Investigating Adoption of Free Beta Applications in a Platform-based Business Ecosystem

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Abstract

Planning NPD activities is becoming increasingly difficult, as contemporary businesses compete at the level of business ecosystems in addition to the firm-level product-market competition. These business ecosystems are built around platforms interlinking suppliers, complementors, distributors, developers, etc. together. The competitiveness of these ecosystems relies on members utilizing the shared platform for their own performance improvement, especially in terms of developing new valuable offering for end-users.

Therefore, managing the development of the platform-based applications and gaining timely end-user input for NPD are of vital importance both to the ecosystem as a whole and to the developers. Subsequently, to succeed in NPD planning developers utilizing beta testing need a thorough understanding of the adoption dynamics of beta products. Developers need to plan for example resource allocation, development costs, and timing of commercial, end-product launches. Therefore, the anticipation of the adoption dynamics of beta products emerges as an important antecedent in planning NPD activities when beta testing is used for gaining end-user input to the NPD process.

Consequently, we investigate how free beta software products that are built upon software platforms diffuse amongst their end-users in a co-creation community. We specifically study whether the adoption of these beta products follows Bass- or Gompertz -model dynamics used in the previous literature when modeling the adoption of stand-alone products. Further, we also investigate the forecasting abilities of these two models. Our results show that the adoption dynamics of free beta products in a co-creation community follow Gompertz's model rather than the Bass model. Additionally we find that the Gompertz model performs better than the Bass model in forecasting both short and long out-of-sample time periods. We further discuss the managerial and research implications of our study.

Introduction

Competition in contemporary markets is increasingly taking place between business ecosystems (e.g. Moore, 1993, Adner, 2006). Business ecosystems are built around common infrastructures, technologies, and platforms (e.g. Iansiti and Levien, 2004, Adner and Kapoor, 2010), for example, mobile phone ecosystems are built around Symbian, iOS, Android, and the Windows operating systems. Although these ecosystems compete with one another based on their platforms, their competitiveness relies on other members of the ecosystem utilizing the platform for their own performance improvement, especially in terms of them developing new offerings and applications for the end-users based on the technological platform. Thus, this creates a network of complex interdependences between actors in the whole ecosystem (Gawer and Cusumano, 2002). Furthermore, application developers seek to fulfill end-user needs and do so in a competitive environment both inside and between ecosystems. Therefore, managing new product development (NPD) and gaining intimate and timely customer input are of vital importance to application developers, as well as to the whole ecosystem. Hence, this paper will consider the usage of beta testing, denoting early customer testing of unfinished products in real-use NPD environments.

The overall importance of beta testing in NPD activities has been well documented and it is now the top-ranked means of gathering user input in PDMA NPD best-practice surveys (Barczak, Griffin and Kahn, 2009). This is at least partially due to the increasing use of virtual co-creation communities as a means to gather customer and user input from markets (Nambisan and Baron, 2007). Similarly, the importance of NPD planning in line with company strategy has become increasingly important in a networked, technology-intensive business world, as the companies and their offerings are increasingly dependent and interlinked in the business and innovation ecosystems (Adner, 2006). PDMA surveys also find that beta testing is used significantly more by the successful companies in their NPD than by the poorer performers (Barczak, Griffin and Kahn, 2009), and, similarly, customer testing in general also differentiates poor from best practices (Kahn, Barczak, Nicholas, Ledwith and Perks, 2012). Therefore, the importance of users in innovating has been well established, and lately there have been calls for research to further understand the user–producer innovation dynamics, especially as “the transfer of knowledge between a user and a producer is a central issue” (Bogers, Afuah and Bastian, 2010), and, as “a producer is better able to innovate when its (tacit) routine allows the producer to solve a user need and the user’s routine relies on *using* (not *inventing*) a product” (ibid., italics original). What is especially important in beta testing is the use of the product in its end-use environment, even if it may be functionally deficient. Continuing with this line of thought, following, for example, Gangi and Wasko (2009), it is the absorptive capacity of a producer that determines the innovations and ideas from user communities that get to be implemented in the product development by the producer. Therefore, it is a central starting point for product development planning, at a minimum, to be able to understand the adoption dynamics of beta products in the user community. This baseline information subsequently facilitates better NPD planning activities and, therefore, enhances the absorptive capacity of the producer.

In the last decade, ICT (Information and Communication Technologies) has transformed the way in which producers and end users are able to interact with one another. The Internet, especially, has made it possible for companies to directly interact with a large body of customers on a regular basis, revolutionizing product development (e.g. Prandelli, Verona and Raccagni, 2006). The connection that producers were able to form with end users was limited prior to the emergence of widespread digital technologies, which have provided the opportunity for efficient connections and the build-up of co-creation communities (Erat, Desouza, Schäfer-Jugel and Kurzawa, 2006). The ability to interact with customers has dramatically changed the product development cycles of producers, since customers are not only a source of ideas for new products and innovations, or a means of merely testing the products, but end users can also be engaged in close co-creation activities during the development of new innovations (e.g. Sawhney and Prandelli, 2000). Prahalad and Ramaswamy (2004) highlight the co-creation communities as “creating an experience environment in which consumers can have active dialogue and co-construct personalized experiences.”

The connectivity with the customer can be built on requirements for efficiency and effectiveness; that is, the costs associated with managing customer involvement in order to gain effective and meaningful input for product development. Consequently, recent studies emphasize the need to support creative collaboration instead of relying on individuals to innovate by themselves, and this is one of the central challenges of producers in organizing customer involvement; namely, how to capture customer knowledge and use it in product development (Nambisan, 2002). Organizing NPD and its activities to support end users is important in order to get the maximum out of all the individuals’ innovativeness (Farooq, Carroll and Ganoe, 2005, Hargadon and Bechky, 2006).

However, as is apparent from the above discussion, for organizations utilizing co-creation communities, for example, in their beta product testing, they would need an understanding of how their beta launch adoption dynamics work for NPD planning activities, for example, in order to manage and plan the timing of their product launches, in anticipating operational costs, for the development resource allocations, and so forth. Furthermore, recent research has called for investigations into adoption dynamics and S-curve applicability over different platforms, designs, and industry contexts (Hauser, Tellis and Griffin, 2006). Additionally, understanding the users, their engagement, and how to manage external knowledge in open innovation have been raised by the JPIM Thought Leadership Symposium (di Benedetto, 2012) to the cutting edge of the academic research agenda.

Therefore, building on the above, the driving force behind this paper is in investigating how the beta software products that are built upon certain hardware platforms diffuse amongst their end users. We perceive this as an especially pertinent question, as the competitiveness of business ecosystems is built on understanding and responding to end-user needs. Although freely distributed software products play a prominent role in keeping digital business ecosystems competitive, further developing and delivering utility to end users, and maintaining the survival of these ecosystems, the dynamics of the adoption of these products is missing in current literature. Therefore, this research specifically studies whether the adoption of beta products based on certain platforms in a co-creation community follows traditional Bass or Gompertz model dynamics, which have been extensively used in modeling stand-alone product adoption. Additionally, we investigate the forecasting abilities of these two models. The results of our study show that the adoption dynamics of free beta products in a co-creation community do not seem to follow Bass-type diffusion paths; rather, the simpler formulation of the Gompertz model outperforms the Bass model. Additionally, we find that Gompertz model outperforms the Bass model for forecasting purposes, although our results do not consistently favor the Gompertz over the Bass model. We further discuss the implications of our findings.

Background and motivation

Product development in business ecosystems and customer involvement

Platform-based product design and development has received increasing attention in the existing product development literature due to the suggested benefits in both the supply and demand sides (e.g. Meyer and Utterback, 1993, Meyer and Lehnard, 1997, Krishnan and Gupta, 2001). Platforms have been argued to create competitive advantage in the supply side through a reduction of fixed costs, the lowering of unit costs, and the responsiveness in developing product variants with the speedy fulfillment of needs for particular, specified market segments (Krishnan and Gupta, 2001), although the platform approach does not necessarily result in design variability in the offering (e.g. Robertson and Ulrich, 1998). In general, introducing new variants in a speedy fashion and platform stability have been found to increase firm performance (Jones, 2003), highlighting the need for careful management of platform-based product development. Similarly, platforms have been suggested as providing customers and end users with demand-side benefits in that new functionalities and product variants are introduced more effectively (Baldwin and Clark, 1997). In order for the platform approach to reap its benefits, product design and development require well-specified inputs from customers, alongside intimate customer involvement in the development process.

Platforms are the basic building blocks of business ecosystems and we may depict the ecosystem as consisting of platforms providing basic functionalities for the ecosystem and modules that provide additional functionalities above the core functions (following Tiwana, Konsynski and Bush, 2010). Therefore, in this paper we consider the business ecosystem concept as a collection of providers gathered around a certain platform in order to develop and provide additional functionalities to end users through modules. In this type of networked business ecosystem, the key to success is in being prepared for delays in a complementary offering (Adner, 2006) and the anticipation of challenges related to the technological performance delivery of various other systemic parties (Dedehayir and Mäkinen, 2011). Similarly, NPD planning needs to account for the evolution of customers' needs and match these with the abilities of the system of producers, as to when and how these needs can be fulfilled (Adner and Kapoor, 2010). However, the development of modules or applications based on the platform crucially depends on the access to market and customer information regarding what additional functions are needed besides the core functionalities provided by the platform.

Customer involvement in NPD as a success factor has been proven in numerous existing studies (see e.g. Rothwell, Freeman and Townsend, 1974, Cooper, 1979, von Hippel, 1988, Cooper, Edgett and Kleinschmidt, 2002, Griffin, 1997, Barczak, Griffin and Kahn, 2009, Kahn, Barczak, Nicholas, Ledwith and Perks, 2012). Traditionally, customer involvement in NPD has included tools such as concept testing, market testing, focus groups, surveys, ethnographics, and so on (e.g. Kahn, Barczak, Nicholas, Ledwith and Perks, 2012). Increasingly, however, company-led product development has been challenged with calls for more intimate customer involvement and empowerment in the product development process (Fuchs and Schreirer, 2011). Especially, with increasing use of the Internet and digital collaboration tools, companies can create and maintain fruitful and close cooperative relationships globally with enormous numbers of customers (Nambisan, 2002, Dahan and Hauser, 2002, Sawhney, Verona and Prandelli, 2005). Increasingly, these virtual tools employed in product development have been used to closely integrate customers and users with the development process (Ogawa and Piller, 2006), and the integration of customers, and use of customer information from this integration differentiates the best performers from the rest of the field (Barczak, Griffin and Kahn, 2009).

Beta testing

As a means of gathering market input, the overall importance of beta testing in NPD has been well documented and it has become the best means of gathering user input in PDMA NPD best-practice surveys (Barczak, Griffin and Kahn, 2009), as a part of the trend of the increasing use of virtual co-creation communities as a means to gather customer and user input from markets (Nambisan and Baron, 2007). PDMA surveys also find that beta testing is used significantly more by the successful companies in their NPD than by the poorer performers (Barczak, Griffin and Kahn, 2009), as well as overall customer testing differentiating the poor from the best practices (Kahn, Barczak, Nicholas, Ledwith and Perks, 2012).

Beta testing has traditionally meant limited numbers of users trying out the product and reporting their experiences on the product (Dolan and Matthews, 1993), and virtual co-creation communities have increased the number of users that can participate in beta testing, even spreading product testing to an open forum of 'public betas'. Beta product launches are in many cases differentiated from normal product launches in that they are managed launches into specific markets (e.g. Fine, 2002). Beta products contain at least some of all the core functionalities, but are not functionally complete (MacCormack, Verganti and Iansiti, 2001). Subsequently, from an NPD point-of-view, the beta products are launched during the later stages of architecture and platform development, when most, or all of the platform design has already taken place, and module development is underway (MacCormack and Verganti, 2003). However, for product development, this is a critical phase, as it allows early feedback from customer experience with the product, albeit with an incomplete product. Beta releases can also be a powerful way to provide additional benefits to customers, as they are the first release of a product in the end-user application context, and are designed to be functionally rather mature (Iyer and Davenport, 2008, MacCormack, Verganti and Iansiti, 2001). Similarly, use of online communities to involve customers early on in product development to gain important clues regarding customer preferences and product attributes has also spread to industries outside of the software field (e.g. Pitt, Watson, Berthon, Wynn and Zinkhan, 2006).

The beta phenomenon builds heavily on platformization and the modularization of technological solutions in business ecosystems (Tiwana, Konsynski and Bush, 2010), although beta testing can also be utilized with stand-alone products to test the customer reactions to the features of products. However, the speedy implementation of customer input in NPD in many cases requires modular design based on platforms so that the product is not completely altered due to customer input. For example, application software may be built on software and hardware platforms like mobile phone applications' beta versions can be developed to work on a certain proprietary mobile phone software and hardware platforms . The software that is tied to a certain platform has been shown to increase the value of the hardware for the end user, in addition to the value and the utility that the software itself produces for the end user (Cottrell and Koput, 1998).

Despite the benefits suggested by beta testing, it has received criticism as well. Views have been raised on possible issues attached to beta testing such as flawed procedures, the increased risk of negative publicity, and inaccurate customer input (e.g. Dolan and Matthews, 1993). Despite these criticisms, the contemporary methods of connecting with customers (Nambisan and Baron, 2007) facilitate the establishment of co-creation communities to intimately interact with innovative users willing to share their experiences (Jeppesen and Frederiksen, 2006).

NPD planning and beta products

NPD planning activities have been shown to increase NPD performance (Salomo, Weise and Gemünden, 2007) and forecasting beta product adoption plays a pivotal role in building premises for these activities. Furthermore, beta testing—whether testing a full product with all the features or a functionally incomplete product—provides important cues and inputs for NPD planning. Early on, the extant research has identified the criticality of beta testing, requiring careful NPD planning to attain its benefits during product development and to minimize the associated risks to the firm (e.g. Dolan and Matthews, 1993). While the product is in beta testing, it is critically important that product development gains efficient (speed, costs), effective (quality, correct) knowledge from the beta users or co-creation community. In addition, since the knowledge boundaries of the firm are extended to include external stakeholders and communities, the firm needs to develop tools and provide resources for understanding the user input and product-testing experiences (Brusoni, Prencipe and Pavitt, 2001, von Hippel and Katz, 2002), which act to increase the need for careful NPD planning activities. Further, the resource allocation for the beta testing also needs to respond to the possible inertial forces and bounded rational search processes as reactions to external changes

(Hill and Rothaermel, 2003), and build up absorptive capacity that facilitates the accumulation and use of external knowledge (Cohen and Levinthal, 1990, Zahra and George, 2002). Consequently, NPD planning should be based on the anticipated needs of the product development that subsequently depend on the evolutionary dynamics of the co-creation community; namely, the adoption dynamics of the beta products as they are launched, no matter whether the launch is open, or to a closed community.

Therefore, effective and efficient product development utilizing input in NPD planning from beta testing necessarily needs to be built on the understanding of the adoption of beta products in the co-creation community. Anticipation of adoption dynamics would facilitate forward-looking resource planning and allocation to acquire, assimilate, transform, and exploit user input from the co-creation community in the product development process, thus facilitating the planned dedication of resources for NPD, which has been shown to lead to increased firm performance (Henard and McFadyen, 2012).

Adoption of beta products

Although a number of studies exist that have examined various aspects of the dynamics of co-creation communities, for example, the characteristics of the users (e.g. Lettl, Cornelius and Gemünden, 2006), how users gather and disseminate information (e.g. Franke and Shah, 2003), the design of virtual customer environments (e.g. Nambisan, 2002), online toolkits (e.g. Franke and von Hippel, 2003, Franke and Piller, 2004), and the motivation to participate (e.g. Dholakia, Bagozzi and Pearo, 2004, Hars and Ou, 2001, Huberman, Loch and Onculer, 2004, Kollock, 1999, Lampel and Bhalla 2007, Wasko and Faraj, 2000), research still remains limited on innovation diffusion in these communities. While there is little existing research specifically on the adoption of beta products in co-creation communities, few studies have considered the diffusion of software products. Earlier literature related to the adoption of beta products includes, for example, the adoption of functionally restricted or time-limited free distribution (Haruvy and Prasad, 2001), the diffusion of digital technologies in online, open-source software environments using social network analysis (Peng and Mu, 2011), OSS diffusion determinants (Zaffar, Kumar and Zhao, 2011), the influence of beta testing on the adoption of final software products (Jiang, Scheibe and Nilakanta, 2011), a study on Hotmail adoption (Montgomery, 2001), the piracy and diffusion of software products (Givon, Mahajan and Muller, 1995), free web-server diffusion (Gallaugher and Wang, 1999), and the diffusion of fully functioning software that is distributed free (Jiang and Sarkar, 2010). Extending the analysis of innovation adoption to domains other than that of consumer durables has been called for, through for example, suggesting that studies be carried out on the diffusion of software products (e.g. Tellis, 2007).

Thus, the present paper investigates the adoption of free beta products in an open virtual forum. Product adoption has, traditionally, mostly been studied through diffusion models (see e.g. Heeler and Hustad, 1980, Gatignon and Robertson, 1985, Gatignon, Eliashberg and Robertson, 1989, Mahajan, Muller and Bass, 1990, Helsen, Jedidi and DeSarbo, 1993, Mahajan and Muller, 1994, Putsis, Balasubramanian, Kaplan and Sen, 1997, Dekimpe, Parker and Sarvary, 1998, Talukdar, Sudhir and Ainslie, 2002, Peres, Muller and Mahajan, 2010). These studies are based on the seminal work of Bass (1969), assuming that

$$\frac{dF}{dt}(t) = \big(p + qF(t)\big)\big(1 - F(t)\big), \tag{1}$$

where $F(t)$ denotes the fraction of individuals who adopt the product by time t (i.e. the installed base fraction) and p and q are positive constant real numbers. Here p and q represent the coefficients of innovation and imitation, respectively. The coefficient p represents the fraction of unmet potential customers that adopt in each period and the initial diffusion rate, while the q represents the fraction of later adopting customers.

By skipping the derivation, the Bass model shows that

$$F(t;p,q) = \frac{1-e^{-(p+q)t}}{\left(\frac{q}{p}\right)e^{-(p+q)}+1}, \tag{2}$$

where time $t > 0$. It has been suggested for the Bass model to include other decision variables in its coefficients of innovation and imitation (e.g. Bass, Krishnan and Jain, 1994), if not explicitly, then implicitly embedded in the coefficients. However, the Bass model has been suggested to have reduced forecasting power, especially before the peak of sales occurs (e.g. Mahajan, Muller and Bass, 1990). At the same time, the questionability of a short time series in fitting the Bass model for forecasting purposes has been long established and in order to understand the adoption dynamics, longer time series have frequently been suggested (e.g. Kamakura and Balasubramanian, 1988). Therefore, we adopted the Bass model as a baseline model for the present study, as it has been used previously in numerous studies, and it has been able to capture the adoption dynamics. Further, we use this approach as the adoption of freely distributed beta software products remains unstudied, and the traditional Bass model presents a representative starting point for the adoption investigation.

However, the Bass model has been shown to be susceptible in its forecasting performance due to a when limited number of data points is available for fitting and this is especially the case during early phases of the adoption process. At the same time, these early phaseshave been argued to be increasingly important in current high-technology markets (e.g. Gnibba-Yukawa and Decker, 2012), and so we selected another model that does not require theoretical behavioral rootings, and that has been shown to be applicable in highly dynamic, high-technology markets. Namely, we follow recent investigations (e.g. Goodwin and Meeran, 2012) that have verified the applicability of the Gompertz model for adoption studies as a rather simple growth model. The Gompertz model traces the time evolution of adoption quantity, for example, without exogeneously determined variables, or their ranges thereof. Therefore, we compared the baseline Bass model with the Gompertz model regarding both whether they are able to capture the adoption dynamics and also in terms of their forecasting abilities. For the Gompertz model, the installed base fraction can be expressed as (Meade and Islam, 1998)

$$F(t; a, b) = e^{-e^{-a(t-b)}}, \tag{3}$$

where a and b are positive constants.

Method and data

Our empirical data on the diffusion of free beta products in a co-creation community considers 25 original beta software releases at Nokia Beta Labs. All the cases considered are software products based on specific technological platforms, and they represent new applications and functionalities intended for mobile phones, but are not commercial launches of finalized products. These products were launched into the co-creation community and the daily adoption rates—that is, the number of downloads of each product, representing the sales figures of the products—were used as data for our analysis of the adoption dynamics. Figure 1 depicts the study setting.

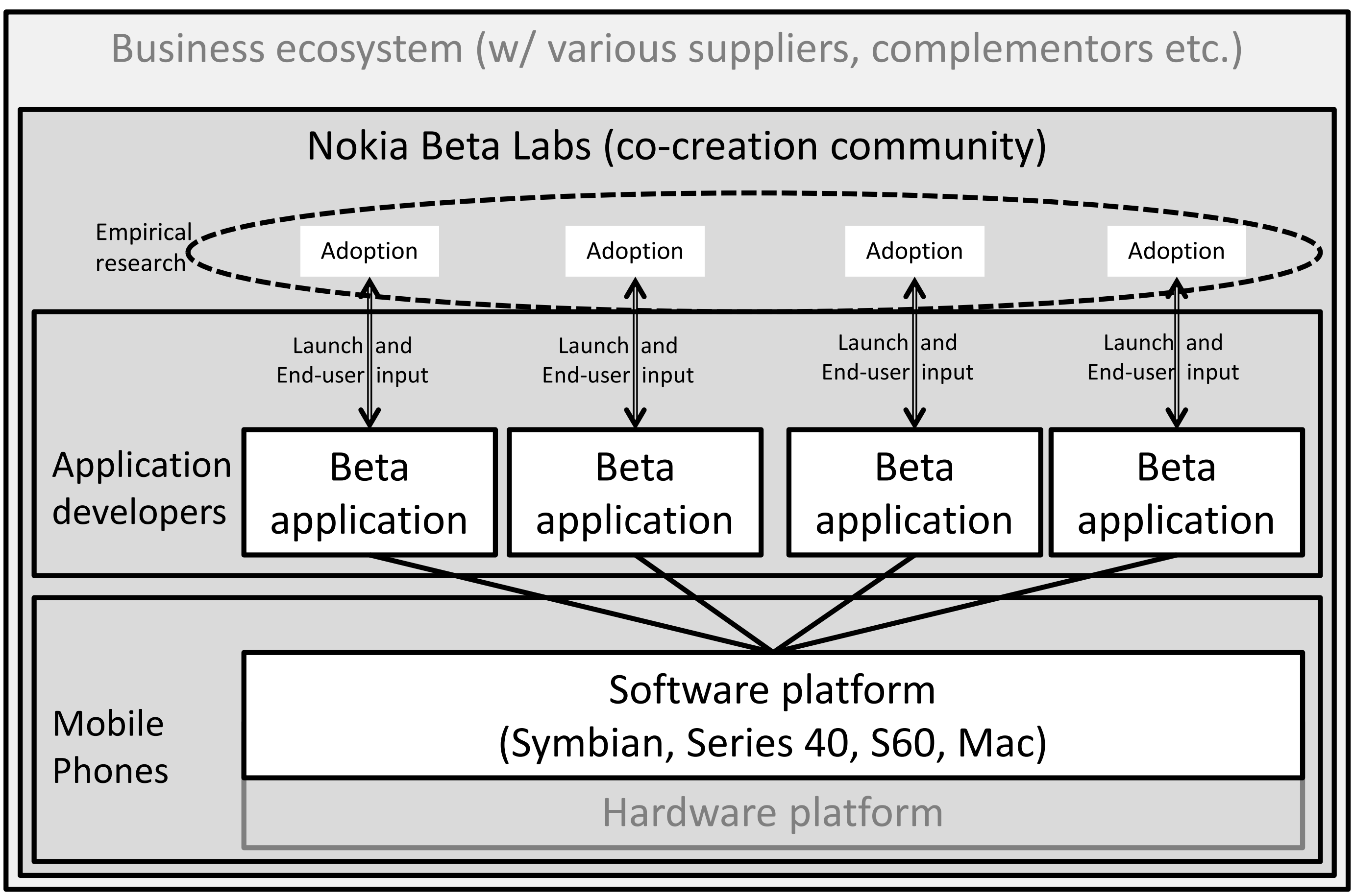

Figure 1. Schematics of the empirical setting.

Fig. 1 shows our area of interest: adoption of free beta products in a co-creation community that is part of a wider interlinked business ecosystem. These beta products were created by third-party developers or by Nokia and launched at Beta Labs in order to gain end-user opinions, inputs, and information on the use of the applications. Additionally, these products are based on different software platforms (which again are based on certain hardware platforms). Our data in this study consider the adoption, in addition to considering the software platform used in each beta product.

We aim at investigating two issues in beta product adoption in a platform-based business ecosystem. Firstly, we study whether the Bass and Gompertz models are able to capture the adoption dynamics of beta products in an open community as a post hoc testing. Secondly, we also investigate the forecasting abilities of both of these models as an ex ante testing. Both of these questions are pertinent to the understanding of how NPD planning could be built upon the anticipation of the beta community's adoption behavior regarding new beta launches.

In order to study whether the models capture the adoption dynamics of free beta products, we firstly obtained the diffusion parameters by fitting the diffusion model to the cumulative adoption data with a nonlinear least-squares (NLS) fitting procedure in EVIEWS. In particular, we denote the observed total number purchasing up to time $t_i > 0$ as $Y(t_i)$, and apply NLS to

$$Y(t_i) = mF(t_i; \theta) + u(t_i) \tag{4}$$

where θ denotes model parameters, m is the total number of adopters[1] and u is an additive error term with variance σ^2. NLS estimation chooses the parameter values, θ, that minimize the sum of the squared residuals, $\sum_i \big(u(t_i)\big)^2$. The NLS approach has been widely used in earlier studies (e.g. Srinivasan and Mason, 1986, Goodwin and Meeran, 2012). Additionally, we also studied whether the adoption dynamics of beta products that were built on different platforms differed from one another through a non-parametric Mann-Whitney test. We also investigated the dynamics of beta product adoption in respect to a 'typical' Bass adoption model with values in a developed national context by following established

[1] We assume, following most of the existing literature, that each adopter buys, i.e. downloads, only one unit.

diffusion coefficients from Talukdar, Sudhir and Ainslie (2002). For this purpose, we plotted the adoption curves of the slowest, minimum (MIN), median (Median), average (AVE), and the fastest, maximum (MAX) beta products, and also the fraction of saturated beta products along with the typical Bass adoption curve. We compare these to highlight the differences in beta product adoption in respect to typical Bass-type dynamics.

For our second task, testing the applicability of the models for forecasting purposes, we used traditional holdout testing. We used 14 first data points to fit our models for all 25 beta products. Then we made out-of-sample forecasts for 7, 14, 21, 28, 35, 42, 49, and 56 data points forward. We compared the Mean Squared Error percentages of the Bass and Gompertz models' forecasting for each time period for across all products with Anova to see whether the two significantly differed from one another.

Research results and discussion

Diffusion parameters were estimated for all 25 adoption time series using the Bass model and the results are presented in Table 1.

Table 1. Parameter estimates for the Bass model, *m* depicting the final population adopting the application.

	p			q			m			
App	coefficient	t-stat	Prob	coefficient	t-stat	Prob	coefficient	t-stat	Prob	R2
1	0,087	6,474	0,000	0,000	0,000	1,000	18885	66,761	0,000	0,780
2	0,106	6,482	0,000	0,000	0,001	0,999	727	48,056	0,000	0,879
3	0,252	3,177	0,003	0,000	0,001	0,999	3184	58,555	0,000	0,745
4	0,081	12,207	0,000	0,000	0,001	0,999	3993	106,020	0,000	0,958
5	0,058	14,862	0,000	0,000	0,001	0,999	52719	92,905	0,000	0,967
6	0,036	10,255	0,000	0,000	0,000	1,000	27064	26,192	0,000	0,867
7	0,001	1,215	0,229	0,883	6,762	0,000	830	103,134	0,000	0,952
8	0,123	10,592	0,000	0,000	0,000	1,000	14151	250,274	0,000	0,908
9	0,041	8,982	0,000	0,000	0,000	1,000	2001	6,562	0,000	0,996
10	0,034	10,161	0,000	0,000	0,001	0,999	41228	42,168	0,000	0,832
11	0,025	14,092	0,000	0,000	0,001	1,000	18826	47,542	0,000	0,904
12	0,023	14,873	0,000	0,000	0,007	0,995	79904	82,154	0,000	0,898
13	0,095	15,259	0,000	0,000	0,000	1,000	17498	269,626	0,000	0,956
14	0,006	7,642	0,000	0,000	0,000	1,000	24043	5,392	0,000	0,920
15	0,010	19,347	0,000	0,000	0,000	1,000	10065	18,938	0,000	0,903
16	0,041	6,409	0,000	0,000	0,001	1,000	5021	91,929	0,000	0,735
17	0,044	4,934	0,000	0,000	0,000	1,000	6836	75,348	0,000	0,634
18	0,016	15,291	0,000	0,000	0,000	1,000	2308	65,690	0,000	0,905
19	0,011	26,069	0,000	0,000	0,007	0,995	15443	70,158	0,000	0,957
20	0,052	1,11,9287	0,000	0,000	0,000	1,000	5529	260,811	0,000	0,864
21	0,005	35,772	0,000	0,000	0,006	0,995	25698	22,181	0,000	0,967
22	0,006	25,449	0,000	0,000	0,001	0,999	25698	16,970	0,000	0,881
23	0,007	78,928	0,000	0,000	0,001	0,999	3551	121,464	0,000	0,992
24	0,011	1,040	0,304	0,000	0,000	1,000	5869	0,996	0,324	0,994
25	0,007	67,046	0,000	0,000	0,000	1,000	1445	67,511	0,000	0,989

As can be seen from Table 1, overall, the Bass model explains fairly high percentages of variation in the adoption time series (R2 being between 0.735 and 0.996). However, we also find that the coefficient of imitation is statistically significant only in the case of Application 7. Similarly, we may conclude that the coefficient of innovation is statistically significant at a 0.01 level in all but the cases of Applications 7 and 24. Therefore, the Bass model does not, in itself, fit to the dynamics of adoption of these beta products in any of the beta products we studied. Additionally, we present one representative analysis of a residual plot on the fitting of the Bass model using the adoption data from Figure 1.

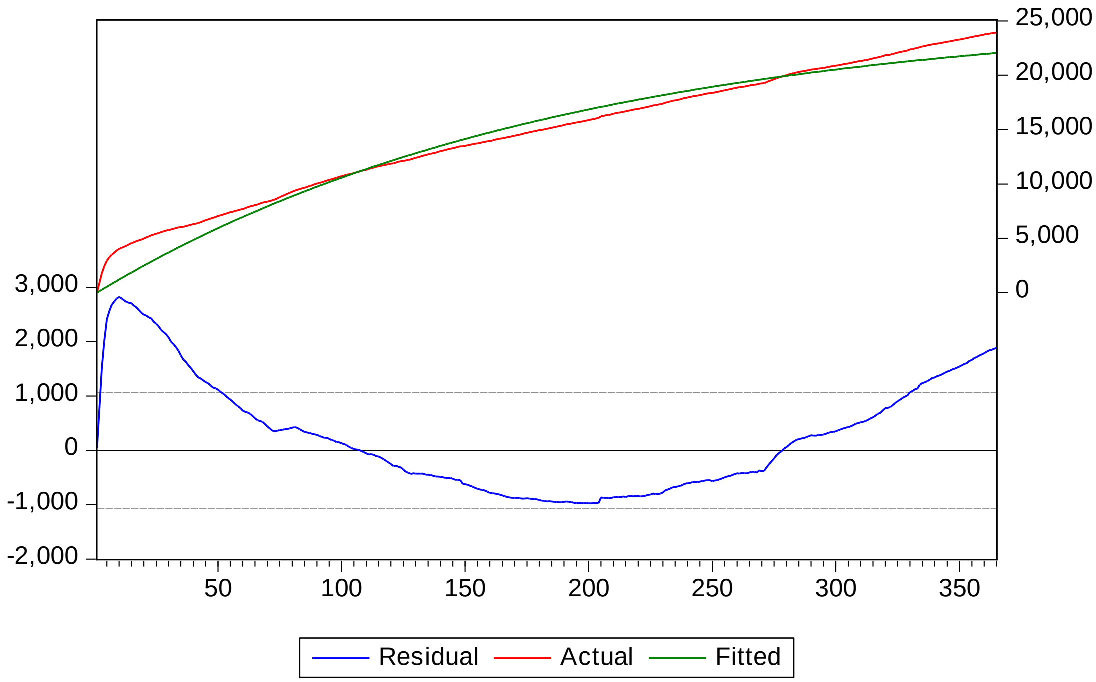

Figure 2. Example: Data and fit with Bass model for Application 25.

As can be seen from Fig. 2, the fitted Bass model lags the actual adoption at the start and then later proceeds faster than the data, finally saturating at a lower level than the actual data. Therefore, the Bass model leads to misrepresentative adoption dynamics.

Following this, we also estimated diffusion parameters for all 25 adoption time series using the Gompertz model and the results are presented in Table 2.

Table 2. Parameter estimates for the Gompertz model, *m* depicting the final population adopting the application.

	a			*b*			*m*			
App	coefficient	t-stat	Prob	coefficient	t-stat	Prob	coefficient	t-stat	Prob	R2
1	0,055	23,734	0,000	0,000	0,000	1,000	19952	142,676	0,000	0,976
2	0,082	12,344	0,000	1,639	2,964	0,005	741	64,227	0,000	0,950
3	0,080	11,666	0,000	0,000	0,000	1,000	3634	65,572	0,000	0,935
4	0,089	34,475	0,000	4,761	21,405	0,000	4026	227,065	0,000	0,987
5	0,063	24,920	0,000	6,876	17,442	0,000	53370	135,070	0,000	0,976
6	0,031	24,088	0,000	6,864	13,367	0,000	27969	79,071	0,000	0,984
7	0,548	8,138	0,000	6,719	36,123	0,000	835	108,799	0,000	0,958
8	0,101	30,890	0,000	1,399	5,065	0,000	14133	405,028	0,000	0,966
9	0,105	14,524	0,000	8,798	21,793	0,000	1559	33,248	0,000	0,988
10	0,031	20,849	0,000	3,757	4,953	0,000	40435	95,042	0,000	0,964
11	0,021	33,880	0,000	12,089	20,622	0,000	19835	116,902	0,000	0,985
12	0,020	42,205	0,000	9,668	15,745	0,000	82894	198,275	0,000	0,983
13	0,099	82,574	0,000	3,231	32,718	0,000	17348	896,300	0,000	0,996
14	0,004	16,308	0,000	220,103	1,10,8034	0,000	50836	1,11,4777	0,000	0,988
15	0,007	17,637	0,000	83,175	12,478	0,000	14409	24,060	0,000	0,974
16	0,017	20,596	0,000	6,349	4,129	0,000	6109	101,449	0,000	0,924
17	0,012	17,672	0,000	9,165	5,193	0,000	9261	61,872	0,000	0,929
18	0,011	40,441	0,000	32,309	34,491	0,000	2753	115,374	0,000	0,985
19	0,010	51,538	0,000	47,290	54,713	0,000	17263	148,928	0,000	0,988
20	0,036	27,644	0,000	3,246	3,759	0,000	5744	319,463	0,000	0,913
21	0,006	51,868	0,000	106,292	49,623	0,000	28679	87,558	0,000	0,993
22	0,008	50,220	0,000	47,253	42,614	0,000	23688	132,756	0,000	0,988
23	0,013	79,771	0,000	59,231	104,871	0,000	3236	319,817	0,000	0,991
24	0,047	15,783	0,000	20,872	18,483	0,000	3130	22,509	0,000	0,990
25	0,010	53,278	0,000	70,261	69,703	0,000	1435	147,647	0,000	0,987

As can be seen from Table 2, the results are statistically significant, and only two b-parameters are not statistically significant at the 0.01 level (Application cases 1 and 3). The other was for Series 40 and the other for Symbian platforms, and also the applications were different, so our data does not give clues as to why these differed from the general pattern. All the other parameters are statistically significant, and the explanatory power of the Gompertz model ranges from 0.913 to 0.996. Similarly to the above case, below, in Figure 2, we present one representative analysis of a residual plot on the fitting of the Gompertz model to the adoption data.

Thus, our study shows that the Bass model does not fit well into estimating the adoption of free beta software products based on platforms in open innovation ecosystems. This is a rather surprising result, since the Bass model has become the standard model in diffusion and adoption modeling. When we look at the estimation results of the present paper, we notice that the Bass model is unable to capture the dynamics of adoption; that is, the adoption is much faster and much slower later in the adoption process than the Bass model would assume. Additionally, the results suggest that only the parameters p and m are statistically significant. The parameter p in the standard Bass model suggests that the influence of innovation, external influences, and advertising are in place and heavily influence the adoption dynamics. Now, in open innovation ecosystems, the companies that maintain the ecosystems and community release information on the new beta product launches, and it seems that this is the sole influence on the adoption dynamics, as suggested by our results. Furthermore, we might expect the parameter q, namely, word-of-mouth and the internal influence, to be present in open innovation ecosystems, which traditionally show vivid and frequent communication patterns among the participants in the ecosystem. Similar to the study by Goldenberg, Lowengart and Shapira (2009), our results may partly be due to the level of aggregation in the empirical data, as our data is daily data. In addition, software diffusion, as an individual-level process, may proceed much quicker than for traditional products (following the assertion by Rogers (1995) that software diffuses faster than hardware), especially as our study was based on freely distributed beta products.

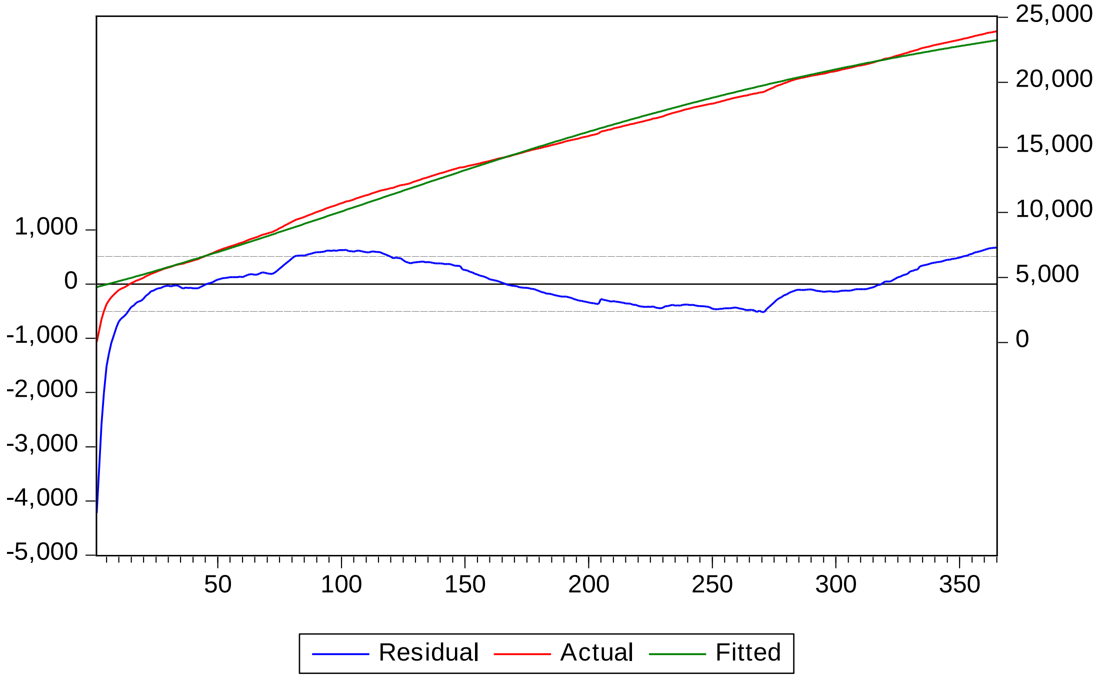

Figure 3. Example: Data and fit with the Gompertz model for Application 25.

When comparing the residual plots of the Bass- and Gompertz-model fitting (in Fig. 3), we find that the Gompertz model consistently outperforms the Bass model. We may also note that Gompertz model fails to capture the initial dynamics of the adoption. However, the residual of Gompertz model shows an overshoot in the first fitting periods, while the Bass model is overly conservative at the start of the fitting process. Consequently, although the Bass model has statistically significant *p* coefficients (except on two occasions), its dynamics force the *p* value to be too small and thus under-estimate the early adoption dynamics. Therefore, *p*, the innovation coefficient, does not represent the innovation effects in a representative manner; rather, its value is governed by the overall dynamics of adoption in the post hoc analysis.

Concluding these findings, the Bass model overshoots and the Gompertz model undershoots the initial dynamics of adoption, although the Gompertz models shows a much better fit with the dynamics. Additionally, both residual plots suggest that the models are not able to fully capture the dynamics, as there are clear trough and peak trends, both models having a trough followed by a peak at the end of the adoption series.

To further study the differences between the dynamics of adoption of the beta applications, we also investigated whether fitting parameters differ between platforms. Sixteen of our sample applications were Symbian-platform beta applications, 4 Series 40, 2 of the applications were S60, and one was a Mac application. Therefore, we carried out statistical analysis of differences in Gompertz parameters between the Symbian and Series 40 beta applications. We selected the Gompertz model, as the parameters were statistically significant in contrast to the Bass-model parameters being non-significant, and the Gompertz model fit of our post hoc analysis was also better than that of the Bass model. Our results show that only the distributions of the *m* parameter (final adopting population) differ between the groups (Mann-Whitney $p = 0.014$), Series 40 receiving much smaller parameter *m* values, indicating a smaller installed base. Therefore, we may conclude that firstly, Series 40-based beta products are indeed adopted by fewer end users than the Symbian products, and secondly, that the adoption dynamics do not differ between these platforms. In post hoc analysis, this is a rather encouraging result, as the installed base of the S40 platform is much smaller amongst the open innovation community users than the Symbian platform, and our results corroborate with this real-life situation. Additionally, this lends credence to the use of the Gompertz model in practical situations for forecasting and using the information for NPD planning purposes.

In addition to the above, we also plotted the minimum (MIN), median (Median), average (AVE), and maximum (MAX) across all our 25 adoption time series in comparison to typical Bass-model dynamics (Bass), scaled to the percentage of adoption, as presented in Figure 3. The parameters for a typical annual Bass-type of dynamics were determined as $p = 0.001$ and $q = 0.51$. (following Talukdar, Sudhir and Ainslie, 2002 as averages for developed contexts, and earlier Givon, Mahajan and Muller, 1995 have suggested values in similar range). Additionally, Fig. 3 presents the fraction of our 25 time series that have saturated (FracSat) to highlight the amount of temporally saturated adoption dynamics.

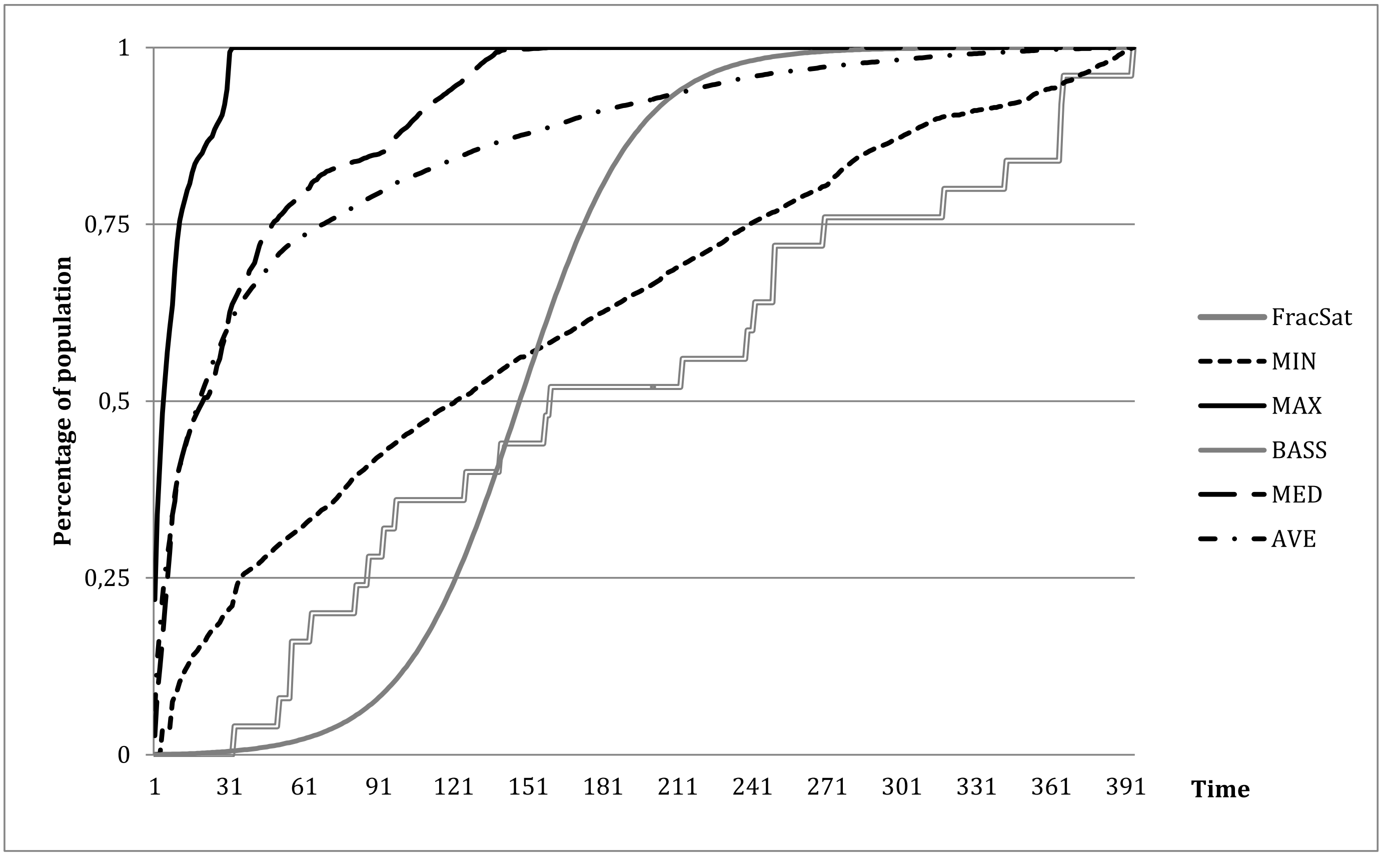

Figure 4. Comparison of the dynamics of our beta product adoption time series with a typical Bass model.

As can be seen from Fig. 4, the Bass model typically, in its initial phases, lags behind the adoption dynamics significantly, and then later in the adoption dynamics, overshoots the average of our beta product adoption time series. Also, the typical Bass model does not reach the median, let alone the maximum of our time series dynamics. Additionally, we see from Fig. 3 that almost 80 % of our beta products have saturated in their adoption before the typical Bass model saturates. Therefore, in conjunction with the earlier statistical analysis, we infer that the Bass model does not seem to capture the dynamics of free beta product adoption, and significantly deviates from the adoption dynamics, especially in the early phases of adoption.

The forecasting abilities of the Bass model and Gompertz model were compared with percentage MSE (mean squared error). The results are shown in Table 3. Table 3 also shows whether the Bass and Gompertz models %MSE differentiate from one another statistically significantly from one another in each out-of-sample period for all the beta products. This was tested with analysis of variance between the models in each out-of-sample period across all beta products.

Table 3. Presentation of %MSEs of Bass and Gompertz models by beta products (discontinued products marked as na, not available)

Out-of-sample period	15-21		15-28		15-35		15-42		15-49		15-56		15-63		15-70	
Beta product	Bass	Gompertz	Bass	Gompertz	Bass	Gompertz	Bass	Gompertz	Bass	Gompertz	Bass	Gompertz	Bass	Gompertz	Bass	Gompertz
1	1,72	0,78	2,84	1,56	3,95	2,41	5,05	3,32	6,11	4,24	7,31	5,31	8,38	6,28	9,19	7,01
2	0,18	0,58	0,65	1,4	1,31	2,35	2,1	3,37	2,94	4,4	3,74	5,34	na	na	na	na
3	0,28	0,27	0,73	0,7	1,36	1,3	2,04	1,98	2,78	2,7	3,51	3,42	na	na	na	na
4	1,53	2,21	0,87	5,35	0,62	8,29	0,48	10,11	0,38	11,24	0,32	12,04	0,28	12,65	0,24	13,11
5	1,55	1,16	1,93	2,74	1,97	4,46	1,84	6,1	1,56	7,91	1,3	9,74	1,11	11,07	0,98	12,08
6	8,62	0,62	12,61	1,57	15,28	2,74	16,82	3,97	16,56	5,57	15,61	7,27	14,76	8,74	13,99	10,03
7	0,94	0,76	1,5	1,28	2	1,76	2,47	2,2	2,86	2,58	3,25	2,95	3,59	3,28	na	na
8	0,68	1,78	0,43	3,24	0,31	4,28	0,25	4,84	0,22	5,22	0,2	5,5	0,18	5,73	0,16	5,94
9	0,03	0,19	0,48	1,01	na	na	na	na	na	na	na	na	na	na	na	na
10	3,65	2,76	4,55	4,93	5,74	6,49	6,61	7,81	7,02	9,05	7,12	10,2	7,08	11,23	6,9	12,19
11	9,72	0,79	16,73	1,51	22,03	2,53	25,43	3,75	27,45	5,04	28,45	6,34	28,83	7,6	28,73	8,81
12	10,15	0,57	17,88	1,14	24,4	1,93	29,26	2,85	32,65	3,84	34,75	4,86	35,86	5,89	36,28	6,92
13	0,74	0,33	0,47	1,14	0,32	2,08	0,24	2,75	0,19	3,17	0,16	3,46	0,14	3,69	0,13	3,87
14	14,73	1,75	27,03	3,57	40,48	5,47	55,55	7,16	71,41	8,68	86,68	10,15	104,08	11,34	122,11	12,39
15	5,36	0,37	9,16	1,56	14,86	2,79	21,54	3,98	28,72	5,09	36,32	6,09	43,94	7	51,1	7,88
16	1,48	1,06	3,18	2,56	4,78	4,03	6,13	5,29	7,26	6,37	8,25	7,31	9,13	8,15	9,94	8,94
17	1,84	1,5	4,25	3,77	6,14	5,58	7,63	7,03	8,78	8,15	9,77	9,11	10,68	10	11,51	10,81
18	14,66	0,67	23,54	1,91	32,98	3,14	41,86	4,33	49,84	5,45	55,68	6,66	59,51	7,93	61,67	9,24
19	7,88	1,74	12,52	4,1	16,25	6,87	19,97	9,43	23,27	11,83	26,15	14,03	28,68	16,04	30,72	17,91
20	4,2	0,9	3,8	3,22	3,17	5,79	2,66	8,09	2,44	9,66	2,36	10,79	2,32	11,69	2,28	12,43
21	23,35	1,44	41,06	3,02	61,88	4,55	84,97	5,93	105,82	7,44	123,81	9,04	140,06	10,61	154,26	12,16
22	15,89	1,22	30,08	2,59	46,68	3,96	66,96	5,05	87,41	6,12	106,32	7,24	123,54	8,37	138,75	9,53
23	1,89	1,58	4,12	3,96	5,39	7,46	5,46	11,65	5,88	15,24	6,06	18,63	6,25	21,67	6,63	24,28
24	0,06	0,61	0,04	2,03	0,41	4,7	1,88	8,69	3,59	12,29	na	na	na	na	na	na
25	0,21	0,11	0,77	0,23	1,2	0,16	1,86	0,18	2,48	0,39	3,27	0,74	3,96	1,31	4,44	2,11
Average	5,2536	1,03	8,8488	2,4036	13,0629	3,9633	17,0442	5,4108	20,7342	6,7363	24,7996	7,6617	30,1124	9,0605	34,5005	10,382
F-value		11,115		8,150		6,822		5,914		5,366		5,294		5,157		4,943
p-value		0,00166		0,00634		0,01212		0,01898		0,02504		0,02619		0,02861		0,03223

na - not applicable

Our Anova analysis reveals that in general the Gompertz outperforms the Bass model in all out-of-sample periods overall at $p < 0.05$ (statistical significance p varying between 0.00166 and 0.03223). In addition, in 15 out of 25 beta products Gompertz model produces better forecasts in all out-of-sample periods than Bass model. Subsequently, we also find that in 10 out of 25 products Bass outperforms Gompertz on at least some of the out-of-sample periods and in 5 beta products Bass outperforms Gompertz in all out-of-sample periods. In summary, Gompertz is better in 124 out-of-sample periods (67%) and Bass model is better in 62 periods (33%) across all time periods used.

Conclusions

NPD planning as a success factor has been well documented in existing literature. Accurate and proficient planning, however, is preceded with a view of the future and planned activities need to be aligned with the expectations of future circumstances. In beta testing this requirement is even more important as beta testing is in many cases used to gain insights on end-users reactions to the product in a real-life use environment. These insights are, in turn, vital to the NPD planning activities as they are used as bases for decision-making during NPD process. Therefore, in beta testing one of the aspects of anticipating future circumstances is the amount of potential end-users adopting beta products as this would inform NPD planning of the baseline of needed activities in the NPD process. This is why we ventured to investigate whether the adoption dynamics of beta products is in line with traditional innovation diffusion models.

Traditionally innovation adoption dynamics has been, amongst other formulations, modeled and anticipated with established Bass-model based forecasting and fitting procedures. However, though the Bass-model overall explains rather high percentages of variation in our beta product adoption time series (explanatory power being between 0.735 and 0.996), the coefficient of imitation is statistically significant only in one application out of 25 and even in this case the coefficient of innovation is not statistically significant. Therefore, the Bass-model does not in itself fit to the dynamics of adoption of beta products in our sample. In contrast, the Gompertz fitting results are statistically significant, and only two b –parameters are not statistically significant at 0.01 level while all other Gompertz coefficients are statistically significant. Additionally, the explanatory power of the Gompertz-models ranges from 0.913 to 0.996. Therefore our findings contradict some existing literature and also raise issues on the generalizability of using Bass model (as suggested eg. by Sultan, Farley and Lehmann, 1990, Bass, Krishnan, and Jain, 1994, Teng, Grover and Guttler, 2002) since we find that the Gompertz model outperforms the Bass model in capturing the adoption dynamics of the beta products. However, the Bass model overshoots and the Gompertz model undershoots the early dynamics of beta product adoption as shown in our representative residual plots. Additionally, both residual plots suggest that the models are not able to capture the dynamics fully as there are clear trough and peak trend, both models having trough followed by peak at the end of adoption series. Further, our findings corroborate recent findings (Goodwin and Meeran, 2012) that rather simple Gompertz model is able to capture adoption dynamics.

From the NPD development planning point-of-view, the development tasks need the feedback from the collaboration community early on, much faster than the Bass-model would suggest. In contrast, Gompertz-model, although initially overshoots the adoption dynamics, much better facilitates the anticipation of the adoption of beta products and therefore, facilitates much better planning of the NPD work Overall, Gompertz-model captures the adoption dynamics of beta products well, as witnessed with high values of explanatory power. Further, in general the Gompertz outperforms the Bass model in forecasting all out-of-sample periods at $p < 0.05$ (statistical significance varying between 0.00166 and 0.03223). Additionally, Gompertz model outperforms Bass model in 67% of our out-of-sample periods in forecasting accuracy. However, we also see that in 5 beta products Bass outperforms Gompertz in all out-of-sample periods. Therefore our findings are somewhat inconclusive but other out-of-sample forecasts may shed light on this limitation of our study. Additionally, as witnessed with our results of platforms statistically significantly differing in their final adoption population, it is possible to anticipate final population adopting beta products with Gompertz-model.

Therefore, Gompertz model facilitates better NPD planning for example to anticipate possible NPD planning activities for each platform and for practical purposes, our results suggest that Gompertz model is better in capturing adoption dynamics and for forecasting purposes since Bass-model is not able to capture the dynamics of beta products' adoption dynamics early on during the adoption. It may, however, in practice be advisable to use both models in combination to have realistic future expectations, this though needs further research to illuminate efficiency and effectiveness of various protocols for using two models in conjunction to one another.

Finally, our study has a number of limitations and one that influences the estimation results dramatically is initial values in estimations since estimation results are sensitive for initial values.

Additionally, the sample of 25 cases in this study was from one virtual community. Still our findings show significant residuals that are not captured by either by Bass of Gompertz models which highlights the need for future investigations of possible alternative formulations for modeling beta product adoption. Future studies should look at forecasting procedures with other out-of-sample periods in addition to studying similar cases of freely distributed products that are based on single technology platform and distributed in other open innovation ecosystems. Additionally future studies could consider different modeling approaches to investigate whether other types of adoption models are able to capture dynamics of diffusion in platform-based innovation ecosystems better like agent-based approaches (following e.g. Zenobia, Weber and Daim, 2009) or other types of traditional extensions of Bass model like differing personal influences modeled (e.g. Roberts and Lattin, 2000), or anticipating the fast adoption early on (following e.g. Golder and Tellis, 1997). Also how well the adoption dynamics captures the amount of customer input coming from the co-creation community may be investigated in future studies. All these are just few fruitful avenues for future research that would aid companies in making more efficient and effective decisions in their NPD planning.

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