A Diffusion Model for Service Products

Abstract:

Despite the fast growth of the service sector, the existing literature has dedicated little effort to modeling the market growth of service products. We develop a diffusion model that can be used to understand and forecast the market growth of service products in a competitive environment.

We propose a choice-type diffusion model that links the issues of service product utility, customers' choice preference, customer switching behavior, and the market growth of service products. We employ the market data of one online product and we assess the performance of the proposed model using this case.

The results demonstrate the model's good fitting and forecasting performance. Specifically, the proposed model has better performance than the benchmarks we choose from the existing literature.

This study shows that market growth of service products can have different diffusion patterns with that of durable goods, which is evidence of the needs for specific models for service diffusion. Further, this study demonstrates the important role of customer switching in service diffusion. Also for marketing practitioners, this study provides an explanation and forecasting tool for the market growth of service products, which can be used for marketing planning in service industry.

Keywords: diffusion; service product; customer switching

1. INTRODUCTION

The service sector in most developed countries is now the central focus for the economy and is responsible for the majority of the gross domestic product (Rust & Chung 2006; Eichengreen & Gupta 2013). For instance, the online service industry has been witnessing tremendous growth (Riedl et al. 2011), due to its more than 2 billion internet users worldwide (InternetWorldStats 2011). Firms are now offering various online services to customers such as email, news, e-commerce, social networking, and entertainment. Highly successful online service providers, such as Google, eBay, Amazon, and Facebook, have all been growing at phenomenal rates.

Competition, however, is fierce in the service industry. Most service products have one or more major competing products throughout their life-cycle. Considering the online search engine market as an example, Yahoo!, which used to be the most popular way for people to search web pages of interest in the 1990s, had a few key competitors such as Magellan, Excite, and Infoseek. Since 2000, Google has become the leader in this market, but it is also facing threats from others such as Microsoft, Yahoo! and Baidu. In such competitive markets, service providers compete with each other for potential customers, while at the same time, they also have to improve constantly the overall satisfaction of their products in order to increase the chance of existing customers remaining with them (Wieringa & Verhoef 2007). Therefore, customer switching, or churn, becomes one of the key issues that service providers concern.

Sales of durable goods increase constantly as customers' refund behavior is considered to be rare, while the user base of service products often decreases due to customer switching. The existing innovation and diffusin literature predominatly focues on durable goods (Barczak 2012). Correspondingly, most models that study the growth pattern of competing products, are developed in order to deal with durable goods. As scholars usually borrow these models of durable goods directly to study service products, some research issues, such as customer switching, have rarely been considered (Krishnan et al. 2000; Peres et al. 2010). This study seeks to model the growth trend of service products in a competitive environment with consideration of customers' switching behavior. This is an important topic because academics have not yet fully understood the role of customer switching in diffusion models, and because practitioners desire a tool to explain and forecast the growth pattern of service products in order to aid their marketing strategies.

It can be argued that this study is closer to the work of Libai et al. (2009), who consider the role of customer switching in service products diffusion based on a Bass-type model. Their suggested model, however, is highly aggregated and experimental, as the authors simply assume the churning customers as distributed according to the relative number of subscribers for each service product. Their approach therefore does not attempt to shed light on the reasons behind customer switching. Our suggested model and its results are, in many ways, of both a conceptual and managerial interest. First, the proposed model uses a choice-type model to incorporate the factor of customer switching. The model shows how the change of product utility influences customers' product preference and thus their switching behavior. Second, the results of this study show that the growth curve of competing service products could have its unique attributes compared against that of durable goods. Therefore, specific models are needed to understand the nature of service diffusion. Third, the proposed model categorizes the new users of a service product into two groups: first-time users of the service and switching users from other competing products. Therefore, the model is capable of exploring the respective role of first-time users and switching users in a competitive environment. Fourth, contrary to most previous studies that only examine the competitive diffusion in a duopoly setting, this study considers a case from the online industry with four competitors, which demonstrates the complex nature of the competitive diffusion phenomena. Finally, the empirical study shows that the proposed model can be a good fitting and forecasting tool for service diffusion. This will especially benefit practitioners in designing marketing strategies to promote their products.

The remainder of the paper is structured as follows. The next section reviews the related literature on this topic. We then present our suggested model for this study. We give empirical validation and discussion of the proposed model based on a real-world case. Finally, conclusions and some possible future directions are provided.

2. RELATED LITERATURE

2.1. Diffusion Models

Diffusion models are either homogeneous or heterogeneous in nature. These two streams of models both illustrate the bell-shaped curve of diffusion with meaningful implications. Both are therefore widely used (Geroski 2000). Most homogeneous diffusion models originate from the two-step flow theory (Katz & Lazarsfeld 1955), which states that information of an innovation will first reach a few individuals through the mass media and then spread to others through the word-of-mouth effect. The pioneering work in this field is mostly credited to the Bass model (1969): if s_t is defined as the new adopters at time t and S_t as the cumulative adopters, the product diffusion process in a market of size M can be modeled in Equation 1, where p and q are the parameters of the mass media effect and word-of-mouth effect respectively. The Bass model has influenced many of the subsequent diffusion studies, as summarized by Geroski (2000), Mahajan et al. (2000), Meade and Islam (2006), and Peres et al. (2010).

$$s_t = \left(p + q\frac{S_t}{M} \right)(M - S_t) \quad (1)$$

Conversely, heterogeneous diffusion models consider the differences of adoption timing between individuals, which take place according to their respective goals, needs and abilities. In other words, the reason why a diffusion process is formed is because customers adopt the innovation at different times when their requirements for adoption are satisfied. One of the more recent developments in the field of heterogeneous diffusion models can be seen in the agent-based diffusion models, where each customer is considered as an agent that exhibits unique characteristics and makes adoption decisions following their own rules (Di Benedetto 2011; Rand & Rust 2011), examples including van Eck et al. (2011), Zhang et al. (2011), and Amini et al. (2012).

There has been another stream of diffusion models that can be referred to as choice-type models. This approach uses a multinomial logit model to calculate customers' choice probabilities between different products based on the corresponding utilities they can obtain from them. Scholars have used this approach to solve various diffusion problems, such as multi-generational diffusion (Jun & Park 1999), the forward-looking effect in diffusion (Jun et al. 2002; Namwoon et al. 2002), repeated purchase in diffusion (Prince 2008), and replacement purchase in diffusion (Jun & Kim 2011).

2.2.Diffusion Models with Competitive Effect

Early diffusion models usually study product growth from a category level, without consideration of the competition between similar products within the same categories. It is commonly observed, however, that although new products may have the monopoly in the market at the beginning, they quickly acquire competing products. Furthermore, competition is also encouraged from a category level, as most previous studies have reported a positive effect of competition on the category growth (Kim et al. 1999).

The main body of the literature suggests a Bass-type model for the competitive diffusion phenomena (Peres et al. 2010). This is based on the proposition that a potential customer adopts a product under three types of influence: the mass media effect, the word-of-mouth effect due to users of the product, and the word-of-mouth effect due to users of other competing products. A generalization of these models can be explained by Equation 2, where $s_{i,t}$ and $S_{i,t}$ are the number and cumulative number of adopters of product i respectively, and p_i, q_i, q_{ij} are the corresponding coefficients of the three types of influence. Many of the competitive diffusion models are variations of Equation 2. For instance, some scholars such as Krishnan et al. (2000) and Kim et al. (1999) consider that the imitation effect equals the cross-brand imitation effect, namely, $q_{ij} = q_i$. Some scholars, such as Parker and Gatignon (1994), argue that each product diffuses in its specific market, namely that the overall market potential M is further divided into sub-markets (replacing M in Equation 2 with M_i).

$$s_{i,t} = \left(p_i + q_i \frac{S_{i,t}}{M} + \sum_{j \neq i} q_{ij} \frac{S_{j,t}}{M} \right)\left(M - S_{i,t}\right) \qquad (2)$$

In an earlier review by Chatterjee et al. (2000), the authors categorize competitive diffusion models into two groups. The models in the first group usually use a Lanchester formulation to show how firms compete to acquire each other's existing customers in a saturated market, while the second group of models usually uses a Vidal-Wolfe formulation to describe how firms compete with each other for the remaining market. Although many studies exist for each of the two groups, few solve both problems at the same time. Therefore, this typology also implicates a need for diffusion models that consider customer switching in a dynamic and competitive market.

2.3.Customer Switching in the Service Industry

Customer switching, or churn, is the opposite concept of customer loyalty, which has been studied extensively in the marketing literature. Customer switching is especially key to the service products in which customers have some kind of longitudinal relationship with the service providers (Bolton & Lemon 1999). This topic is important for the service industry because most service providers have to face new competitors and, thus, they must address customer switching in order to maintain their market share (Wieringa & Verhoef 2007). The factors that influence customer switching can be various, such as a low perception of service quality (Rust & Zahorik 1993) and previous negative experiences (Kelley et al. 1993). The study conducted by Keaveney (1995) identifies eight categories with more than 800 behaviors of service firms that could cause customers to switch service, showing that customer switching is a common and non-negligible phenomenon in the service industry.

Scholars in the marketing science literature (Berger & Nasr 1998; Schweidel et al. 2007; Borle et al. 2008; Fader & Hardie 2010; Braun & Schweidel 2011) have used duration models to relate customers' propensities to retain service to their lifetime value. However, the literature shows little effort to model the market growth of competing service products with consideration of customer switching. The first and perhaps the only important work in this field is that by Libai et al. (2009), who examine this issue based on a modified version of the Bass-type diffusion model with competition effect. The way they consider the effect of customer switching can be explained by Equation 3, where parameter δ_k indicates the percentage of existing users who switch from product k to other competing products. The model first models each service product individually using the Bass model. Then the authors assume the churning customers as distributed according to the relative number of subscribers for each service product. Their work, however, is very much a trial attempt. According to this model, the size of a product's customer base becomes the key determinant for the number of users who switch. In other words, an increased customer base will result in more existing users leaving. This approach does not reflect the real reason behind customer switching: customers switch because they perceive higher utility of other products.

$$s_{k,t} = \left(p_k + q_k \frac{S_{k,t-1}}{M} \right)\left(M - S_{k,t}\right) - \delta_k S_{k,t-1} + \sum_{l \neq k}^{N} \left(\delta_l S_{l,t-1} \left(\frac{S_{k,t-1}}{\sum_{j \neq l}^{N} S_{j,t-1}} \right) \right) \tag{3}$$

3. THE PROPOSED MODEL FOR SERVICE DIFFUSION

We propose a choice-type model for competing service products diffusion. Consider a service category that has N competing service products. Potential customers, after evaluating the performance of each product, choose their preferred ones that maximize their (the customers') utility. Existing users in the service category can also switch from one service product to another at any time, if they feel they will receive more utility from the latter.

Consider the *i*-th customer who is now using service product l at time t, where $l = 0$ indicates the customer is a *potential* customer of the service category. We let $U_{i,t}^{k,l}$ be the utility customer i would obtain by choosing product k, where $k = 0$ indicates the customer will not choose any the products from the category. Below we list five scenarios that can happen based on the above setting.

- ***Scenario 1:*** potential customer i chooses product k at time t ($U_{i,t}^{k,0}$);
- ***Scenario 2:*** customer i of product l switches to product k at time t ($U_{i,t}^{k,l}$);
- ***Scenario 3:*** customer i of product l stays with product l at time t ($U_{i,t}^{l,l}$);

- ***Scenario 4:*** potential customer i remains a potential customer at time t ($U_{i,t}^{0,0}$);
- ***Scenario 5:*** customer i of product l leaves the service category at time t ($U_{i,t}^{0,l}$).

We specify $U_{i,t}^{k,l}$ in Equation 4. Here, V and ε are the deterministic term and the error term of the utility. According to Jun and Park (1999), the deterministic term is related only to the attributes of the service products, such as price, advertisement, service quality, network effect, etc.. The error term captures both random taste variations across the population and model specification error.

(4) $$U_{i,t}^{k,l} = V_t^{k,l} + \varepsilon_{i,t}^{k,l},\ l = 0,1,2,..,N,\ k = 0,1,2,..,N$$

For ***Scenario 1*** and ***Scenario 2***, we specify the deterministic term of utility as in Equation 5. V_0^k denotes the initial utility offered by the service product k, namely, utility of product k at time 0. δ_t^k is a coefficient, denotes the change of the product's utility during time t-1 and time t, relative to the product's initial utility V_0^k. Hence, $\delta_t^k V_0^k$ indicates the change of the product's utility during time t-1 and time t.

(5) $$V_t^{k,l} = V_0^k + \sum_{t'=1}^{t} \delta_{t'}^k V_0^k,\ l \neq k \text{ and } k \neq 0$$

For ***Scenario 3***, we further consider an additional utility p offered by the service products, if users decide to stay with them (see Equation 6). This is because users can manage their current service products more efficiently, as they have become familiar with them. Also the users do not need to pay the switching cost, if they decide to stay with their current products.

(6) $$V_t^{k,l} = V_0^k + \sum_{t'=1}^{t} \delta_{t'}^k V_0^k + p,\ k = l \text{ and } k \neq 0 \text{ and } l \neq 0$$

For ***Scenario 4 and Scenario 5***, we assume that the expected utility of not using the service category is a constant during the studied period. Hence, Equation 7 indicates the deterministic utility of not using the service category, where c is a constant.

(7) $$V_t^{k,l} = c\ ,\ k = 0$$

In Equation 5 and Equation 6, V_0^k can be further extended as by Equation 8, where X denotes the attributes influencing the consumer's utility (such as price, advertisement, service quality, network effect, etc.) and β denotes the effect of these attributes on utility. Correspondingly, δ In Equation 5 and Equation 6 becomes a vector of coefficients, denotes the change of each of the product's attributes during time t-1 and time t, relative to the product's initial attributes. We give Equation 8 here to show the model's extensibility. However, without Equation 8, our suggested model is also sufficient for explaining and forecasting the market growth of most service products.

(8) $$V_0^k = \beta_0^k X_0^k$$

Following the typical approach of the choice-type diffusion models, we assume that the error terms ε follows independent and identically Gumbel distribution (for justification, see Ben-Akiva and Lerman (1985) and Jun and Park (1999)). Then, we have Equation 9 for the probability that the potential service users choose product k at time t. Equation 9 indicates that all the customers have the same choice probability, as the deterministic terms of utility are independent of the individual. Consequently, the number of customers who first enter the service category and choose product k can be calculated in Equation 10, if we let $M_t^{Potential}$ be the number of potential service users at time t.

(9) $$P_t^{First,k} = \frac{\exp\left(V_t^{k,0}\right)}{\exp\left(V_t^{0,0}\right) + \exp\left(V_t^{1,0}\right) + \exp\left(V_t^{2,0}\right) + \ldots + \exp\left(V_t^{N,0}\right)}$$

(10) $$s_t^{First,k} = P_t^{First,k} M_t^{Potential}$$

Similar to Equation 9, Equation 11 explains the probability that the existing users of product l switch to product k at time t. Then similar to Equation 10, we have Equation 12 for the number of switching users from product l to product k at time t.

(11) $$P_t^{Existing,k,l} = \frac{\exp\left(V_t^{k,l}\right)}{\exp(V_t^{0,l}) + \exp(V_t^{1,l}) + \exp(V_t^{2,l}) + \ldots + \exp(V_t^{N,l})}$$

(12) $$s_t^{Existing,k,l} = P_t^{Existing,k,l} S_{l,t-1}$$

Finally, the number of users of product k at time t (S_t^k) can be explained by Equation 13.

(13) $$S_t^k = S_{t-1}^k + s_t^{First,k} + \sum_{l=1;l\neq k}^{N} s_t^{Existing,k,l} - \sum_{l=0;l\neq k}^{N} s_t^{Existing,l,k}$$

4. METHODOLOGY

We employ the case of internet web browsers to show how the suggested model can be implemented in real world cases, to assess the performance of the suggested model, and to analyses the issues of interest for both academics and practitioners.

4.1.Data

A web browser is naturally a software application. Web browsers are now provided to customers free of charge. They are, however, different in their architecture, user interface, features, and supported technologies. In this study we consider web browsers as service products for customers to retrieve, exploit, present, and communicate information on the World Wide Web. Due to technological developments, web browsers in today's online environment are no longer simple information accessing tools. They serve as headquarter or a gateway for many other online products. For instance, with embedded technologies, toolbars and plug-ins, most web browsers are capable of providing seamless connectivity to other online services such as search engines, email, calendar, news, online shopping, and so on. Also, a web browser serves as an advertisement channel and represents the company's image and reputation. If customers choose one web browser, they are more likely to use the online services/products that are suggested by the web browser. Therefore, the competition between web browsers is one of the most intense battlefields in today's online service industry.

The data employed in this study involve the market share of web browsers between September 2008 and August 2012, from the time when Chrome was first released, and cover 48 data points (see Table 1 and Figure 1). We chose the three major web browser products in the market: Internet Explorer, Firefox and Chrome. We have categorized all other products into the 'Others' group. More specifically, Internet Explorer used to dominate the market in 2008 with nearly 70% of the market share, but its market is constantly shrinking due to the rapid development of other web browser products. The market share of Firefox is relatively stable in the selected data period for this study, but tends to experience a slight decreasing trend recently. The users of other web browsers, especially Chrome, are increasing dramatically. By August 2012, Chrome had become the market leader in web browsers, followed by Internet Explorer, Firefox, and other web browser products.

INSERT TABLE 1 HERE

INSERT FIGURE 1 HERE

The growth of web browser users is largely influenced by the growth of internet users, since the web browser is a valuable product only for internet users. Therefore, we also obtained the yearly data of internet users between 1993 and 2010. We use the Bass model to fit the growth trend of internet users and get the estimated parameter value. Then, we use the estimated parameter value to predict the monthly number of internet users between September 2008 and August 2012 ($M_t^{Internet}$). Due to the essential role of web browsers in the online environment, we assume that a web browser is a necessary tool for internet users, namely that any internet user must choose one of the web browsers. Based on the above assumption, we argue that: (1) the number of potential web browser users at time t ($M_t^{Potential}$) equals to the number of increased internet users, which can be calculated directly from Equation 14 (see Figure 2); (2) not using the service category is not an option for internet users, thus $\exp(V_t^{0,0}) = 0$ in Equation 9 and $\exp(V_t^{0,l}) = 0$ in Equation 11.

(14) $$M_t^{Potential} = M_t^{Internet} - M_{t-1}^{Internet}$$

INSERT FIGURE 2 HERE

4.2.Parameter Estimation Technique

Generic algorithm (GA) (Venkatesan et al. 2004) is used in this study for the parameter estimation. We consider that a global estimation tool should be more appropriate here than a non-global one (such as the non-linear least square estimation), as it is more likely to reach a global optimum when the number of estimated parameters is large (Del Moral & Miclo 2001; Venkatesan et al. 2004). We estimate the parameters of the proposed model by minimizing Function 11, where $s_k(t)$ is the observed number of users of product k at time t, and $E(s_k(t))$ is the value estimated by the model.

(14) $$\sum_{t=T_0}^{T}\left(\sum_{k=1,2,\ldots}\left(E(s_k(t)) - s_k(t)\right)^2\right)$$

The software MatLab is used to compute the GA estimation result. The population size of the estimation is set as 200 (200 sample solution vectors are generated in each iteration). We use the software default value for the crossover and mutation (0.8 and 0.25). The stopping rule for estimation is as follows: terminate if there is no improvement (less than 1E-09) in the objective function for 100 consecutive generations. We run the GA estimation for each model 100 times repeatedly. The reported values in this study are the mean and the standard deviation of the 100 estimates obtained from the repeats. The standard error and p value of each parameter can be calculated correspondingly based on the mean value and standard deviation from the results.

5. RESULTS AND DISCUSSIONS

5.1. Curve Fitting Result

Table 2 reports the estimated parameter values of our new model. All the reported parameter values are statistically significant, which is evidence of the importance of their respectively represented roles in the diffusion process.

INSERT TABLE 2 HERE

Figure 3 shows the observed diffusion trends of the studied web browsers and the estimated curves by our suggested model. As can be seen, the suggested model explains the diffusion trend of each web browser extraordinarily well. For each of the competing products, the estimated curve almost superposes the observed curve. Also, interestingly, the growth pattern of these service products follows neither a bell-shape curve nor an S-shape curve, as suggested by previous diffusion studies of durable goods such as home electronics, agriculture and medical innovations (Sultan et al. 1990). This implies that service products have their unique nature and attributes, and thus should be modeled differently from the diffusion of durable goods.

INSERT FIGURE 3 HERE

Table 3 reports the statistical results of the model's fitting performance. We use R squared (R^2) as the measure of descriptive performance. All results show that our suggested model explains the diffusion process of each web browser very well. Table 3 also reports the fitting performance of a choice-type model without the customer switching effect and a Bass-type model with the customer switching effect (see Equation 3). Although the choice-type model without the customer switching effect explains the growth curves of Chrome and Firefox well, it is incapable to fit the growth trends of Internet Explorer and 'Others' web browsers. Especially, it cannot explain why the number of Internet Explorer users is decreasing through time, which indicates that the customer switching effect cannot be neglected in service diffusion models. The Bass-type model, however, fails to explain the case with this study in an accurate manner.

INSERT TABLE 3 HERE

5.2. Model's Forecasting Performance

We adopt a similar approach from Kim and Srivastava (2007) and Decker and Gnibba-Yukawa (2010) to test the suggested model's predictive performance. We divide the data into a calibration period and a forecasting period. Using the parameter values estimated from the calibration period, we forecast the curve trend in the forecasting period. In this study, we chose the 8 most recent data points as the forecasting period and use the rest of the data as the calibration period. The forecasting result is reported in Figure 4 and Table 4. Both graphical and statistical results indicate a good forecasting performance of our suggested model in this study.

INSERT FIGURE 4 HERE

INSERT TABLE 4 HERE

5.3. Change of Product Utility

Figure 5 shows the utility change of each web browser through time. Initially, the performance of Internet Explorer ($U_o^1 = 0.8953$, see Table 2) and Firefox ($U_o^2 = 1.7318$) is significantly better than all the others ($U_o^3 = 0.4447$ and $U_o^4 = 0.0847$). Chrome and other web browsers, however, have overtaken them and become the best web browsers in today's market, which was a result of their remarkable efforts in improving their product utilities.

INSERT FIGURE 5 HERE

Moreover, the reported results show that 'Others' web browsers have the highest improvement ($\delta^4 = 0.9473$). We give three possible reasons for this. First, and perhaps key here, is the rapid development of web browsers that are specially designed for mobile devices, due to the popularization of smartphones and tablet computers. According to the data from StatCounter (2012), the market share of mobile web browsers has increased from less than 1% in 2009 to 11.78% in August 2012. Some web browsers, such as Safari and Opera, have achieved notable success in this market. The second reason we considered here is the network effect in the market. For instance, the current success of Apple's hardware such as iMac, MacBook, iPad, and iPhone will certainly popularize their embedded web browser, Safari. Finally, many web browsers are based on open source projects nowadays, which provide the newcomers a good starting point for further development. For instance, Chrome is actually based on an open source web browser project named Chromium. Besides Chrome, many other web browsers are also based on Chromium, but with features that target specific internet users. For instance, Combodo Dragon removes Chromium's potentially privacy-compromising features and provides additional security measures; Flock specializes in providing social networking facilities with its built in user interface based on the architecture of Chromium.

5.4.First-Time Users

Strictly speaking, the first web browser that a new internet user is likely to use is the one embedded in the operating system (OS) of their hardware. In this case, as Internet Explorer is suggested by the Microsoft Windows OS that has nearly 70% market share of PC OS, this will be the first web browser of most new internet users. In the current study, however, we define the choice of first-time users as the decision after they become aware of the major web browser products in the market. Our assumption can be further validated by the fact that Microsoft is facing complaints regarding its monopoly behavior, and therefore has been asked to unbundle Internet Explorer from its OS in many countries (BBC 2009).

Figure 6 illustrates the growth of web browser users due to first-time users. As can been seen, increasingly less internet users are choosing Internet Explorer as their first web browser, perhaps due to the company's relative poor performance on its improvement of product utility. The number of first-time users who choose Firefox is also decreasing. Both Internet Explorer and Firefox hardly attract any first-time users in today's online environment. Chrome, on the other hand, has gradually dominated the market share for first-time web browser users. This is consistent with the findings from the product utility section that Chrome is the best web browser product in today's market (see Figure 5). The model and its results also demonstrate that there have been a small number of internet users that have selected other web browsers as their first choice.

INSERT FIGURE 6 HERE

5.5.Customer Switching during Diffusion

We use three figures (Figures 7.1, 7.2, and 7.3) to illustrate how the customers' switching behavior influences web browser diffusion. More specifically, Figure 7.1 shows the overall change of web browser users due to customer switching; Figure 7.2 explains the number of users each web browser receives due to customer switching; and Figure 7.3 shows the number of users each browser loses due to customer switching.

INSERT FIGURE 7 HERE

Overall, customer switching behavior has a significant role in the user growth of web browsers. For instance, the decreased number of Internet Explorer users is mainly because its users are gradually switching to other web browsers. Also, it is apparent from the figures that customer switching contributes significantly to the rapid growth of Chrome and other web browser users.

Initially, Internet Explorer and Firefox could still attract users of other web browsers. Due to the relative slow improvement of their product utility, however, they are both losing their attraction to internet users. Not only do they not attract many users of other web browsers, the products are also constantly losing their current users at a significant rate. The fact that they are still holding a notable market share today is because many of their existing users are still reluctant to change, due to their familiarity in using the products ($p = 6.6283$). It can be imagined, however, that the loyalty users of Internet Explorer and Firefox will finally switch to other products if the utility difference between the two and other web browsers continues to grow.

Conversely, Chrome and other web browsers have been gradually gaining the upper hand in this competition. Although recently they have been also losing some customers to its competitors (see Figure 7.3), they are attracting more users from their competitors (see Figure 7.2), leaving the overall change of their user base due to customer switching still positive (see Figure 7.1). Customer switching is especially important for Chrome. Compared the curves of Chrome in Figures 6 and 7.1, it can be seen that more than half of Chrome's new users are switchers from other products. The number of these is even larger than the first-time users the product obtains.

6. CONCLUSIONS

In many countries, service sector has become the most important and fastest-growing sector of today's economy. Especially, the online service industry has been witnessing tremendous growth due to the huge amount of internet users. It is critical for service providers to monitor and forecast the market growth of their products in order to possess a competitive advantage over its rivals. The existing literature, however, has dedicated little effort to this field. In this study, we have proposed a model to explain how service products compete with each other and diffuse in the market. More specifically, the proposed model is capable of exploring the effect of customer switching on the growth of competing products. This model is perhaps the first one in its type that establishes a relationship between service product utility, customers' choice preference, customer switching behavior, and the market growth. Contrary to previous models of competitive diffusion that mostly consider cases with a duopoly setting, the proposed model is applied in a case with four competitors.

This study could provide useful implications to both academics and practitioners in service industries, from several perspectives. First, we show that the market growth of service products can have different diffusion patterns with that of durable goods. As prior diffusion models mostly deal with durable goods, this study alerts the misuse of previous models for today's service products, and underscores the needs for specific models for service diffusion. Second, different with those Bass-type models that seek to generalize drivers of product growth, our suggested model use products' dynamic utility and customers' corresponding adoption choices to explain the market performance of service products as well as customers' switching behaviors in the process. As the empirical analysis demonstrates our model's superior to the benchmarks, we argue that those Bass-type models that have been widely used in the existing literature, may not be a better option for all cases of service products. Perhaps this will also encourage modelers to further explore other alternatives that could better fit the attributes of service diffusion phenomena. Third, our model and its results re-emphasize the important role of customer switching in service diffusion, and they implicate the importance of the distinction between first-time customers and switching customers in modeling service diffusion. In our employed case, we show that a service product can quickly lose its user base due to customer switching, such as the market performance of Internet Explorer. We also argue and empirically demonstrate that customer switching can be the key driver for the market growth of service products and sometimes it is even more important than competing for the new market potential. Therefore, first-time customers and switching customers should be understood and treated in both respective and collective manners in order to better understand the service diffusion phenomena. Last but not least, our suggested model could be a useful tool for practitioners, which can be used for assessing competing service products' relative utility, for estimating the market potential of the service category, for explaining and predicting the market growth of competing service products, and for making the corresponding marketing planning in the service industry.

We view this study as an important step for understanding the diffusion of online service products, as our suggested model is expected to influence future studies that will explore further issues such as service diffusion, the competition effect in diffusion, and customer switch behavior in diffusion. The results of this study could be enhanced and extended in a number of directions and we list some of them in what follows. First, we have implemented our model to a case from the online industry. The suggested model and its results should be further further tested and extended to other service products and other service industries. Second, in this study we have focused on customer switching. Although it was included in our proposed model, we did not consider customers who leave the service category in the case study as we considered a web browser to be necessary for all internet users. The issue of customer dis-adoption, however, should not be neglected in many other cases; for instance, in the online banking sector the dis-adoption rate is reported at 16% (Libai et al. 2009). Hence, further case studies are needed. Third, the suggested model has examined the case in which the customer can only choose one product from the service category. For some online service products, however, such as emails, customers can use the services of multi-service providers. Last but not least, the model can be further extended to include other factors such as marketing mix variables, in order to provide more managerial implications.

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Table 1: Web Browsers

Product	Company	Release Date	Market Share (Sep. 2008)	Market Share (Aug. 2012)
Internet Explorer	Microsoft	Aug. 16, 1995	67.16%	32.85%
Firefox	Mozilla Corporation and Mozilla Foundation	Nov. 9, 2004	25.77%	22.85%
Chrome	Google	Sep. 2, 2008	1.03%	33.59%
Others			6.04%	10.71%

Table 2: Estimated Parameter Value

Parameter	*Mean*	*Standard Deviation*
V_0^1 **	0.8953	0.0549
V_0^2 **	1.7318	0.0786
V_0^3 **	0.4447	0.0450
V_0^4 **	0.0847	0.0091
δ^1 **	0.0579	0.0093
δ^2 **	0.0195	0.0045
δ^3 **	0.2647	0.0314
δ^4 **	0.9473	0.0620
p **	6.6283	0.2165

**: Parameter is significant at p<0.01.

Table 3: Curve Fitting Performance

Product	*Proposed Model*	*Bass-type Model with Customer Switching Effect*	*Choice-type model without Customer Switching Effect*
	R^2	R^2	R^2
Internet Explorer	0.9249	0.1464	0.0685
Firefox	0.9471	0.3264	0.9512
Chrome	0.9936	0.9845	0.9952
Others	0.9435	0.0062	0.7726

Table 4: Results of Forecasting Performance (CP = 40)

Product	*MAPE*
Internet Explorer	2.48%
Firefox	9.87%
Chrome	10.83%
Others	22.34%

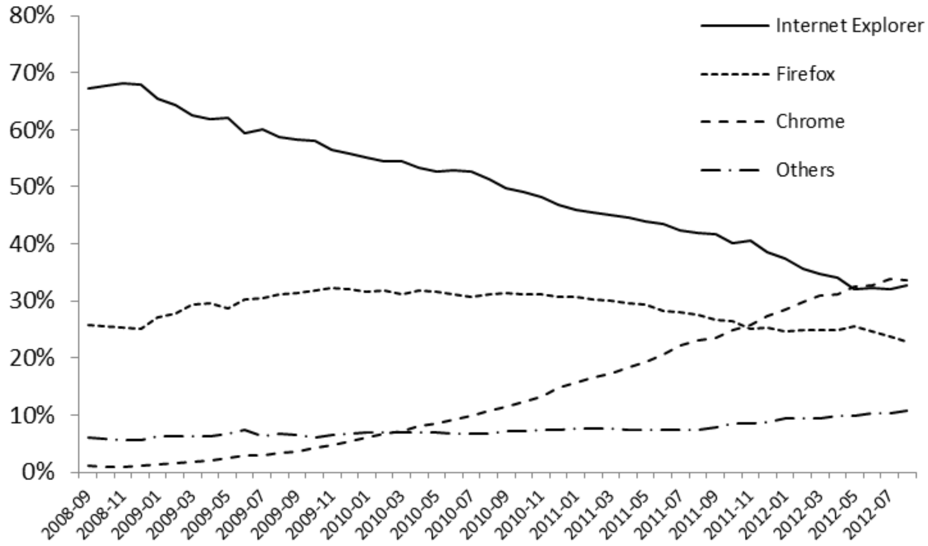


Figure 1: Market Share of Web Browsers

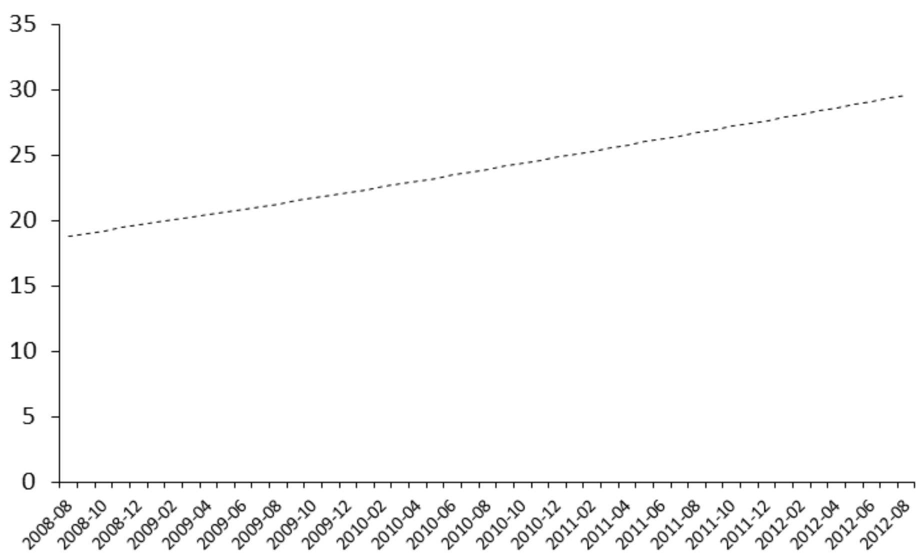


Figure 2: New Internet Users (Unit in Million)

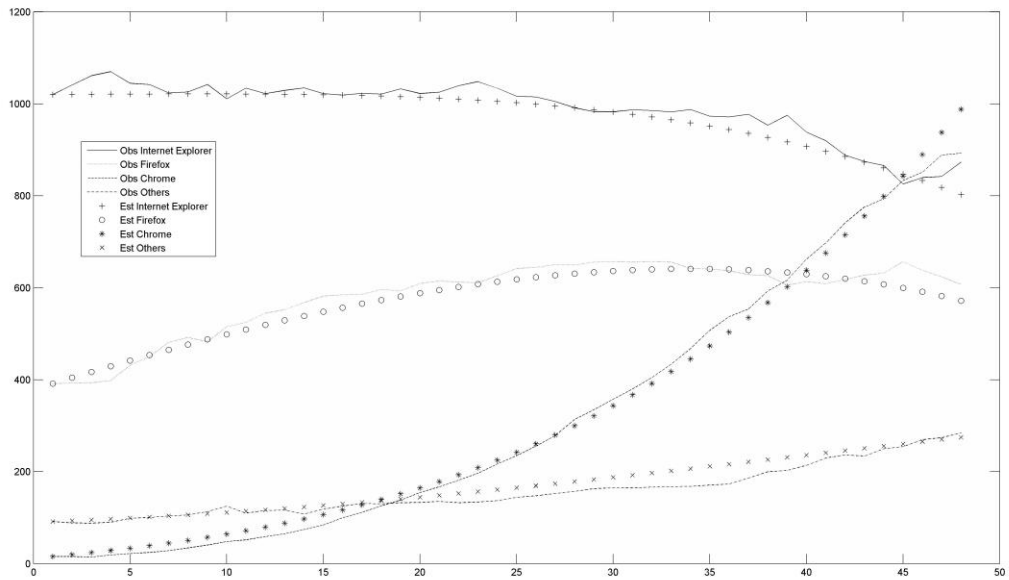


Figure 3: Curve Fitting Performance (Unit in Million)

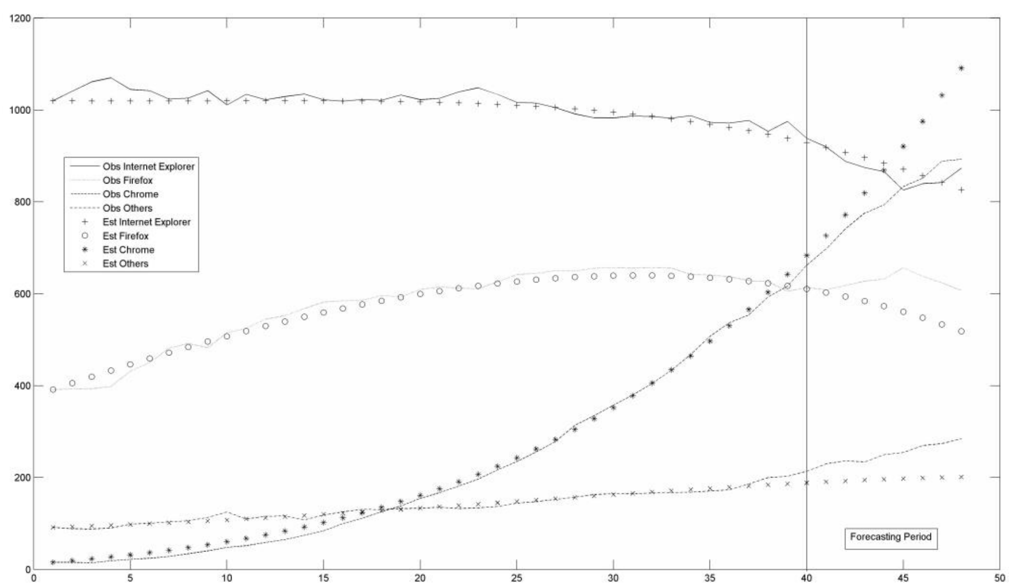


Figure 4: Forecasting Performance (Unit in Million)

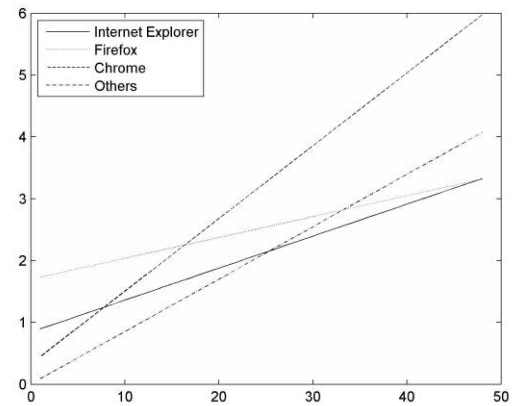


Figure 5: Product Utility through Time

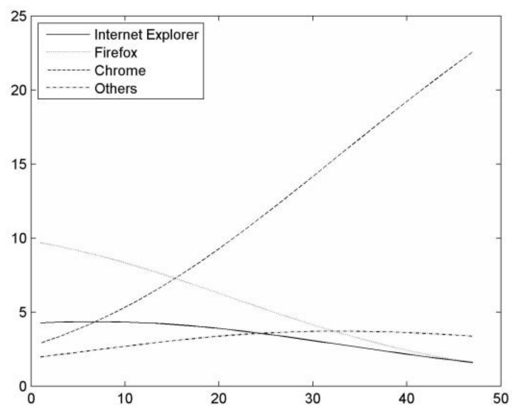
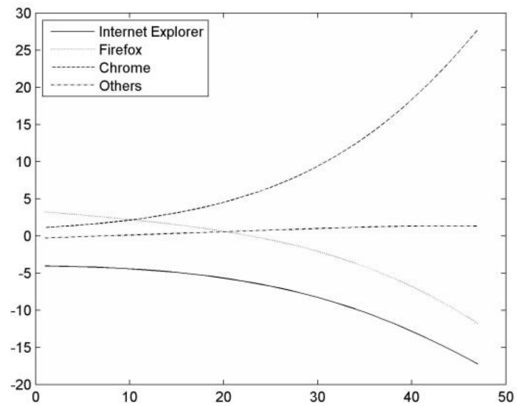
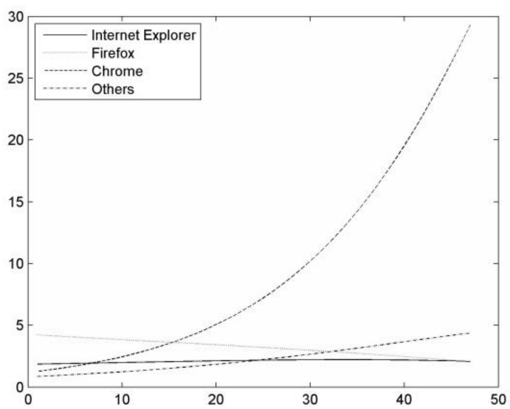
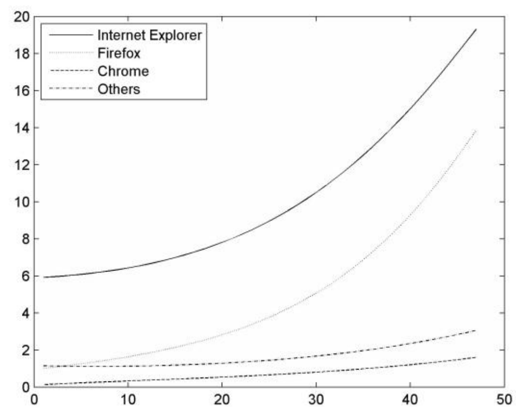


Figure 6: First Time Users



6.1: Change of Web Browser Users due to Customer Switching





6.2: New customers who switch from other web browsers

6.3: Customers who switch to other web browsers

Figure 7: Churn Users of Web Browsers (Unit in Million)