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How Does Competition Affect High-Tech Firms' Time-to-Market Decision?

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Abstract

In fast-paced industries such as high-tech industry, time-to-market is one of the key strategic decisions to be made. With competition, firms not only need to consider market readiness but also should try to optimize new product launch timing by balancing the tradeoff between advantages and disadvantages of becoming a pioneer. Would a firm compete head-to-head by accelerating the project, or wait and then follow-up quickly after uncertainties clear up? The current paper illustrates how we can examine this issue by introducing an empirical modeling approach based on duration analysis. Specifically, a hazard function approach is taken to analyze time-based competition, and the proposed model demonstrates for the first time in the marketing literature the possibility to capture the relational structure between two competing hazard rates. Though the empirical question could not be answered due to data availability, a Monte-Carlo simulation study assures the usefulness of the model.

Keywords: hazard model, time-to-market, R&D race, competition

INTRODUCTION

Time-to-market is becoming an increasingly important strategic decision in fast-moving high-tech industries such as computers and electronic devices. Being first to market has long been one of the key commitments that many successful

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technology-based companies such as Du Pont, 3M, Hewlett Packard and Intel have made. However, after observing failure of several “great” firms(e.g. IBM, Apple, Xerox, Digital, etc.) in the last decade or so, high-tech firms have come to realize that being first does not guarantee success. In fact, the firms need to *optimally* choose time-to-market strategy in a way that maximizes the market premium from early(or not too late) entry while minimizing potential costs of entering an immature market.

Time-to-market decision gets even more complicated when competition is involved. That is, firms not only need to consider market readiness, but they also should try to well balance the tradeoff between advantages and disadvantages of becoming a pioneer. However, despite the vast literature on whether it is better to be a pioneer or a fast follower, marketing scholars don’t seem to have reached a clear conclusion. The main objective of the current paper is to illustrate how we can examine this issue using hazard function approach.

Recently, Datar et al.(1997a) defined three critical stages of the product development process(concept generation, prototype completion, and volume production) and examined the lead-time advantages in those stages. Their main findings are as follows. First, the lead-time advantage exists at each stage, the benefit being greatest at volume production stage. Second, the lead-time threshold is present in both the concept generation and volume production stage, i.e. no market share gain of first-mover is observed if a competitor catches up within threshold. Datar et al. (1997b) also examined, in another paper, the impact of R&D strategies on time-to-market for the latter two stages(prototype completion, volume production) using a proportional hazard function model. They tested several hypotheses about which factors influence the time until the completion of each of the two stages. The factors they considered include the number of potential customers, product design expenditures, engineering expenditures, and the number of concurrent projects.

The current study extends Datar et al.(1997b)’s research in the sense that it incorporates into the model the relational structure of competing firms’ new product launch hazard rates. Specifically, Datar et al.(1997b) assumed that the time-to-market, whether it is prototype release or volume production, depends only on the firm's *own* capabilities and efforts, thereby ignoring one of key characteristics of high-tech industry, i.e. competition. Their assumption may hold if becoming first in introducing a new product is the only goal that a firm may pursue, since they just need to work hard without worrying about the competitor's time-based strategy. However, a firm may well be responsive to the competitor's behavior if it wants to optimize their new product launch timing by achieving first-mover advantages while minimizing costs of head-to-head competition.

RESEARCH QUESTION

Among practical managers as well as academicians, it is now well accepted that there exists a tradeoff between market preemption(so called "first-mover advantage") vs. minimizing market development costs and uncertainty("late-mover advantage"). Therefore, a firm would want to optimally choose its market entry timing to maximize profit by avoiding possible substantial costs from both immature entry and missed opportunity. In high-tech industries such as telecommunication devices and computer software, the timing decision becomes much more difficult due to high uncertainty[1)] and relatively high switching cost. High cost of switching(e.g. operating system such as Windows) provides a firm with more incentive to become a technology leader since it can gain more valuable customers and easily maintain their loyalty by making it harder to switch to another product. We can easily find examples of firms that have locked up the competition by "design-in" victories.

On the other hand, high uncertainty in both market and technology not only makes firms hesitate to become a first-mover but also tend to avoid head-to-head competition. Due to the fact that the price competition is severe and that product differentiation is relatively easy,[2)] high-tech firms feel more

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1) In their paper on high-tech marketing, Moriarty and Kosnik (1989) characterize the world of high technology by high levels of both *market uncertainty* and *technological uncertainty*.

2) There are two factors that facilitate differentiation of high-tech products. First is fast-improving technology, which enables to develop products of

inclined to become “unique” in their products than others do. In addition, it is very critical in high-tech industry to become a leader in a well-chosen segment rather than compete in an attractive-to-all market(Moore 1991). Therefore, the competitor’s product launch schedule(or its pattern) is an important factor a firm should consider when making its own timing decision. In sum, the timing of new product launch should always be considered in relation to those of the rival firms. And thus, the answer to the following question may be meaningful to both academicians and practitioners.

Q: “Given the information on the imminence(hazard rate) of rival firm’s new product introduction, would greater likelihood (hazard rate) of rival product’s launch make a firm accelerate or decelerate the launch of its new product?”

Clarification of the above question follows. First, the two competing firms are assumed to be comparable in size and market power. So, they are not like Microsoft and Netscape. Second, this question is not about the equilibrium behavior of firms. Rather, the focus of this paper is on a firm’s *responsive* behavior to the marginal probability of rival firm’s new product launch. Thirdly, I do not argue that the above question has a universal answer. Instead, industry-specific and firm-specific factors may well be taken into account. That is, our empirical results may not be generalized to other industries. The main purpose of this paper lies in illustrating how firms could utilize the proposed model with their own data. Here are the two competing propositions on the above question.

Proposition 1: You should speed up, because you can attain “pioneering advantage” if you become the first to market, or at least you will be more likely to be within “lead-time threshold.”

Proposition 2: Slow down if the competitor’s product launch is imminent, since it seems unwise to compete head-to-head in this industry. You would be better off by waiting until the market

better quality with better technology in relatively short time periods. The second factor is that high-tech products generally have more flexibility forimprovement due to many functions and features.

uncertainties clear up and differentiating your product from the competitor's.

Note that the answer to the question, i.e. the time-to-market strategy of a firm, relies on whether the driving forces of the first proposition dominate those of the second or vice versa. For example, if the first-mover advantages prevail, firms would want to become a pioneer by all means. Under that circumstance, if a firm knew that its competitor is putting the final touches to their product, the felt pressure to the firm would be so high that it would try to do its best to expedite market entry. Proposition 1 seems more valid in this case. On the contrary, if the pioneering advantage is more than offset by the potential costs of market competition, a firm would tend to rather avoid competition and fine-tune its new product.

The current research does not intend to give a normative answer to the question. Rather, with real industry data, it aims to answer the above hypothetical question by empirically determining how the competing firms' hazard rates for new product introduction are related.

MODEL

Hazard Function Approach

Jain and Vilcassim(1991) first introduced the hazard function approach to marketing field as an alternative method to stochastic models for analyzing time-related variables. Helsen and Schmittlein(1993) then demonstrated how effective hazard rate models are in handling peculiar aspects of duration times. Since then, we've seen the hazard function approach settling down as a standard tool for analysis of duration times such as household interpurchase times.

Though there are a variety of contexts where a hazard rate model can be effectively used, this is one of the first studies in marketing that addresses new product launch competition in high-tech marketing context. Further, the current paper is differentiated from others in that it focuses on the relational structure of two competing hazards, instead of assuming independent hazard rates(cf. Gonul and Srinivasan 1993).

In biometrics and econometrics literature, a reduced-form approach assuming an ad hoc bivariate distribution has been often used to study two interdependent hazard rates. Alternatively, a recent paper by Fallick and Ryu(1997) takes account of structural correlation between two competing hazards. They examined lay-off unemployment spell and showed a negative correlation between the hazard rate of job recall from previous employer and that of new job acceptance. The current paper mostly follows their empirical modeling approach with the exception that we assume the two hazard rates(i.e. new product launch hazard rates of competing firms) to be influencing each other in both directions. Fallick and Ryu(1997) assumed that one hazard rate(i.e. recall hazard) is exogenously given and that the other hazard rate(i.e. new job) is affected by it, but not the other direction, which seems to hold only in their specific application context.

Assumptions

Several assumptions are made to simplify the analysis. First, we assume that there are *two firms* competing in a product market who develop and market their own products. The two firms are assumed to be comparable in size, R&D capability, and in other measures of market power. Second, we also assume that the two rival firms have *limited knowledge* about the competitor's new product development processes, including schedule. That is, a firm is thought of as having no specific information about the competitor's new product development project such as the amount of engineering expenditures. However, we suppose that the firms know from experience their competitor's *average* behavior in the sense that they know the probability of its competitor's introducing a new product *with the average level of efforts*. In other words, firms are not able to predict when the competitor will launch new products(or release prototypes) due to lack of knowledge about a certain project. However, from past experience, a firm has a general knowledge of how much time and money the other firm typically invests for a NPD project, and of the *conditional* probability of new product launch at the average level of investment. Technically speaking, we assume that a firm knows a *baseline hazard rate* of a competitor's new product launch, and the typical pattern of R&D spending and other variables that influence("shift") the hazard rate. Combining a baseline hazard rate with *time-varying* explanatory variables such as typical R&D expenditure, a firm would have a general sense of the competitor's "normal" hazard rate of new product launch.

Finally, in order to focus on the timing issue, other supply-side factors such as quality are not considered in the model. Future research may well endogenously determine the quality level of a product since developing high-quality products generally needs more time and expenditures.

Time Durations

We define below the two competing time durations of interest (T1 and T2).

T1 = time between concept introduction and new product launch by firm A.[3)]

T2 = time between concept introduction and new product launch by the rival firm(firm B).

Depending on the researcher's interest, the new product launch timing can be measured in two different ways. One is the point of *prototype release*, and the other is the *completion of volume production*. We take the first approach, i.e. prototype release. In the context of high-tech marketing, prototype release timing may seem more interesting to researchers than volume production, since the former is more strategically chosen by firms. Take software development as an example. A firm has more flexibility in terms of timing of beta-version release, which has potential flaws("bugs"), than the volume production, which happens after a strong commitment for the product has been made.

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3) The duration of interest can also be the duration from technology availability (within or outside industry) until new product launch. However, we define the duration as that from concept introduction until prototype release since it is not easy to determine when a new technology becomes available in most cases.

Model Specification

A general form of mixed proportional hazard rate function is the following.

$$h(t) = r_0(t) \cdot \exp(X_t \beta + e_t)$$

The term $r_0(t)$ represents the baseline hazard, and $\exp(X_i\beta)$ is the proportionality term(i.e. observed heterogeneity), and the final term "e_t" accounts for unobserved heterogeneity. Time-varying explanatory variables (X_t) in our model may include number of potential customers, engineering expenditure of the focal firm, and so on.

As we explained in the previous section, companies are assumed to have a general knowledge about the rival company's average behavior and thus normal(or "regular") hazard rate of new product introduction. Taking that into consideration, we can rewrite the above equation as the following.

$$\begin{aligned} h(t) &= r_0(t) \cdot \exp(X_t \beta + e_t) \\ &= r_0(t) \cdot \exp(\overline{X}_t \beta) \cdot \exp[(X_t - \overline{X}_t)\beta + e_t] \\ &= r(t) \cdot \exp[(X_t - \overline{X}_t)\beta + e_t] \end{aligned}$$

The notation $r(t)$ represents "normal" hazard rate, which implies the new product launch hazard rate at, say, typical investment size.

To reflect the relational structure of hazard rates, we explicitly model a firm's new product introduction hazard rate as a function of the competitor's hazard rate. That is,

$$\begin{aligned} & h(t) = \\ & r_i(t) \cdot \exp(X_{it} - \overline{X}_{ti})\beta + \alpha \ln r_j(t) + e_{it}], \quad t < T_j \\ & r_i(t) \cdot \exp[(X_{it} - \overline{X}_{it})\beta + \gamma + \delta(t - T_j) + e_{it}], \quad t \geq T_j \end{aligned}$$

where i, j = 1 or 2, and T_j being the time of new product launch by firm j. Note that we are assuming that the parameters α, β, γ, δ do not depend on the index i. This is a realistic assumption if we analyze competition between firms of comparable size and power. However, we can easily relax this assumption by simply introducing more parameters.

More importantly, note that there are two different cases: $t < T_j$ and $t \geq T_j$. In the latter case where a competitive firm has already introduced a new product ($t \geq T_j$), the follower firm's new product launch time is supposed to be affected in proportion to the length of the lead-time ($t - T_j$). In other words, after a firm observes the competitor launch a new product, it would be motivated to expedite the development so that it may catch up the pioneer firm within threshold. And the pressure would get higher and higher as the lead-time increases. A positive value of δ captures the effect.

On the other hand, in the first case where a firm hasn't seen the competitor's product ($t < T_j$), it is not clear whether it would increase or decrease the R&D pace. As previously discussed, a firm may either want to speed up to become a pioneer (Proposition 1) or wait and slow down until they can see what the competitor has done(Proposition 2). Therefore, in the above model specification, α captures the relational structure between the two hazard rates. That is, $\alpha > 0$ would support proposition 1, whereas $\alpha < 0$ would claim that proposition 2 is more appropriate.

It might be questioned whether we should model the hazard rate as a function of competitor's hazard rate $h(t)$ itself or only of "normal" hazard $r(t)$. As explained before, $r(t)$ symbolizes *limited* information about the competitor whereas $h(t)$ would represent the *full* information scenario where the focal firm has detailed knowledge about its competitor. In this sense, $r(t)$ provides more conservative modeling approach. That is, showing that a firm's launch timing is affected even by a typical(average) pattern of the rival firm's behavior will be sufficient to argue that the two firms' timing decisions *with more knowledge*(which is often the case in reality) would be correlated more heavily.

ESTIMATION

Baseline hazard function

The hazard function for firm A can be rewritten as follows.

$$
\begin{aligned}
h_1(t) &= r_1(t) \cdot \exp[(X_{1t} - \overline{X}_{1t})\beta + \alpha \cdot \ln r_2(t) + e_{1t}] \\
&= r_{10}(t) \cdot \exp(\overline{X}_{1t}\beta) \cdot \exp[(X_{1t} - \overline{X}_{1t})\beta + \alpha \cdot \ln(r_{20}(t) \cdot \exp(\overline{X}_{2t}\beta)) \\
&\quad + e_{1t}] \\
&= r_{10}(t) \cdot \exp[X_{1t}\beta + \alpha \cdot (\ln r_{20}(t) + \overline{X}_{2t}\beta) + e_{1t}] \\
&= \exp[\ln r_{10}(t) + X_{1t}\beta + \alpha \cdot (\ln r_{20}(t) + \overline{X}_{2t}\beta) + e_{1t}], \quad t < T_2 \\
h_1(t) &= \exp[\ln r_{10}(t) + X_{1t}\beta + \gamma + \delta(t - T_2) + e_{1t}], \quad t \geq T_2
\end{aligned}
$$

where $r_{10}(t)$ and $r_{20}(t)$ are baseline hazard functions for firms A and B, respectively. To estimate the parameters, we should first determine which parametric model to use for baseline hazard function.

The econometrics literature contains a number of choices for hazard functions, including exponential, Weibull, log-normal, log-logistic, gamma and many others. With no prior knowledge about the functional shape, a step function may also be considered. However, in terms of parsimony, Weibull distribution can be thought of as a strong candidate. Weibull distribution also has a nice property that it is *monotonically* increasing or decreasing depending on the parameter, which seems plausible in our application context.[4)]

The hazard function of Weibull distribution is the following.[5)]

$$r_0(t) = \phi\lambda^{\phi} t^{\phi-1}$$

or

$$\ln r_0(t) = a + b \ln t$$

4) In terms of parsimony, exponential distribution might be the best. However, it assumes *constant* hazard rates across time, which is unrealistic.

5) The Weibull hazard function monotonically increases if $\phi > 1$ (or $b > 0$), and decreases when $\phi < 1$ (or $b < 0$).

where $b = \phi - 1$. Therefore, by adopting Weibull distribution as the baseline hazard function, we have now six parameters to estimate.

Maximum Likelihood Estimation

Maximum likelihood method is used for model estimation. Suppose that the firms A and B compete in the same product market and that the firm A launched the new product at t_1 (i.e. $T_1 = t_1$) and the firm B at t_2 (i.e. $T_2 = t_2$). Since the duration data are *interval censored*,[6)] the joint probability that the two firms launch the new products at t_1 and t_2 will be expressed as $P(t_1 - 1 < T_1 \le t_1,\ t_2 - 1 < T_2 \le t_2)$. Recall that T_1 and T_2 are related through the two firms' competitive behavior, and are reflected in their new product launch hazard functions. Since our model fully reflects the relational structure in the specification of $r_1(t)$ and $r_2(t)$, it is not unreasonable to assume that T_1 and T_2 are independent given $r_1(t)$ and $r_2(t)$. Therefore, $P(t_1 - 1 < T_1 \le t_1,\ t_2 - 1 < T_2 \le t_2) = P(t_1 - 1 < T_1 \le t_1)\ P(t_2 - 1 < T_2 \le t_2)$. This probability is the likelihood contribution of each observation(project). To compute these probabilities, we need to know which of the following cases each observation belongs to.

(1) Case 1: Firm A introduces a new product first, i.e. $t_1 < t2$.
(2) Case 2: Firm B introduces a new product first, i.e. $t_1 > t2$.
(3) Case 3: Firm A and B introduce new products in the same period, i.e. $t_1 = t_2$.

The likelihood contribution of each observation is computed from the following formula using corresponding hazard functions.

$$\begin{aligned} P(t_i - 1 < T_i \le t_i) &= S(t_i - 1) - S(t_i) \\ &= \exp[-R(t_i - 1) - \exp[-R(t_i)], \quad i = 1, 2 \end{aligned}$$

6) An observation is *interval censored* if all you know about T is that $a < T < b$, for some values of a and b. For duration data, this sort of censoring is likely to occur when observations are made at infrequent intervals (e.g. quarterly) and there is no way to get retrospective information on the exact timing of events.

where $S(t)$ is the *survival function*, and $R(t)$ is the *integrated hazard rates*. $R(t)$ is computed as the following.

$$R(t_1) = \sum_{u=1}^{t_1} h_1(u) = \sum_{u=1}^{t_1} \exp[\ln r_{10}(u) + X_{1u}\beta + \alpha(\ln r_{20}(u) + \overline{X}_{2u}\beta) + e_{1u}],$$
$$t_1 < T_2$$
$$R(t_1) = \sum_{u=1}^{t_1} h_1(u) = \sum_{u=1}^{T_2} \exp[\ln r_{10}(u) + X_{1u}\beta + \alpha(\ln r_{20}(u) + \overline{X}_{2u}\beta) + e_{1u}]$$
$$+ \sum_{u=T_2+1}^{t_1} \exp[\ln r_{10}(u) + X_{1u}\beta + \gamma + \delta(u - T_2) + e_{1u}], \quad t_1 > T_2$$

$$R(t_2) = \sum_{u=1}^{t_2} h_2(u) = \sum_{u=1}^{t_2} \exp[\ln r_{20}(u) + X_{2u}\beta + \alpha(\ln r_{10}(u) + \overline{X}_{1u}\beta) + e_{2u}],$$
$$t_2 < T_1$$
$$R(t_2) = \sum_{u=1}^{t_2} h_2(u) = \sum_{u=1}^{T_1} \exp[\ln r_{20}(u) + X_{2u}\beta + \alpha(\ln r_{10}(u) + \overline{X}_{1u}\beta) + e_{2u}]$$
$$+ \sum_{u=T_1+1}^{t_2} \exp[\ln r_{20}(u) + X_{2u}\beta + \gamma + \delta(u - T_1) + e_{2u}], \quad t_2 > T_1$$

For unobserved heterogeneity, we assume a bivariate discrete distribution proposed by Heckman and Singer(1984). That is, (e_{1t}, e_{2t}) follows a discrete bivariate distribution which takes value of (e_{1ti}, e_{2tj}) with probability p_{ij}, $i = 1, \cdots, I$ and $j = 1, \cdots, J$. Here, I and J denote the number of support points for e_{1t} and e_{2t}. Since $0 \le p_{ij} \le 1$, for computational convenience, it is better to use unbounded parameter q_{ij} to represent p_{ij}'s as follows.

$$P_{ij} = \frac{e^{q_{ij}}}{\sum_{j=1}^{I}\sum_{j=1}^{J} e^{q_{ij}}}, \quad i = 1, \text{L}, I, \quad J = 1, \text{L}, J$$

By taking the expectation with regard to e_{1t} and e_{2t}, we can derive *unconditional* probabilities. That is,

$$P(t-1 < T_r \le t) = E[P(t-1 < T_i \le t \mid e_{1t},\ e_{2t})]$$
$$= \sum_{i=1}^{I}\sum_{j=1}^{J} P_{ij} \cdot P(t-1 < T_i \le t \mid e_{1ti},\ e_{2tj}),\ \ r = 1, 2.$$

MONTE-CARLO SIMULATION

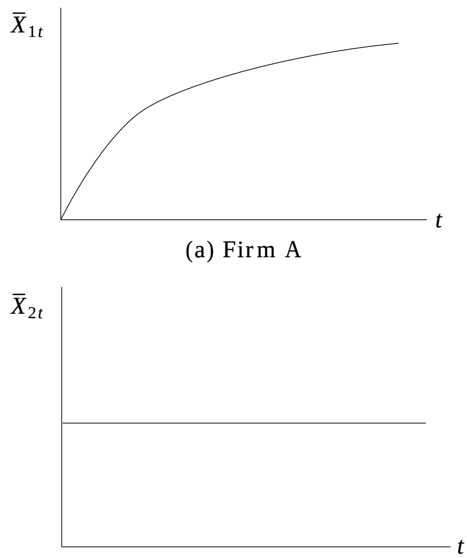
To examine how well the proposed method could capture the structural relationship between hazard rates, an exploratory Monte-Carlo simulation study was carried out.

Assumptions

For expository purpose, a few simplifying assumptions are made. First, we assume away the *unobserved* heterogeneity across NPD projects as well as across firms. That is, $e_{1t} = e_{2t} = 0$ for all t. For observed heterogeneity, we consider only one explanatory variable (X_{it}) and its typical pattern over time ($\overline{X}_{it}$). Second, it is assumed that a new product development project of each firm starts in the same period. That is, the starting points of the two firms' NPD durations are synchronized. Under limited information, this assumption doesn't seem to be too unrealistic because a firm would tend to assume that the rival firm might also have begun the development about the same time. Finally, we assume that the parameters (α, β, γ, δ) are the same between the two firms. The true parameter values are: $\alpha = 0.2$ and -0.5, $\beta = 0.5$, $\gamma = 0$, $\delta = 0.3$. As discussed in model specification, the sign of parameter α would suggest which proposition is empirically supported. Since we don't have real data, the current simulation study covers both scenarios. As for parameter δ, we believe that it should always be positive.

Procedures

For each of the two different scenarios, $\alpha > 0$ and $\alpha < 0$, 100 observations are generated according to the following procedure. First, typical patterns of explanatory variable X_{it} (e.g. R&D expenditure) over time are assumed for firms A and B. (From now on, let us use "R&D expenditure" for the explanatory



(a) Firm A

(b) Firm B

Figure 1. Patterns of explanatory variable X_{it}

variable in order to facilitate exposition.) To eliminate the possible multicollinearity problem, the two firms are supposed to have different R&D spending patterns such that firm A increases R&D expenditure over time and firm B tends to spend the same level of amount over time. However, the size of the total spending is set to be comparable between the two companies. The figure below shows the general pattern of R&D spending for the two firms.

Secondly, the actual R&D expenditures for firm A (X_{1t}) and firm B (X_{2t}) are determined by multiplying a normal error term with mean 1.0 and variance σ^2 to the patterns described above. I.e., $X_{it} = \bar{X}_{it} \times \varepsilon_{it}$, where $\varepsilon_{it} \sim N(1, \sigma^2)$. The standard deviation $\sigma = 0.1$ was chosen so that 95% of the observations are to be within 20% deviation from the mean ($P(0.8 < \varepsilon_{it} < 1.2) = 0.95$). This way, we get the values of R&D spending (X_{it}) as deviating *in proportion* from the typical pattern ($\bar{X}_{it}$) instead of having same scale of variations regardless of the size of typical spending.

Finally, given the values of explanatory variables and the reasonably chosen baseline hazard functions, the *weekly* hazard rates are computed using the formula given in the previous section. The baseline hazard functions, which are assumed to be the same for both firms, are:

$r_0(t) = \exp(-4 + 0.2 \ln t)$ for scenario 1 ($\alpha = 0.2$), and
$r_0(t) = \exp(-6 + 0.1 \ln t)$ for scenario 2 ($\alpha = -0.5$).

Now, consider the fact that, with small time intervals, the hazard rate $h(t)$ is approximated by the conditional probability that an event would occur at time t given that it has not occurred by t–1. That is,

$$h(t) = \frac{f(t)}{1-F(t)} = \lim_{dt \to 0} \frac{P(t \le T \le t + dt \mid T \ge t)}{dt}$$
$$\approx \frac{p(t \le T \le t + \Delta t \mid T \ge t)}{\Delta t} = P(t \le T \le t + 1 \mid T \ge t)$$

when $\Delta t = 1$.

Accordingly, we are able to determine the time duration until a new product launch is made by one of the two firms by drawing a random number and comparing against the hazard rate of the specific period. Specifically, a random draw was made from a uniform distribution $U(0,1)$ and compared with the corresponding hazard rate computed above, to decide whether an event(i.e. new product launch) has occurred. If the random number is smaller than the hazard rate, we suppose that the firm introduced a new product in the corresponding period (week). Otherwise, we move along to the next period and repeat the same procedure. Note that once an event occurs to a firm, the hazard rate of the other firm changes into a different functional form that includes δ term. From the scenario 1 (α = 0.2), firm A first introduced a new product in 39 observations (out of 100), and firm B turned out to be a pioneer in 57 observations. For the four remaining observations, both firms introduced new products in the same week. Therefore, the proportion of $T1 < T2$ is 0.39. The scenario 2 ($\alpha = -0.5$) yielded 44 observations of firm A being first and 54 of firm B's lead.[7)]

7) There are more observations that represent firm B's lead than those that imply firm A's. This is partly due to the fact that firm B's the R&D expenditure levels are generally higher in earlier periods (weeks 1-50), when most events have occurred, although the total expenditures are set to be

Average duration times for scenario 1 was 24 weeks, and 13.7 weeks for scenario 2, which doesn't seem too unreasonable as prototype development durations of high-tech products.

Estimation Results

Based on the proposed model, the parameters are estimated using the simulated observations for each of the two scenarios. The estimation results for scenario 1 are summarized in Table 1(a). The parameter estimates are close to the true values, and some of the estimates are statistically significant.[8] For example, the "catch-up" behavior is well captured by the parameter δ = 0.35, whose true value is 0.3, and it was significantly different from zero (t = 8.14). And, the parameter of our major concern, which is α, was estimated as 0.19 that is very close to the true value 0.2, though not statistically significant. However, this result relies on the set of data generated under certain parameter values, and therefore should not be generalized. In other words, if we'd chosen a much smaller value of δ, say 0.05, in generating observations, we might not have gotten strong effect of δ. Therefore, dominance of δ effect does not come from the model itself but from the choice of true parameter values. Table 1(b) summarizes similar estimation results for scenario 2.[9]

After justifying our method, I further investigated the modeling possibilities using real data. The dataset came from part of the data used by Datar et al.(1997b). With two explanatory variables, CUST(number of customers expressing intent to buy) and ENGG (engineering expenditure for new product development), the proposed model was calibrated three times. Model 1 of Table 2 summarizes the estimation results for the model having no heterogeneous parameters, i.e. same coefficients for the two competing firms. Model 2 has heterogeneous parameters but doesn't incorporate unobserved heterogeneity. Model 3 has both of them.

The estimation results in Table 2 indicate that in this case the

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almost equal for the whole period of consideration (120 weeks).

8) Note that the true value for γ was set to be zero, and the estimate is expected to be not statistically significant.

9) The limited simulation study indicates the need for a large number of observations.

Table 1. Simulation Results

(a) Simulation Results: Scenario 1*

parameters	Estimates	standard error	t-statistic	p-value
a	-4.2547	2.2200	-1.917	0.0276
b	0.2081	0.1881	1.106	0.1343
α	0.1890	0.6994	0.270	0.3935
β	0.7965	0.5429	1.467	0.0712
γ	-0.1032	1.8961	-0.054	0.4783
δ	0.3495	0.0429	8.140	0.0000

*True parameter values are a = -4, b = 0.2, α = 0.2, β = 0.5, γ = 0, δ = 0.3.

(b) Simulation Results: Scenario 2*

parameters	estimates	standard error	t-statistic	p-value
a	-6.4591	9.7163	-0.665	0.2531
b	0.2402	0.3323	0.723	0.2349
α	-0.5258	0.7684	-0.684	0.2469
β	0.6038	0.4177	1.446	0.0741
γ	-0.5084	9.2594	-0.055	0.4781
δ	0.3366	0.0430	7.829	0.0000

*True parameter values are a = -6, b = 0.1, α = -0.5, β = 0.5, γ = 0, δ = 0.3.

two firms compete in a way that supports proposition 1, i.e. acceleration. The alpha coefficient is positive in two of the three models. Model 1 only has non-significant alpha, possibly due to specification error in heterogeneities. The alpha coefficients of Model 2 and Model 3 are similar in size and statistically significant, whereas the covariate effects of two time-varying variables differ across the two firms.

The baseline hazards were estimated with a step-function(of 6 levels). Except the early periods of Model 3, the baseline hazards tend to increase over time, which suggests that Weibull may be a good alternative. Further, the positive "lead time" effect(reflected by delta coefficients) was also secured. That is, the pressure of catching up gets higher as the lead time increases. Although the interpretation of the estimation results warrants caution, it somehow represents the validity and usefulness of the proposed model.

Table 2. Estimation Results from Datar et al.(1997b) data

(a) Model 1: homogeneous parameters

Parameters	Estimates		
alpha(corr)	-0.053		
beta1(CUST)	2.971		
beta2(ENGG)	-7.395		
gamma	-0.105		
delta	0.15		
Baseline hazard:			
log $r_o(t)$			
firm A		firm B	
a1	-9.576	b1	-9.927
a2	0.617	b2	0.446
a3	2.108	b3	2.621
a4	3.105	b4	5.407
a5	4.068	b5	5.181
a6	10.506	b6	8.132

(b) Model 2: heterogeneous parameters

Parameters	Estimates		
alpha(corr)	1.048		
firm A		firm B	
beta1(CUST)	12.703	beta1(CUST)	-3.242
beta2(ENGG)	-18.384		
beta2(ENGG)	-5.516		
gamma	3.525	gamma	-0.493
delta	0.147	delta	1.593
a1	-8.207	b1	-9.542
a2	8.296	b2	-6.508
a3	3.052	b3	0.756
a4	4.103	b4	2.332
a5	7.397	b5	2.228
a6	12.519	b6	9.466

Table 2. continued

(c) Model 3: unobserved heterogeneity*

Parameters	Estimates		
alpha(corr)	1.011		
q12*	-2.597		
q21	-2.433		
q22	12.015		
e2*	7.456		
v2*	8.039		
firm A		firm B	
beta1(CUST)	12.642	beta1(CUST)	-3.963
beta2(ENGG)	-18.093	beta2(ENGG)	-5.592
gamma	-5.741	gamma	0.995
delta	0.135	delta	1.639
a1	-8.378	b1	-13.426
a2	18.396	b2	-24.159
a3	-6.018	b3	2.308
a4	-4.957	b4	3.907
a5	-1.799	b5	3.827
a6	16.969	b6	8.504

*q11, e1, v1 set to be zero for identification

CONCLUSION

There are several limitations to be addressed. First, our empirical question couldn't be answered due to lack of real data. Instead, we illustrated how we can perform the analysis by carrying out two simulations. Therefore, if we could obtain any real data containing information on competitive new product development such as launch timing and R&D expenditures, we might be able to answer which proposition better explains the time-based competition in a certain high-tech product market. With real data, we can also gain insights about how critical it is for a firm to keep up with the rival firms in a certain market. The second limitation of our study relies on the lack of ability to explain the competitive behavior of firms in equilibrium. More rigorous analytical modeling approach can provide better understanding of the R&D race and facilitate developing better empirical model.

In addition, the R&D acceleration vs. deceleration decision is likely to depend on the characteristics of product markets. Thus, one of the valuable future research venues is the identification of variables that affect or moderate the decisions.[10)]

Despite the limitations, this paper has made several contributions in the following sense. First, this is the one of the first attempts in marketing that examines R&D competition using duration analysis. Time-based strategies are extremely important in high-technology based industries such as electronic devices and software. Second, from a modeling perspective, the hazard function approach has a lot of potential for analyzing time-based competition. And the current paper demonstrated for the first time in the marketing literature the possibility to capture the relational structure between competing hazard rates. Although we assumed two hazard rates, the model can be extended to cases where three or more hazard functions are involved.

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