list to promote, and how much.

2.1. Promotion of Ranking List

Performers are more concerned about the comparison with their close competitors in the audience's perceived ranking list. They care less about the comparison with performers out of their league, for better or worse. To capture the essence of such peer comparison, we assume that the set of performers in the analysis are in the same league: No one performer is dominated by others in all performance dimensions.

We focus on the short-run scenario where performers cannot improve their ranking on R_1 and R_2, and hence, take them as given. A performer can influence the audience's perception of its ranking only by promoting the appropriate ranking list. It is easy to show that, if a performer promotes, it will promote only the list where it is ranked relatively favorably (i.e., the higher ranking). A performer promotes neither list if it receives the same rankings.

To illustrate the equilibrium solution to the above problem, we consider a linear utility function where performer i's utility function is specified as a follows:

$$U_i(d_{pi}) = u_0 - \theta r_i - d_{pi}, \text{ subject to } d_{pi} \geq 0, \tag{1}$$

where, d_{pi} is performer i's promotion spending on agency p's list which is ranked more favorably, $p = \{1, 2\}$, and r_i is the audience' perceived ranking of performer i.

2.2. Audience's Perceived Ranking

The audience does not have any prior belief of each performer's ranking, and forms its perceived ranking by assigning different weights to each of the two agencies' ranking lists based on the lists' influence. As research in mass communications and advertising suggests, a list with a wider distribution grabs more attention from information recipients, and hence, is more influential (e.g., Kent and Allen 1994). We thus model the weights the audience assigns t R_1 and R_2 based on the relative "loudness" of the two lists, that is, the "shares of the voice".

Specifically, we denote the aggregate promotion of R_1 as $D_1 = \Sigma_i d_{1i}$, and that of R_2 as $D_2 = \Sigma_i d_{2i}$. We define the weight as $D_p/(D_1+D_2)$, $p = \{1, 2\}$, and specify the audience's perceived ranking of performer i as

$$r_i = \frac{D_1}{D_1 + D_2} R_{1i} + \frac{D_2}{D_1 + D_2} R_{2i} \,. \tag{2}$$

As a special case, when neither list is promoted, the audience just averages the rankings on the two lists to form its perceived rankings.

2.3. Agencies' Objective and Compilation of Ranking Lists

We assume that the two agencies simultaneously compile their lists at no cost. Each agency's objective is to maximize the aggregate promotion of its list by the performers. Although we do not specifically model the agency's utility function in this paper, it is well understood that an agency benefits from its influential ranking lists (Schatz and Crummer 1993). For example, an influential ranking list can increase the readership of any media publications by the agency, which will increase advertising revenue. An influential ranking list can help the agency offer other related information products that the agency can collect revenue from, purchase or subscription.

This paper is not about information transmission where performers control the flow of its performance information to agencies (e.g., Li 2010) . Hence, we assume that ranking agencies can freely access the full information of the multiple attributes of the performance of each performer. Agencies need to convert the measures of the multiple attributes into a single score for ranking. To do so, agencies need to decide certain weights for different attributes. Note that agencies do not necessarily use the same set of attributes. Attributes excluded from ranking criteria can be regarded as being assigned a zero weight.

The usage of different weights leads to different ranking outcomes (Policano 2007). To illustrate this notion, consider a ranking list based on four key attributes of five performers. None is dominated in all four attributes by the others, as assumed by this paper. Based on the attribute levels presented in the following table, performer a, b, c, and e can either be ranked as the top performer when a bigger weight is assigned to the attribute they ace. For performer d, if the weights are chosen as .6, .25, .05 and .1, it will seize the top rank with the single score of overall performance given in the second column to the right.

Performer	Attribute 1	Attribute 2	Attribute 3	Attribute 4	Overall score (weight used: .6, .25, .05, .1)	Rank
a	1.00	2.00	3.00	5.00	17.5	5
b	2.00	3.00	5.00	1.00	23	4
c	3.00	5.00	4.00	4.00	36.5	2
d	4.00	4.00	1.00	3.00	37.5	1
e	5.00	1.00	2.00	2.00	35.5	3

Based on the notion above, in this paper we assume that agencies have freedom to adjust their ranking lists for a cohort of non-dominant performers. Yet, the ranking lists, once compiled, are irreversible. The agencies receive no financial gains from performers for ranking them favorably, or entice legal disputes for ranking them unfavorably.

3. Equilibrium Promotion Spending and Optimal Ranking Lists

We substitute the perceived ranking into performer *i*'s utility function:

$$U_i(d_{pi}) = u_0 - \theta \frac{(d_{pi} + D_p^{-i})R_{pi} + D_q R_{qi}}{d_{pi} + D_p^{-i} + D_q} - d_{pi}\,. \tag{3}$$

where $D_p^{-i} = \Sigma_{j\neq i} d_{pj}$, is the aggregate promotion of Agency p's list, excluding performer i's; D_q is the aggregate promotion of the competing Agency q's list, $p, q \in \{1, 2\}, p \neq q$.

We then constitute a Lagrangian function: $L = U_i(d_{pi}) + \lambda d_{pi}$. The Kuhn-Tucker condition implies that, depending on the value of λ, the optimal d_{pi} can be either positive or zero: i.e., if $\lambda > 0$, $d_{pi} = 0$; if $\lambda = 0$, $d_{pi} > 0$. That is, in equilibrium some performers promote and some do not.

3.1. Performers' Equilibrium Promotional Decision

Defining $\Delta_1 = \max_i\{R_{2i} - R_{1i} \,|\, R_{2i} - R_{1i} > 0\}$, and $\Delta_2 = \max_i\{R_{1i} - R_{2i} \,|\, R_{1i} - R_{2i} > 0\}$. Δ_1 and Δ_2 are the biggest ranking difference (hereafter the BRD) on R_1 and R_2, respectively. Note that multiple performers can enjoy the BRD on the same ranking list. Based on the definition of BRD, Lemma 1 answers the question as to who promotes.

Lemma 1. *In equilibrium, if* $R_{qi} - R_{pi} < \Delta_p$, *then* $d_{pi} = 0$, *where* $p, q \in \{1, 2\}, p \neq q$.

Lemma 1 suggests that, in equilibrium, only the biggest beneficiaries of a ranking list are likely to promote the corresponding list. The perceived ranking of the audience is a public good, and other performers will free ride without any promotion. Since the equilibrium total amount of promotion is determined due to the additive structure in $D_p = d_{pi} + D_p^{-i}$, whatever performer i spends less on promotion, it will entice the same amount of spending by other performers who also favor R_p. Since the performer(s) enjoying the BRD receive the highest marginal benefit of promotion, they have the strongest incentive to promote, and eventually, be the only ones who promote, contributing a total amount of D_p.

Next we answer the question as to how much to spend on promotion. In equilibrium, if performer i enjoys the BRD equal to Δ_p, its pending d_{pi} is given by

$$d_{pi} = \sqrt{\theta \Delta_p D_q} - D_q - D_p^{-i}, \tag{4}$$

where D_q is the total promotional spending on the competing list R_q. The relationship depicts how the aggregate promotional spending on the competing ranking list, D_q, affect performer *i's* promotional spending. On the one hand, a large D_q spurs performer i to promote more. This is because its perceived ranking takes a bigger hit if the audience believes in R_q more (caused by a large D_q). On the other hand, when D_q is large, the marginal change to balance with R_q by spending a dollar is low, and performer i is discouraged. In short, when facing a greater D_q, performer i has a greater incentive to reverse the audience's perceived ranking, but it is also more difficult to do so. The net effect then depends on the BRDs of the two ranking lists.

Proposition 1 provides the equilibrium aggregate promotional spending of the two ranking lists.

Proposition 1. *Suppose* $\Delta_1 > 0$, $\Delta_2 > 0$. *In equilibrium, the total aggregate promotions of the two ranking lists are*

$$D_1^* = \frac{\theta \Delta_1^2 \Delta_2}{(\Delta_1 + \Delta_2)^2}, \quad D_2^* = \frac{\theta \Delta_1 \Delta_2^2}{(\Delta_1 + \Delta_2)^2}.$$

Proposition 1 suggests that the equilibrium aggregate promotion on each ranking list depends not only on the BRD received by the performers promoting its ranking list, but also on the BRD received by the performers promoting the *competing* list. As each agency wants to make their lists more influential, they can achieve that by using the BRD as the decision variable. Yet, since both BRDs are jointly determined by the rankings from both agencies, no single agency fully controls the each of the two BRDs. We investigate this issue in the next subsection.

3.2. Agency's Ranking Decisions

It is thus interesting to understand how the change of the two BRDs affects the aggregate promotion received by each agency. Following Proposition 1, we have the following property regarding D_1^* and D_2^*.

Lemma 2. *The following relationships between the equilibrium aggregate promotion and the BRD hold:*

$$\frac{\partial D_p^*}{\partial \Delta_p} > 0, \quad \frac{\partial D_p^*}{\partial \Delta_q} \begin{cases} > 0 & \text{if } \Delta_p > \Delta_q \\ = 0 & \text{if } \Delta_p = \Delta_q \\ < 0 & \text{if } \Delta_p < \Delta_q \end{cases} \quad \textit{for } p, q \in \{1, 2\}, p \neq q.$$

Lemma 2 suggests that it is a dominant strategy for an agency to increase the BRD on its ranking list. A large BRD boosts promotion on its own list. This is because performers who enjoy the BRD have a greater incentive to influence audience's perceived ranking. In addition, when the BRD is larger than that on the competing list, that is, $\Delta_p > \Delta_q$, the performers who promote R_p will spend more when the competing agency q tries to increase Δ_q to simulate the aggregate promotion of R_q.

Alternatively, when Δ_p is set small, such that $\Delta_p < \Delta_q$, any increase in Δ_q by the competing agency makes the corresponding performers promote less on R_p. those performers yield to the competitive ranking in anticipating that those performers who enjoy Δ_q will spend more promoting R_q in response to an increased Δ_q, where $p, q \in \{1, 2\}$, $p \neq q$.

While each agency aims at maximizing the BRD on their lists, to what extent it can do so also depends on the other agency's ranking decision. For example, when the two ranking agencies provide two identical lists, the BRD is zero for both agencies, and performers promote neither list. The following proposition provides a ranking equilibrium where both agencies jointly maximize the two BRDs of the two lists.

Proposition 2. *Let* (R_p, R_q) *be the pair of ranking lists compiled by agencies p and q* $\in \{1, 2\}$. *The pair forms a pure-strategy ranking equilibrium if, and only if, there exist performers i and j for which* $R_{pi} = R_{qj} = N$, $R_{pj} = R_{qi} = 1$.

Proposition 2 suggests that Agency 1 would like to rank the bottom-ranked performer of ranking 2 as her top position, since doing so it creates the largest possible marginal benefit of promotion for the applicable performer. At the same time, Agency 2 would do the same thing: assigning top rank to the bottom-ranked performer on R_1. In equilibrium, where both agencies rank the other agency's top performer at its bottom, neither agency can deviate from this outcome to further increase its BRD.

4. Heterogeneous Performer Responses

In this section, we extend the benchmark model to investigate a case where different performers display different degrees of sensitivity to the audience's perceived rankings. Some performers derive a higher marginal utility of perceived ranking than do others. We thus rewrite performer's utility function as

$$U_i(d_{pi}) = u_0 - \theta_i r_i - d_{pi}, \text{ subject to } d_{pi} \geq 0. \qquad (5)$$

To account for the heterogeneous θ_i, we redefine BRD as follows

$$\Delta_1 = \max_i \{\theta_i (R_{2i} - R_{1i}) | R_{2i} - R_{1i} > 0\}$$

$$\Delta_2 = \max_i \{\theta_i (R_{1i} - R_{2i}) | R_{1i} - R_{2i} > 0\}.$$

As shown in the Technical Appendix, the essence of the benchmark result on promotion spending is largely preserved, where equilibrium aggregate promotional spending is $D_1^* = \Delta_1^2 \Delta_2 / (\Delta_1 + \Delta_2)^2$ for R_1, and $D_2^* = \Delta_1 \Delta_2^2 / (\Delta_1 + \Delta_2)^2$ for R_2, with θ now becoming part of the BRDs

The ranking agencies now maximize the aggregate promotions by choosing their ranking lists. Suppose performers a and b have a bigger degree of sensitivity than other performers. When $\theta_a = \theta_b$, the equilibrium rankings are the same: Each of the two performers is ranked at the top on one list and at the bottom on the other list.

Next we consider a more general case where $\theta_a \neq \theta_b$. Without loss of generality, we assume that $\theta_a > \theta_b$. We first constitute two ranking lists where Agency 1 assigns the top rank to performer a (i.e., $R_{1a} = 1$), and the rank N to performer b (i.e., $R_{1b} = N$); and Agency 2 assigns the top rank to performer b and the rank $M \leq N$ to performer a. We then decide the biggest M that makes the ranking lists equilibrium.

By the definition of BRD, $\Delta_1 = \theta_a(M-1)$ and $\Delta_2 = \theta_b(N-1)$. Only performer a will promote R_1. By Lemma 2, Agency 1 will not decrease Δ_1, and it cannot increase Δ_1 for its part. Nor can Agency 1 increase Δ_2 since it is already maximized. Hence, Agency 1 can deviate only by decreasing Δ_2, that is, by setting $R_{1b} \geq 2$. Denoting the new BRD as $\Delta_2^- = \theta_b(N-2)$, the sufficient and necessary condition for Agency 1 not to deviate is that $D_1^*(\Delta_2) \geq D_1^*(\Delta_2^-)$, it follows that

$$D_1^*(\Delta_2) - D_1^*(\Delta_2^-) = \frac{\Delta_1^2(\Delta_1^2 - \Delta_2\Delta_2^-)(\Delta_2 - \Delta_2^-)}{(\Delta_1 + \Delta_2)^2(\Delta_1 + \Delta_2^-)^2}. \tag{6}$$

Since $\Delta_2 > \Delta_2^-$, $\mathrm{sign}(D_1^*(\Delta_2) - D_1^*(\Delta_2^-)) = \mathrm{sign}(\Delta_1^2 - \Delta_2\Delta_2^-)$. $D_1^*(\Delta_2) \geq D_1^*(\Delta_2^-)$ suggests that $\Delta_1^2 \geq \Delta_2\Delta_2^-$, which leads to

$$M \geq \frac{\sqrt{(N-1)(N-2)}\theta_b}{\theta_a} + 1. \tag{7}$$

Now let's examine Agency 2's ranking decision. Agency 2 will not decrease Δ_2; neither can Agency 2 increase it. By Lemma 2, Agency 2 can benefit from an increased or decreased Δ_1, depending on the comparison of Δ_1 and Δ_2.That is, Agency 2 can deviate in both directions. To decreaseΔ_1 to $\Delta_1^- = \theta_a(M-2)$, Agency 2 can make R_{2a} more favorable (i.e., by setting $R_{2a} = M - 1$). Alternatively, Agency 2 can make R_{2a} less favorable (i.e., by setting $R_{2a} = M + 1$) to increase Δ_1 to $\Delta_1^+ = \theta_a M$. For Agency 2 not to deviate, $D_2^*(\Delta_1) \geq D_2^*(\Delta_1^-)$ and $D_2^*(\Delta_1) \geq D_2^*(\Delta_1^+)$ must be satisfied. These two conditions are equivalent to

$$M \geq \frac{\sqrt{\theta_a^2 + 4\theta_b(N-1)^2} - \theta_a}{2\theta_a}. \tag{8}$$

$$M \leq \frac{\sqrt{\theta_a^2 + 4\theta_b(N-1)^2} + \theta_a}{2\theta_a}. \tag{9}$$

Based on the three inequities regarding M, we have the following finding.

Proposition 3. *There exists an integer* $0 < M \leq N$ *that satisfies*

$$\max\left\{\frac{\sqrt{(N-1)(N-2)\theta_b} + \theta_a}{\theta_a}, \frac{\sqrt{\theta_a^2 + 4\theta_b(N-1)^2} + \theta_a}{2\theta_a}\right\} \leq M \leq \frac{\sqrt{\theta_a^2 + 4\theta_b(N-1)^2} + 3\theta_a}{2\theta_a}, \tag{10}$$

a pure-strategy ranking equilibrium exists where Agency 1 *assigns the top rank to performer a, and the rank N to performer b; Agency* 2 *assigns the top rank to performer b, and the rank M to performer a.*

Two interesting results come from Proposition 3. First, when performer b becomes more sensitive to its ranking (i.e., θ_b increases), performer a will be ranked further lower on the competing list. As θ_b approaches θ_a, M approaches N. Second, Agency 2 does not need to rank all N performers since what matters is its ranking of performers a and b. Thus, the ranking equilibrium is still the same when only M performers are ranked on R_2, with performer b ranked at the top and performer a ranked at the bottom (which is M). Thus, the essence of the top-bottom assignment is still reserved in the case of heterogeneous performers across the ranking lists of different lengths.

5. Empirical Studies of Ranking Decisions

We collected some data to test the theoretical predictions on ranking agencies' ranking decisions. We use the most recent rankings of U.S. business schools from five agencies: *Financial Times* (FT), *Bloomberg Businessweek* (BW), *U.S. News and World Report* (UN), *the Economist* (EC), *and Forbes* (FB). Note that FT and EC compile rankings for business schools globally. We thus created a new list of relative rankings for U.S. schools based on the global lists. The two relative rankings are frequently used by websites for MBA applications as well as by the pertinent business schools. Please refer to Table 1 for the detailed ranking information of these five agencies.

The five agencies use different ranking criteria, and assign different weights to the attributes of business schools ((DeAngelo, DeAngelo and Zimmerman 2005; Siemensa, et al. 2005). In the appendix, we provide the ranking criteria for the five agencies.

Table 1. Summary of the Five Rankings

Agency Name	FT	BW	EC	UN	FB
Year of compilation	2012	2012	2012	2012	2011
No. of US schools ranked	53	63	48	102	74
Number of MFR granted*	15 (4)	18 (2)	17(6)	17(5)	23(3)

*The first number indicates the number of schools that get their most favorable ranking from the agency. The numbers in parentheses indicate the counts of ties of most favorable ranking given by other agencies.

5.1. Newson 2002Correlation of Ranking Lists

We first investigate whether the five rankings yield any correlation between any two of them. We use Kendall's tau test, which is similar to Spearman's test, but provides a more valid statistical inference regarding the dependency of the ordinal data (Newson 2002).

The null hypothesis of Kendall's tau is that the two ranking lists are independent. To compute the test statistic, concordance and discordance in the two rankings are collected and compared.

$$S_{pq} = \sum_{i<j} \left\{ \text{sign}(R_{pj} - R_{pi}) * \text{sign}(R_{qj} - R_{qi}) \right\} . \tag{11}$$

Given $D = N(N-1)/2$, Kendall's tau is computed as S_{pq}/D.

We calculate the Kendall's tau for different tiers of schools. We first generate a list of top 40 business schools based on the average ranking across the five lists (we assign equal weights to each ranking list), then we compute Kendall's tau for different tiers. The results are presented in Table 2.

We find that the Kendall's tau is significant among all of the five lists for the top 25 business schools and for the top 40 business schools, suggesting that the five lists correlate with each other. Yet, a careful examination of each tier reveals an opposite story. In each tier of schools (e.g., top ten, top 11 to top 20, top 21 to top 30, as well as some overlapping tiers such as top 21 to top 40), the five ranking lists are statistically independent of each other most of time, suggesting a pervasive discrepancy among those ranking lists. Combining these two results, we conclude that the significance of the Kendall's tau is due to the fact that the ranking among the tiers are preserved in the five lists. Yet, such ranking varies within each tier.

Table 2 Kendall's Tau Test for the Correlation of Five Ranking Lists

Top 25					Top 40				
	FT	BW	EC	UN		FT	BW	EC	UN
BW	.543**				BW	.587**			
EC	.500**	.383*			EC	.580**	.594**		
UN	.799**	.600**	.500**		UN	.726**	.694**	.670**	
FB	.638**	.630**	.518**	.733**	FB	.570**	.602**	.579**	.605**
Top 1-10					**Top 11-20**				
	FT	BW	EC	UN		FT	BW	EC	UN
BW	.244				BW	.378			
EC	-.200	-.067			EC	.200	.022		
UN	.722**	.535*	-.349		UN	.674**	.180	.045	
FB	.511*	.467	.111	.535*	FB	.289	.289	-.244	.360
Top 21-30					**Top 31-40**				
	FT	BW	EC	UN		FT	BW	EC	UN
BW	-.278				BW	-.019			
EC	.0556	0.00			EC	-.029	.275		
UN	0.00	-.122	-.322		UN	.130	.295	.328	
FB	.0.111	.722**	.143	-.426	FB	-.176	-.046	-.231	-.309

*: sig. at 5%. **: sig at 1%.

5.2. Regression Analysis

Next, we conduct a regression analysis to investigate the relationship among the ranking lists. Based on the theoretical model, we consider two factors of interest: 1) the most favorable ranking (MFR) a performer receives from other agencies; and 2) the dispersion of the rankings given by other agencies. We predict a negative interaction effect of the two factors. That is, the focal ranking agency is more likely to rank a performer favorably if that performer is ranked more unfavorably with greater discrepancy by other agencies.

To illustrate the rationale behind this hypothesis, let us consider a case where a focal ranking agency decides to rank two performers, *m* and *n*. Both performers receive the same MFR, denoted as *K*, from some other agency; and performer *m*'s rankings from other agencies has a greater variance than performer *n*. This suggests that there is a smaller consensus among other agencies towards the ranking of *m* than that of *n*. If the focal agency has a better ranking *H*, $H < K$, to allocate, it is more likely to allocate *H* to performer *m* since *m* is much more motivated to promote the focal ranking list given the bigger discrepancy of other (unfavorable) rankings it is up against.

We thus specify the current ranking of the focal agency (t = year 2012) for a performer as a linear function of the MFR received by the performer from other agencies, and the variance of its rankings (VAR), as well as the interaction. To avoid the endogeneity problem, we used the rankings compiled in the previous year to compute MFR and VAR. Since Forbes did not release its ranking list in 2012, we end up with four regressions, one for each agency: FT, BW, EC and UN.

$$R_{ki,2012} = \alpha + \beta_1 MFR_{\text{-}ki,\ 2011} + \beta_2 VAR_{\text{-}ki,\ 2011} + \beta_3 MFR_{\text{-}ki,\ 2011} * VAR_{\text{-}ki,\ 2011} + \varepsilon\ , \qquad (12)$$

where $R_{ki,\ 2012}$ is agency k's ranking of school i in 2012. $MFR\text{-}_{ki,\ 2011}$ is the most favorable ranking school i received from other agencies, excluding agency k in year 2011, $MFR\text{-}_{ki,\ 2011} = \min\ (R\text{-}_{ki,\ 2011})$; $VAR\text{-}_{ki}$ is the variance of school i's rankings from other agencies in year 2011. Table 3 reports the regression results.

Table 3. Regression Results of Ranking Decisions of Four Ranking Agencies

	FT	BW	EC	UN
Intercept	5.464	4.052	4.206	-.986
MFR	.864**	1.005**	.894**	1.301**
VAR	.104**	.061**	..085**	.072**
MFR*VAR	-.002**	-.001**	-.002**	-.002*
df	48	53	41	58
R^2	.739	.829	.826	.752
Shapiro–Wilk' s *W*	.939	.962	.984	.942

*: sig. at 5%. **: sig at 1%, two-tailed test.

Overall, the model fits the data well. The coefficient of regression (R^2) is reasonably high (> 70%) in all four regressions. The Shapiro–Wilk's *W* test for normality assumption is well kept for all regressions, suggesting that the ordinal data behave well in the regression analysis. The interaction effect is negatively significant in all four regressions ($p < 5\%$), in support of the hypothesis. That is, an agency is more likely to compete with other agencies in assigning MFR to a performer that has a lower MFR out of all other lists, and a bigger discrepancy in its rankings.

Further, the t-test on the estimates of MFR suggests that in three out of four regressions (except UN), the coefficient of MFR is statistically insignificant from one. This result implies that ranking agencies start the ranking of a performer from its MFR given by other agencies, and adjust down according to the variance of its rankings (giving a bigger ranking number). When the interaction is large, ranking agencies then adjust up the ranking (giving it a smaller ranking number).

6. Conclusion

This paper studies how ranking agencies strategically decide their ranking lists in pursuing influence through the promotion of performers of their lists. In a two-agency model, we find that it is an equilibrium for the two agencies to adopt a top-bottom approach, where each agency puts the top ranked performer by the other agency at the bottom of its ranking list. Accordingly, when performers are homogeneous, only the top ranked performers promote the corresponding list, and other performers do not promote. When performers are heterogeneous in terms of their sensitivity to perceived rankings, the performer who receives the biggest perceived ranking difference promotes. We then test the theoretical prediction using the ranking data of US business schools from five agencies, and find that a ranking agency is more likely to rank a performer favorably when it is ranked less favorably by other agencies with greater discrepancy.

This paper offers insights into understanding the co-existence of multiple ranking lists in many industries, and sheds light on the explanation of discrepancy across different lists. It treats multiple ranking lists as different but well-positioned information products rather than the measures of unobservable quality of a set of products, brands or organizations. It shows that the discrepancy may not be due to measurement errors, but that each agency decides to alienate some performers and to align with others.

Due to the scope and the objective of this paper, there are several limitations in the modeling approach. First, this paper does not allow performers to interact with ranking agencies. In the extension, we partially alleviate this issue by allowing that agency takes the performers sensitivity into ranking decision. This passive approach does not fully address this issue. It is desirable to have a comprehensive investigation into the ranking game played by both performers and ranking agencies.

Another limitation of this paper is the assumption of naïve audience. In many situations, the audience has a preconceived notion regarding certain ranking lists, and weighs the two ranking lists differently even in the absence of promotion. In other situations, the audience may predetermine perceived rankings for certain performers, either positively or negatively, and does not update these perceived rankings of those performers. These responses will affect performers' promotion decisions, and, in turn, the ranking list compilation. More research (probably via behavioral studies) is needed to understand how an audience interprets and responds to different ranking lists.

Appendix. Five Ranking Agencies' Ranking Criteria of Business Schools

Ranking Agency	Code Name	Ranking Frequency	Weight and Ranking Criteria
Financial Times[1]	FT	Annual	39% alumni response 20% weighted salary 31% faculty and student profile 3% international course experience Other factors
Bloomberg Business Week[2]	BW	Every even year	45% students' satisfaction survey 45% recruiters' survey 10% faculty publications in selected journals
The Economist[3]	EC	Annual	35% new career opportunities 35% educational experience 20% increased salary 10% potential network
The US News and World Report[4]	UN	Annual	40% quality assessment 35% placement success 25% student selectivity
Forbes[5]	FB	Every odd year	Financial gain of MBA graduates in the first five years post-MBA compared to their pre-MBA salary

[1] http://www.ft.com/intl/cms/s/2/03bd60fe-609b-11e2-a31a-00144feab49a.html
[2] http://www.businessweek.com/stories/2006-10-22/how-we-come-up-with-the-rankings
[3] http://www.economist.com/node/14488732
[4] http://www.usnews.com/education/best-graduate-schools/top-business-schools/articles/2013/03/11/methodology-best-business-schools-rankings
[5] http://www.forbes.com/sites/kurtbadenhausen/2011/08/03/the-best-business-schools/

References

Chen, Y. B., J. H. Xie. 2005. Third-Party Product Review and Firm Marketing Strategy. *Marketing Science*. 24(2). 218-240.

Corley, K. G., D. A. Gioia. 2000. The Rankings Game: Managing Business School Reputation. *Corporate Reputation Review*. 3(4). 319-333.

DeAngelo, H., L. DeAngelo, J. L. Zimmerman. 2005. What's Really Wrong with U.S. Business Schools? *SSRN Working Paper*. http://ssrn.com/abstract=766404.

Free, C., S. E. Salterio, T. Shearer. 2009. The Construction of Auditability: Mba Rankings and Assurance in Practice. *Accounting, Organizaions and Society*. 34. 119-140.

Kent, R. J., C. T. Allen. 1994. Competitive Interference Effects in Consumer Memory for Advertising: The Role of Brand Familiarity. *Journal of Marketing*. 58(3). 97-105.

Li, W. 2010. Peddling Influence through Intermediaries. *American Economic Review*. 100(June). 1136-1162.

Martins, L. L. 2005. A Model of the Effects of Reputational Rankings on Organizational Change. *Organization Science*. 16(6). 701-720.

Newson, R. 2002. Parameters Behind "Nonparametric" Statistics: Kendall's Tau, Somers' D and Median Differences. *The Stata Journal*. 2(1). 45-64.

Policano, A. J. 2007. The Rankings Game:And the Winner Is. *Jouranl of Management Development*. 26(1). 43-48.

Reinstein, D. A., C. M. Snyder. 2005. The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics. *Journal of Industrial Economics*. 53(1). 27-51.

Schatz, M., R. E. Crummer. 1993. What's Wrong with Mba Ranking Surveys? *Management Research News*. 16(7). 15-18.

Senecal, S., J. Nantel. 2004. The Influence of Online Product Recommendations on Consumers' Online Choices. *Journal of Retailing*. 80(2). 159-169.

Siemensa, J. C., et al. 2005. An Examination of the Relationship between Research Productivity in Prestigious Business Journals and Popular Press Business School Rankings. *Journal of Business Research*. 58(4). 467-476.

Smith, D., S. Menon, K. Sivakumar. 2005. Online Peer and Editorial Recommendations, Trust, and Choice in Virtual Markets. *Journal of Interactive Marketing*. 19(3). 15-38.

Forbes.com. 2012. A Better Way to Rank Business Schools? By Yeaple, R. Published on 9/11/2012, available at http://www.forbes.com/sites/ronaldyeaple/2012/09/11/a-better-way-to-rank-business-schools/.

Zhang, Z., et al. 2010. The Impact of E-Word-of-Mouth on the Online Popularity of Restaurants: A Comparison of Consumer Reviews and Editor Reviews. *International Journal of Hospitality Management*. 29(4). 694-700.