**Dynamic Effect of Rating and Observational Learning on the Demand of Supplementary Products**

**Meisam Hejazi Nia**

Naveen Jindal School of Management

University of Texas at Dallas

[mxh109420@utdallas.edu](mailto:mxh109420@utdallas.edu)

[**Advisor: Dr.**](http://jindal.utdallas.edu/faculty-and-research/elisabeth-honka/) **Norris Bruce**

Naveen Jindal School of Management

University of Texas at Dallas

[nxb018100@utdallas.edu](mailto:nxb018100@utdallas.edu)

**Abstract**

Firms in many industries facilitate the emergence of supplementary products, especially in the context of experience goods. Researches have shown that consumers’ decision to purchase experience goods is under influence of others consumers’ opinion, captured by product ratings and other consumers’ actions, or observational learning. Thus, product rating and observational learning can play an important and distinct role in simulating new product demand. In this article, the authors construct a dynamic linear model to study the intertemporal dynamic effects of product rating and observational learning on demand for heterogeneous products. They further apply the model to examine the effect of product rating and observational learning of 52 add-ons of Firefox on their daily downloads and estimate the parameters using Kalman filtering/smoothing and Markov chain Monte Carlo methods. The results show that product rating and observational learning exerts dynamic, yet diverse, influence on demand for supplementary products in the context of experience goods. This finding suggests that if the model does not allow for such dynamic and heterogeneity, the estimation will be biased. Moreover, they find that product rating effect could be increasing return and that observational learning affects daily download positively when there is low uncertainty in consumer valuation.

Keywords: dynamic effect, heterogeneity, product rating, observational learning, experience goods, supplementary products, uncertainty

1. **Introduction**

Consumers search different sources of information before making purchase decision. One important source of information is consumer product review that in many cases complements other sources of information such as business-to-consumer and offline word of mouth. In the global trust in advertising report 2012, Nielsen asserts that consumer product reviews are the second most trusted source of brand information and messaging. Studies have further shown that consumers rely on product reviews more than on their own experience on the product category and that consumers rely on recommendations for experience goods significantly more than any other types of products (Zhang et al. 2012). Therefore, the relationship between product rating and sales has been modeled and tested in different contexts including books (Chevalier and Mayzlin 2006; Sun 2012), video games (Zhu and Zhang 2010), movie box office (Dellarocas et al. 2007; Duan et al. 2008; Chintagunta et al. 2010), and beauty products (Moe and Trusov 2011), yet there is a potential gap in literature on this effect in the context of software.

In response to the aforementioned importance of product reviews, not only e-commerce websites that sell experience goods, but also web sites that offer fee software such as sourceforge.com and Google play have made the distribution of ratings available using bar charts on their website. Mozila.org web site even goes one step further and makes the size of user base of add-ons[[1]](#footnote-1) available to its consumers. Studies have suggested that WOM and observational learning, learning by observation of past decisions of others, are complementary, and that purchase statistics can help mass market products without hurting niche products (Chen et al. 2011). Therefore, we hypothesize that user base size acts as a signal and facilitate observational learning for add-ons (Bikhchandani et al. 1998).

Studies have identified two fundamentally distinct approaches to commercialize a technology platform. First approach entails allowing outsider to participate in technology development and commercialization, whereas the second entails holding control over the platform and thereby not providing interface for extension of technology (Boudreau 2010). Mozilla Firefox web-browser, hereby called Firefox, adopted the first approach, leading to its stronger position in competition with Microsoft Internet Explorer (Oshri et al. 2010; Krishnamurthy 2009). In other word, Firefox allows community of developers, consisting of independent authors, to develop complementary products, called add-on, and distributed it on its website. Many other industries such as video game, mobile phone, web publishing, computer devices and movie adopt the same approach. These supplementary products play the role of complementary product for these platforms, so they are important due to their effect on consumer switching (Lattin and McAlister 1985). Consequently, it could be interesting for platform owners in various industries to know how supplementary products’ rating and user base size signal affects those products’ demand.

Online customer rating is proved to have significant effect on product sales (Chavelier and Mayzlin 2006; Clemsons et al. 2006; Dellarocas et al. 2007). Research has shown that word of mouth has dynamic effect on revenue (Bruce et al. 2012), so as a type of word of mouth, product rating could have dynamic effect on the demand. Since observational learning also acts as a type of information, complementing advertising, it is probable that observational learning also has dynamic effect on demand (Chen et al. 2010). Moreover, researcher tried to control for observable heterogeneity in estimating the effect of product rating on demand (Chavelier and Mayzlin 2006, Moe and Trusov 2011). This also suggests that heterogeneity, both observable and unobservable, in both product rating and observational learning could play an important role in affecting estimation results.

Researcher may be able to explain heterogeneity based on institutional characteristics of the context. In our context three different economic agents play role. First is Firefox platform owner that facilitates the development and commercialization of supplementary products. Second one is Add-on’s author, independent agents who develops and commercializes his add-on and third one is consumers, or so called users. Add-on’s author may decide either to ask for money contribution or just makes his contact available for professional purposes. Moreover, the author is able to optimize its response to platform changes and bugs found in its add-on via issuing new version. Consumers on the other hand are exposed to alternative products that they may otherwise have to pay for it. Despite zero monetary cost, time and effort cost of using an add-on is not zero, because the consumer has to download and learn to use the add-on. Therefore, consumers may be risk averse and sensitive to uncertainty in the product rating (Sun 2012). Other contextual factors may also affect consumer’s decision.

Consumer’s decision to consider product rating is also influenced by the number of viable choices available in the market, which is relevant to whether the author is generalist or specialist. To develop the add-on, authors may decide to work with other authors in team. Since, team with more members have higher resources, authors working in team are prone to act like a generalist, rather than specialist (Lambkin and Day 1989). Specialists play their role in a niche market, which has less intense competition. Less intense competition is translated into less option for consumers. Therefore, size of author’s team may affect sensitivity to rating. Another relevant factor could be segments of the market. In the word of mouth referral process homophily, similarity with others, is found to have a significant role (Brown and Reingen 1979). In the context of add-on we can segment consumers based on operating system they use, i.e. Windows, Linux, Mac. Due to different size of market share of these three operating systems, and effect of homophily in the diffusion of word of mouth, we expect that type of operating system explain part of the heterogeneity.

Therefore, several substantive questions arise on the effect of product rating and observational learning on the demand for a supplementary product: How product rating and observational learning affects the demand? Whether there is any intertemporal dynamic in the effect of product rating valence and observational learning on demand? Is there any heterogeneity in these effects? Can we explain heterogeneity in terms of institutional characteristics such as share of operating system and team size? How does uncertainty play a role in moderating the effect of different processes?

To accomplish this, we propose a dynamic linear model (DLM) that links add-on’s download to a latent measure that captures attractiveness of download of and add-on. This latent measure parsimoniously summarizes the influence of current and past product rating valence and user base signal. The model extends prior study of effect of product rating on sales by incorporating dynamic and product heterogeneity into the model. We apply the model to a context of Firefox add-ons, and estimate the parameters using Kalman filtering/smoothing and Markov chain Monte Carlo (MCMC) methods. (Bruce et al. 2012; Van Heerde et al. 2004).

Our results show that product rating and observational learning exerts dynamic, yet diverse, influences on demand. These results suggest that if the model does not account for such dynamic and heterogeneity the estimation tend to be biased. Moreover, we found out that observational learning has positive effect on demand for the product when uncertainty is low, and that consumers tend to ignore low product rating for specialist products.

In the next section, we review existing literature pertaining to the effect of consumer product review. Included in this review are empirical and theoretical researches that reveal how product reviews affect different business metrics. After the literature review, we describe our model that relates product rating valence and user base signal to product’s demand. We then describe the data used in this article. Finally, we present the results and highlight some of the implications.

1. **Literature**

Given the broad impact of online product rating, there is growing body of research in both marketing literature and information technology literature that examines the effects and dynamics of product rating. We review the literature in three categories: (i) the effect of product review (ii) generation of consumer product review dynamic and (iii) best response of firms to product reviews.

*The effect of product review*

Product review is captured through three main metrics, including valence, variance and volume, in different researches and its effect on sales and revenue is assessed (Moe and Trusov 2011). Volume of rating is commonly represented by the number of product reviews. On the other hand, from distribution point of view valence of rating is captured through average rating (Chavelier and Mayzlin 2006; Clemons et al. 2006; Dellarocas et al. 2007; Duan et al. 2008; Chintagunta et al. 2010), while variance of it is captured through statistical variance (Clemons et al. 2006; Sun 2012) or entropy (Godes and Mayzlin 2004).

Although the effect of product reviews on business performance, such as sales and revenue is substantially understudied, the empirical results are not unanimous (Moe and Trusov 2011). Chavelear and Mayzlin 2006 after controlling for product heterogeneity by comparing different in sales ranks for a sample of books sold on Amazon.com and Barnsandnoble.com found positive significant impact of rating valence on sales, and Dellarocas et al. 2007 also found out that both valence and volume of movie rating can significantly ameliorate the prediction of diffusion model of box office sales. However, Duan et al. 2008 found that after accounting for endogeneity online user review has insignificant impact on box office revenue. Another study by Chintagunta et al. 2010 found that endogeneity does not distort the positive effect of valence of consumer product reviews on box office performance. Table 1 summarizes these findings. Finally Moe and Trusov 2011 found out, after decomposing the effect of rating into baseline and social dynamics component, that there are substantial rating dynamics, and their effects on sales are noticeable.

*Generation of consumer product review dynamic*

There is growing stream of literature that studies how consumers generate product reviews. Moe and Schweidel 2011 studied how previously posted ratings will affect individual’s decision on whether and what to contribute. They found out that there is selection effect in the decision of whether to contribute, and adjustment effect that influences what to contribute. Other studies found downward trend of valence of rating over time and are subjected to self-selection bias (Godes and Silva 2009; Li and Hitt 2008). The argument for downward bias attributes this effect to heterogeneity of consumer preferences, and assumes that early consumers are those to whom the product is most fit, while late consumers have more distant preferences.

On the other hand Brandes et al. 2013 provides survey evidence that confirms that consumers who post an online review tend to have more extreme opinions than those consumers who don’t. This finding implies an alternative explanation to downward trend of valence, which is that reviews that arrive after a long time tend to be similar to the opinion of non-responders. Furthermore, Li and Hitt 2008 nudges to this effect with the name of idiosyncratic preference of early buyer, and suggest that firms adapt their marketing mix to generate more positive word-of-mouth at early stages. Moe and Trusov 2011 adopt these explanations and allowed rating dynamic in their study by modeling the effect of volume of posted rating on subsequent rating behavior.

-- Insert Table 1 here --

*Best response of firms to product reviews*

Parallel with studies on how word of mouth is generated, and how it impacts business performance, another stream of literature focus on normative models based on analytical studies. Chen and Xie (2005, 2008) suggest that when and how sellers ought to adjust their marketing strategies in response to consumer reviews. They treat product reviews as a new source of information, which could be complemented by firms signal to optimize firms objective. Other studies examine firm’s incentive to post fake reviews, concluding that organizational forms affect this incentive and that in equilibrium consumer can exert some information on product quality (Mayzlin 2006; Dellarocas 2006; Mayzlin et al. 2012)

In this article, we consider potential intertemporal influence of product rating on demand for the product by modeling the effect of product rating and user base size signal on a latent measure that captures attractiveness of download. We also control for new version, product category need, and weekends seasonality. Moreover, our model is flexible to account for heterogeneity in the effect of rating and user base size signal of different add-ons. In the next section we will elaborate more about it.

1. **Model Development**

We formed DLM to evaluate the dynamic effect of daily product rating on demand. DLM has been used in marketing to assess the dynamic effects of weekly advertising (Bruce et al. 2012), and to address dynamic market structure (Van Heerde et. al 2004). Here DLM connects demand of supplementary product (Firefox add-on) to its product review and user base size through aggregate sales response function. Moreover, this approach offers flexibility to account for heterogeneity across supplementary products.

* 1. **Aggregate Demand and Goodwill Stock**

Given our interest in assessing the effect of product rating on demand, we exercise aggregated sales response model. We capture attractiveness of download of add-on i at day t in a latent measure  that in turn drives the download  of corresponding add-on. This model is similar to the discrete time analog model of Nerlove and Arrow (1962). Therefore consistent with DLM literature, our observation equation is as follows:

, where (1)

We controlled seasonality of data using which is weekend dummy variable. We assume the error term  has normal distribution with mean zero and variance. Finally, in the model and  are parameters to estimate.

We assume latent measure of attractiveness of download  decays in proportion to its lagged value, yet it is maintained by drift of previous period. Again according to DLM definition our system equation is as follows:

, where (2)

We assume error term  has normal distribution with mean zero and variance, and,  and  are parameters to estimate. Drift of previous period captures the effect of a vector of related variables. The vector  includes average rating valence, quadratic term of average rating valence, user base size, number search of product category, and dummy variable that captures new version. In the context of our study, a new version of add-on may be issued due to different reasons. The first probable reason is that a new problem is discovered by a user, or an author himself, and the author decides to correct it. The second probable reason is that new version of Firefox is published, and the author of add-on issues a new version to make it compatible with new version of platform. Number of search of product category is available on Google trends. We first searched the name of the product in Google trend to get search interest of the product normalized between zero and one hundred. However, for some plug-ins due to low level of search, such data was not available, so we used keyword of “Firefox Add-on” as a proxy to capture search interest in those specific add-ons. Google trend has been used in literature to control for consumer interest in different product categories in the same way (Moe and Schwidel 2012).

* 1. **Heterogeneity**

The effects of average product rating valence, user base size, short term economic shock and carryover may differ across products, as for example effect of advertising, need category, and competition in the market of the supplementary goods may be different. Thus, we also acknowledge such potential heterogeneity by linking carryover rate, effect of average rating valence, user base size, product category search, and new version from equation 1 and 2 to a set of supplementary product characteristics, such as platform share of the product and size of team of developers.

, where  (3)

, where (4)

, where (5)

We tested 47 variables including but not limited to the total followers of the package that includes the add-on, popularity of the add-on, number of users of add-on’s used with this add-on, dummy variable of product category, life of the add-on, and number of versions of it, yet we only winded up into four variables that could explain the heterogeneity of carry-over, user base size effect, average rating valence effect, and search of product category. Therefore, table 2 provides definition of variables that used to explain heterogeneity. None of 47 variables could explain heterogeneity in the effect of weekends and new version, so and are null vectors. Error terms in equation 3-5 are assumed to be normal with variances.

-- Insert Table 2 here --

1. **Empirical Study**
   1. **Data**

The data that is used for our analysis is from a sample of 52 Firefox Add-ons. Add-ons are complementary software that is developed by independent author, but it is made available on Firefox main website. Consumers can only benefit from add-on when Firefox is installed on their system. Time period under study is from 2008 to 2013, and different add-ons are launched during this time span at different points. Despite consumer review that is publicly available, time series data related to number of downloads and user base size are publicly available only if the author of the add-on has decided to make the dashboard public. Therefore, our sample is only limited to those add-ons that its author left the dashboard public. We collected all the available reviews, user base size, and download during our time span for each of these 52 popular add-ons. Add-ons in our samples are categorized into one to two categories each. Add-ons are from different categories including appearance (17%), bookmarks (6%), download management (6%), photo and multimedia (17%), game and entertainment (6%), privacy and security (12%), language support (13%), alerts updates (12%) and web development (25%).

Firefox makes two main signals available on add-on download page. First signal is distribution of add-on rating that is presented through bar chart, and second one is the size of user base of add-on, presented with the name of “users”. Of the 52 add-ons in our sample 19,211 ratings were posted. To use distribution of rating in our model for each day we calculated average, variance, and number of product reviews of a given add-on from the launch day until the given day, available on Firefox website. Since there was not enough variation in data, we further on had to narrow down variable of distribution only to rating valence average. Average rating on the last cross section ranged from 2.5 to 4.7, with 79% of add-ons in our sample received at least four star average rating. Figure 1-3 show the evolution of daily download, user base size, and average rating valence for four add-ons as an example.

-- Insert Figure 1 here –

-- Insert Figure 2 here --

-- Insert Figure 3 here –

To the best of our knowledge, user base size includes all active and inactive users who have not removed add-on from their browser. Since add-ons under our study are free, consumer may download and install it on his system, but then they may find it useless and remove it. Add-on author(s) on the other hand can play an active role to maintain consumers by issuing new version. Add-on author(s) may issue a new version either to response to changes in Firefox platform, or to response to bugs and issues found by him (them) or current consumers. Therefore, new version could be an important determinant of attractiveness of download of an add-on. Figure 4 illustrates evolution of number of versions issued by add-on author(s) for four add-on samples. To control for the effect of new version we defined a dummy variable that captures whether a new version is issued on a given date.

-- Insert Figure 4 here --

In the context of our study, author(s) of add-on act as an independent firm and define whether they want to ask consumer for discretionary contribution or just make their contact available for networking purposes. They further can define how much they want to ask consumer for discretionary money contribution, or whether they want to feature their add-on on the front page. These independent authors, who are analogous to application developers on app-stores, have control on pictures or tags they want to attach to their add-on, but platform owner, here Firefox, reviews these add-ons to ensure stable and safe experience for users before publishing these add-ons and all their attachments. In addition to the shocks on supply side there could be shocks on demand.

To control for shocks on the demand side we used product category search data, similar to Moe and Schewidel 2011. For this purpose we used Google trend for the keyword of name of the product. For those add-ons that such search data was not available, we exerted search for keyword of more general category such as “Firefox Add-on”. Moreover, we observed seasonality in the download and usage data. Therefore, to account for this seasonality we adopted weekend dummy variable.

Add-ons under our study did not have features explicitly stated on the download page. This characteristic makes them similar to other experience goods such as books and movies that their quality could only be ascertained after consumption. Therefore, to explain heterogeneity in demand response we used a set of 47 add-on characteristics derived from each add-ons page. These characteristics included add-on category dummy, rating and number of followers of collection that the add-on belongs to, number of users and level of rating of other add-ons that author(s) of current add-on has developed, size of team of developer, age of add-on in days, number of tags, and so on. The basic statistics of relevant variables that significantly affect our results is presented in Table 3.

-- Insert Table 3 here --

* 1. **Estimation**

To describe the estimation procedure used in this study, it is convenient to bind ourselves to formal notation of state space model of West and Harrison (1997). According to this definition we can rewrite equation 1 representing observation equation and equation 2 representing state equation as follows. Here constant variable F reflects the impact of latent measure, as driven by current and past product review and user base size signal. The unobserved state variable  captures add-on attractiveness of download. The transition vector  captures decay. Furthermore, we assume that error term and  to be independent normal random variables with zero means.

 (1’)

 (2’)

Recall that Equation 3-5 links all time-invariant non-state parameters from the preceding equations to add-on characteristics. As a result, Equation 1’, 2’, and 3-5 constitute our final DLM.

We estimate the model using MATLAB programming on the entire observed data series of Add-ons. The procedure nests a Kalman filter forward and backward smoothing inside MCMC Gibbs sampler with conjugate priors (Bruce et al. 2012). The primary goal is to estimate the joint posterior distribution of state and non-state parameters for each add-on. Using conjugate prior enables us to analytically derive and directly sample the conditional posterior of the state parameters given non-state parameters and vice versa (Bruce et al. 2012). Conditional posterior of state parameters given non-state parameters is a linear state-space model, so it can be sampled with standard Kalman filter forward and backward smoothing algorithm. Moreover, given the state parameters, we will have multivariate linear model with hierarchical priors, so we can sample directly by using standard MCMC methods (Bruce et al. 2012). In other word, Kalman filter forward and backward smoothing updates the evolution of the state parameters conditional on the non-state parameters, where MCMC Gibbs sampler updates the nonstate parameters given the state parameters. Consequently, we sample from joint distribution of state and non-state parameters.

* 1. **Model Comparison**

We benchmarked the proposed model against three alternatives based on Deviance information criterion (DIC) (Table 4). DIC is generalization of Akaike information criterion (AIC) and Bayesian information criteria (BIC) for hierarchical models (Gelman et al. 2003). Model 1 assumes static product rating and user base size signal effects (i.e. ). Model 2 assumes no product heterogeneity in product rating and user base size signal effects (i.e. ), and model 3 leaves heterogeneity of dynamic model unexplained.

-- Insert Table 4 here –

Overall both DIC and log likelihood consistently and clearly favor the model with dynamic and heterogeneity, suggesting that there is dynamic and heterogeneity in the effect of product rating and user base size signal on demand. This result points out the potential bias in the estimation of product rating sales response model, if it does not account the dynamics.

Table 5 compares the result of estimation of dynamic with estimates of static and non-heterogeneous models. On our data static model overestimates the effect of product rating and product category search and it underestimates the effect of mean of rating valence and new version. On the other hand, non-heterogeneous model underestimates the effect of carryover, mean of rating valence, and versioning, yet it overestimates the effect of user base size signal and product category search. Table 6 compares number of add-ons with significant effect in static model versus dynamic model. The result suggests that the significance of the effect of user base size and rating plunges from 90% of add-ons to 60% of add-ons as we use dynamic rather than static model. Finally, figure 5 displays in sample one step ahead forecast versus actual demand, and table 7 presents mean absolute deviation (MAD) and mean square error (MSE) corresponding to this figure. They both indicate that the proposed model offers a good fit with the data.

-- Insert Figure 5 here –

-- Insert Table 5 here –

-- Insert Table 6 here –

-- Insert Table 7 here –

* 1. **Parameter Estimate**

Figure 6 illustrates the histogram of posterior mean across all 52 add-ons. Table 8 reports posterior means, standard deviation, and 95% high probability density interval (HDPI) of non-state parameters of proposed model across all 52 add-ons. Table 9 summarizes number of add-ons that had significant parameter for each effect. Table 10 displays the estimate of add-on characteristics that contribute to the heterogeneity in carry over, and effects of product rating, user base size, product category and new version. Recall that these characteristics are survivors out of 47 cross sectional characteristics of add-ons.

-- Insert Figure 6 here –

-- Insert Table 8 here –

-- Insert Table 9 here –

-- Insert Table 10 here –

First consider carry-over effect. On the carry-over histogram majority of add-ons have carry over close to one, except one add-on which has carryover close to zero. The add-on that has carryover close to zero has the name of “Romanian Language Pack”. This different effect could probably be attributed to the effect of culture on decision making process (Money et al. 1998). Add-ons are of type of experience goods, and consumers are known to rely on recommendation for experience goods significantly more than other types of the products (Zhang et al. 2010). Therefore, this high persistency is probably because add-ons are dependent on referral, and that referral in offline words requires active decision making, causing delay (Greenleaf and Lehmann 1995). We could explain the heterogeneity in carry-over based on add-on’s share of Windows operating system. The higher add-on’s share of windows operating system the higher is the persistency of download attractiveness. This result also could be explained by referral diffusion process. Homophilious ties are more likely to be activated for a flow of referral information (Brown and Reingen 1987). As Microsoft Windows operating system (OS) has more than 80 percent share of computer devices in the world, due to homophily there is higher likelihood of referral on this OS compared to other OS’s, such as Linux or Mac. Therefore, attractiveness of download for add-ons with higher share of windows is more persistent than other add-on’s.

Next consider the effect size of user base on demand. We found out that 13 add-ons have significant positive effect of user base size, while 12 add-ons have significant negative effect. Two different primitive processes could explain this result: First observational learning, and second diffusion model. Observational learning explains the positive effect of user base size signal, and diffusion model explains the negative effect. In other word, for those add-ons that the effect of user base size on demand is positive, observational learning overcomes the bass diffusion model, and usage of product by previous consumers positively affects new consumer’s decision to adopt the product (Bikhchandani et al.1998). On the other hand, when diffusion model overcomes observational learning, higher user base size translates into saturation of the market, leading fewer consumers to adopt the product (Bass 1969). Figure 7 illustrates an example of add-on that diffusion model is dominant to observational learning model. Variance of rating could explain heterogeneity in the effect of user-base size. Higher variance of rating leads to lower effect of user base size. In other word, when there is higher uncertainty in rating, consumers learn less from others action than when there is low uncertainty in rating.

-- Insert Figure 7 here –

Product rating showed two types of effect on demand. Figure 7 and 8 shows these two types of effects. On 9 add-ons we found type 1 significant, and on 19 add-ons we found type 2. Individual analysis of type 2 effect suggests that two different processes during early and late stage of product cycle could account for this effect. The behavior in the first stage could be attributed to diffusion model. At the early stage innovators will download the product, and due to their high valuation first rating would be positive, yet this high rating does not lead to a jump in downloads. As the add-on ages more consumer will use it, but due to their different taste, the rating will have negative trend (Godes and Silva 2012; Li and Hitt 2008). Consumers are not sensitive at later stage to this negative trend. This insensitivity could be result of lack of substitute product. As a result, our model captures this response as a negative effect. Figure 9 illustrates this dynamic for an example add-on. On the other hand, type 1 effect suggests increasing return on rating of add-ons. This type of effect could be attributed to risk aversion (Sun 2012). Author team size explained this heterogeneity. We found that higher author team size pushes add-on to have the effect of type 1, i.e. being sensitive to product rating. This could probably be related to nature of the market that an add-on is operating in. Larger author team is translated into greater resource. This greater resource enables the add-on to become generalist rather than specialist (Lambkin and Day 1989). Generalists compete in the market that has multiple players, which means more product substitutes. Therefore, consumers elasticity of rating is higher for add-ons that are developed and supported by larger team of authors.

-- Insert Figure 8 here –

-- Insert Figure 9 here –

-- Insert Figure 10 here –

Except one, almost all of the add-ons with significant effect of new version had positive effect of new version. The one with negative effect of new version suggests that although the author has frequently issued new version, new versions may not have satisfied consumer needs. Moreover, product category need has positive significant effect on demand for 33 add-ons, but negative significant effect for 3 add-ons. The data is not informative for those 3 add-ons that product category search has negative effect, but heterogeneity in product category effect is explained by volume of product reviews. Higher volume of product reviews lead to higher effect of product category search on demand. This relation could be explained by risk aversion. Since consumers are risk averse they tend to select experience product that they know more about its upside and downside (Erdem and Keane 1996). As a result, shocks in product category need tend to affect demand for products with higher volume of product rating, and therefore with less uncertainty. Moreover, weekends has negative effect on demand. This could be due to downtime on the servers on supply side, or consumers limited access to internet, or consumer’s engagement in activities that does not require usage of add-ons. We did not find a variable that explains heterogeneity in the effect of new version and weekends on demand.

1. **Conclusion**

Supplementary product is vital to the profitability and survival of many industries -- video game, mobile phone, web publishing, computer devices and movie being a few exemplars. To help achieve these profits firms often face decisions on how to facilitate supplementary product development and commercialization. In this business setting three main actors interact: First, the firm, known as platform owner, second, independent product developer, and third customers. These three actors’ decision is dependent on signals such as word of mouth, capture through product rating, and observational learning, captured through user base size available on web-site. In this study, we constructed a model to quantify the dynamic sales-response model of product rating, and observational learning to quantify intertemporal and heterogeneous effects across products. We estimate the proposed state-space model, applied to firefox add-ons, with Kalman forward filtering backward smoothing nested within MCMC methods. As a result, we are able to investigate a crucial yet unexplored area – namely, the dynamic effect of product rating and observational learning on the demand for supplementary products – and implications of these effects for best response of three actors.

We believe that several novel findings emerge from this work. First, it supplies empirical evidence that product rating has dynamic, yet diverse, and increasing return effect on demand. Second, observational learning, found to be beneficial for product demand (Chen.et al. 2010), dynamically affects product demand, and this effect is heterogeneous. In addition, observational learning affects product demand more when uncertainty in product rating is low. Consequently, product rating affects demand both directly and indirectly through enhancing observational learning effectiveness. Fourth, we explained heterogeneity in the effect of product rating, and observational learning in terms of contextual characteristics of add-on, such as size of team of authors, share of MS Windows, and number of product reviews. Finally, although our study focuses on the software industry, the findings underscore the value of investigating the dynamic effect of product rating, and observational learning across different products. It also suggests that if such effects are not taken into account in estimation, the estimates would be biased.

Notwithstanding these contributions, this research has limitations that could lead to future inquiries. For example, we did not account for endogeneity in our model. Further research could control for endogeneity in estimation, and examine whether the estimation result would change. Furthermore, we did not have enough variation in our data to estimate the direct effect of variance, mean, and volume of product rating jointly on demand. Future studies could not only investigate the effect of variance, mean and volume of product rating on demand, but they can also account for dynamic interaction between product rating and observational learning. Another extension of this study could account for heterogeneity in the preference of consumers of different supplementary products, in the form of latent model and integrated them out, to compare estimates with our proposed model.

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Table 1 Previous Research on Consumer Product Ratings and Reviews

|  |  |
| --- | --- |
| **Empirical Studies** |  |
|  |  |
| Chavalier and Mayzlin (2006) | Positive impact of average rating on sales, and higher impact of one-star reviews than five-star-reviews |
| Moe and Trusov (2011) | The impact of social dynamics in the rating environment on both sales and subsequent rating behavior. |
| Godes and Silva (2012) | Residual average temporal pattern of product reviews is increasing, after controlling for calendar date. Consumer product ratings tend to plunge over time. |
| Zhao et al. (2012) | Consumers learn more about an experience good from online consumer product reviews than their own experience of product category |
| Moe and Schweidel (2012) | Individual’s decision to provide a product rating is subjected to selection effects, and adjustment effect. Positive ratings environment increases positing incidence, yet negative rating environment discourage posting. |
| Dellarocas et al. (2007) | Better predictability of diffusion model that incorporates consumer review for box office revenue data |
| Duan et al. (2008) | Insignificance of the impact of online user reviews on movies’ box office revenues after accounting for endogeneity |
| Godes and Mayzlin (2004) | Dispersion of conversations across communities can explain dynamic of TV ratings |
| Zhu and Zhang (2010) | Consumer product ratings are more influential for less popular products |
| Gao et al. (2006) | Significant impact of public opinion on consumer product reviews |
| Liu (2006) | Aggregate and weekly box office revenue can significantly be explained by online word of mouth, especially at early weeks of movie release |
| Clemons et al. (2006) | Variance of ratings play significant role in determining which new products grow fastest in the market. |
| Chintagunta et al. (2010) | Valence rather than volume of consumer product reviews drive box office performance |
| Li and Hitt (2008), Brandes et al. (2013) | Online product reviews are subject to self-selection. |
| Ye et al. (2009) | Online consumer reviews have significant relationship with business performance of hotels. |
| **Theoretical Studies** |  |
| Monic Sun (2012) | Informational role of variance of product rating on the product subsequent demand |
| Chen and Xie (2008) | Firm’s best response to consumer product reviews |
| Chen and Xie (2005) | Firm’s strategy to adapt consumer product reviews |
| Mayzlin (2006) ,Dellarocas (2006), Mayzlin et al. (2012) | Firm’s online manipulation of consumer product reviews |
| Awad and Etzion (2006) | Firms’ filtering of consumer product reviews |
| Jiang and Chen (2007) | Firm’s dynamic strategy to leverage consumer product review |

Table 2 Definition of variables that explain heterogeneity

|  |  |
| --- | --- |
| Variable | Definition |
|  | Vector that includes one for intercept and share of windows to explain carryover |
|  | Vector includes one for intercept and variance of rating to explain user base size heterogeneity |
| , | Vector that includes one for intercept and variance of rating to explain heterogeneity in the effect of average rating valence |
|  | Vector that includes one for intercept and number of reviews to explain heterogeneity in the effect of product category search |

Figure 1 Examples of Demand for Firefox Add-ons

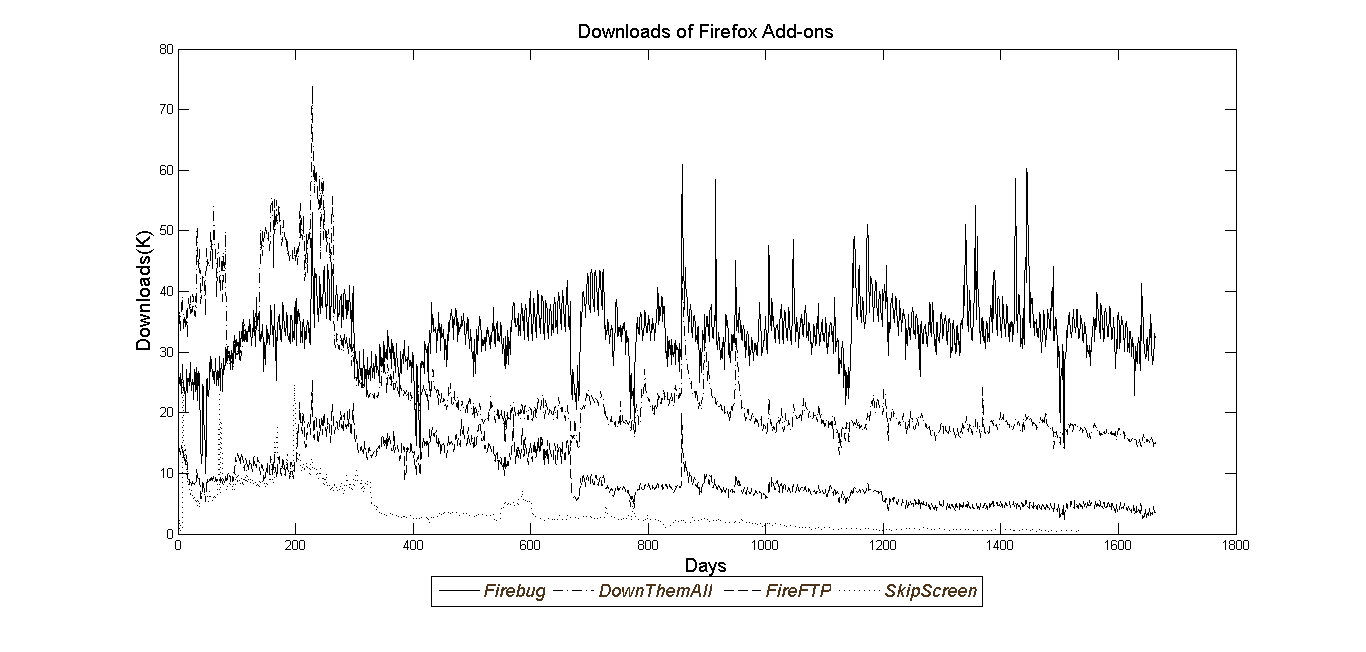


Figure 2 Examples of Size of Usage Base for Firefox Add-ons

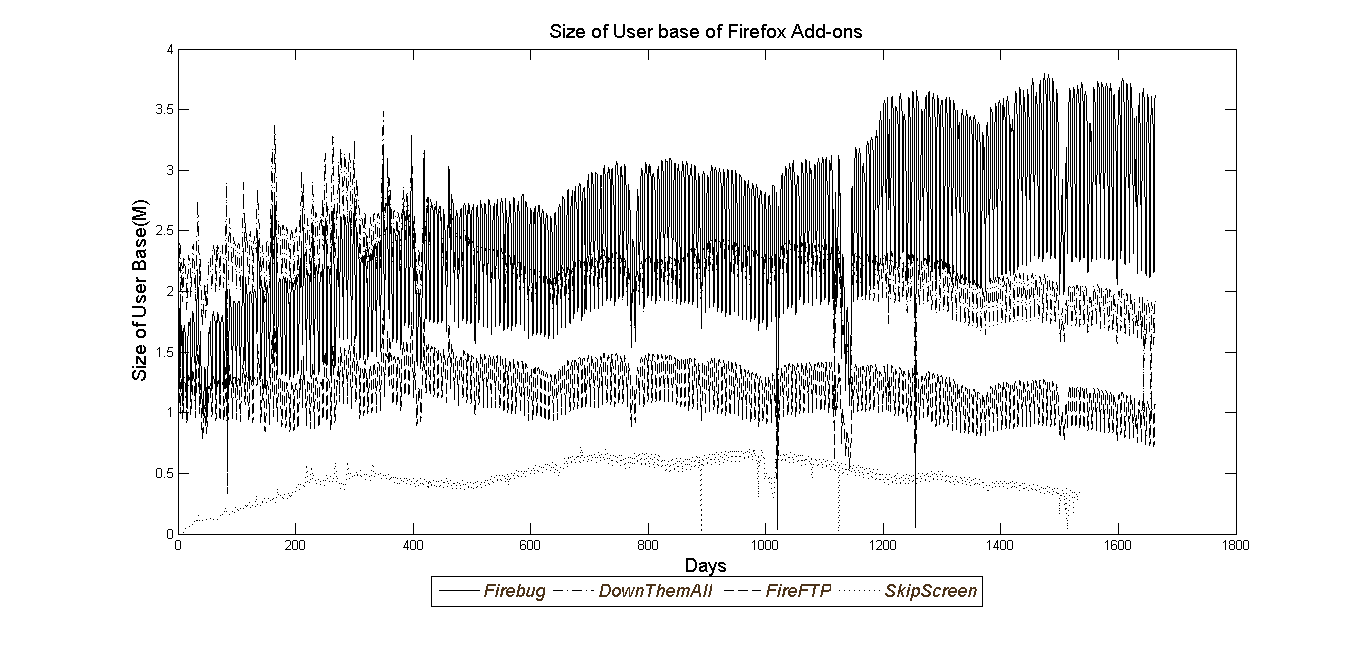


Figure 3 Examples of Valence of Rating for Firefox Add-ons

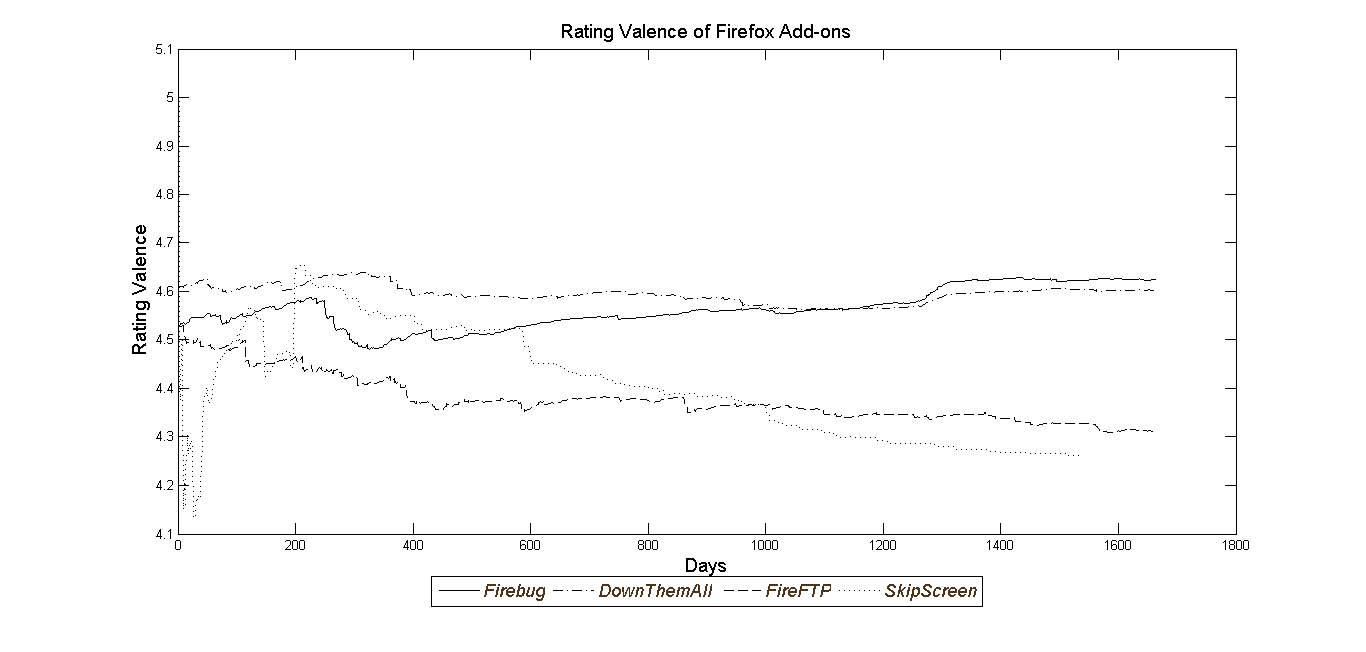
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Figure 4 Examples of Number of New Versions for Firefox Add-ons

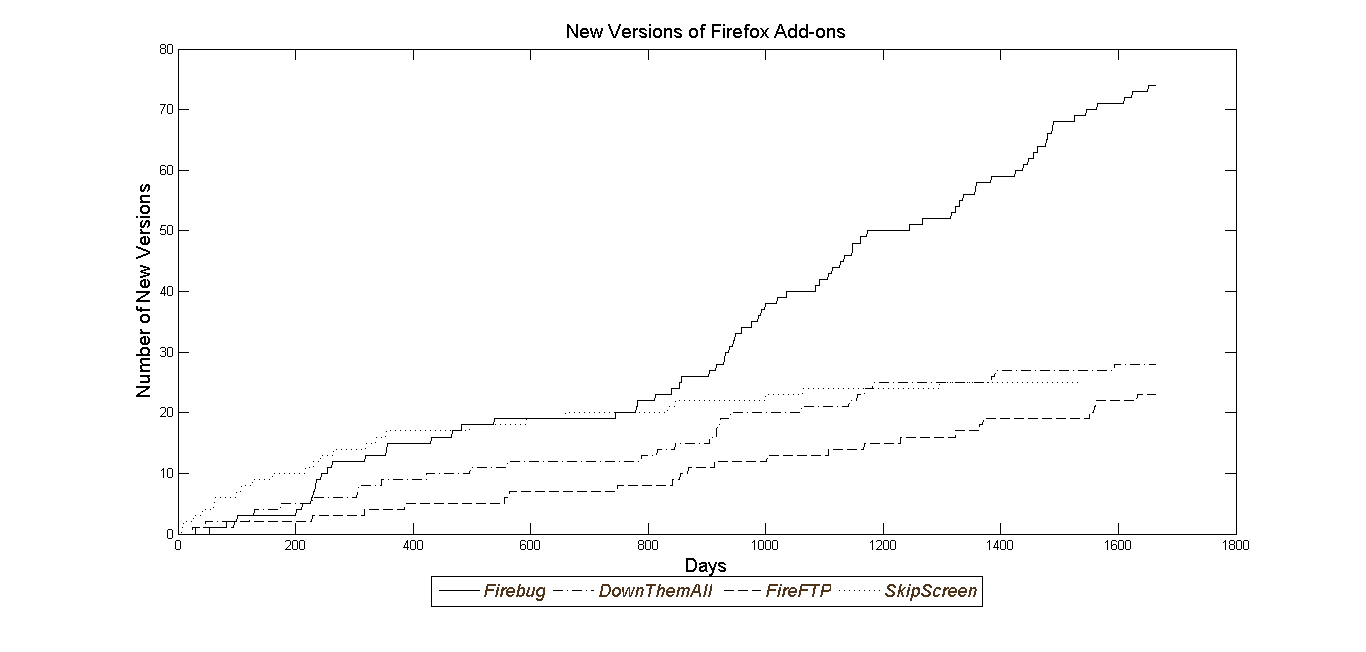
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Table 3 Basic Statistics

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Mean | SD | Min | Max |
| Downloads (K) | 7.641 | 18.502 | 11.79 | 283.44 |
| User Base Size (M) | 0.883 | 1.955 | 1.00E-06 | 16.97 |
| Rating Valence Mean | 4.275 | 0.499 | 1 | 5 |
| New Version of Product | 0.015 | 0.123 | 0 | 1 |
| Product Category Search | 38.753 | 17.566 | 0 | 100 |
| Share of Windows | 0.86 | 0.15 | 0.03 | 1 |
| Number of Reviews | 382.64 | 584.93 | 2 | 3686 |
| Variance of Rating | 1.46 | 0.76 | 0.48 | 4.2 |
| Size of Developer Team | 1.32 | 0.72 | 1 | 4 |
| Length of time series | 1321.9 | 456.6 | 260 | 1686 |

Table 4 Model Comparison

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Mode | Description | Deviance information Criteria (DIC) | Penalty Term  () | Log Likelihood |
| 1 | Static Model ( | 2.1117e9 | 6.2517e8 | 1.4865e9 |
| 2 | No Heterogeneity  ( | 1.2861e7 | 4.5981e6 | 8.2633e6 |
| 3 | Unobserved Heterogeneity | 9.6729e6 | 3.8847e6 | 5.7882e6 |
| 4 | Proposal Model | 9.6733e6 | 3.8848e6 | 5.7885e6 |

Table 5 Mean Elasticity Parameter Estimate in Static versus Dynamic Models

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | |  | Static Model | Dynamic Model | Without heterogeneity |
| Carry Over | | 0 | 0.878 | 0.0047 |
| User Base Size | | 1.1229 | -0.307 | 0.1696 |
| Mean of Rating Valence | | -1.1549 | 0.047 | -0.2378 |
| Mean of Rating Square | | 0.4358 | 0.009 | -0.0064 |
| Product Category Search | | 2.0921 | 0.012 | 0.0651 |
| Version | | 0.0999 | 0.629 | -0.0056 |
|  | | 19.2227 | 0.109 | 422.0243 |
| Weekend Dummy() | | -69.7692 | -39.799 | 0.3155 |
|  | | 7.481 | 4.168 | 7.7308 |

Table 6 Number of add-ons with significant effect in Static versus Dynamic Models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | |  | Static Model | Dynamic Model |
| User Base Size | | 41 | 25 |
| Mean of Rating Valence | | 43 | 30 |
| Mean of Rating Square | | 42 | 29 |
| Product Category Search | | 15 | 18 |
| Version | | 45 | 36 |
|  | | 52 | 52 |
| Weekend Dummy() | | 52 | 52 |
|  | | 52 | 52 |

Figure 5 Examples of one step ahead forecast versus actual demand

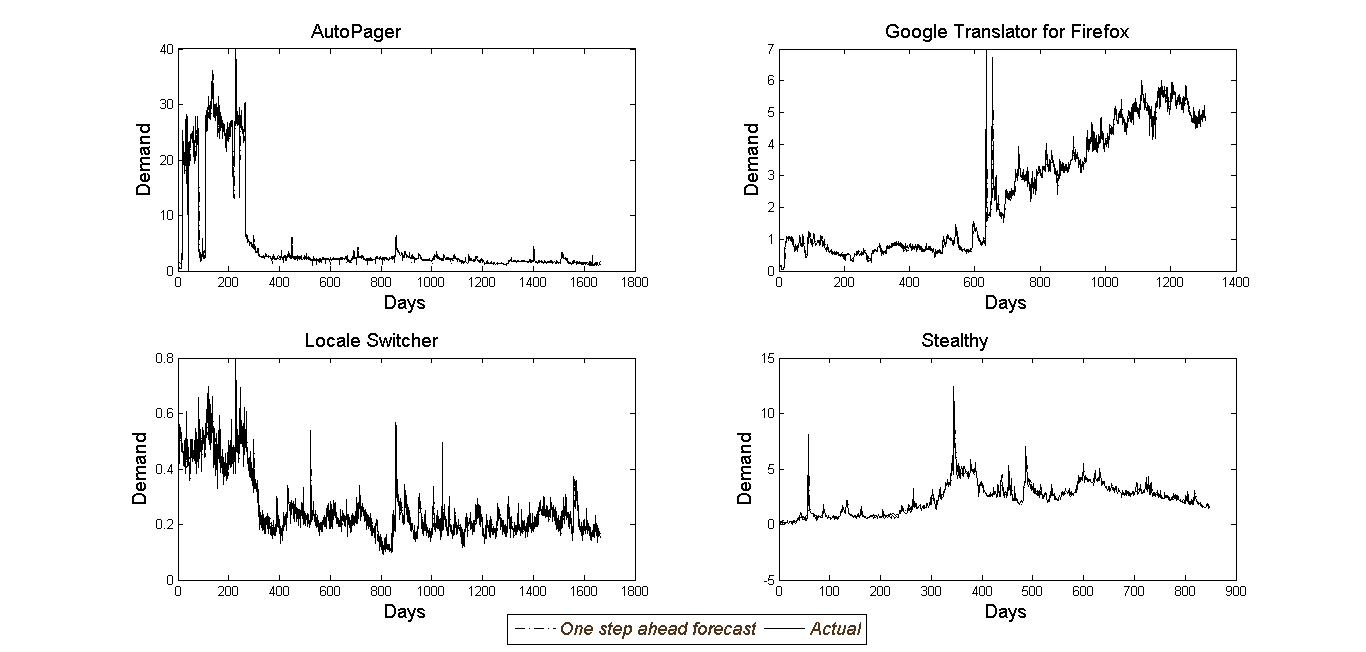
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Table 7 Examples of fit statistics

|  |  |  |
| --- | --- | --- |
| Examples of Add-on | Mean Absolute Deviation (MAD) | Mean Square Error (MSE) |
| Auto Pager | 0.522 | 2.413 |
| Local Switcher | 0.026 | 0.001 |
| Google Translator for Firefox | 0.325 | 0.340 |
| Stealty | 0.264 | 0.257 |

Figure 6 Histogram of Latent Variable Elasticity across Supplementary Products

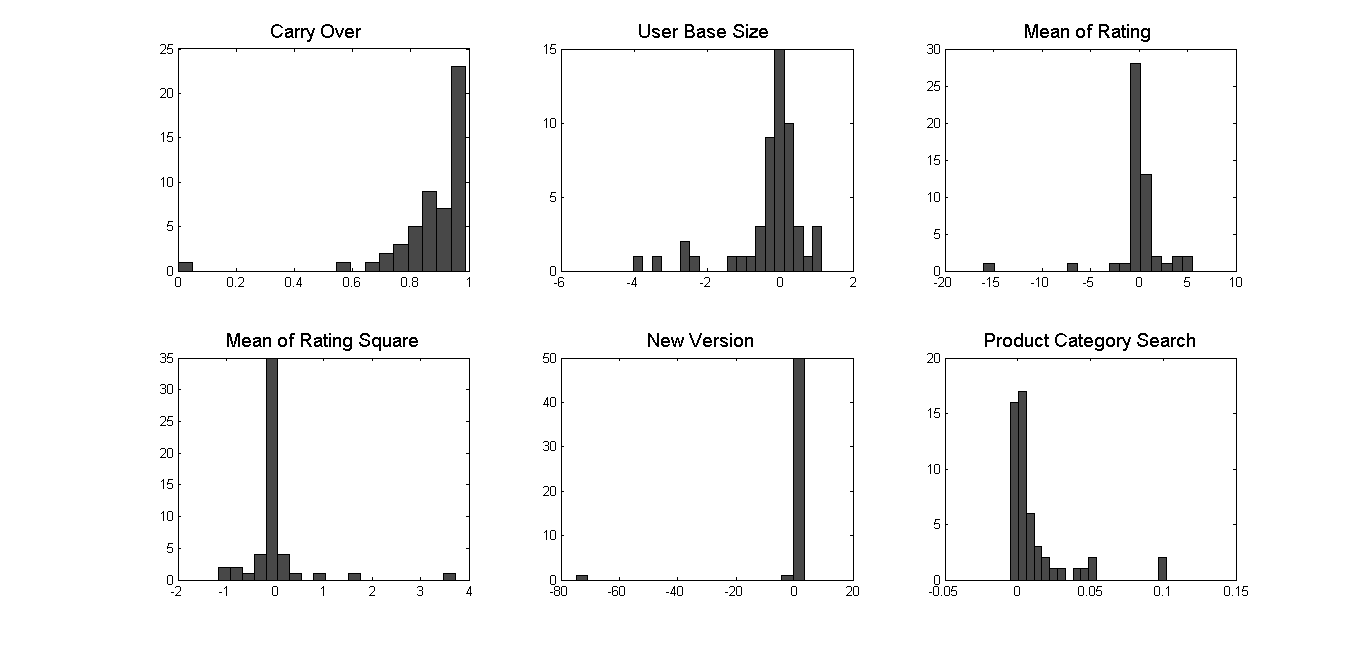


Table 8 Mean Elasticity Parameter Estimate across Supplementary Products

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Mean | SD | 2.5 % | 97.5 % |
| Carry Over | 0.878 | 0.158 | 0.835 | 0.921 |
| User Base Size | -0.307 | 1.064 | -0.596 | -0.018 |
| Mean of Rating Valence | 0.047 | 2.866 | -0.732 | 0.826 |
| Mean of Rating Square | 0.009 | 0.651 | -0.168 | 0.186 |
| Product Category Search | 0.012 | 0.023 | 0.006 | 0.018 |
| Version | 0.629 | 2.986 | -0.183 | 1.440 |
|  | 0.109 | 0.267 | 0.036 | 0.181 |
| Weekend Dummy() | -39.799 | 0.000 | -39.799 | -39.798 |
|  | 4.168 | 16.664 | -0.361 | 8.697 |

Table 9 Significance of effect

|  |  |
| --- | --- |
|  | Number of Add-on’s |
| Carry Over | 52 |
| User Base Size | 25 |
| Mean of Rating Valence | 30 |
| Mean of Rating Square | 29 |
| Product Category Search | 18 |
| Version | 36 |
|  | 52 |
| Weekend Dummy() | 52 |
|  | 52 |

Table 10 Parameter Heterogeneity

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | Estimate | SD | 2.5 % | 97.5 % |
| Carry Over | Intercept | 0.239 | 0.107 | 0.062 | 0.412 |
|  | Share of Windows | 0.746 | 0.122 | 0.541 | 0.948 |
| User Base Size | Intercept | 0.402 | 0.400 | -0.270 | 1.047 |
|  | Variance of Rating | -0.482 | 0.248 | -0.889 | -0.109 |
| Mean of Rating Valence | Intercept | 1.989 | 0.939 | 0.416 | 3.506 |
|  | Author Team Size | -1.318 | 0.549 | -2.253 | -0.441 |
| Mean of Rating Square | Intercept | -0.426 | 0.201 | -0.752 | -0.076 |
|  | Author Team size | 0.291 | 0.120 | 0.085 | 0.486 |
| Product Category Search | Intercept | 0.004 | 0.008 | -0.009 | 0.018 |
|  | Number of Reviews | 0.000 | 0.000 | 0.000 | 0.000 |
|  |  | 0.017 | 0.007 | 0.010 | 0.030 |
|  |  | 1.378 | 0.540 | 0.710 | 2.410 |
|  |  | 9.151 | 3.461 | 4.801 | 15.525 |
|  |  | 0.465 | 0.162 | 0.253 | 0.775 |
|  |  | 0.003 | 0.001 | 0.002 | 0.004 |

Figure 7 Negative Effect of User Base Size

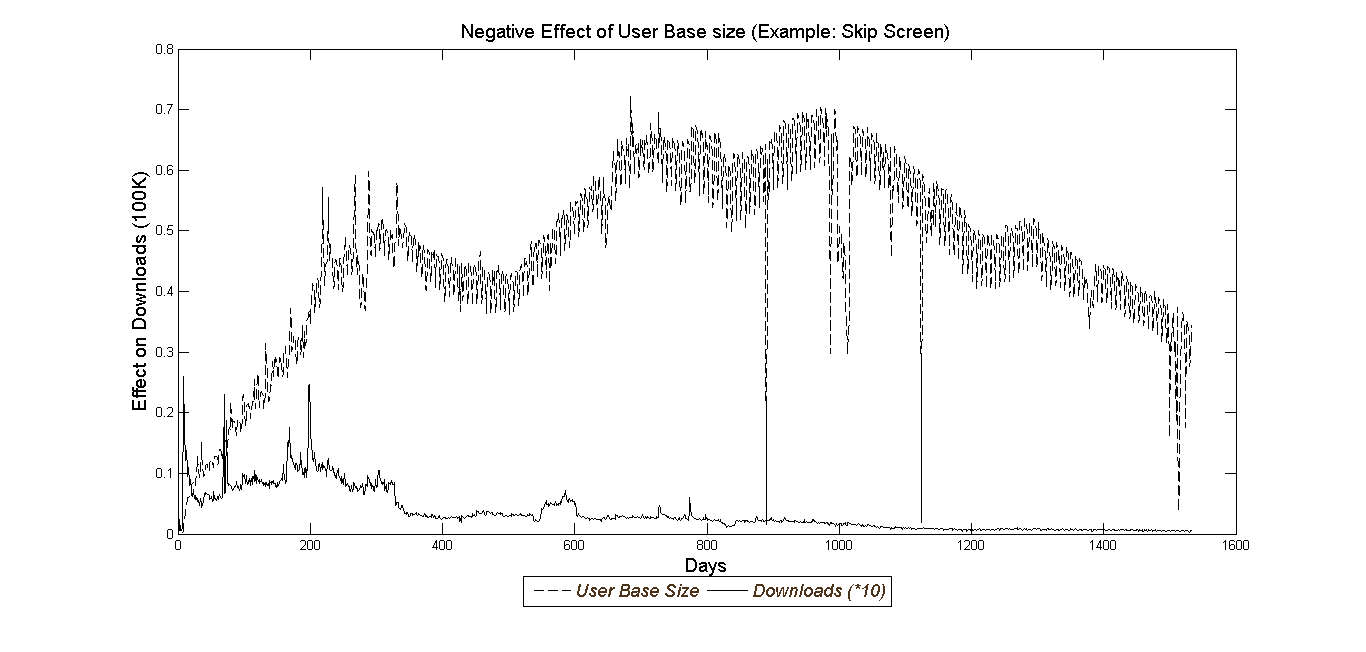
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Figure 8 Effectiveness of rating valence type 1 response example

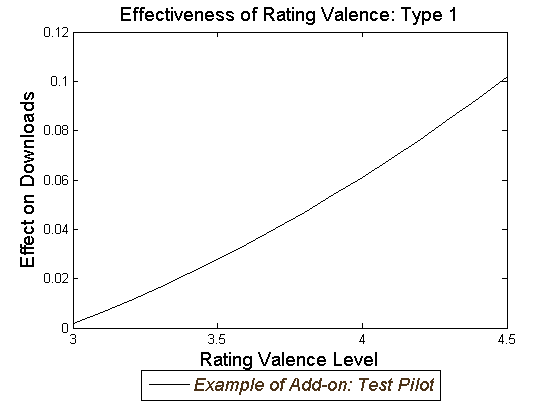
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Figure 9 Effectiveness of rating valence type 2 response examples

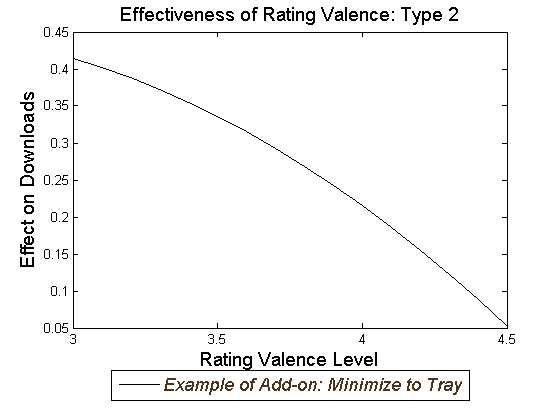
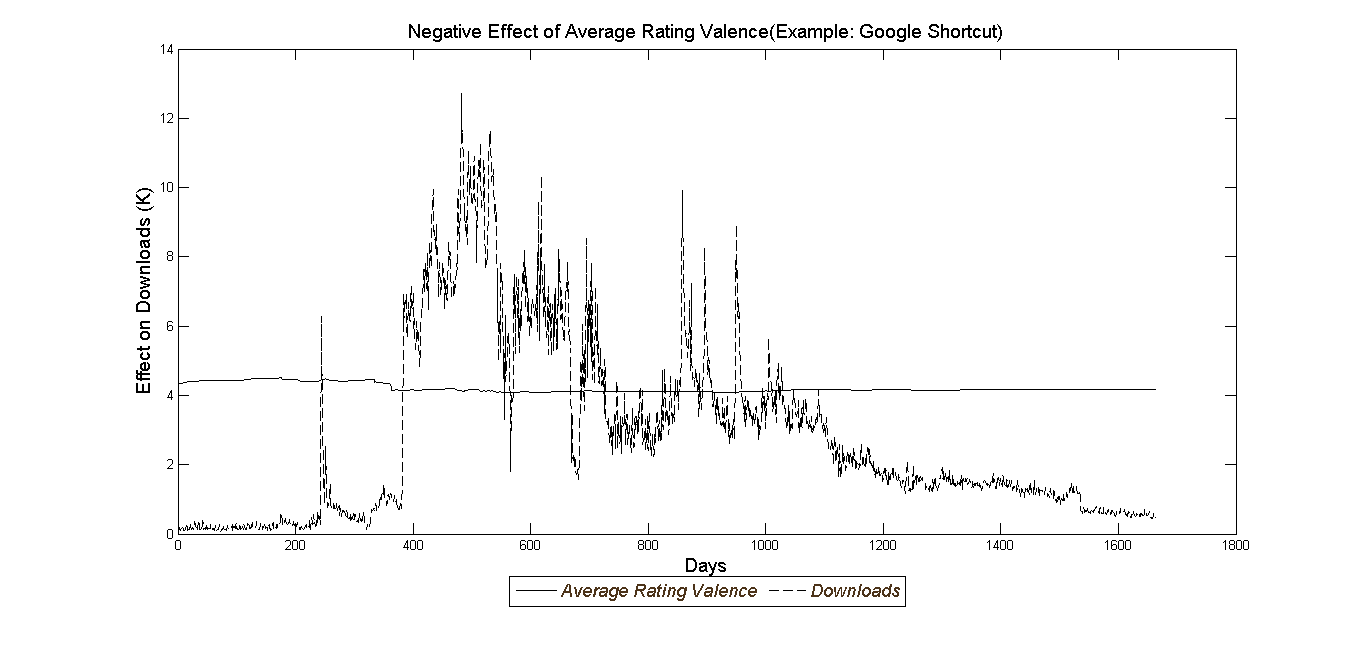
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Figure 10 Negative Effect of Average Rating Valence

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1. Add on is a complementary software that is added to Firefox browser to add new functionality to it. [↑](#footnote-ref-1)