MICRO MOVE OF COMPETITIVE INTERNET TECHNOLOGY DIFFUSION: HOW FIRMS' ACTIONS COULD HELP?

Tian Lu, School of Management, Fudan University, Shanghai, P.R. China, lutian@fudan.edu.cn

Ping Gao, School of Management, Fudan University, Shanghai, P.R. China, gping12@fudan.edu.cn

Cheng Zhang, School of Management, Fudan University, Shanghai, P.R. China, zhangche@fudan.edu.cn

Chenghong Zhang, School of Management, Fudan University, Shanghai, P.R. China, chzhang@fudan.edu.cn

Abstract

This research explores the extent to which Internet technology firms' competitive actions shape the diffusion of their respective products in competition with rivals. Combining competitive dynamics perspective with technology diffusion, we extend macro innovation diffusion model by incorporating four micro-level firm actions, including firms' competitive intensity, action timing, action simplicity and action dissimilarity. We validate the model with longitudinal field data from two pairs of competing Internet technology products in search engine and consumer-to-consumer electronic markets. The results reveal how firms' competition efforts at action level influence technology products diffusion rate. Specifically, action timing has a negative effect on the diffusion of Internet technology products while action dissimilarity has a positive effect, which indicates that quick response and differentiation of strategies can help Internet technology firms obtain competitive advantages. This study has filled out prior research gaps of both competitive innovation diffusion and competition dynamics, by combining them together. Furthermore, this study conveys important practical implications to Internet businesses.

Keywords: Internet technology, technology diffusion, competitive action, competitive effect.

1 INTRODUCTION

Internet businesses are highly competitive in various electronic markets because of commonly low entry barriers, easy imitation of product and service offerings, and low information searching cost for consumers (Porter 2001). In 2003, eBay entered the Chinese C2C market and then fell into fierce fight with Taobao.com, an incumbent Chinese C2C platform providing similar services. Eventually, eBay lost high-profile bids and failed to dominate the Internet auction markets in China (Lemon 2009). Similarly, Baidu.com won the competition with Google in the Chinese search engine market and jd.com, a Chinese online shopping platform, won a seat in Chinese online shopping market, faced with major competition from Taobao.com and Tmall.com, Alibaba's shopping platforms. An interesting question arises here that what firms' specific market-oriented actions function in the market competition process, apart from the technological features of products.

While prior studies have demonstrated that the competitive effects should be taken into consideration when understanding multi-product diffusion (e.g. Mahajan and Muller 1996; Kim et al. 2000; Krishnan et al. 2000; Chu and Pan 2008), they have taken the hidden premise for granted, that the competitive effect across products or brands is the mix outcome of competition across the firms and the inherent products' substitutive features. Using these diffusion models, firms cannot measure the marketing effects of their competitive moves, which is very important for current Internet companies. Hence, it is of practical importance to tease out the effects, caused by firm's competitive actions, from the mixed competitive effects. Competition is a dynamic process in which firms continually take actions to outperform each other (Schumpeter 1934). Thus, the success of technology product innovations may not only rely on the technological features of the products but on the dynamics of vendors' specific competitive actions (Calantone et al. 2006). Scholars working from this perspective have demonstrated that the characteristics of firms' competitive actions and the responses of their rivals will influence profitability (Chen and Miller 1994; Miller and Chen 1996; Young et al. 1996), relative market share (Ferrier 2001; Ferrier et al. 1999), market value (Bettis and Weeks 1987; Ferrier and Lee 2002; Lee et al. 2000), and firm reputation (Basdeo et al. 2006). Although these studies are on action-level variables and focusing on temporary advantages resulting from competition dynamics, they did not shed a light on how firms' micro move may affect their technology diffusion in competition with rivals.

Therefore, to fill out the research gaps discussed above in technology diffusion theory in competition context, our study is aimed at investigating the marketing strategies' competitive effects in the co-diffusion process of multi-technologies by incorporating marketing strategies' competitive effects into the multi-technology diffusion model and analyzing the competitive effects in the multi-technology diffusion process. In this study, we focus on the case of co-diffusion of two Internet technologies, followed by precedent research on multi-product diffusion (e.g. Mahajan and Muller 1996; Kim et al. 2000; Krishnan et al. 2000; Chu and Pan 2008). In this way, the research context requires the almost duopoly market, which can minimize the confounding effects from other technologies. We choose two appropriate study contexts, C2C market and search engine market in China. The total C2C (consumer-to-consumer) market share (measured by the dollars of market transactions) of eBay and Taobao in China was 80% in 2003 and 92% in 2007. Similarly, Baidu and Google (China) collectively occupied 88% of the search engine market at the time of this study.

2 LITERATURE REVIEW

2.1 Competitive Co-diffusion of Multiple Innovations

Innovation often does not diffuse in isolation and interactions across technology innovations often influence the diffusion of individual innovation (Rogers 2003). In general, competition between firms triggers substitutive effects across technology innovations (Kim et al. 2000; Krishnan et al. 2000). However, these studies have the shared premise that the competitive effect across multiple innovations is the mix outcome of competition across the firms and the inherent products' substitutive features. Though, indeed, this stream of research has demonstrated that the competitive effects exist in the co-diffusion process of multiple innovations, products or brands, they do not directly analyze the influence of the competitive actions or strategies on the multi-product diffusion, which is practical for product managers to evaluate and adjust the marketing strategies.

Some researches suggest that the success of technology product innovations does not rely solely on the technological features of the products but rather on the dynamics of vendors' specific market-oriented actions (Zhang et al. 2011; Calantone et al. 2006). However, the dynamics of firms' competitive actions, taken by the firms to seize the market share of their Internet technology products have not been well understood. Therefore, this study will put emphasis on the dynamic relationship between competitors' competitive actions and the diffusion of their products.

2.2 Dynamic Competition in the Market Process

Another stream of competition studies in strategy literatures focus on competitive dynamics between leaders and challengers in the market, rooted in the Austrian view (e.g., Chen and Miller 1994; Miller and Chen 1996; Young et al. 1996; Ferrier et al. 1999; Zhang et al. 2011). From the perspective of Austrian economics, to truly understand competition, one must examine the process and consequences of competitive activity among leading firms (Ferrier et al. 1999). The Austrian perspective views competition as a dynamic process in which firms continually take actions to outperform each other (Schumpeter 1934). Specifically, in the dynamic market process, some firms take actions attempting to seize the leading place, while others try to imitate or take specific strategies in an attempt to challenge (Ferrier et al. 1999). Schumpeter (1934) described the market process as a perennial gale and stressed "disequilibrating" nature, whereby firms are swept into the turbulent confluence of competitive rivalry that creates clear winners and losers. Some acting firms that are temporarily successful in the dynamic competition will manage to reap profits. However, excess profits of the leading firms motivate losers or non-responders to respond and imitate the leaders (Smith et al. 1991). More often than not, some challengers may take more aggressive actions in an attempt to dethrone the market leaders (Ferrier et al. 1999). Therefore, long-term equilibrium in the process is never reached and no leadership position is secure or sustainable. And firms must continuously undertake actions to create new competitive advantages for the current competitive advantage is temporary and short-lived (Zhang et al. 2011).

Till now, rich studies have demonstrated that the characteristics of firms' competitive actions and the responses of their rivals will influence profitability (Chen and Miller 1994; Miller and Chen 1996; Young et al. 1996), relative market share (Ferrier 2001; Ferrier et al. 1999), market value (Bettis and Weeks 1987; Ferrier and Lee 2002; Lee et al. 2000), and firm reputation (Basdeo et al. 2006). Furthermore, Zhang et al. (2011) contend that competitive action plays an important role in the diffusion of Internet technology product, especially in emerging markets and examine the effects of the characteristics of competitive actions on the Internet product diffusion. However, these studies cannot tell how the dynamic competition process twisted in product diffusion. We argue that the influence of competition should be analyzed from the process perspective, which is very important for the firms to evaluate and adjust the competitive actions or strategies.

3 COMPETITIVE ACTIONS

Based on the competition dynamics perspective, the central analysis in describing the characteristics of the market process is competitive actions. We define competitive action as any newly developed market-based move that challenges the status quo of the market process (Jacobson 1992), status quo is defined here as routine, ordinary, and patterned competitive behavior (Nelson and Winter 1982). We mainly consider four characteristics of firm's competitive action aggressiveness, followed by former relate research: total competitive activity (Young et al. 1996; Ferrier et al. 1999), action timing (Chen et al. 1992; Chen and Hambrick 1995), action repertoire simplicity (Miller and Chen 1996), and competitive dissimilarity (Gimeno 1999).

Total Competitive Activity Total competitive activity is defined as the total number of new competitive moves a firm implements in a given period (Ferrier et al. 1999). The Austrian view suggests that all actions are undertaken to pursue competitive advantage and to discover profit opportunities (Kirzner 1997). In general, a firm that implements multiple new competitive activities is considered more aggressive (Young et al. 1996). Some researchers have suggested that firms that remain competitively aggressive have a better chance of gaining and maintaining their competitive advantage. For example, Ferrier et al. (1999) find that market leaders were more likely to experience market share erosion and dethronement when they were less aggressive than their challengers.

Action Timing Action timing is defined as the time elapsed between the actions carried out by a firm and those carried out by a rival. From the Austrian perspective, dynamic market processes constitute a race in which there is a high payoff for speed of action (Schumpeter 1934). And it has been argued that the faster a firm acts with regard to its rival's actions, the more aggressive are its intentions (Smith et al. 2001). In addition, the faster a firm acts compared with its rival's actions, the more it can use these new actions to outperform its rival, which in turn slows down the rival's actions (Chen and MacMillan 1992). A key principle of dynamic competition is that firms that quickly respond to their rivals' new competitive moves slow down rivals' competitive activities (Smith et al. 1992).

Action Repertoire Simplicity Action repertoire simplicity is defined as a firm's propensity to concentrate on carrying out a narrow range of action types (Miller and Chen 1996). Followed by the forgoing study (Ferrier et al. 1999), we contend that firms tend to be more aggressive when they undertake a broader set of actions than their rivals. Moreover, firms that carry out a broad set of action types will be regarded as more capable and perhaps less predictable (D'Aveni 1994). Schumpeter (1934) describe competitiveness as the ability to carry out a range of competitive actions to capture and sustain the leading place. Kirzner (1973) describe this range of activity as a constellation of qualities, prices, styles, color, packaging, and so on, to which firms can make systematic changes based on market forces. Thus, according to the Austrian view, competitiveness is a firm's ability to conduct a range of competitive actions, and a firm's repertoire of competitive actions has a broad influence on its competitive advantage (Ferrier et al. 1999).

Action Dissimilarity Action dissimilarity is defined as the degree to which two competing firms differ in their competitive actions. Some researchers have examined the outcomes of strategic dissimilarity among rivals. For example, Gimeno (1999) finds that strategic heterogeneity among airline industry participants contributed to changes in market share. Similarly, Gimeno and Woo (1996) find that strategic similarities among rivals increased the intensity of the competition. The literature on product differentiation (Tirole 1988) argues that competing firms may strategically differentiate their product offerings to avert competition (the strategic effect); alternatively, they may target their product offerings more closely to obtain a larger market share (the market share effect). Furthermore, Tirole (1988) demonstrates that, in general, the strategic effect dominates the market share effect; therefore, firms tend to adopt a differentiation strategy.

Furthermore, in this study we further take the effect of firm's ***market advantage*** into consideration, measured by the market share gap at certain period between two competing firms. The first mover in the market process can enjoy the reputation and brand-identification benefits (Smith et al. 2001), which constitutes the leading firm's temporary competitive advantage. Thus, we contend that market advantage can influence the market performance of Internet technology products.

4 MODEL DEVELOPMENT

Based on the competitive Bass model as expressed in equation set (1) (Libai et al. 2009; Song et al. 2011), we try to integrate firm competitive actions into the diffusion model. After developing the extended model for competitive diffusion, we validate the model with longitudinal field data of the two pairs of technology product in three ways: running a regression analysis to test the model's explanation power and fitness with the data, and figure out the impact of different action features on technology diffusion, checking the model's robustness by re-estimating the models using 20% higher values and 20% lower value of market size respectively, plus running a forecasting simulation to test the model's accuracy in estimating the change of the data.

$$\begin{cases} f_1(t) = \left[a_1 + b_1 \dfrac{F_1(t-1)}{M(t-1)} - c_1 \dfrac{F_2(t-1)}{M(t-1)}\right]\left[M(t-1) - F_1(t-1)\right] \\ f_2(t) = \left[a_2 + b_2 \dfrac{F_2(t-1)}{M(t-1)} - c_2 \dfrac{F_1(t-1)}{M(t-1)}\right]\left[M(t-1) - F_2(t-1)\right] \end{cases} \quad (1)$$

Competitive diffusion model (equation set (1)) describes a duopoly case with two competing technology products, denoted by the subscript i = 1, 2. Coefficient a represents the extent of influence of competitive actions on a product's diffusion in a market; and such actions result from awareness from consumers, such as by advertising, media reports, sales efforts and other external influences. Coefficient *b* tells the network externality effect, such as by the world-of-mouth through consumer network contact or other positive feedback driven by the population of adopters. More importantly, *c* denotes the coefficient of the competitive effect of product one (two) on product two (one). When $c > 0$, it means a technology product meets a substitutive effect from the other product. The larger the value of *c* is, the greater the tendency for the product to slow down the diffusion of its competitor. When $c < 0$, it means technology product one meets a complementary effect from the other product. $c = 0$ means there is no interactive effect interplaying.

Prior literatures and the theoretical background have shown us that a firm's competitive actions will have quite significant influence on their technology diffusion in the market. Action volume, action repertoire simplicity, action responsiveness (represented by action timing), and action dissimilarity will contribute to the progress of technology performance. Further, we also need to consider the effect of market advantage in the diffusion process. After all, first-mover advantage cannot be ignorable especially in the rapid-progressing technological market. Therefore, the model we proposed is as:

$$\begin{cases} f_1(t) = [(a_{11} \cdot volume + a_{12} \cdot simplicity + a_{13} \cdot timing + a_{14} \cdot market\,advantage + a_{15} \cdot dissimilarity) \\ \qquad + b_1 \dfrac{F_1(t-1)}{M(t-1)} - c_1 \dfrac{F_2(t-1)}{M(t-1)}][M(t-1) - F_1(t-1)] \\ f_2(t) = [(a_{21} \cdot volume + a_{22} \cdot simplicity + a_{23} \cdot timing + a_{24} \cdot market\,advantage + a_{25} \cdot dissimilarity) \\ \qquad + b_1 \dfrac{F_2(t-1)}{M(t-1)} - c_2 \dfrac{F_1(t-1)}{M(t-1)}][M(t-1) - F_2(t-1)] \end{cases} \quad (2)$$

Specifically, we use a group of action feature-related variables to represent the influence of competitive actions rather than a single coefficient *a*. The underlying notion to extend the effects of competitive actions as we proposed is that on one hand, since a firm has conducted many actions to the market, or a firm could fast respond to its competitor's actions, it will be helpful for the firm to gain more shares from the potential market. On the other hand, action repertoire simplicity and action dissimilarity as two kinds of action patterns, have been shown to have significant effects on gaining market shares (Rindova et al. 2010).

However, there might be a problem to interpret the results when we directly use a group of variables to denote coefficient *a*. Hence we must ensure the group of variables we choose be independent from both $F_1(t\text{-}1)/M(t\text{-}1)$ and $F_2(t\text{-}1)/M(t\text{-}1)$ to guarantee the validity and effectiveness of network effects and competitive effects.

5 RESEARCH METHODOLOGY

5.1 Data Collection

We verified the model using two sets of second-hand longitudinal field data. One set of data included the technology diffusion rate of Taobao.com and eBay (China) while the other set was that of Baidu.com and Google (China). We selected these datasets for two reasons. First, diffusion data in a duopoly market, where two main technological products dominate, can verify the model better because the current model was originally a bi-product diffusion model. In the current case, the total

C2C (consumer-to-consumer) market share (measured by the dollars of market transactions) of eBay and Taobao in China was 80% in 2003 and 92% in 2007. Similarly, Baidu and Google (China) collectively occupied 88% of the search engine market at the time of this study. Therefore, the competition between these two companies in the Chinese C2C market can be best characterized as a duopoly. Second, eBay and Google are two typical examples of highly competitive technologies in global electronic markets. For example, in addition to facing global competitors like Microsoft and Yahoo, Google competes with various regional competitors such as Naver in Korea and Baidu in China. Similarly, eBay has fought for e-service platform service in China, Japan, and Taiwan in recent years (Lemon 2009).

Therefore, we collected competitive events information and diffusion rate data of these two pairs of Internet technology products. For the pair of data from Taobao and eBay (China), we collected data from 2003 October to 2006 December (39 months in total); while for the pair of data from Baidu and Google (China), we collected data from 2004 January to 2008 December (60 months in total). Market diffusion data of Taobao and eBay were collected from Alexa Internet, one of the largest third-party data companies tracking online traffic. Alexa provides reach information of numerous websites, which is the amount of unique Internet protocol addresses accessing the websites Alexa tracks. The data provide a good estimation of the user base of C2C electronic markets. To further validate model generality, market diffusion data of Baidu and Google were collected from another third party vendor, Google Trends, which provided search volume indexes to assist in objectively measuring the extent of users' interests in a particular technology. Search volume indexes shows how often Baidu and Google are searched relative to the total number of searches across time. Because search is usually the predominant function of a search engine, this index serves as a reasonable approximation of user adoption of a search engine. To restrict our analysis to the regional market, we used Internet protocol addresses of access provided by Google Trends to distinguish Chinese users from other worldwide users.

We collected competitive events information of the two pairs of Internet technology products by searching the headlines and abstracts of published news reports using two dominate search engines in China (Baidu and Google). To ensure the accuracy of the reports, we cross searched both search engines to validate the sources of the reports. We identified 2009 unduplicated news records over a five-year period. Following previous research, we defined newly created competitive actions as externally directed, specific, and observable new moves initiated by a firm to enhance its competitive position (Chen and MacMillan 1992; Young et al. 1996). This definition includes only actions that have been implemented; were observable to customers, competitors, and other industry players; and were described in the business press. Following this definition, we content-analyzed the 2009 headlines and articles and coded them into the following competitive action types: marketing actions, new product research and development (R&D), pricing and earnings actions, legal actions, signaling actions, capacity actions, and service actions. The category aligns well with market-oriented resource classification in resource advantage theory (Hunt and Morgan 1995, 1997). Other studies of competitive dynamics have also used the structured content analysis technique and categorization approach (Ferrier et al. 1999; Young et al. 1996). Table 1 shows the keywords and sample headlines for each of these action categories. To check the reliability of our coding further, two academic researchers separately recoded three random subsamples (n=100, 50, 10) of individual firm competitive actions into each of the seven categories. We used Perreault and Leigh's (1989) reliability index to test the coding reliability. This test yielded the values of 0.92, 0.94, and 0.92, respectively, indicating a high degree of coding reliability.

Classification	Key Words	Examples
Marketing action	Marketing, advertising, promotion, target, brand, word of mouth, agreement, events, channel, customer	eBay loyalty scheme launches into Pointsxchange.
Product R&D	Product, launch, develop, function, R&D, challenge, update, introduce, solution	eBay launches new look for daily deals.

Pricing and Earnings	Pricing, rate, discount, rebate, earnings, free, market share	Amazon provides the 259-dollar device to subscribers of Amazon Prime…to thwart the threat posed by Apple's new iPad.
Legal action	Sue, litigate, court, copyright, piracy, investigation	eBay defeats Tiffany in counterfeit jewelry suit.
Signaling action	Charity, donation, superstar, campus, image, ranking, interview, events	eBay turns to packaging to boost green credentials.
Capacity action	Raise, increase, talent, employee, recruit, capacity, capability	eBay acquires industry leading mobile application developer.

Table 1. Classification for Competitive Action

5.2 Measures

We define action volume as the total number of newly created competitive actions carried out by a technological company during each month. We measured action timing by the number of days elapsed between the date of one vendor's competitive action and the date of the competitor's immediately following action. We calculated response time in the action and reaction dyads for both the competitors. Then, we calculated action timing as the average action timing measure for each firm respectively in every month. We measured action repertoire simplicity using the Herfindahl index in each quarter. This index is commonly used to evaluate the level of diversification in economic behavior. We can express its calculation as follows: $HI = \sum_{i=1}^{n}\left(\frac{x_i}{x}\right)^2$, where *($x_i/x$)* was the proportion of the firm's total actions in the ith category in a given month. A low level of *HI* means that the firm employed a broad range of different actions. We measured the market advantage by dividing each previous month's market share gap between the two vendors by their combined market shares for the same month. Moreover, we defined a firm's action dissimilarity in month *t* as the ratio of the number of actions its competitors didn't take in month *t* and the competitor's action volume in the same month[1]. Namely, for example, if during a whole month Baidu took actions S_1= {A, B, A, C, D, B, A, C, F, G, F} sequentially, while Google took actions S_2 = {C, A, D, E, B} in the same month, then the action dissimilarity of Baidu is [# of S_1 /($S_1 \cap S_2$)]/[# of S_2]=[# of {F, G, F}]/5=3/5=0.6. Similarly, the action dissimilarity of Google in certain month equals [# of {E}]/10=1/10=0.1. At last, in contrast, we added action similarity as variable to measure that to what extent a vendor's action strategy is similar to its competitors by dividing the number of actions which are the same with the competitors in each month by its action volume in the same month.

For e-platforms, the dependent variable was the diffusion rate (adoption rate) of the e-service measured by the monthly change in the reach of websites, in another word the websites' traffic volume. While we used search volume indices (SVI) provided by Google Trends to measure the adoption rate of search engine technologies. Table 2 depicts summary statistics of the competitive actions.

Action Variables	Taobao		eBay (China)		Baidu		Google (China)	
	M	SD	M	SD	M	SD	M	SD
Product R&D action	0.18	0.45	0.38	0.94	3.20	3.45	4.40	2.79
Pricing action	0.36	1.39	0.28	0.92	1.13	1.66	0.88	1.25
Marketing action	2.18	3.52	1.72	2.41	3.17	4.04	1.92	2.04
Capability action	0.26	0.44	0.10	0.38	0.70	1.48	0.68	1.12

[1] Here we didn't adopt the measure of action dissimilarity as suggested by Zhang et al. (2011) like: $\sum_{i}^{n}\left(\frac{x_i}{x}-\frac{y_i}{y}\right)^2$, as we thought this definition could hardly depict the effect of the unique competitive action a firm adopts on the competitors; and it might overemphasize the action differences between the pair of firms. We also employed this definition of action dissimilarity to test our model, but the results were unsatisfactory.

Legal action	0.41	0.97	0.33	0.81	1.23	2.98	0.63	0.78
Signaling action	1.67	2.58	0.77	1.37	4.38	4.35	2.65	2.80
Service action	0.33	0.66	0.10	0.31	0.17	0.42	0.08	0.33
Action volume	5.38	5.56	3.69	3.78	13.97	10.75	11.27	6.21
Action timing	10.83	11.30	11.45	12.04	3.78	5.36	4.75	10.69
Action simplicity	0.65	0.31	0.57	0.37	0.42	0.22	0.40	0.17
Action similarity	0.40	0.45	0.38	0.42	0.74	0.30	0.72	0.30
Action dissimilarity	1.69	2.37	1.30	2.45	0.53	0.93	1.45	5.07
Adoption rate	0.74	0.30	0.41	0.18	0.60	0.41	0.27	0.10

Notes: Shadowed cells indicate that the firm is superior in the specific action to its competitor.

Table 2. Action Characteristics in the Competitions between Firms

5.3 Regression Designs

As suggested by Zhang et al. (2011), ordinary least squares (OLS) is still a valid choice to verify the model and estimate its parameters. As we stated in the section of Model Development, in order to guarantee the action feature variables (*a*) have the independent relationships with both network (*b*) and competitive effect variable (*c*), we need to conduct regression of adoption rate on $F_1(t\text{-}1)/M(t\text{-}1)$ and $F_2(t\text{-}1)\ /M(t\text{-}1)$ respectively to gain residuals y_{r2}; and then regress action feature variables on $F_1(t\text{-}1)/M(t\text{-}1)$ and $F_2(t\text{-}1)\ /M(t\text{-}1)$ respectively to gain residuals x_{ir}. Finally, plot y_{r2} against x_{ir} to obtain the coefficients. Path coefficients in OLS can be estimated more accurately this way.

After running regression analyses to estimate path coefficients and the model's explanatory power to determine its fit to the data, we further re-estimated the models using 20% higher and 20% lower values of market size, respectively to assure the model's robustness. And then we ran a forecasting simulation to test the model's accuracy and estimated the predictive validity regarding the change in the data by splitting the empirical dataset into an estimation set and validation set, respectively.

6 DATA ANALYSIS

6.1 Model Estimation

6.1.1 Study One: Taobao vs. eBay (China)

We can find that our model to assess competitive technology diffusion is better than the competitive diffusion model with a superior explanatory power (see Table 3). The *R* square values of our extended competitive technology diffusion model for Taobao and eBay has increased from 0.644 to 0.701 and from 0.671 to 0.703 respectively. The addition explanatory power for the model in Taobao and eBay's case is 0.057 and 0.032 respectively, meaning the added action feature variables increase 5.7% and 3.2% variance explanation and prediction power of competitive technology diffusion.

		Taobao		eBay (China)	
Un-standardized Coefficients		Origianl Competitive Model	Extended Competitive Model	Origianl Competitive Model	Extended Competitive Model
(Constant)		-2.647*** (0.682)	-2.647*** (0.682)	2.656*** (0.684)	2.656*** (0.684)
Awareness effect (*a*)	Action volume (*a1*)	0.062** (0.025)	0.227* (0.123)	0.036*** (0.009)	-0.246 (0.191)
	Action simplicity (*a2*)		0.040 (0.125)		-0.118 (0.176)
	Action timing (*a3*)		-0.028** (0.012)		-0.019* (0.011)
	Market advantage (*a4*)		0.056 (0.181)		-0.003 (0.008)

	Action similarity (*a5*)		-0.065 (0.148)		0.008 (0.007)
	Action dissimilarity (*a6*)		0.171* (0.096)		0.313** (0.140)
Network effect (*b*)		0.131*** (0.040)	0.131*** (0.040)	0.184*** (0.054)	0.184*** (0.054)
Competitive effect (*c*)		-0.328*** (0.088)	-0.328*** (0.088)	0.106*** (0.025)	0.106*** (0.025)
Adjusted R square		0.644	0.701	0.671	0.703
Sample size		39	39	39	39

Note: *: p <0.10, **: p<0.05, ***: p <0.01; robust standard error in parentheses.

Table 3. Regression Analysis of the Extended Competitive Diffusion of E-Platforms

The results are consistent with the findings of Song et al. (2011). The significance of competitive variable in the model, i.e., c1 = -0.131 (p<0.01) in Taobao's case and c2 = 0.184 (p<0.01) in eBay's case, revealing that the two-way interaction between the diffusion of Taobao.com and eBay (China) is asymmetric: whereas the diffusion of Taobao.com significantly slowed down that of eBay, the diffusion of eBay (China) significantly increased the diffusion of Taobao.

What's more, we can find that action timing and action dissimilarity are significant. The effects of action timing are negative for both Taobao and eBay cases, telling that fast responsiveness to the rival's actions are always helpful for the technology diffusion of the firm. While action dissimilarity has positive effects on the technology diffusion of the two e-platforms, which implies that the competitive strategy of differentiation is beneficial for technological companies. We can also find that action volume of Taobao.com has positive impact on its technological product diffusion in the market. However, neither the action simplicity nor action similarity nor market advantage is significant, although in the study of Zhang et al. (2011), they found that action simplicity and market advantage are strongly related with diffusion rate gap for Local-MNC technological products.

6.1.2 Study Two: Baidu vs. Google (China)

Table 4 shows the regression results for the search engine technologies. The R square values of our extended competitive technology diffusion model for Baidu and Google has increased from 0.714 to 0.770 and from 0.650 to 0.747 respectively. The addition explanatory power for the model in Baidu and Google's case is 0.056 and 0.097 respectively, meaning the added action feature variables increase 5.6% and 9.7% variance explanation and prediction power of competitive technology diffusion.

		Baidu		Google (China)	
Un-standardized Coefficients		Origianl Competitive Model	Extended Competitive Model	Origianl Competitive Model	Extended Competitive Model
(Constant)		-1.796*** (0.583)	-1.796*** (0.583)	-3.014*** (0.982)	-3.014*** (0.982)
Awareness effect (*a*)	Action volume (*a1*)	0.023* (0.012)	0.095 (0.077)	0.142* (0.075)	-0.013 (0.087)
	Action simplicity (*a2*)		0.006 (0.006)		-0.088 (0.084)
	Action timing (*a3*)		-0.188** (0.094)		-0.025* (0.015)
	Market advantage (*a4*)		0.253** (0.117)		-0.924*** (0.134)
	Action similarity (*a5*)		0.109 (0.111)		0.099 (0.148)
	Action dissimilarity (*a6*)		0.149** (0.066)		0.161* (0.092)

Network effect (*b*)	0.045*** (0.011)	0.045*** (0.011)	0.145*** (0.013)	0.145*** (0.013)
Competitive effect (*c*)	-0.221*** (0.031)	-0.221*** (0.031)	0.053*** (0.005)	0.053*** (0.005)
Adjusted R square	0.714	0.770	0.650	0.747
Sample size	60	60	60	60

Note: *: p <0.10, **: p<0.05, ***: p <0.01; robust standard error in parentheses.

Table 4. Regression Analysis of the Extended Competitive Diffusion of Search Engines

The results are similar with those of Taobao/eBay cases. The significance of competitive variable in the model, i.e., c1 = -0.221 ($p<0.01$) in Baidu's case and c2 = 0.053 ($p<0.01$) in Google's case, revealing that the two-way interaction between the diffusion of Baidu and Google (China) is asymmetric: whereas the diffusion of Baidu significantly slowed down that of Google, the diffusion of Google significantly increased the diffusion of Baidu.

What's more, we can find that action timing and action dissimilarity are significant. The effects of action timing are negative for both Baidu and Google cases, telling that fast responsiveness to the rival's actions are always helpful for the technology diffusion of the firm. While, action dissimilarity has positive effects on the technology diffusion of the two search engine technologies, which implies that the competitive strategy of differentiation is beneficial for technological companies. We can also find that market advantage of Baidu has positive impact on its technological product diffusion while market advantage of Baidu has negative impact on Google's product diffusion in the market. This demonstrates the first-mover advantages. However, neither the action volume nor action simplicity nor action similarity is significant.

6.2 Robust Checks

As suggested by Dewan et al. (2010), we conducted robustness checks to evaluate the stability of the results presented above. Similarly, to the approach proposed in past studies (Dewan et al. 2010), we estimated the diffusion model with 20% higher/lower values of the market size (i.e., each data point of market size was manually increase/decrease 20%) to address the concern that the Bass diffusion model might underestimate the influence of a dynamically growing market size (Van den Bulte and Lilien 1997). As shown in Tables 5 and 6, the results are quantitatively similar to those in Tables 3 and 4, respectively. Further, the significance of coefficients in the competitive diffusion results was unchanged. These additional tests ensured the robustness of the estimation results.

		Taobao			eBay (China)		
Un-standardized Coefficients		Original	Higher M	Lower M	Original	Higher M	Lower M
(Constant)		-2.647*** (0.682)	-2.159*** (0.674)	-2.973*** (0.685)	2.656*** (0.684)	2.570*** (0.680)	2.792*** (0.686)
Awareness effect (*a*)	Action volume (*a1*)	0.227* (0.123)	0.214* (0.116)	0.230** (0.092)	-0.246 (0.191)	-0.224 (0.174)	-0.230 (0.180)
	Action simplicity (*a2*)	0.040 (0.125)	0.040 (0.125)	0.046 (0.123)	-0.118 (0.176)	-0.118 (0.176)	-0.119 (0.180)
	Action timing (*a3*)	-0.028** (0.012)	-0.025** (0.011)	-0.032** (0.014)	-0.019* (0.011)	-0.017* (0.010)	-0.021* (0.011)
	Market advantage (*a4*)	0.056 (0.181)	0.052 (0.171)	0.060 (0.179)	-0.003 (0.008)	-0.006 (0.009)	-0.018** (0.008)
	Action similarity (*a5*)	-0.065 (0.148)	-0.042 (0.145)	-0.066 (0.140)	0.008 (0.007)	0.007 (0.007)	0.004 (0.006)
	Action dissimilarity (*a6*)	0.171* (0.096)	0.161* (0.090)	0.191** (0.096)	0.313** (0.140)	0.311** (0.138)	0.317** (0.142)
Network effect (*b*)		0.131*** (0.040)	0.090** (0.037)	0.144*** (0.046)	0.184*** (0.054)	0.176*** (0.041)	0.197*** (0.056)
Competitive effect (*c*)		-0.328***	-0.283***	-0.340***	0.106***	0.102***	0.110***

	(0.088)	(0.083)	(0.096)	(0.025)	(0.024)	(0.025)
Adjusted R square	0.701	0.656	0.703	0.703	0.645	0.713
Sample size	39	39	39	39	39	39

Table 5. Extended Competitive Diffusion Model with Higher/Lower Market Growing Size M on E-Platforms Data

		Baidu			Google (China)		
Un-standardized Coefficients		Original	Higher M	Lower M	Original	Higher M	Lower M
(Constant)		-1.796*** (0.583)	-1.762*** (0.559)	-1.817*** (0.586)	-3.014*** (0.982)	-3.000*** (0.978)	-3.029*** (0.986)
Awareness effect (*a*)	Action volume (*a1*)	0.095 (0.077)	0.093 (0.074)	0.096 (0.077)	-0.013 (0.087)	-0.012 (0.087)	-0.015 (0.088)
	Action simplicity (*a2*)	0.006 (0.006)	0.005 (0.006)	0.006 (0.007)	-0.088 (0.084)	-0.088 (0.084)	-0.088 (0.084)
	Action timing (*a3*)	-0.188** (0.094)	-0.185** (0.092)	0.190** (0.093)	-0.025* (0.015)	-0.023* (0.015)	-0.026* (0.014)
	Market advantage (*a4*)	0.253** (0.117)	0.255** (0.114)	0.255** (0.119)	-0.924*** (0.134)	-0.921*** (0.134)	-0.926*** (0.134)
	Action similarity (*a5*)	0.109 (0.111)	0.108 (0.111)	0.109 (0.112)	0.099 (0.148)	0.099 (0.148)	0.099 (0.148)
	Action dissimilarity (*a6*)	0.149** (0.066)	0.146** (0.061)	0.150** (0.067)	0.161* (0.092)	0.159** (0.079)	0.168** (0.084)
Network effect (*b*)		0.045*** (0.011)	0.044*** (0.011)	0.045*** (0.011)	0.145*** (0.013)	0.143*** (0.013)	0.149*** (0.013)
Competitive effect (*c*)		-0.221*** (0.031)	-0.226*** (0.030)	-0.281*** (0.029)	0.053*** (0.005)	0.052*** (0.005)	0.054*** (0.005)
Adjusted R square		0.770	0.765	0.771	0.747	0.746	0.750
Sample size		60	60	60	60	60	60

Note: *: p <0.10, **: p<0.05, ***: p <0.01; robust standard error in parentheses.

Table 6. Extended Competitive Diffusion Model with Higher/Lower Market Growing Size M on Search Engines Data

6.3 Model Forecasting Ability

Then we try to validate the forecasting power of the extended competitive diffusion model because brand managers and IT managers are interested in gauging how well their IT products would diffuse in relation to competing products. To check the reliability of the predictions, we tested the model in three rounds of experiments. In the first round, we regressed our model with *N - 3* records (*N* refers to the number of months each pair of sample has), and used the results to forecast the market for competitive technology diffusion in the next quarter (3 months), in the second round used *N – 6* to forecast the market for the next half year (6 months), and in the third round used *N – 12* to forecast the market for the next year (12 months). Again, we used competitive diffusion model of single product diffusion as a base model for benchmarking.

The root mean-squared error (RMSE) and the mean absolute percent error (MAPE) were used as indicators of forecasting efficiency. The root mean-squared error measures the square root of variance representing the differences between each forecast and the corresponding observation and MAPE measures the average forecast error by the absolute percentage difference between each forecast and the corresponding observation. In essence, both RMSE and MAPE measure the error in forecasting. In both cases, a smaller value indicates less error. Table 7 shows that, by factoring in the effect of substitution, our proposed model provided a more accurate forecasting of the empirical data than did the base model.

Competitive Technology	Model Type	RMSE			MAPE		
		R1	R2	R3	R1	R2	R3
Taobao	Origianl Competitive Model	4.2619	4.2619	4.4097	0.3367	0.3845	0.3911
	Extended Competitive Model	4.0072	3.9390	3.2086	0.3173	0.3367	0.3888
eBay (China)	Origianl Competitive Model	4.9068	4.8163	6.6497	0.5680	0.6343	1.1610
	Extended Competitive Model	0.7576	0.6365	0.4880	0.4201	0.6182	0.9272
Baidu	Origianl Competitive Model	1.3700	2.4168	3.6000	0.2317	0.3475	0.5257
	Extended Competitive Model	0.2563	0.2721	0.2594	0.1886	0.2353	0.1893
Google (China)	Origianl Competitive Model	0.7880	1.3319	1.2645	0.7605	1.5436	2.1276
	Extended Competitive Model	0.0606	0.1757	0.0295	0.0330	0.1715	0.5031

Note: R1/R2/R3: first / second / third round of experiment.

Table 7. RMSE and MAPE of the Forecast Error for E-Platforms/Search Engines Diffusion

7 DISCUSSIONS AND CONCLUSIONS

Distinct from previous research on technology diffusion treats product substitution and firms' competitive actions separately, we proposed an integrated/extended and predictive model and validated it with longitudinal data of e-commerce platforms and search engine technologies in the Chinese market. We validated the model in three ways: conducted a regression analysis to test the model's explanation power and fitness with the data, conducted a forecasting simulation to test the model's accuracy in estimating the change of the data, and checked the model's robustness by re-estimating the models using 20% higher lower values of market size, respectively. The findings of the current investigation suggest that product diffusion can be better predicted by a model that incorporates competition in a dynamic market than by one that treats a product in isolation. More importantly, we demonstrated that several action feature-related factors such as a firm's responsiveness to the market and the strategy of differentiation have quite significant influences on the technological product diffusions in the intensely competing market. Specifically, action timing and action dissimilarity have significant effects on the technological product diffusion in both study settings, while the other two characteristics of competitive action have no significant effects. These findings indicates that action responsiveness and action differentiation is more useful competitive strategies to enhance their technological products for competitive Internet companies.

This study opens the door to a wealth of knowledge for high-technology product diffusion in competition context. To our best of knowledge, this study is the first to inspect the effects of action feature-related factors and the product diffusion process at the same time in an integrated model. Besides the network effect and competitive effect during the product diffusion, we showed that firm's competitive action dissimilarity and timing will have significant impact on product diffusion process. This research has made theoretical contributions to the researches on dynamic competition strategies of companies.

The proposed model further provides important managerial implications. First, our research stress that fast responsiveness to the rival's actions will always avoid the product lose shares in the market. That is to say, timing is important. Figure 1(a) and 1(b) illustrates that when a technological company takes "counterattack" actions immediately after the rival's behaviours, its product adoption rate is always raise. Second, firms need pay special attention to the strategy of differentiation in order to obtain more market share. Figure 2(a) and 2(b) depicts the relationship between firm's action dissimilarity and their product adoption rate. We can find that differentiation competitive strategy can bring a chance for the leader company to further enlarge its advantage, while render the follower a chance to narrow the product adoption gap. Firms in the market must be insightful and flexible. Moreover, we showed that first-mover advantage has much positive effects for several technological companies. Then how to be ahead and keep advantages are inevitable for every technology firm to carefully consider.

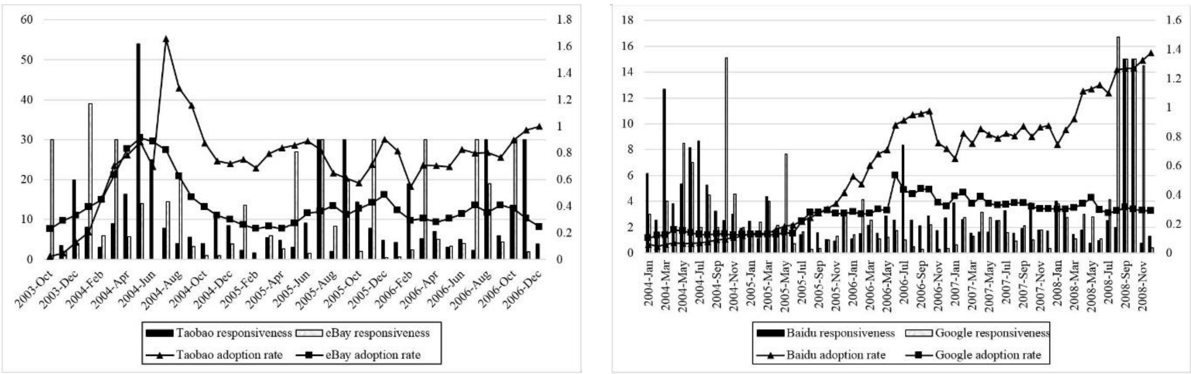

Figure 1(a)(b). Firms' Action Responsiveness and Their Diffusion Rate in the Market

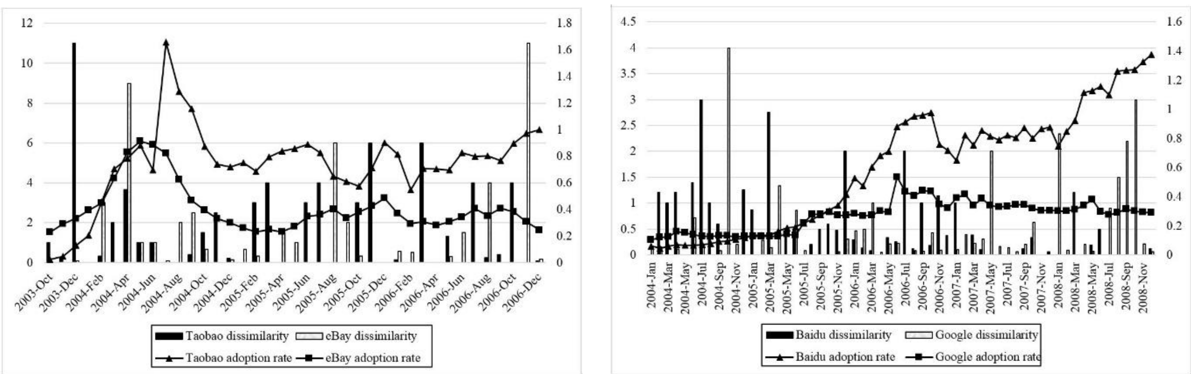

Figure 2(a)(b). Firms' Action Dissimilarity and Their Diffusion Rate in the Market

Figure 2(b). Firms' Action Dissimilarity and Their Diffusion Rate in the Market (Baidu & Google)

The current study is not without limitations; however, and it could be expanded in several ways. First, we believe the precision of the model's parameters can be improved by applying different regression techniques and larger sample size in practice. Second, since the current study examined extended diffusion patterns and competition scenarios only for Taobao/eBay and Baidu/Google cases, the findings of this study may be limited by these existing scenarios. Future study may investigate more pairs of competing firms in different industries and time to gain interesting findings. Lastly, if we can depict the proposed model of both competitive innovation diffusion and dynamic competition with multi-stage models, there will be more meaningful findings and contributions.

REFERENCES

Basdeo, D.K., Smith, K.G., Grimm, C.M., Rindova, V.P., and Derfus, P.J. (2006). The impact of market actions on firm reputation. Strategic Management Journal, 27 (12), 1205-1219.

Bettis, R. and Weeks, D. (1987). Financial returns and strategic interaction: the case of instant photography. Strategic Management Journal, 8 (6), 549-563.

Calantone, Roger, J., Kwong, Chan, and Anna, S. Cui. (2006). Decomposing product innovativeness and its effect on new product success. Journal of Product innovation Management, 23 (5), 408-421.

Chen, M. and Hambrick, D. (1995). Speed, stealth and selective attack: How small firms differ from large firms in competitive behavior. Academy of Management Journal, 38, 453-482.

Chen, M. and Ian, C. MacMillan. (1992). Nonresponse and delayed response to competitive moves. Academy of Management Journal, 34 (2), 539-570

Chen, M-J. and Miller, D. (1994). Competitive attack, retaliation and performance: an expectancy-valence framework. Strategic Management Journal, 15 (2), 85-102.

Chen, M., Smith, K., and Grimm, G. (1992). Action characteristics as predictors of competitive responses. Management Science, 38, 439-455.

Chu, C.P. and Pan, J.G. (2008). The forecasting of the mobile Internet in Taiwan by diffusion model. Technological Forecasting & Social Change, 75 (7), 1054-1067.

D'Aveni, Richard, A., and Robert Gunther. (1994). Hypercompetition: Managing the dynamics of strategic maneuvering. The Free Press, New York.

Dewan, S., Ganley, D., and Kraemer, K. L. (2010). Complementarities in the diffusion of personal computers and the Internet: Implications for the global digital divide. Information Systems Research.

Ferrier, W. (2001). Navigating the competitive landscape: the drivers and consequences of competitive aggressiveness. Academy of Management Journal, 44, 858-877.

Ferrier, W. and Lee, H. (2002). Strategic aggressiveness, variation, and surprise: how the sequential pattern of competitive rivalry influences stock market returns. Journal of Managerial Issues, 14, 162-180.

Ferrier, W., Smith, K.G., Grimm, C. (1999). The role of competitive action in market share erosion and industry dethronement: a study of industry leaders and challengers. Academy of Management Journal, 42, 372-388.

Gimeno, Javier. (1999). Reciprocal threats in multimarket rivalry: Staking out 'spheres of influence' in the U.S. airline industry. Strategic Management Journal, 20 (1), 101-128.

Hunt, S.D. and Morgan, R.M. (1995). The comparative advantage theory of competition. The Journal of Marketing, 1-15.

Jacobson, R. (1992). The "Austrian" school of strategy. Academy of Management Review, 17, 782-807.

Kim, Namwoon, Dae, R. Chang, and Allan, D. Shocker. (2000). Modeling intercategory and generational dynamics for a growing information technology industry. Management Science, 46 (4), 496-512.

Kirzner, Israel, M. (1997). Entrepreneurial discovery and the competitive market process: An Austrian approach. Journal of Economic Literature, 35 (1), 60-85.

Krishnan, Trichy, V. Frank, M. Bass, and V. Kumar. (2000), Impact of a late entrant on the diffusion of a new product/service. Journal of Marketing Research, 37 (May), 269-278.

Lee, H, Smith, K.G, Grimm, C.M, Schomburg, A. (2000). Timing, order and durability of new product advantages with imitation. Strategic Management Journal, 21 (1), 23-30.

Lemon, S. 2009. Yahoo accepts eBay offer to buy Korea's Gmarket, IDG News Service.

Libai, B., Muller, E., and Peres, R. (2009). The role of within-brand and cross-brand communications in competitive growth. Journal of Marketing, 73 (3), 19-34.

Mahajan, V. and Muller, E. (1996). Timing, diffusion, and substitution of successive generations of technological innovations: The IBM mainframe case. Technological Forecasting & Social Change, 51 (2), 109-132.

Mahajan, Vijay, Subhash, Sharma, and Robert, D. Buzzell. (1993). Assessing the impact of competitive entry on market expansion and incumbent sales. Journal of Marketing, 57 (July), 39-52.

Miller, D. and Chen, M-J. (1996). The simplicity of competitive repertoires: an empirical analysis. Strategic Management Journal, 17 (6), 419-439.

Nelson, R. and Winter, S. (1982). An evolutionary theory of economic change. Harvard University Press, Cambridge, MA.

Perreault, W.D. and Leigh, L.E. (1989). Reliability of nominal data based on qualitative judgments. Journal of Marketing Research, 26 (2), 135-148.

Porter, M.E. (2001). Strategy and the Internet. Harvard Business Review, 79 (3), 62-79.
Rindova, V., Ferrier, W.J., and Wiltbank, R. (2010). Value from gestalt: how sequences of competitive actions create advantage for firms in nascent markets. Strategic Management Journal, 31 (13), 1474-1497.
Rogers, E.M. (2003). Diffusion of innovations. 5th Edition. The Free Press, New York.
Schumpeter, J. (1934).The theory of economic development. Harvard University Press, Cambridge, MA.
Smith, K.G., DiGregorio, D. (2002). Bisociation, discovery and the role of entrepreneurial action. In Strategic Entrepreneurship: Creating a New Mindset, Hitt M, Ireland RD, Sexton D (eds), p. 129-149, Blackwell Publishers, Malden, MA.
Smith, K.G., Curtis M. Grimm, and Martin, J. Gannon. (1992). Dynamics of competitive strategy. Sage Publications, Thousand Oaks, CA.
Smith, K.G., Ferrier, W.J., and Grimm, C.M. (2001). King of the hill: Dethroning the industry leader. The Academy of Management Executive, 15 (2), 59-70.
Song, P., Zhang, C., Xu, Y., Xue, L., Wang, K., and Zhang, C. (2011). Asymmetric interaction in competitive Internet technology diffusion: Implications for the competition between local and multinational online vendors. Journal of Global Information Management 19 (3): 45-64.
Tirole, Jean. (1988). The theory of industrial organization. MIT Press, Cambridge, MA.
Van den Bulte, C. and Lilien, G.L. (1997). Bias and systematic change in the parameter estimates of macro level diffusion models. Management Science, 16 (4), 338-353.
Young, G., Smith, K.G., and Grimm, C. (1996). 'Austrian' and industrial organization perspectives on firm-level competitive activity and performance. Organization Science, 7, 243-255.
Zhang, C., Song, P., and Qu, Z. (2011). Competitive action in the diffusion of internet technology products in emerging markets: Implications for global marketing managers. Journal of International Marketing, 19 (4), 40-60.