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Leveraging online customer reviews in new product development: a differential game approach

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Abstract

Large volumes of online product reviews generated by customers have important strategic values for new product development. We consider a duopoly setting where two manufacturers aim to develop their own new products and services. Applying a differential game framework, we examine how online customer reviews can be leveraged as external knowledge for manufacturers to develop new products. In our base models, we assume that the products supplied by the manufacturers are homogenous. First, we consider a closed innovation setting as a benchmark case in which both manufacturers develop new products by their internal R&D without leveraging online customer reviews. Second, we propose a model in which one manufacturer leverages online customer reviews as external knowledge, while the other manufacturer only relies on internal R&D effort. We derive analytical equilibrium solutions to both models. We find that when one manufacturer uses online customer reviews, if the manufacturer's R&D process becomes more effective in improving its new product performance or reducing its cost, it certainly hurts the other manufacturer, but it may sometimes hurt this particular manufacturer as well. Furthermore, we demonstrate that when the manufacturer utilizes online customer reviews more in R&D, both manufacturers' profits can either increase or decrease. In an extended model, we relax the product homogeneity assumption and obtain the equilibrium solution analytically. We show that main managerial insights still hold in the extend model.

Keywords Online customer reviews · New product development · Customer agility · Customer involvement · Differential game

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1 Introduction

Nowadays, global competition becomes increasingly intense, and technology advances more quickly than ever. Therefore, innovation becomes essential to ensure a firm's survival and growth in such a dynamic business environment. Companies are willing to invest considerable resources in research and development (R&D) for new product development (NPD). NPD is an innovation process that conceives better new products, which are different or unique in some ways from existing products (Chesbrough 2006a, b). A recent study finds that the main reason for low returns on NPD is lack of knowledge about market needs (CB Insights 2018). Because of the information asymmetry between firms and customers, firms need to find a way to acquire customers' preference and need information that can be used to evaluate the potential of NPD projects (Courtney et al. 2017). Hence, to alleviate the information gap, both scholars and practitioners propose relevant strategies, such as subsidization strategies (Li et al. 2020) and leveraging online customer reviews (Zhou et al. 2018), to involve market participants in product development. These strategies may help customers signal their potential needs that firms understand and lead to a joint creation of innovative products that meet market demands (Creane 2002; Tams 2018). In the era of open innovation, the absorption of external knowledge has become crucial to improve NPD performance (Robert and Candi 2014; Chuang and Lin 2015; Lichtenthaler 2016). Nonetheless, there are a few challenges in involving customers in NPD (Sashi 2012; Bowden et al. 2015). One key challenge is simply to get in touch with customers in an effective way (Nambisan 2002), because information related to customers' needs is often costly for product developers to capture (Füller et al. 2006). However, emerging information technology has turned the average customers into an incessant generator of transactional, traditional, structured data as well as unstructured, behavioral data (Wamba et al. 2015). The magnitude and diverse richness of big data such as online customer reviews are transforming NPD (Zhan et al. 2018).

New product development is driven by technical factors and market factors jointly, which is a complex process that requires sound investment in research and development, as well as significant marketing expertise that focuses on satisfying customers' wants and needs (Dunk 2011). Empirical evidence shows that about 50% output of product innovation is pushed by market factors (Myers and Marquis 1965). Internal R&D has been considered costly and vague in technical factors aspect (Prahalad and Ramaswamy 2004; Steinfeld and Beltoft 2014). Many firms transfer internal R&D procedures to incorporate customer-oriented components into NPD swiftly (Maruping et al. 2009). On the one hand, products that meet customers' demand will increase their willingness to purchase (Priem 2007). On the other hand, internal R&D alone may hinder the firms from identifying new market trend (Von Hippel 2005), and customers sometimes may propose better innovative ideas than R&D personnel (Poetz and Schreier 2012). Therefore, customers are important sources of information and knowledge (Cooper 2014), and it is well acknowledged that customer involvement can improve NPD (Cooper and Kleinschmidt 2011). Customer involvement has been extensively employed as an approach to stiffening the feedback loop in the process of NPD (Robert and Candi 2014).

Traditionally, firms often gain access to customers' ideas about their products through surveys and interviews with representative sample users (or lead users) to develop and improve their products. These customers' ideas only represent general users' partial needs rather than their diversified demands (Von Hippel 2005). In recent years, emerging information technologies (i.e., Web2.0, mobile internet) have promoted rapid development of online platforms such as review platforms, online stores, and innovation communities. These platforms have accumulated a large amount of online customer reviews for various products and services since it has become increasingly convenient for customers to post reviews on online platforms. Customers can easily share their experience on online platforms and propose suggestions for product improvement. Additionally, online platforms promote the flow and sharing of knowledge, break the boundaries of traditional laboratory and innovative activities, and provide sources of technology and information for the firms to execute open innovation using online customer reviews (Chesbrough 2003). Many researchers point out that firm can understand customers' preferences and needs better by leveraging the data available through online platforms in the process of NPD (Tsai et al. 2013; Wamba and Carter 2014). The big data of online customer reviews play a critical role in customer involvement and constitute an important data resource that enables value co-creation between firms and customers (Priem 2007; Zhan et al. 2018). Therefore, firms that are able to recognize customers' latent needs via online customer reviews will be much more likely to achieve successful NPD (Sarin and O' Connor 2009; Robert and Candi 2014).

From a practice perspective, it is a curial strategy for firms to incorporate online customer reviews into NPD (Von Hippel 2001). There are many successful cases in which various firms aggregate customers' reviews for product development through online platforms. For example, Procter & Gamble releases R&D tasks to search for innovative ideas on its incentive online platform which accounts for 35%. Nike, Dell, Starbucks, and Xiaomi have collected customers' ideas and suggestions through self-sponsored online platforms. Furthermore, many independent online platforms also accumulate a large volume of online customer reviews. For example, in 2015, approximately 145 million visitors posted 102 million reviews each month on Yelp, a primary U.S. e-commerce site (Zhou et al. 2018). In Apple's App Store, more than 17.4 million app reviews have been generated for 3101 game apps since the store opened in 2008. Online customer reviews can be considered as big data due to their high volume, velocity, and variety. It is often difficult for firms to utilize demand-side knowledge which is embedded in large-volume online customer reviews due to the complexity and high costs (Boudreau 2012). Hence, there is a trade-off between cost and revenue when firms incorporate online customer reviews into NPD.

Our research focuses on NPD driven by the acquisition of external knowledge, which refers to innovations that source demand-side knowledge from online customer reviews. The extant papers regarding open innovation highlight the necessity of absorbing customers' demand-side knowledge for product development (Priem et al. 2012). However, they often focus on a relatively small group of lead customers (Nishikawa et al. 2013). Large volumes of online customer reviews enable firms to gain knowledge from regular customers, making the embedded demand-side knowledge less biased and more valuable (Poetz and Schreier 2012). In addition, prior studies on online customer reviews focus on how reviews could influence other customers' purchasing decisions through word-of-mouth effect (Duan et al. 2008a, b; Zhu and Zhang 2010). These papers have mainly focused on review ratings, depth, volume, and sentiment with little attention to review text. For example, Mudambi and Schuff (2010) examine the impact of review rating extremity and review depth on the helpfulness of customer reviews. Duan et al. (2008a) show that review volume would significantly influence box office sales. Zhu and Zhang (2010) find that review volume, review rating, and the variance of ratings all have a positive impact on unpopular online games. Salehan and Kim (2016) conduct a sentiment analysis on review texts and find a positive relationship between review sentiment and helpfulness of online customer reviews. However, these studies do not consider utilizing rich information embedded in the review texts, which contain valuable customer feedback. Zhan et al. (2018) investigate a new product development project at an electronics company and introduce a customer involvement approach as a new means of customer-centered new product development. Zhou et al. (2018) adopt a big data analytical approach to investigate the impact of online customer reviews on customer agility and subsequent product performance. Customer agility is a specific type of capability that product developers need to have in order to detect and respond to demands embedded in online customer reviews (Roberts and Grover 2012). These studies have explored the effect of online customer reviews empirically by text analytics, econometrics, and survey approach in NPD.

In summary, prior studies on online customer reviews often focus on how reviews influence other customers' purchasing decisions, how valuable reviews are in NPD, and how to mine demand-side knowledge embedded in large-volume online customer reviews. But little is known about: (1) how product manufacturers can respond to these reviews by incorporating customers' requests into NPD? (2) what's the impact of customer agility on product performance when manufacturers leverage online customer reviews in NPD? (3) how the firms can make optimal decisions to develop new products by internal R&D and leveraging external online customer reviews jointly. To answer these research questions, we develop a differential game model to examine the impact of both internal R&D and leveraging online customer reviews on product performance in NPD.

The existing literature focuses on the static sequential game (Yoon et al. 2018). However, NPD is a long-term and dynamic process. In order to capture the dynamic and strategic interactions between the two manufacturers, we propose a differential game model in this paper and derive the equilibrium R&D effort levels for two manufacturers in a duopoly setting. Differential game can be considered as a fusion of game theory and optimal control theory. They not only incorporate strategic decision making and continuous change simultaneously, but also combine the dynamic effects of the current state and decision with future states and decisions (Ouardighi et al. 2020). Dockner et al. (2000) provide a detailed discussion of differential game. Due to the inherent difficulty in solving differential game, there are only a few studies using differential game approach in the field of Information System (Mookerjee et al. 2011; Liu et al. 2012; Demirezen et al. 2016).

The remainder of this paper is organized as follows. Section 2 introduces the problem description and definitions. In Sect. 3, we propose and investigate a base scenario where both manufacturers only invest in internal R&D for their NPD. In Sect. 4, first, we analyze our main model in which one manufacturer utilizes both internal R&D and external knowledge (i.e., online customer reviews) in NPD, while the other manufacturer exercises internal R&D only; second, we present managerial implications of the main model. In Sect. 5, we relax the product homogeneity assumption by studying an extended model in which the two manufacturers' products are heterogeneous. Section 6 concludes the study and provides directions for future research. All mathematical proofs are provided in the "Appendix".

2 Problem description and notation definitions

We consider a duopoly market of homogenous products. The products are supplied by two manufacturers, which are represented by subscripts A and B. We denote the R&D effort level of manufacturer i $(i = A, B)$ at time t by $I_i(t)$. Inspired by Demirezen et al. (2016), we model the respective outputs of the manufacturers, denoted by $q_i(t)$ $(i = A, B)$, as continuous, twice differentiable, strictly concave nondecreasing functions of $I_i(t)$. Manufacturer i's output is related to its R&D effort level and external knowledge (i.e., online customer reviews). In addition, there exist natural loss in output because of defective products, improper management of product inventory, etc. In sum, following Nerlove and Arrow (1962), we model the instantaneous increase in the output of manufacturer i as

$$\dot{q}_i(t) = r\tilde{\alpha}_i(K_i)I_i(t) - \delta q_i(t) \tag{1}$$

where r is the productivity multiplier, and δ is the natural loss multiplier of output with $\delta \geq 0$, and customer agility (K_i) here is defined as the extent that manufacturer i leverages online customer reviews in its R&D process for its NPD. Moreover, according to Tsai et al. (2013) and Zhan et al. (2018), $\tilde{\alpha}_i(K_i)$ is a function of customer agility, which measures the effectiveness of utilizing online customer reviews. Inspired by Fonseca and Domingues (2017), we define $\tilde{\alpha}_i(K_i)$ as follows:

$$\tilde{\alpha}_i(K_i) = \begin{cases} \alpha_i + \beta_i K_i, & if \quad K_i \leq \bar{K}_i \\ \bar{\alpha}_i, & if \quad K_i > \bar{K}_i \end{cases} \tag{2}$$

where $\alpha_i + \beta_i \bar{K}_i = \bar{\alpha}_i$, $\alpha_i < \bar{\alpha}_i$, and $\beta_i > 0$ measures the marginal change in $\tilde{\alpha}_i$ per unit of customer agility. $\tilde{\alpha}_i(0) = \alpha_i$ represents the case in which manufacturer i does not utilize online customer reviews. Leveraging online customer reviews can offer manufacturers supportive product ideas, and hence it can improve manufacturers' efficiency in NPD (Tsai et al. 2013; Bharadwaj et al. 2012). However, overresponding to online customer reviews would eventually suppress new product improvement (e.g. features, functions) due to excessive emphasis on customers' current needs (McAfee and Brynjolfsson 2012). Therefore, we assume $\tilde{\alpha}_i(K_i)$ in Eq. (2) follows the following dynamics: when manufacturer i's customer agility is below a certain threshold ($\bar{K}_i = \frac{\bar{\alpha}_i - \alpha_i}{\beta_i}$), a higher customer agility means that the customers' reviews are more helpful, and so the manufacturer's R&D effort can achieve a higher performance; when customer agility reaches the threshold ($\bar{K}_i$), the manufacturer's product performance improved by its R&D effort will also reach a maximum level and remain constant thereafter.

Since we consider a duopoly market where products are supplied by manufacturers A and B, we have

$$q_A(t) + q_B(t) = Q(t) \tag{3}$$

where Q(t) denotes the aggregate output in the market at time t. We assume the inverse demand function in this duopoly market is as follows (Elsadany and Awad 2019)

$$p(t) = a - bQ(t) \tag{4}$$

where a denotes the maximum price when the outputs of the manufacturers are zero, b denotes the sensitivity coefficient of the price to the market demand.

Manufacturer i's cost is directly related to its R&D effort involved and customer agility. For instance, such costs should be increasing with its R&D effort level. Following Tsay and Agrawal (2000) and Bertinelli et al. (2014), we assume manufacturer i's cost is

$$C_i(t) = \frac{\tilde{c}_i(K_i)}{2} I_i^2(t) \tag{5}$$

where $C_i(t)$ denotes manufacturer i's cost at time t. $\tilde{c}_i(K_i)$ measures the cost multiplier for the R&D effort level exerted by manufacturer i, which is a function of customer agility.

Leveraging online customer reviews is a continuous process of learning and experimentation in NPD, which affects manufacturer i's cost multiplier for its R&D effort. The large amount of reviews posted by diverse customers represent heterogeneous preferences and feedback from the customers. Product developers or designers need to identify such heterogeneous requests, detect product defects, and incorporate a variety of new functions into new

Table 1 Notations and definitions in the model

Notation	Definition
Parameters	
$p_i(t)$	Price of the manufacturer i at time t, i = A, B
a	Maximum price when the outputs of the manufacturers are zero,$a > 0$
b	The sensitivity coefficient of the market price to the market demand,$b > 0$
K_i	Customer agility, $K_i \geq 0$ (Here, customer agility is defined as the extent that manufacturer i leverages online customer reviews in NPD)
$\tilde{\alpha}_i(K_i)$	Effectiveness for efforts exerted by manufacturer i for utilizing internal R&D and external online customer reviews
r	Productivity multiplier,$r > 0$
β_i	Marginal change in $\tilde{\alpha}_i$ per unit of customer agility (K_i),$\beta_i > 0$
$\tilde{c}_i(K_i)$	Cost multiplier for efforts exerted by manufacturer i for utilizing internal R&D effort and online customer reviews.
γ_i	Marginal change in $\tilde{c}_i$ per unit of customer agility (K_i),$\gamma_i > 0$
ρ	Discount rate, $\rho \geq 0$
δ	Natural loss multiplier of output, $\delta \geq 0$
Variables	
$q_i(t)$	Output of the manufacturer i at time t (*state variable*)
$I_i(t)$	R&D effort level of the manufacturer i at time t (*decision variable*)
Objective function	
j_i	Overall profit of the manufacturer i in an infinite horizon.

products, so the product development costs are heightened (Zhou et al. 2018). Consequently, in the initial stage, cost multiplier for R&D effort increases with an increase in customer agility. However, after the introductory stage, an increase in customer agility may lead to a reduction in cost multiplier for R&D effort due to economies of scale. Additionally, we assume that the cost multiplier for R&D effort will become constant when customer agility exceeds the threshold value $(\bar{K}_i)$. That is, we model the relationship between the cost multiplier for R&D effort and customer agility as an inversed "U" shape curve, defined formally as below

$$\tilde{c}_i(K_i) = \begin{cases} c_i + K_i - \gamma_i K_i^2, & if \quad K_i \leq \bar{K}_i \\ \bar{c}_i, \quad if \quad K_i > \bar{K}_i \end{cases}, \tag{6}$$

where $c_i + \bar{K}_i - \gamma_i \bar{K}_i^2 = \bar{c}_i$, and $\tilde{c}_i(0) = c_i$ denotes the cost multiplier for R&D effort without leveraging online customer reviews.

We summarize the key notations of our model parameters and variables in Table 1 below.

3 Benchmark: R&D without leveraging online customer reviews

In this section, we only consider a closed innovation setting in which both manufacturers A and B develop new products by their internal R&D effort only without leveraging online customer reviews. Manufacturer i's ($i = A, B$) objective is maximizing its overall profit, J_i^N, by choosing its R&D effort level, $I_i(t)$, in an infinite horizon, where superscript N signifies neither manufacturer leverages online customer reviews in the process of NPD.

$$\max_{I_i} J_i^N = \int_0^\infty e^{-\rho t}[q_i(t)p(t) - C_i(t)]dt \tag{7}$$

$$\text{subject to} \quad \dot{q}_i(t) = r\alpha_i I_i(t) - \delta q_i(t) \tag{8}$$

$$C_i(t) = \frac{c_i}{2} I_i^2(t) \tag{9}$$

where ρ is the discount rate for manufacturer i in the infinite horizon with $\rho \geq 0$ following Demirezen et al. (2016) and Jorgensen and Gromova (2016). Note that due to the product homogeneity, the prices of manufacturers A and B are equal and their inverse demand function satisfies $p_i(t) = p(t) = a - bQ(t)$.

In the Eq. (7), $q_i(t)p(t)$ measures the total revenue of manufacturer i which is a product of its output and market-clearing price at time t. Hence, $q_i(t)p(t) - \frac{c_i I_i(t)^2}{2}$ represents the overall profit of manufacturer i at time t. According to the optimal control theory, $V_i^N(q_i)$ is the optimal value function of the manufacturer i satisfying the Hamilton–Jacobi-Bellman (HJB) equation for $q_i \geq 0$.

$$\rho V_i^N(q_i) = \max_{I_i}\left[q_i(t)p(t) - \frac{c_i I_i(t)^2}{2} + V_{iq_i}^{N'}\dot{q}_i\right] \tag{10}$$

We assume that both manufacturers decide on their respective R&D effort levels simultaneously. This assumption is valid as long as neither party knows the other party's decision when it makes its own decision, even if they do not make their decisions at the same time. Thus, the intersection point of the manufacturers' best-response functions will be the equilibrium. By solving the best response functions simultaneously, we obtain the equilibrium which is formally presented below.

Lemma 1 *In equilibrium, if manufacturers develop new products by their internal R&D without leveraging online customer reviews,*

(*a*) *respective R&D effort levels for manufacturers A and B are*

$$I_A^{N*} = \frac{r\alpha_A c_B \delta a}{r^2\alpha_A^2 c_B b + r^2\alpha_B^2 c_A b + (\rho+\delta)\delta c_A c_B}, I_B^{N*} = \frac{r c_A \delta a}{r^2\alpha_A^2 c_B b + r^2\alpha_B^2 c_A b + (\rho+\delta)\delta c_A c_B}$$

(*b*) *respective outputs for the manufacturers A and B are*

$$q_A^{N*} = \frac{r^2\alpha_A^2 c_B a}{r^2\alpha_A^2 c_B b + r^2\alpha_B^2 c_A b + (\rho+\delta)\delta c_A c_B}, q_B^{N*} = \frac{r^2\alpha_B^2 c_A a}{r^2\alpha_A^2 c_B b + r^2\alpha_B^2 c_A b + (\rho+\delta)\delta c_A c_B};$$

(*c*) *respective profits for manufacturers A and B are*

$$J_A^{N*} = \frac{(2\rho+\delta)\,\delta r^2\alpha_A^2 c_A c_B^2 a^2}{2(r^2\alpha_A^2 c_B b + r^2\alpha_B^2 c_A b + (\rho+\delta)\,\delta c_A c_B)^2}, J_B^{N*} = \frac{(2\rho+\delta)\,\delta r^2\alpha_B^2 c_B c_A^2 a^2}{2(r^2\alpha_A^2 c_B b + r^2\alpha_B^2 c_A b + (\rho+\delta)\,\delta c_A c_B)^2}.$$

4 R&D with leveraging online customer reviews

In the previous section, we study the benchmark case in which both manufacturers do not utilize their online customer reviews in the process of NPD. However, in recent years, more and more manufacturers acquire innovative ideas from external sources, such as competitors, suppliers, distributors, and customers. Especially, nowadays it is getting easier for customers to post their reviews about the price, function, and appearance of products on social media, which provides valuable external knowledge for NPD. NPD is now as an open innovation of a closed-loop process with internal R&D and external knowledge (i.e., online customer reviews here). Due to differences in technology, business process and strategies, some manufacturers may be able to utilize online customer reviews sooner than other manufacturers in NPD. Therefore, we assume one manufacturer develops its new product using online customer reviews, but the other **manufacturer does not utilize online customer reviews. In Sect. 4.1, we formally present our model and its equilibrium outcomes. In Sect. 4.2, we provide some managerial insights.

4.1 Model formulation and results

Without loss of generality, we assume manufacturer A utilizes online customer reviews, but manufacturer B does not. The superscript D denotes that manufacturer A develops its new product leveraging online customer reviews. The superscript DN denotes that manufacturer B develops its new product without leveraging online customer reviews. Hence, manufacturer i's ($i = A,B$) objective is maximizing its overall profit by choosing its R&D effort level, i.e., I_i, in an infinite horizon

$$\max_{I_A} J_A^D = \int_0^\infty e^{-\rho t}[q_A p - C_A(t)]dt \tag{11}$$

where $\dot{q}_A(t) = r\tilde{\alpha}_A(K_A)I_A(t) - \delta q_A(t)$, $C_A(t) = \frac{\tilde{c}_A(K_A)}{2} I_A^2(t)$,

$$\max_{I_B} J_B^{DN} = \int_0^\infty e^{-\rho t}[q_B p - C_B(t)]dt \tag{12}$$

where $\dot{q}_B(t) = r\alpha_B I_B(t) - \delta q_B(t)$, $C_B(t) = \frac{c_B}{2} I_B^2(t)$. Note that when $K_A > \bar{K}_A$, the effectiveness and the cost multiplier, i.e., $\tilde{\alpha}_A(K_A)$ and $\tilde{c}_A(K_A)$ become constant, so the equilibrium results are independent on K_A. Hence, we only consider the interesting case such that $K_A \le \bar{K}_A$.

According to optimal control theory, $V_A^D(q_A)$ and $V_B^{DN}(q_B)$ are the respective optimal value functions of manufacturers A and B satisfying the Hamilton–Jacobi-Bellman (HJB) equations for $q_A \ge 0$ and $q_B \ge 0$. Hence, we have

$$\rho V_A^D(q_A) = \max_{I_A}\left[q_A p - \frac{\tilde{c}_A I_A(t)^2}{2} + V_{Aq_A}^{D\prime}\dot{q}_A\right] \tag{13}$$

$$\rho V_B^{DN}(q_B) = \max_{I_B}\left[q_B p - \frac{c_B I_B(t)^2}{2} + V_{Bq_B}^{DN\prime}\dot{q}_B\right] \tag{14}$$

The equilibrium solutions to problems (13) and (14) are provided in the following lemma.

Lemma 2 *In equilibrium,*

(*a*) *respective R&D effort levels for manufacturers A and B are*

$$I_A^{D*} = \frac{r\tilde{\alpha}_A(K_A)c_B\delta a}{r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B},$$
$$I_B^{DN*} = \frac{r\alpha_B\tilde{c}_A(K_A)\delta a}{r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B};$$

(*b*) *respective outputs for manufacturers A and B are*

$$q_A^{D*} = \frac{r^2\tilde{\alpha}_A(K_A)^2c_Ba}{r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B},$$
$$q_B^{DN*} = \frac{r^2\alpha_B^2\tilde{c}_A(K_A)a}{r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B};$$

(*c*) *respective profits for manufacturers A and B are*

$$J_A^{D*} = \frac{(2\rho+\delta)\delta r^2\tilde{\alpha}_A(K_A)^2\tilde{c}_A(K_A)c_B^2a^2}{2(r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B)^2},$$
$$J_B^{DN*} = \frac{(2\rho+\delta)\delta r^2\alpha_B^2c_B\tilde{c}_A(K_A)^2a^2}{2(r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B)^2}.$$

where $\tilde{\alpha}_A(K_A) = \alpha_A + \beta_A K_A$, $\tilde{c}_A(K_i) = c_A + K_A - \gamma_A K_A^2$. Lemma 2 enables us to conduct some sensitivity analysis on various model parameters to draw managerial insights in Sect. 4.2 below.

4.2 Managerial implications

In this subsection, we explore how variations in model parameters would affect both manufacturers' decisions and profits in equilibrium.

4.2.1 Natural loss multiplier of output

The effect of a change in the natural loss multiplier of output on the equilibrium R&D effort levels, and outputs can be characterized as follows. For simplicity of exposition, we define $S = D$ when $i = A$ and $S = DN$ when $i = B$ for the remainder of this paper.

Proposition 1 *When δ increases, we have*

(*a*) q_i^{S*} *($i = A, B$) decreases;*

(*b*) *if $\delta < \hat{\delta}$, then I_i^{S*} increases, otherwise, I_i^{S*} decreases, where* $\hat{\delta} = \sqrt{\frac{r^2\tilde{\alpha}_A(K_A)^2c_Bb + r^2\alpha_B^2\tilde{c}_A(K_A)b}{\tilde{c}_A(K_A)c_B}}$.

Part (a) of Proposition 1 shows that when the natural loss multiplier of output (δ) increases, both manufacturers' equilibrium outputs would decrease. Moreover, part (b) of Proposition 1 implies that it may not always incentivize the manufacturers to increase their R&D effort levels when δ increases. When the natural loss multiplier of output is low (i.e., $\delta < \hat{\delta}$),

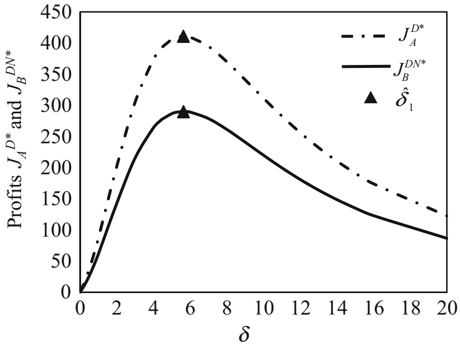


Fig. 1 Manufacturers A and B's equilibrium profits in natural loss multiplier of output (δ)

both manufacturers would increase their R&D effort levels with an increase in δ in order to compensate for their output loss. However, if the natural loss multiplier of output is too high (i.e., $\delta > \hat{\delta}$), increasing the manufacturers' R&D effort levels would raise their R&D costs too much. Hence, in this case, both manufacturers would become more conservative in their R&D effort in equilibrium.

Note that Proposition 1 does not specify how manufacturer i's equilibrium profit (J_i^{S*}) would change as δ increases. Our numerical experiments show that J_i^{S*} may either increase or decrease in δ. As an illustrative example, we use $\alpha_A = 5$, $c_A = 2$, $\alpha_B = 5$, $c_B = 3$, $\rho = 0.8$, $r = 1, a = 50$, $b = 0.5$, $\beta_A = 0.75$, $\gamma_A = 0.2$, $K_A = 1$ and vary δ. Figure 1 shows the numerical result.

As shown in Fig. 1, when δ is low, manufacturer i's profit increases with δ, but the reverse is true at the higher values of δ. Since both manufacturers' equilibrium outputs decrease with an increase in δ, the prices would increase as a result. When the increase in the price outweighs the increase in the output, the manufacturer's profit would increase, otherwise, it would decrease.

4.2.2 Discount rate

Next, we shall discuss the effect of the discount rate on the equilibrium R&D effort levels, outputs, and profits.

Proposition 2 *When ρ increases, we have*

(a) I_i^{S*} and q_i^{S*} ($i = A, B$) both decrease;

(b) if $\rho < \hat{\rho}$, then J_i^{S*} increases, otherwise, J_i^{S*} decreases,

where $\hat{\rho} = \frac{r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b}{\delta\tilde{c}_A(K_A)c_B}$.

The discounting rate here reflects the excess risk involved in the manufacturers' R&D process (Fibich et al. 2003). In the presence of discounting, part (a) of Proposition 2 indicates that both manufacturers tend to invest less in their R&D efforts and produce less with an increase in ρ, because manufacturers are facing higher risks. As shown in part (b) of Proposition 2, when the discount rate increases, both manufacturers' profits first increase then decrease.

4.2.3 Effectiveness of effort

In Proposition 3, we characterize the impact of effectiveness of manufacturer A's effort on the equilibrium R&D effort levels, outputs, and profits below.

Proposition 3 *If α_A or β_A increases, then $\tilde{\alpha}_A(K_A)$ increases, and we have*

(a) q_A^{D*} *increases and* q_B^{DN*} *decreases;*
(b) I_B^{DN*} *and* J_B^{DN*} *both decrease;*
(c) *if* $\tilde{\alpha}_A(K_A) < \hat{\alpha}_A(K_A)$, *then* I_A^{D*} *and* J_A^{D*} *increase; otherwise,* I_A^{D*} *and* J_A^{D*} *decrease, where* $\hat{\alpha}_A(K_A) = \sqrt{\frac{\tilde{c}_A(K_A)\alpha_B^2}{c_B} + \frac{(\rho+\delta)\delta\tilde{c}_A(K_A)}{r^2 b}}$.

When α_A or β_A increases, the effectiveness of manufacturer A's effort, i.e., $\tilde{\alpha}_A(K_A)$, increases, which means that the efficiency of manufacturer A's R&D effort in utilizing its online customer reviews improves. Part (a) of Proposition 3 indicates that when manufacturer A's R&D effectiveness increases, this manufacturer tends to produce more, because its demand increases in its product performance (e.g., functions and features). While the other manufacturer B produces less. As shown in part (b) of Proposition 3, when manufacturer A's R&D effectiveness improves, the other manufacturer B, as the competitor, would become more conservative in investing in its own R&D effort and achieve a lower profitability. Interestingly, part (c) of Proposition 3 shows that when manufacturer A improves its own R&D effectiveness, it may not necessarily benefit the manufacturer itself. When manufacturer A's R&D effectiveness is low (i.e., $\tilde{\alpha}_A(K_A) < \hat{\alpha}_A(K_A)$), manufacturer A has an incentive to increase its R&D effort level with an increase in $\tilde{\alpha}_A(K_A)$. In this case, manufacturer A's revenue gain outweighs the cost increase in its R&D effort, which means that there is an incentive for this manufacturer to explore and leverage more online customer reviews in NPD. However, if manufacturer A's R&D effectiveness is already high (i.e., $\tilde{\alpha}_A(K_A) > \hat{\alpha}_A(K_A)$), the decrease in the market price, due to the increase in the market aggregate output, outweighs the increase in its output q_A^{D*}, so manufacturer A's profit decreases.

4.2.4 Cost multiplier for R&D effort

In Proposition 4 below, we will discuss the effect of manufacturer A's cost multiplier for R&D effort on the equilibrium R&D effort levels, outputs, and profits.

Proposition 4 *If c_A increases or γ_A decreases, then $\tilde{c}_A(K_A)$ increases, and we have*

(*a*) q_A^{D*} *decreases and* q_B^{DN*} *increases;*
(*b*) I_A^{D*} *decreases and* I_B^{DN*} *increases;*
(*c*) J_B^{DN*} *increases;*
(*d*) *if* $\tilde{c}_A(K_A) < \hat{c}_A(K_A)$, *then* J_A^{D*} *increases, otherwise,* J_A^{D*} *decreases, where* $\hat{c}_A(K_A) = \frac{r^2\tilde{\alpha}_A(K_A)^2 c_B b}{r^2\alpha_B^2 b+(\rho+\delta)\delta c_B}$.

It follows directly from Eq. (6) that when c_A increases or γ_A decreases, the cost multiplier for manufacturer A's R&D effort, i.e., $\tilde{c}_A(K_A)$, increases. As manufacturer A's R&D effort becomes more expensive, manufacturer A naturally tends to produce less, while the other manufacturer (B) tends to produce more. Hence, part (a) of Proposition 4 echoes with our intuition. As shown in part (b) and (c) of Proposition 4, when manufacturer A's cost multiplier for its R&D effort increases, it is quite intuitive that manufacturer A would invest less effort in its R&D, while the other manufacturer (B) tends to invest more in its R&D effort and achieve a higher profitability. Interestingly, part (d) of Proposition 4 shows that when manufacturer A suffers from its own cost inflation in R&D effort, it may not necessarily hurt itself. The reason is that, an increase in $\tilde{c}_A(K_A)$ would reduce the market aggregate output in equilibrium, thus lead to an increase in the equilibrium market-clearing price. When manufacturer A's cost multiplier for R&D effort is low (i.e., $\tilde{c}_A(K_A) < \hat{c}_A(K_A)$), the increase in its price and the decrease in its R&D effort level would outweigh the decrease in output. Thus, manufacturer A's overall profit would increase in this case. However, if manufacturer A's cost multiplier for R&D effort is already high (i.e., $\tilde{c}_A(K_A) > \hat{c}_A(K_A)$), manufacturer A's R&D effort becomes too expensive which would hurt its profitability as $\tilde{c}_A(K_A)$ further increases.

4.2.5 Customer agility

As discussed in Sects. 4.2.3 and 4.2.4, the effect of effectiveness and cost multiplier on equilibrium results are significantly different when manufacturer A leverages online customer reviews in NPD. Hence, in this subsection, we will investigate the direct impact of customer agility (K_A) on the equilibrium R&D effort level, output, and profit. It follows directly from Eqs. (2) and (6) that effectiveness and cost multiplier for manufacturer A's R&D effort become constant when its customer agility is greater than a threshold, i.e., $K_A > \bar{K}_A$. In this case, the equilibrium outcomes become independent of K_A. Hence, here we focus on the more interesting case in which manufacturer A's customer agility is less than the threshold ($0 \le K_A < \bar{K}_A$), which includes the benchmark model ($K_A = 0$) shown in Sect. 3 where both manufacturers don't utilize online customer reviews in NPD. In other words, we can also analyze the difference of the manufacturers' equilibrium decisions between the benchmark model ($K_A = 0$) of Sect. 3 and the main model ($0 < K_A < \bar{K}_A$) of Sect. 4 in the following Proposition.

Proposition 5 *When K_A increases, we have*

(a) if $0 \le K_A \le \bar{K}_{A2}$, then q_A^{D*} decreases, I_B^{DN*}, q_B^{DN*}, and J_B^{DN*} increase where $\bar{K}_{A2} = \frac{\alpha_A - 2\beta_A c_A}{2\alpha_A\gamma_A + \beta_A}$;

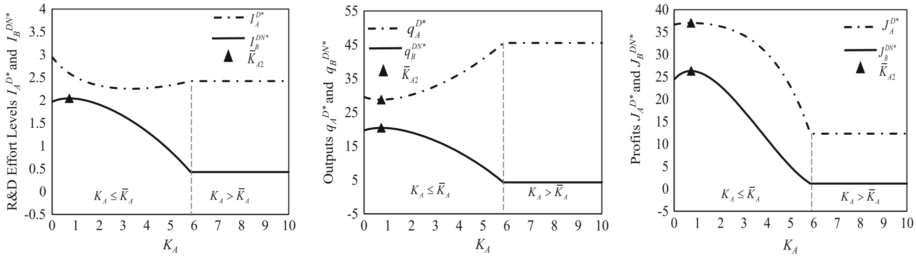
(b) if $K_A > \bar{K}_{A2}$, then q_A^{D*} increases, I_B^{DN*}, q_B^{DN*}, and J_B^{DN*} decrease.

It follows from Eq. (6) that the cost multiplier of manufacturer A's R&D effort first increases then decreases as K_A increases. Hence, as shown in Proposition 5, manufacturer A tends to produce less when $K_A \le \bar{K}_{A2}$ and produce more when $K_A > \bar{K}_{A2}$. Manufacturer B, as the competitor, would become more positive in investing in its R&D effort, and achieve a higher output and profitability as K_A increases when $K_A \le \bar{K}_{A2}$. When $K_A > \bar{K}_{A2}$, manufacturer B would invest less in R&D, produce less, and obtain a lower profit as K_A increases.

Note that Proposition 5 does not specify how manufacturer A's equilibrium R&D effort level $\left(I_A^{D*}\right)$ and equilibrium profit (J_A^{D*}) would change as K_A increases. Our numerical experiments show that both I_A^{D*} and J_A^{D*} either increase or decrease in K_A. To illustrate these results, we use the following numerical example with $\alpha_A = 5$, $c_A = 2$, $\alpha_B = 5$, $c_B = 3$, $\delta = 0.5$, $\rho = 0.8$, $r = 1$, $a = 100$, $b = 2$, $\beta_A = 0.75$, $\gamma_A = 0.2$. Figure 2 shows the results of numerical analysis.

As K_A increases, Eq. (2) implies that the effectiveness of manufacturer A's R&D effort, i.e., $\tilde{\alpha}_A(K_A)$, always improves, but Eq. (6) implies that the cost multiplier of manufacturer A's R&D effort, i.e., $\tilde{c}_A(K_A)$, first increases then decreases. Therefore, these two conflicting driving forces could incentivize manufacturer A either increase or decrease its R&D effort level. Additionally, when K_A increases, it means that manufacturer A utilizes online customer reviews more significantly in NPD, which may benefit or hurt manufacturer A's profitability. Therefore, there exists an optimal level of customer agility which would maximize manufacturer A's overall profit.

Since the benchmark model of Sect. 3 corresponds to $K_A = 0$ in the main model of Sect. 4, Proposition 1 and Fig. 2 also establish the difference of the manufacturers' equilibrium



(a) *A* and *B*'s R&D effort levels **(b)** *A* and *B*'s outputs **(c)** *A* and *B*'s profits

Fig. 2 Manufacturers *A* and *B*'s equilibrium changes in K_A

outcomes between the benchmark model and the main model. That is, when manufacturer *A* utilizes its online customer reviews in its NPD, both manufacturers' R&D effort levels, outputs, and profits in the main model could be higher or lower than those in the benchmark model depending on the specific values of customer agility (K_A). This result is driven by the fact that utilizing online customer reviews not only improves the effectiveness of the manufacturer's R&D effort but also increases its R&D cost.

4.3 Extension: product differentiation

In the previous sections, we assume that the manufacturers' products are homogenous. In this section, we relax this assumption and study an extended setting in which the products are heterogeneous with different prices and outputs. Specifically, we use a competition framework inspired by Singh and Vives (1984), Fanti and Gori (2012), where manufacturer *i* (*i* = *A, B*) faces an inverse demand function

$$p_i(t) = a - b\big(q_i(t) + Rq_j(t)\big) \tag{15}$$

where the parameter R measures the degree of product differentiation with $0 \le R \le 1$. The two boundary cases, $R = 0$ and $R = 1$, represent the maximum (independent products) and the minimum (homogeneous products) degree of differentiation, respectively.

Since the benchmark model in Sect. 3 is just a special case of the main model in Sect. 4, we here only follow the main model setup, i.e., manufacturer *A* utilizes online customer reviews, but manufacturer *B* does not. Hence, we have

$$\rho V_A^D(q_A) = \max_{I_A}\left[q_A p_A - \frac{\tilde{c}_A I_A(t)^2}{2} + V_{Aq_A}^{D\prime}\dot{q}_A\right] \tag{16}$$

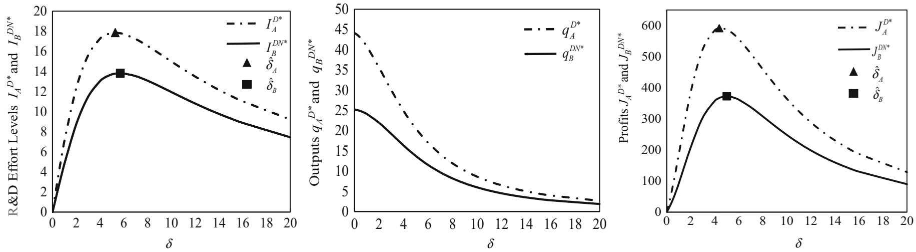
$$\rho V_B^{DN}(q_B) = \max_{I_B}\left[q_B p_B - \frac{c_B I_B(t)^2}{2} + V_{Bq_B}^{DN\prime}\dot{q}_B\right] \tag{17}$$

where $p_A = a - bq_A - bRq_B$ and $p_B = a - bq_B - bRq_A$. We obtain the equilibrium solutions to problems (16) and (17), formally presented in the following Lemma.

Lemma 3 *In equilibrium,*

(*a*) *respective R&D effort levels manufacturers A and B are*

$$I_A^{D*} = \frac{r\tilde{\alpha}_A(K_A)\delta a\big((\rho+\delta)\delta c_B + (1-R)r^2\tilde{\alpha}_A(K_A)^2 b\big)}{L},$$



(a) *A* and *B*'s R&D effort levels **(b)** *A* and *B*'s outputs **(c)** *A* and *B*'s profits

Fig. 3 Manufacturers *A* and *B*'s equilibrium changes in δ

$$I_B^{DN*} = \frac{r\alpha_B\delta a\big((\rho+\delta)\delta\tilde{c}_A(K_A) + (1-R)r^2\alpha_B^2 b\big)}{L};$$

(*b*) *respective outputs for manufacturers A and B are*

$$q_A^{D*} = \frac{r^2\tilde{\alpha}_A(K_A)^2 a\big((\rho+\delta)\delta c_B + (1-R)r^2\tilde{\alpha}_A(K_A)^2 b\big)}{L},$$
$$q_B^{DN*} = \frac{r^2\alpha_B^2 a\big((\rho+\delta)\delta\tilde{c}_A(K_A) + (1-R)r^2\alpha_B^2 b\big)}{L};$$

(*c*) *respective profits for manufacturers A and B are*

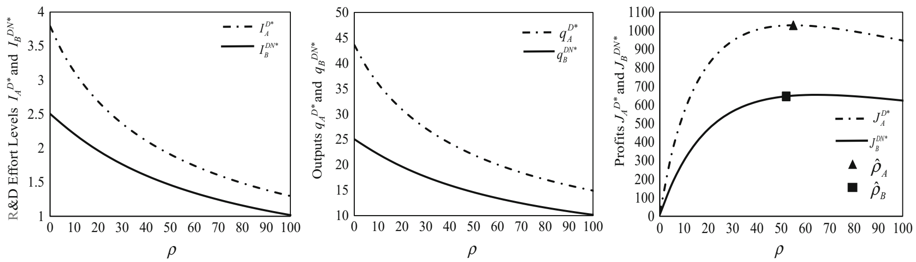
$$J_A^{D*} = \frac{(2\rho+\delta)\delta r^2\tilde{\alpha}_A(K_A)^2\tilde{c}_A(K_A)a^2\big((\rho+\delta)\delta c_B + (1-R)r^2\tilde{\alpha}_A(K_A)^2 b\big)^2}{2L^2},$$
$$J_B^{DN*} = \frac{(2\rho+\delta)\delta r^2\alpha_B^2 c_B a^2\big((\rho+\delta)\delta\tilde{c}_A(K_A) + (1-R)r^2\alpha_B^2 b\big)^2}{2L^2}.$$

where $L = r^2(\rho+\delta)\delta b\big(\tilde{\alpha}_A(K_A)^2 c_B + \alpha_B^2\tilde{c}_A(K_A)\big) + (\rho+\delta)^2\delta^2\tilde{c}_A(K_A)c_B + r^4\tilde{\alpha}_A(K_A)^2\alpha_B^2 \big(1-R^2\big)b^2$.

Similar to Sect. 4.2, we also explore how variations in the model parameters would affect the equilibrium outcomes of manufacturers when the manufacturers' products are differentiated. Due to the complexity of the equilibrium in Lemma 3, we are not able to conduct the sensitivity analysis on these parameters (δ, ρ, $\tilde{\alpha}_A(K_A)$, $\tilde{c}_A(K_A)$ and K_A) analytically. Our numerical experiments show that the effect of a change in any of the parameters on the equilibrium I_i^{S*}, q_i^{S*} and J_i^{S*} is similar to those of Propositions 1-5. As an illustrative example, we use $\alpha_A = 5$, $c_A = 2$, $\alpha_B = 5$, $c_B = 3$, $\delta = 0.5$, $\rho = 0.8$, $r = 1$, $a = 50$, $b = 0.5$, $\beta_A = 0.75$, $\gamma_A = 0.2$, $K_A = 1$, and $R = 0.5$ as the basis and vary one parameter at a time.

First, the effect of a change in the natural loss multiplier of output (δ) on the equilibrium R&D effort levels and outputs can be characterized in Fig. 3 by varying δ. We find that when δ increases, q_i^{S*} *(i = A, B)* decreases, I_i^{S*} and J_i^{S*} first increase and then decrease, which are the same as Proposition 1. The only difference is the specific values of the threshold $\hat{\delta}$ because of the product differentiation.

Second, the effect of a change in discount rate (ρ) on the equilibrium R&D effort levels and outputs can be characterized in Fig. 4 by varying ρ. We find that when ρ increases, q_i^{S*} and I_i^{S*} both decrease, J_i^{S*} first increases and then decreases, which are same as Proposition 2. The only difference is the values of the threshold $\hat{\rho}$.



(a) *A* and *B*'s R&D effort levels **(b)** *A* and *B*'s outputs **(c)** *A* and *B*'s profits

Fig. 4 Manufacturers *A* and *B*'s equilibrium outcome changes in ρ

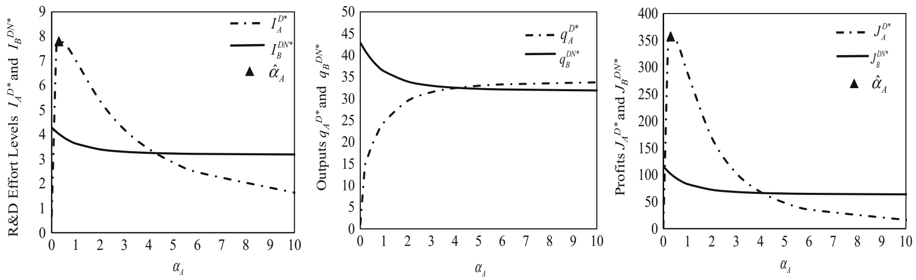


Fig. 5 Manufacturers *A* and *B*'s equilibrium changes in $\boldsymbol{\alpha_A}$

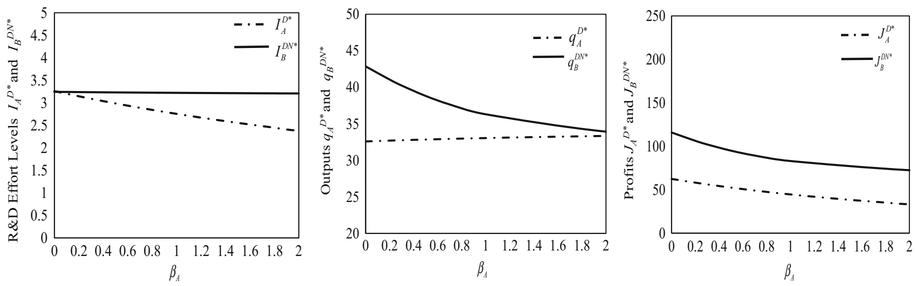


Fig. 6 Manufacturers *A* and *B*'s equilibrium changes in β_A

Third, the effect of a change in the effectiveness of effort on the equilibrium R&D effort levels and outputs can be characterized in Figs. 5 and 6 by varying α_A or β_A, repectively. We find Proposition 3 still hold except that the threshold values ($\hat{\alpha}_A$ and $\hat{\beta}_A$) change.

Fourth, the effect of a change in cost multiplier for R&D effort on the equilibrium R&D effort levels and outputs can be characterized in Figs. 7 and 8 by varying c_A or γ_A, repectively. We observe that Proposition 4 is still valid except that the threshold values ($\hat{c}_A$ and $\hat{\gamma}_A$) change.

Last but not the least, the effect of a change in customer agility on the equilibrium R&D effort levels and outputs can be characterized in Fig. 9 by varying K_A using $R = 0.97$ instead of $R = 0.5$ to ensure that the threshold $\bar{K}_{A2} > 0$ and $\bar{K}_A > 0$, as shown in Fig. 9. We find that Proposition 5 still holds here.

Note that when $R = 0.5$, then $\bar{K}_{A2} < 0$ and $\bar{K}_A < 0$, Proposition 5 (a) is an invalid case, only Proposition 5 (b) is valid. As shown in Fig. 10, as K_A increases, I_B^{DN*}, q_B^{DN*}, and

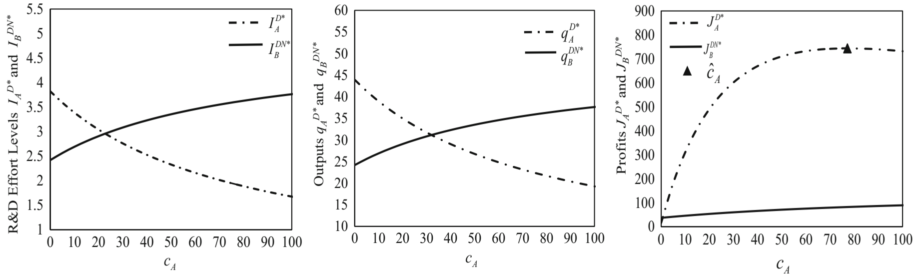


Fig. 7 Manufacturers A and B's equilibrium changes in c_A

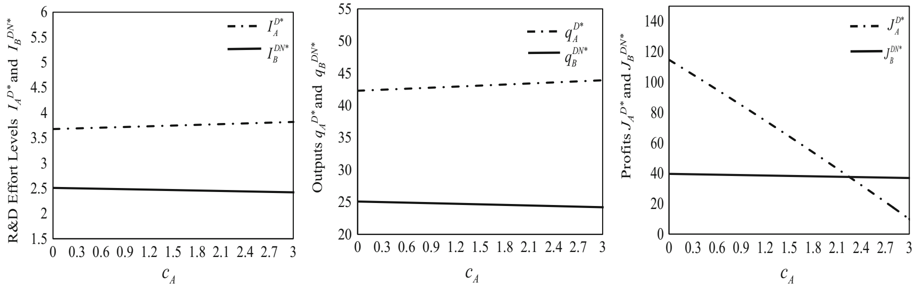
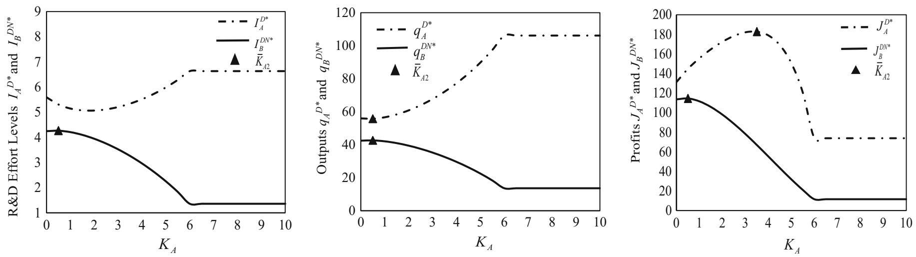
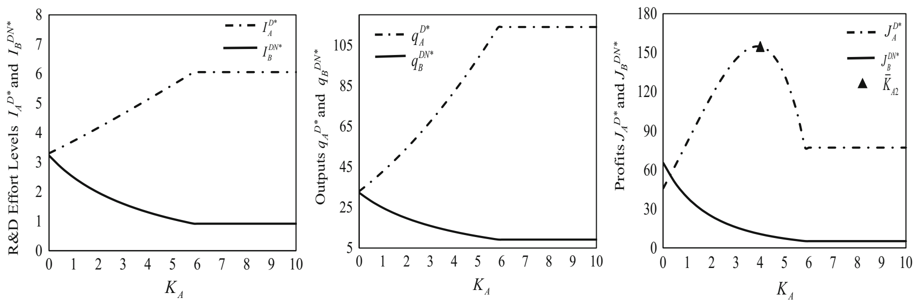


Fig. 8 Manufacturers A and B's equilibrium changes in γ_A



(a) A and B's R&D effort levels **(b)** A and B's outputs **(c)** A and B's profits

Fig. 9 Manufacturers A and B's equilibrium changes in K_A



(a) A and B's R&D effort levels **(b)** A and B's outputs **(c)** A and B's profits

Fig. 10 Manufacturers A and B's equilibrium changes in K_A

J_B^{DN*} decrease,I_A^{D*} and q_A^{D*} increase, J_A^{D*} first increase and then decrease. The results are consistent with Proposition 5 (b).

5 Conclusions and implications

5.1 Conclusions

To improve new product performance, firms progressively embrace online customer reviews to innovate their NPD process. We address two different NPD settings using a differential game approach in this study. First, we discuss the impact of online customer reviews on NPD by considering a duopoly setting where the products supplied by two manufacturers are homogenous. In the benchmark model, we propose a closed NPD setting, in which both manufacturers depend on their internal R&D effort to develop new products without leveraging online customer reviews. In our main model, we study an open NPD setting in which one manufacturer develops new products leveraging online customer reviews, but the other manufacturer only depends on their internal R&D. Second, we extend our main model by relaxing the product homogeneity assumption. We derive the equilibrium solutions analytically for all the models.

Based on the equilibrium solution, we draw a number of managerial insights which are consistent in both the main and the extended models. Our results indicate that when a manufacturer's effectiveness of its R&D effort by leveraging online customer reviews increases, or when a manufacture's cost multiplier of its R&D effort decreases, it always hurts the other manufacturer (the competitor), but it may not necessarily benefit this particular manufacturer. In addition, we show that when manufacturer A's customer agility increases, both manufacturers' profits either increase or decrease.

5.2 Implications for research and practice

In terms of theoretical contributions, our study extends the boundaries of product innovation theory and provides important evidence to support the role of online customer reviews on the customer-driven NPD approach. Prior customer-oriented innovation studies have focused primarily on utilizing demand-side knowledge from a small group of accessible customers (Nishikawa et al. 2013; Colazo 2014). In the era of big data, it is more convenient and easier for firms to collect online customer reviews and access a massive amount of general customers' opinions from a variety of websites including review platforms, online stores, and innovation communities (Zhou et al. 2018). Leveraging big data of online customer reviews in NPD enables firms to move away from product-focused innovation and to turn their attention to innovation around customers' preferences and needs. This is a paradigm-shifting customer involvement approach (Zhan et al. 2018), because massive online customer reviews could lead to a more comprehensive understanding of the market and thus inspire more novel ideas (Sambamurthy et al. 2003). However, the implementation of customer involvement approach utilizing online customer reviews also put considerable strain on firms such as IT infrastructure, analytical technique of unstructured big data, organizational culture, etc. We know little about how firms' performance would be affected by utilizing online customer reviews in NPD. Our study fulfills this gap to present several settings about this tension between the benefits and costs of utilizing online customer reviews in NPD. The findings may direct future studies to pay more attention to the negative side of utilizing online customer reviews and to encourage firms to balance customer involvement in NPD.

Our study also provides some managerial implications to practice. As illustrated in this paper, big data of online customer reviews nowadays plays an important role in firms' NPD. We intend to provide helpful insights into how online customer reviews can be used to enhance firms' customer involvement in developing new products. First, our results imply that firms should make sufficient investment in utilizing online customer reviews in their NPD processes, but at the same time, not to exceed a certain threshold since its costs might exceed its benefits. Second, our findings help managers to design more specific NPD strategies that match various internal and external conditions. For instance, firms need to execute different strategies in customer agility when the volume of online customer reviews or its NPD phrase is different. Finally, it is necessary for managers to identify customers' real needs from online customer reviews and to plan the customer involvement approach carefully to balance potential costs and expected benefits.

5.3 Limitations and future directions

There are several limitations in this study which need further exploration in the future. First, we assume only one manufacturer uses online customer reviews in NPD, while the other manufacturer does not. It would be interesting to explore firms' performance when both manufacturers leverage online customer reviews. Second, we propose a differential game approach here. It is worthwhile to verify if our conclusions and managerial insights still hold using other game methodology. Third, empirical studies are needed to test what factors of online customer reviews would influence firms' customer agility and performance in NPD. Finally, text mining approaches can be utilized to analyze massive online customer reviews in our future research.

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Appendix: Mathematical Proofs

Proof of Lemma 1 We differentiate $\rho V_i(q_i)$, given by Eq. (10) with respect to I_i, then equate them to zero to get

$$I_i(t) = \frac{\gamma\alpha_i V_{iq_i}^{'}}{c_i} \tag{18}$$

Substituting $I_i(t)$ into the HJB Eq. (10), assuming that the value functions $V_i(q_i)$ with respect to q_i is

$$V_i(q_i) = m_1 q_i + m_2 \tag{19}$$

where the parameters m_1,m_2 are constants. Substituting (18) and its first-order derivative of Eq. (19) with respect to q_i into (10), then we have:

$$\hat{I}_i(t) = \frac{\gamma\alpha_i(a - bQ)}{(\rho + \sigma)c_i} \tag{20}$$

where $Q = q_A^* + q_B^*$. Substituting (20) into (1), we have

$$q_i(t) = \frac{\gamma^2 \alpha_i^2 (a - bQ)}{(\rho + \sigma)\delta c_i} \tag{21}$$

Substituting (21) into (3), we can solve the optimal R&D effort levels and outputs of manufacturer i provided in part(c) and part(b) of Lemma 1. Then substituting them into (7), we can solve the optimal profit of manufacturer i, as shown in part(c) of Lemma 1. Therefore, in equilibrium the market-clearing price is

$$p^* = \frac{(\rho + \sigma)\delta c_A c_B a}{r^2 \alpha_A^2 c_B b + r^2 \alpha_B^2 c_A b + (\rho + \delta)\delta c_A c_B} \tag{22}$$

□

Proof of Lemma 2 The proof of Lemma 2 is similar to that of Lemma 1. Specifically, when manufacturer A utilizes online customer reviews, its effectiveness of effort changes from α_A to $\tilde{\alpha}_A(K_A)$, and its cost multiplier for R&D effort changes from c_A to $\tilde{c}_A(K_A)$. We differentiate $\rho V_A^D(q_A)$ and $\rho V_B^{DN}(q_B)$, given by (13) and (14), with respect to I_A and I_B, respectively, then equate them to zero to get

$$I_A(t) = \frac{\gamma \tilde{\alpha}_A(K_A) V_{Aq_A}^{D'}}{\tilde{c}_A(K_A)} \tag{23}$$

$$I_B(t) = \frac{\gamma \alpha_B V_{Bq_B}^{DN'}}{c_B} \tag{24}$$

Substituting $I_A(t)$ and $I_B(t)$ into the HJB Eqs. (13) and (14), respectively. Assuming that the value functions $V_A^D(q_A)$ and $V_B^{DN}(q_B)$ with respect to q_A and q_B, respectively, are

$$V_A^D(q_A) = n_1 q_A + n_2 \tag{25}$$

$$V_B^{DN}(q_B) = x_1 q_B + x_2 \tag{26}$$

where parameters n_1, n_2, x_1, x_2 are constants. Substituting (23) and its first-order derivative of (25) with respect to q_A into (13), and substituting (24) and its first-order derivative of (26) with respect to q_B into (14), we have

$$\hat{I}_A(t) = \frac{\gamma \tilde{\alpha}_A(K_A)(a - bQ)}{(\rho + \sigma)\tilde{c}_A(K_A)} \tag{27}$$

$$\hat{I}_B(t) = \frac{\gamma \alpha_B (a - bQ)}{(\rho + \sigma) c_B} \tag{28}$$

where $Q = q_A^* + q_B^*$.. Substituting (27) and (28) into (1), we have

$$q_A(t) = \frac{\gamma^2 \tilde{\alpha}_A(K_A)^2 (a - bQ)}{(\rho + \sigma)\delta \tilde{c}_A(K_A)} \tag{29}$$

$$q_B(t) = \frac{\gamma^2 \alpha_B^2 (a - bQ)}{(\rho + \sigma)\delta c_B} \tag{30}$$

Substituting (29) and (30) into (3), we can solve the optimal R&D effort levels and outputs of manufacturer i provided in part(c) and part(b) of Lemma 2. Then, substituting them into (11) and (12), we can solve the optimal profits of manufacturer i, as shown in part(c) of Lemma 2. Hence, the equilibrium market-clearing price is

$$p^* = \frac{(\rho+\sigma)\delta\tilde{c}_A(K_A)c_B a}{r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B} \tag{31}$$

□

Proof of Proposition 1 Taking the first derivative of Lemma 2(a) with respect to δ, we have

$$\frac{\partial I_A^{D*}}{\partial\delta} = \frac{r\tilde{\alpha}_A(K_A)c_B a\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b - \delta^2\tilde{c}_A(K_A)c_B\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2},$$

$$\frac{\partial I_B^{DN*}}{\partial\delta} = \frac{r\alpha_B\tilde{c}_A(K_A)a\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b - \delta^2\tilde{c}_A(K_A)c_B\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2}.$$

As δ increases, it follows directly that if $\delta < \sqrt{\frac{r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b}{\tilde{c}_A(K_A)c_B}}$, then I_A^{D*} and I_B^{DN*} increase, otherwise,I_A^{D*}andI_B^{DN*} decrease. And taking the first derivative of q_A^{D*} and q_B^{DN*} given in Lemma 2(b) with respect to δ, we have

$$\frac{\partial q_A^{D*}}{\partial\delta} = -\frac{r^2\tilde{\alpha}_A(K_A)^2 c_B a(\rho+2\delta)\tilde{c}_A(K_A)c_B}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0,$$

$$\frac{\partial q_B^{DN*}}{\partial\delta} = -\frac{r^2\alpha_B^2\tilde{c}_A(K_A)a(\rho+2\delta)\tilde{c}_A(K_A)c_B}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0.$$

Hence, as δ increases,q_A^{D*} and q_B^{DN*} decrease. □

Proof of Proposition 2 Taking the first derivative of I_A^{D*} and I_B^{DN*} given in Lemma 2(a) with respect to ρ, we have

$$\frac{\partial I_A^{D*}}{\partial\rho} = -\frac{r\tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)c_B^2 a\delta^2}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0,$$

$$\frac{\partial I_B^{DN*}}{\partial\rho} = -\frac{r\alpha_B\tilde{c}_A(K_A)^2 c_B a\delta^2}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0.$$

Hence, as ρ increases, I_A^{D*} and I_B^{DN*} decrease. Taking the first derivative of q_A^{D*} and q_B^{DN*} given in Lemma 2(b) with respect to ρ, we have

$$\frac{\partial q_A^{D*}}{\partial\rho} = -\frac{r^2\tilde{\alpha}_A(K_A)^2\tilde{c}_A(K_A)c_B^2 a\delta}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0,$$

$$\frac{\partial q_B^{DN*}}{\partial\rho} = -\frac{r^2\alpha_B^2\tilde{c}_A(K_A)^2 c_B a\delta}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0.$$

Therefore, as ρ increases, q_A^{D*} and q_B^{DN*} decrease. And taking the first derivative of J_A^{D*} and J_B^{DN*} given in Lemma 2(c) with respect to ρ, we have

$$\frac{\partial J_A^{D*}}{\partial\rho} = \frac{r^2\tilde{\alpha}_A(K_A)^2\tilde{c}_A(K_A)c_B^2 a^2\delta\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b - \rho\delta\tilde{c}_A(K_A)c_B\right)}{(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B)^3},$$

$$\frac{\partial J_B^{DN*}}{\partial\rho} = \frac{r^2\alpha_B^2 c_B\tilde{c}_A(K_A)^2 a^2\delta\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b - \rho\delta\tilde{c}_A(K_A)c_B\right)}{(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B)^3}$$

Then, it is straight forward to show that if $\rho < \frac{r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b}{\delta\tilde{c}_A(K_A)c_B}$, then J_A^{D*} and J_B^{DN*} increase as ρ increases, otherwise,J_A^{D*} and J_B^{DN*} decrease. □

Proof of Proposition 3 As shown in Lemma 2, $\tilde{\alpha}_A(K_A) = \alpha_A + \beta_A K_A$, so if α_A or β_A increases, then $\tilde{\alpha}_A(K_A)$ increases. Taking the first derivative of I_A^{D*} and I_B^{DN*} given in Lemma 2(a) with respect to $\tilde{\alpha}_A(K_A)$, we have

$$\frac{\partial I_A^{D*}}{\partial\tilde{\alpha}_A(K_A)} = \frac{rc_B\delta a\left(r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B - r^2\tilde{\alpha}_A(K_A)^2 c_B b\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2},$$

$$\frac{\partial I_B^{DN*}}{\partial\tilde{\alpha}_A(K_A)} = -\frac{2r^3\tilde{\alpha}_A(K_A)\alpha_B\tilde{c}_A(K_A)c_B\delta ab}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0.$$

It can then be easily verified that when $\tilde{\alpha}_A(K_A)$ increases, if $\tilde{\alpha}_A(K_A) < \frac{\tilde{c}_A(K_A)\alpha_B^2}{c_B} + \frac{(\rho+\delta)\delta\tilde{c}_A(K_A)}{r^2 b}$, then I_A^{D*} increases; otherwise,I_A^{D*} decreases. As $\tilde{\alpha}_A(K_A)$ increases, I_B^{DN*} decreases. And taking the first derivative of q_A^{D*} and q_B^{DN*}given in Lemma 2(b) with respect to $\tilde{\alpha}_A(K_A)$, we have

$$\frac{\partial q_A^{D*}}{\partial\tilde{\alpha}_A(K_A)} = \frac{2r^2\tilde{\alpha}_A(K_A)c_B a\left(r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} > 0,$$

$$\frac{\partial q_B^{DN*}}{\partial\tilde{\alpha}_A(K_A)} = -\frac{2r^4\tilde{\alpha}_A(K_A)\alpha_B^2\tilde{c}_A(K_A)c_B ab}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0.$$

It follows directly from Lemma 2(c) that we have

$$\frac{\partial J_A^{D*}}{\partial\tilde{\alpha}_A(K_A)} = \frac{(2\rho+\delta)\delta r^2\tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)c_B^2 a^2\left(r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B - r^2\tilde{\alpha}_A(K_A)^2 c_B b\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^3},$$

$$\frac{\partial J_B^{DN*}}{\partial\tilde{\alpha}_A(K_A)} = -\frac{2(2\rho+\delta)\delta r^4\tilde{\alpha}_A(K_A)\alpha_B^2 c_B^2\tilde{c}_A(K_A)^2 a^2 b}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^3} < 0$$

After some algebra, we can show that when $\tilde{\alpha}_A(K_A)$ increases, if $\tilde{\alpha}_A(K_A) < \frac{\tilde{c}_A(K_A)\alpha_B^2}{c_B} + \frac{(\rho+\delta)\delta\tilde{c}_A(K_A)}{r^2 b}$, then J_A^{D*} increases; otherwise, J_A^{D*} decreases. And as $\tilde{\alpha}_A(K_A)$ increases, J_B^{DN*} decreases. □

Proof of Proposition 4 As shown in Lemma 2, $\tilde{c}_A(K_i) = c_A + K_A - \gamma_A K_A^2$, so if c_A increases or γ_A decreases, then $\tilde{c}_A(K_A)$ increases. It follows directly from Lemma 2(a) that we have

$$\frac{\partial I_A^{D*}}{\partial\tilde{c}_A(K_A)} = -\frac{r\tilde{\alpha}_A(K_A)c_B\delta a\left(r^2\alpha_B^2 b + (\rho+\delta)\delta c_B\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0,$$

$$\frac{\partial I_B^{DN*}}{\partial\tilde{c}_A(K_A)} = \frac{r^3\tilde{\alpha}_A(K_A)\alpha_B c_B\delta ab}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} > 0.$$

Hence, we show Proposition 4(a) holds. After some algebra, Lemma 2(b) directly implies that

$$\frac{\partial q_A^{D*}}{\partial\tilde{c}_A(K_A)} = -\frac{r^2\tilde{\alpha}_A(K_A)^2 c_B a\left(r^2\alpha_B^2 b + (\rho+\delta)\delta c_B\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} < 0,$$

$$\frac{\partial q_B^{DN*}}{\partial \tilde{c}_A(K_A)} = \frac{r^4\tilde{\alpha}_A(K_A)^2\alpha_B^2 c_B ab}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2} > 0.$$

Therefore, Proposition 4(b) holds. It follows directly from Lemma 2(c) that we have

$$\frac{\partial J_A^{D*}}{\partial \tilde{c}_A(K_A)} = \frac{(2\rho+\delta)\delta r^4\tilde{\alpha}_A(K_A)^4 c_B^3 a^2\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b - r^2\alpha_B^2\tilde{c}_A(K_A)b - (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)}{2\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^3},$$

$$\frac{\partial J_B^{DN*}}{\partial \tilde{c}_A(K_A)} = \frac{2(2\rho+\delta)\delta r^4\tilde{\alpha}_A(K_A)^2\alpha_B^2 c_B^2\tilde{c}_A(K_A)a^2 b}{(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B)^3} > 0$$

After some algebra, we can show that when $\tilde{c}_A(K_A)$ increases, if $\tilde{c}_A(K_A) < \frac{r^2\tilde{\alpha}_A(K_A)^2 c_B b}{r^2\alpha_B^2 b+(\rho+\delta)\delta c_B}$, then J_A^{D*} increases; otherwise, J_A^{D*} decreases. Hence, Proposition 4 (c)-(d) hold. □

Proof of Proposition 5 Taking the first derivative of I_B^{DN*} in Lemma 2(a) with respect to K_A, we have

$$\frac{\partial I_B^{DN*}}{\partial K_A} = -\frac{r^3\tilde{\alpha}_A(K_A)\alpha_B c_B\delta ab\left(2\tilde{\alpha}_A(K_A)'\tilde{c}_A(K_A) - \tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)'\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2}.$$

And taking the first derivative of q_A^{D*} and q_B^{DN*} give in Lemma 2(b) with respect to K_A, we have

$$\frac{\partial q_A^{D*}}{\partial K_A} = \frac{r^2\tilde{\alpha}_A(K_A)c_B a\left(r^2\alpha_B^2 b + (\rho+\delta)\delta c_B\right)\left(2\tilde{\alpha}_A(K_A)'\tilde{c}_A(K_A) - \tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)'\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2},$$

$$\frac{\partial q_B^{DN*}}{\partial K_A} = -\frac{r^4\tilde{\alpha}_A(K_A)\alpha_B^2 c_B ab\left(2\tilde{\alpha}_A(K_A)'\tilde{c}_A(K_A) - \tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)'\right)}{\left(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B\right)^2}.$$

Next, taking the first derivative of J_B^{DN*} in Lemma 2(c) with respect to K_A, then we have

$$\frac{\partial J_B^{DN*}}{\partial K_A} = -\frac{(2\rho+\delta)\delta r^4\tilde{\alpha}_A(K_A)\alpha_B^2 c_B^2\tilde{c}_A(K_A)a^2 b\left(2\tilde{\alpha}_A(K_A)'\tilde{c}_A(K_A) - \tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)'\right)}{(r^2\tilde{\alpha}_A(K_A)^2 c_B b + r^2\alpha_B^2\tilde{c}_A(K_A)b + (\rho+\delta)\delta\tilde{c}_A(K_A)c_B)^3}.$$

where $2\tilde{\alpha}_A(K_A)'\tilde{c}_A(K_A) - \tilde{\alpha}_A(K_A)\tilde{c}_A(K_A)' = 2\beta_A c_A - \alpha_A + (\beta_A + 2\alpha_A c_A)K_A$. We find that when K_A increases, if $0 \le K_A \le \bar{K}_{A2}$, then q_A^{D*} decreases,I_B^{DN*},q_B^{DN*}, and J_B^{DN*} increase; otherwise,q_A^{D*} increases,I_B^{DN*}, q_B^{DN*}, and J_B^{DN*} decrease. □

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