① new paper at writing

First Year summer paper

Dynamic Effect~~s~~ of Product Rating and Observational Learning on the Demand ~~of~~ for Supplementary Products

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Sentence level
① subj.-verb agreement
② plural or singular
③ idioms

Recognize that it is problem & working on it

foot note

1

During time go back keep on polish it

Think about positioning

Intertemporal ⇒ remove from dynamic

Abstract

Firms in many industries facilitate the emergence of supplementary products, especially when type of their product is experience good. Researchers have shown that consumers' decision to purchase experience goods is under influence of their peers' opinion, and their peers' actions, or observational learning. Consumers measure peers' opinion by product rating, and peers' action by user base size of the product. Thus, product rating and user base size signal can play an important and distinct role in simulating supplementary product's demand. In this article, the authors construct a dynamic linear model to study the intertemporal dynamic effects of product rating and observational learning on the demand of supplementary products. They further apply the model to examine the effect of product rating and observational learning on the daily demand of 52 add-ons of Firefox and estimate the parameters using Kalman forward filtering backward smoothing and Markov chain Monte Carlo methods. The results show that product rating and observational learning exerts dynamic, yet diverse, influence on the demand of supplementary products. This finding suggests that if the model does not allow for such dynamic and heterogeneity, the estimation will become biased. Moreover, their findings suggests that: Demand response to product rating is increasing return, and when there is low uncertainty in consumer valuation, observational learning affects daily download more.

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. Two important sources of information are peers opinion and peers actions, or observational learning. Consumers measure peers' opinion by product rating. Nielsen, in the global trust in advertising report 2012, asserts that product reviews are the second most trusted source of brand information and messaging. Studies have further shown that consumers rely on product reviews of experience goods more than on their own experience on the product category (Zhang et al. 2012). 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). In this paper we analyze this relationship in software industry.

① Concise

not only measure but also ...

remove

Software firms such as Google and Mozilla not only have made the distribution of product ratings available using bar charts on their websites, but also they have gone one step further and made the size of user base of products available to their consumers. This size of user base signals other consumers' action, which could in turn facilitate observational learning (Bikhchandani et al. 1998). Studies showed that observational learning complements product rating, and both these mechanism affect sales (Chen et al. 2011). However, user base size information is not always available for firms outside software industry. In software market some firms develop a technology that enables the creation of products and processes that support current and future development, called technology platform.

Volume make simple

transition

② Cohision is missing

Conv of rating & user base size

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 third party to extend 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 that consists of independent authors to develop complementary products, add-ons, and then Firefox distributes these add-ons on its website. Many other industries such as video game, mobile phone, web publishing, computer devices and movie have adopted 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).

keep simple & direct & keep voice Active

on sampling

Send appendix & make sure there is no problem

Technical appendix A: about mathematic of code in simple language

Bass et al

Consequently platform owners, as a policy maker, in various industries may find it interesting to know how supplementary products' rating and user base size signal affects those products' demand.

Several issues arise in studying product rating and observational learning with regard to supplementary products. Studies have shown that product rating has significant effect on product sales (Chavelier and Mayzlin 2006; Clemsons et al. 2006; Dellarocas et al. 2007). These studies only consider effect of current period on rating, static effect. However, other studies proved that advertising and word of mouth could also have intertemporal dynamic effect on revenue, i.e. immediate and long term effect (Bruce et al. 2012, Little 1979). Thus, as a type of word of mouth, product rating may have dynamic effect on the demand. Since observational learning also acts as a type of information that complements advertising, it is likely that observational learning also exerts intertemporal dynamic effects on demand (Chen et al. 2010). Moreover, researchers tried to control for observable heterogeneity in estimating the effect of product rating on demand (Chavelier and Mayzlin 2006), but heterogeneity could be unobservable. In addition, it could be interesting to know how the effect of rating varies across supplementary products. This also suggests that heterogeneity in both product rating and observational learning may influence estimation results.

Researcher may be able to explain heterogeneity based on institutional characteristics of the market. In the market we study there are three different economic agents playing role. First is Mozilla that facilitates the development and commercialization of supplementary products. Second one is Add-on's author, independent agents who develop and commercialize their add-on, and third one is consumers, or so called users. Add-on's authors may decide either to ask for money contribution or just make their contacts available for professional purposes. Moreover, the authors are able to optimize their response to platform changes and bugs found in their add-on via issuing new version. Consumers on the other hand are exposed to free

Lot of work to do

then come back for Journal

① motivated better (importance & what other have done)

② Better writing (Concise)

③ managerial ⇒ simulation policy & implication alternative to commercial software. 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. Consumers are risk averse, and sensitive to uncertainty (Erdem and Kean 1996), and uncertainty is measured by the variance of product rating (Sun 2012), so consumers may be sensitive to the variance of add-on ratings.

Number of available choices in the market may also affect consumer's sensitivity to product ratings, because competition influences sales response to advertising (Gatignon 1984), a type of which is product rating. Competition and number of available choices in the market may be 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 that work in team are prone to act as a generalist, rather than as a specialist (Lambkin and Day 1989). Specialists, in contrast to generalists, select a niche market, a market with less intense competition, for their offering. Less intense competition implies less option for consumers. Therefore, size of author's team may affect sensitivity to product rating.

Another relevant factor may be segments of the market. Market segments are identified by similarity between customers. Referral generates demand for the product, but similarity between customers, homophily, significantly affects it (Brown and Reingen 1979). Therefore, market segments, due to their homogeneous nature, may affect demand's dynamic. In the context of add-on we can segment consumers based on operating system they use, i.e. Windows, Linux, and Mac. Due to different size of market share of these three operating systems, and effect of homophily in the cascade of information, we expect that type of operating system explains part of the heterogeneity.

Subsequently, 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

present it MoT sci

methodologically stronger

Depth important

read literatures

Sharper understanding

End at next semester better & better

take time off & come back

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 an 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 forward filtering backward 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 more 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 product review and observational learning. Included in this review are empirical and theoretical researches that reveal how product reviews and observational learning affect different business metrics. After the literature review, we describe our model that relates product rating valence and user base size to product's demand. We then describe the data used in this article. Finally, we present the results and highlight some of the implications.

take one to the end ⇒ it is important to take one & take to the end ⇒ You have to go the end

polish it up & make it work

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

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IN Email to Ernan

- Recognize that it could be better work on to polish it up

→ work on it Quickly then we go section by section

① sentence by sence
② Paragraph by paragraph
③ linkages

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Not only today's ratings, but past rating effect

Intertemporal paper John little

immediate effect & long term effect

advertising

Abstract

Firms in many industries facilitate the emergence of supplementary products, especially when their product is experience good. Researchers have shown that consumers' decision to purchase experience goods, more than any other type of goods, is under influence of their peers' opinion, captured by product ratings, and their peers' actions, or observational learning, captured by user base size of the product. Thus, product rating and user base size signal can play an important and distinct role in simulating new product's demand. In this article, the authors construct a dynamic linear model to study the intertemporal dynamic effects of product rating and observational learning on the demand of supplementary products. They further apply the model to examine the effect of product rating and observational learning on the daily demand of 52 add-ons of Firefox and estimate the parameters using Kalman forward filtering backward smoothing and Markov chain Monte Carlo methods. The results show that product rating and observational learning exerts dynamic, yet diverse, influence on the demand of supplementary products. This finding suggests that if the model does not allow for such dynamic and heterogeneity, the estimation will become biased. Moreover, our findings suggests that: Demand response to product rating is increasing return, and when there is low uncertainty in consumer valuation, observational learning affects daily download more.

Normally introductions in 4 pages

push the rest in literature review

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

main idea

- Recognize that the writing is not good
- Thinks it is publishable, but has to be written too good
- from reader it is not good

1. Introduction

crisp & short

don't do this too often

Take things in b/w out

put this in next sentence

Consumers search different sources of information before making purchase decision. Two important sources of information, which complement offline sources, are peers opinion, captured by product review, and peers actions, or observational learning, captured through user base size of the product. In the global trust in advertising report 2012, Nielsen asserts that product reviews are the second most trusted source of brand information and messaging. Studies have further shown that consumers rely on product reviews of experience goods more than on their own experience on the product category (Zhang et al. 2012). Therefore, the

problem of Connection

link is not clear

- Joseph

sentence → scientific
paragraph
group of

- Forget about rest of paper
- go through sentence by sentence
- Then after writing sentence, then is it organized correct well

- Don't put too much b/w subject & verb

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 the extent of this effect for supplementary products in the software industry.

Not clear link

doesn't convey

we have not considered ....

too long

- Since you pieced them off since left them waiting

Given the importance of product reviews, ~~not only e-commerce websites that sell experience goods, such as Amazon.com, but also~~ web sites that offer free software, such as sourceforge.com and Google-play, have made the distribution of product ratings available using bar charts on their websites. Mozila.org web site even goes one step further and makes the size of user base of add-ons[1] available to its consumers. Size of user base signals other consumers' action, which could in turn facilitate observational learning (Bikhchandani et al. 1998). Studies showed that observational learning complements product rating, and both these mechanism affect sales (Chen et al. 2011). However, user base size information is not ~~ubiquitously~~ always available on different platforms yet.

go back where You started

Bring fro

disappointment

Say key information first

This

Fixed the sences & dont worry about connecting together

website Distribution channel

Firms

thus is ....

Bridge the term

Bracket

identify who the party is

Electronic retails, like amazon, but also software developers firms

Wikipedia defines platform as a term for technology that enables the creation of products and processes that support current and future development. 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 third party to extend 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

many software firms do not measure on their web

most soft developers do not measure

selling point

link is Problem

Pays to work on Intro

find better link

[1] Add on is a complementary software that is added to Firefox browser to add new functionality to it.

it is not is about platform, but for diffusion

To measure the success of this strategy they such as video game, mobile phone, web publishing, computer devices and movie have adopted 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, as a policy maker, platform owners in various industries may find it interesting to know how supplementary products' rating and user base size signal affects those products' demand.

with regard to supplementary product

what do you mean by that

Several issues arise in studying product rating and social learning. Studies have shown that product rating has significant static effect on product sales (Chavelier and Mayzlin 2006; Clemsons et al. 2006; Dellarocas et al. 2007). However, some other studies proved that word of mouth could also have dynamic effect on revenue (Bruce et al. 2012). Thus, as a type of word of mouth, product rating may have dynamic effect on the demand. Since observational learning also acts as a type of information, complementing (that Complements) advertising, it is likely that observational learning also exerts intertemporal dynamic effects on demand (Chen et al. 2010). Moreover (furthermore), researchers tried to control for observable heterogeneity in estimating the effect of product rating on demand (Chavelier and Mayzlin 2006, Moe and Trusov 2011), but heterogeneity could be unobservable. This also suggests that heterogeneity in both product rating and observational learning may influence estimation results.

They don't Control for indiv level response

it Could be interesting rating is effective in different way

Researcher may be able to explain heterogeneity based on institutional characteristics of the market. In the market we study there are three different economic agents playing 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

Could vary across supplementary items

how effect of rating different across samplementary items

it is good, but it is unobservable

→ if fits poorly & say that Dynamic is import

don't estimate δ

	DIC	penalty term	log likelihood

✓

Dynamic Effect of Supplementary Product Rating

Run the model & set carry over to zero ✓

don't pick up Git-1

Report penalty term as well

Back

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Further issue to address ⇒ endogeneity is a question

- Don't tell about Gap or you have to say that Gap needs to fill this (motivate) ⇒ why fill Gap?

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- Why dynamic important
- why supplementary product different
- say that developer team is important
- You write & come back

Voice → to be less certain when you are not certain

→ You have to talk about uncertainty before

→ You have to talk it before

evidance from litratere

- finish it up & then motivation is not enough
- abstract only when paper is finished
- I have to show whether it is enough ⇒ Don't say it when you run model
- repitition ✗
- Big words Bad ✗
- multi si ✗
- crisp & simplicity is good

- You have to motivate Before
- lead the reader to it
- motivate every part
- uncertain
- develope...
- user bas...

enough motivation about it

Abstract

Researches have shown that product ratings, formed under social influence, affects sales of a product. Thus, product rating can play important and distinct role in simulating new product demand. In this article, the authors construct a dynamic linear model to study the dynamic effects of product rating for heterogeneous products. They further apply the model to examine the effect of product rating and user base size signal 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 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 user base size signal affects daily download positively when there is low uncertainty in valuation.

Keywords: Dynamic effect, Product rating, Experience Goods, Supplementary products, Uncertainty

1. Introduction

- Think many pages on the road that you made promise - You answer this

Consumers search different sources of information before making purchase decision. The search issue becomes more critical in the context of experience good, a type of good that its characteristics can easily be ascertained only upon consumption (Zhang et al. 2012). 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. Nielsen in the global trust in advertising report 2012 asserts that consumer product reviews are the second most trusted source of brand information and messaging. Studies also have shown that consumers rely on product reviews more than on their own experience on the product category (Zhao et al. 2012). Therefore, online customer rating is proved to have significant effect on product sales (Chavelier and Mayzlin 2006; Clemsons et al. 2006; Dellarocas et al. 2007).

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

- make promise & then answer it completely
- sensitive to it

- neat & Gramatical for the rest

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 gap in literature on the dynamic of this effect in the context of online supplementary software. In response to this importance of product reviews, not only e-commerce websites, but also web sites that offer free open source products such as sourceforge.com and Google play are making the distribution of ratings available using bar charts on their website. Some websites, such as Mozilla.org, even go one step further and make the size of user base of product available to consumers.

too quickly doesn't fit

Think again

explain this paragraph

- each paragraph should have common tongue
coherent link b/w paragraph & transition

Studies have identified two fundamentally distinct approaches to opening a technology platform. First approach entails granting access to a platform and thereby opens up market for complementary components around the platform, while the second entails giving up control over the platform (Boudreau 2010). Between these two strategies, the first one is exerted by Mozilla Firefox web-browser, hereby called Firefox, 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 to develop complementary products, called add-on, and distributed it on its website according to the business model of the author. This in turn is similar to supplementary products in various industries such as video game, mobile applications, and online contents.

Say planely

Jargon

Make it clear

Say in english if

Subject + action

identify who the subject is what they are doing

person + action

Add-on's author based on his economic incentive may decide either to ask for money contribution or just makes his contact available for professional purposes. Moreover, the author has 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. Add-ons due to their nature can be categorized as experience good, since its characteristics are difficult to observe in advance. Thus, signals such as average product rating

Clear up & writ crispy sentence

Explain it for non experts don't use Jargons

- in first sentence what paragraph is
- lead logical point in last sentence (transition)

all mozila should lead to developer

- signal ⇒ all institutional should lead to why user base important

valence and usage base size may play an important role in consumer's decision (Zhang et al. 2010). - all lead to supplentary product ① uncertainty, why it is important ② Heterogen

Therefore, several substantive questions arise on the effect of product reviews on demand for a supplementary product: Whether product rating valence has dynamic effect on demand? How product rating of different supplementary products affects their demand? Whether signals such as user base size and developer team size explain heterogeneity in products demands? What is the role of uncertainty in moderating the effect of different signals?

- explain Context.

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 user base signal 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 user base size signal has positive effect on demand for the product when uncertainty is low, and that consumers tend to ignore low product rating for some add-ons.

Follow UP Joseph williams go back & review

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.

- point: perhapse it is an opportunity about the Gap (allows you to say it later on) turn in then he will

1 Full document & press hard

2 look & william & critic your writing & Go back

side by side Joseph william check

2. 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.

3 Read Good article & Come back to your paper

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

4 Scientific america & Compare with your writing (Intro & literature review)

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 --

publish

S Richard Dawkins - Oxford
scientific writing
Steven Gool ⟹ Read those books

1 you can use beta to compare result & say they are biased

① clean up

Paper submitted for first year summer paper → clean up
August 28/2013

② action: discussion of individual effect

have to explain hetrogeneity with movie paper

Discussion about the hetrogenity ⇒ offline things they have done

Dynamic Effect of Supplementary Product Rating

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Key words: Supplementary Products, Experience Goods, Product Rating, Product Review, Uncetainty, Dynamic Effect, DLM, Kalman Filter, User Base, Platform, Firefox Addon

Back

1. INTRODUCTION

Several substantive questions arise on the effect of product reviews on demand for a supplementary product: How supplementary product rating affects its demand? How product rating of different supplementary products affects their demand? Whether share of platform affects persistency of product rating effect? Whether developer team size, observed by consumer, affects consumers evaluation of the supplementary product? How does uncertainty on product rating in the context of experience good affects consumers valuation of user base size signal?

2. LITRATURE

3. MODEL DEVELOPMENT

{ explain i and t what it is

$t=1\dots T$ days

3.1. Aggregate Demand and Goodwill Stock

Given our interest in assessing the effect of product rating on demand, we excercise aggregated sales response model. The model is constructed on the discrete time analog of Nerlove and Arrow's (1962) model. Specifically, Nerlove and Arrow suggest the use of "goodwill stock," to capture persistent effect of advertising on demand. To demonstratet this more clearly in the supplementary product context, we assumed that product rating build the goodwill stock (G) of the supplementary product. In turn, this goodwill drives the demand for the supplementary product, oprationalized as the daily download divided by 1k (y_{it}). That is,

$i=1\dots 52$

model section should be very precise

if variance big

Z_i → is avector

format

$$y_{it} = G_{it} + \beta_i * Z_{it} + \epsilon_{it}, \text{ where } \epsilon_{it} \sim N(0, V_i) \quad (1)$$

- only write when ready to write when thought is complete

} word document
12.
double space

Goodwill → latent measure that captures attractiveness of download

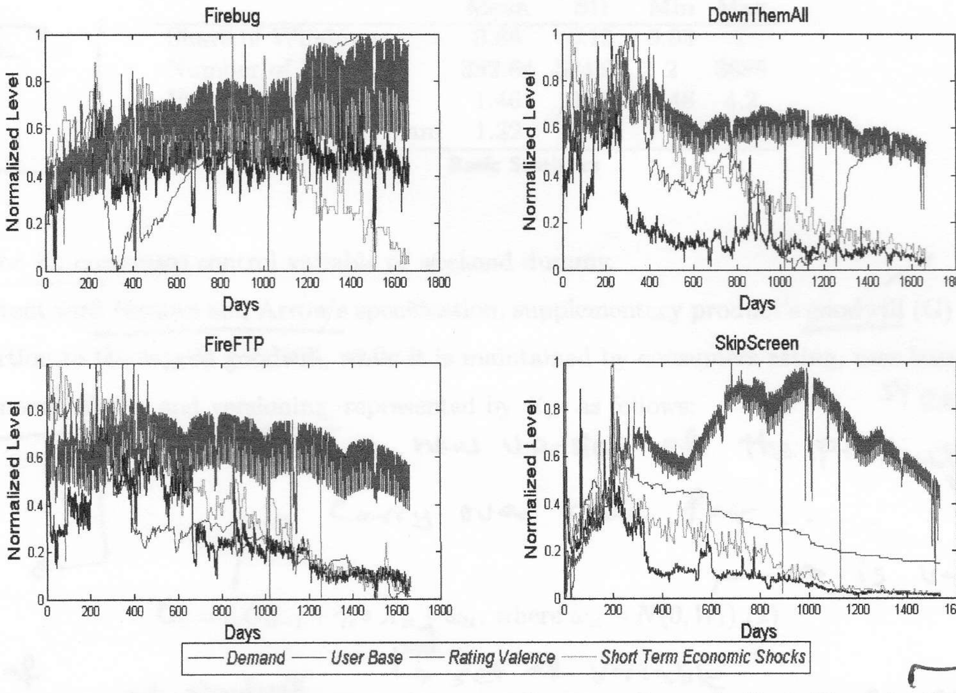


Figure 1 Examples of Demand, Rating Valence, Usage and Short term Economic Shock (Normalized)

plot dependent & independent in differect curve

Show various shape of download curve

explain it it is Z-score

* write them active users

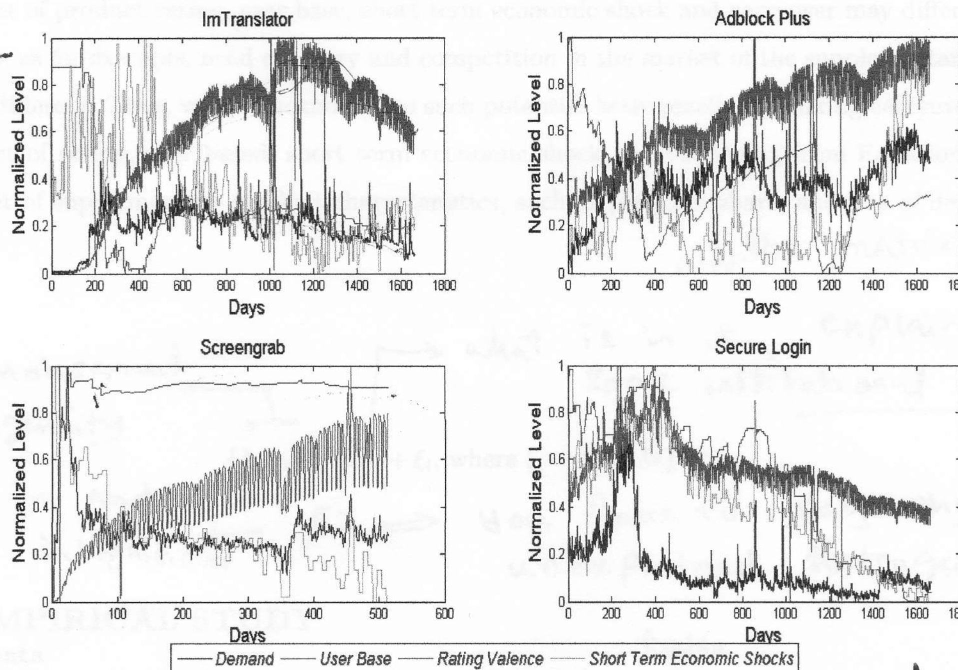


Figure 2 Examples of Demand, Rating Valence, Usage and Short term Economic Shock (Normalized) Cont.

on plot
Download
user base
Demand

use # download

put explanation

don't use normalization since it hides data

problem of black & white may be reduce to couple

first explain then name
and use it

Do not use Jargon

	Mean	SD	Min	Max
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

Table 1 Basic Statistics

over used
Just say
it is latent
measure

The vector Z_{it} comprises control variable of weekend dummy.

Just
invoke
one
similar
to ...

Consistent with Nerlove and Arrow's specification, supplementary product's goodwill (G) decays in proportion to the lagged goodwill, while it is maintained by consumers rating, user base, short term economic shock, and versioning, represented by X_{it}, as follows:

size

over-used
as a Construct

new version of the product ⟹ Typically
these products
are ...

Carry over rate for ...

is variance of

say exactly
what it is

$$G_{it} = \delta_i G_{it-1} + \gamma_i * X_{it} + \omega_{it}, \text{ where } \omega_{it} \sim N(0, W_i) \ (2)$$

set of variable

is the number of
search of name of product
available on google trend
according to ... paper short

$\delta_i, \gamma_i, \omega_{it}$

Precise

Clear
rather
than

3.2. Heterogeneity

The effect of product rating, user base, short term economic shock and carryover may differ across products, as for example, need category and competition in the market of the supplementary good may be different. Thus, we also acknowledge such potential hetrogeneity by linking carryover rate, and effect of rating, user based, short term economic shock and versioning from Equation 1 and 2 to a set of supplementary product characteristics, such as platform share, and size of developer team.

whether matrix or vector

what is in it
explain in detail
Some institutional charact upfront

why unobserved
hetrogeneity

$$\{\delta_i, \gamma_i\} = \Psi U_i + \xi_i, \text{ where } \xi_i \sim N(0, M) \ (3)$$

put that in and
say insignificant

β_i ⟹ you have to say why
unexplained hetrogenity

4. EMPIRICAL STUDY

table

4.1. Data

Our data are from 50 Add ons of firefox and span around five year period (1686 days) from 2008 to 2013.

- write how avg is Calculated
- ~~effect of rating on download~~
- marginal download
- which one maximum & which one
minimum

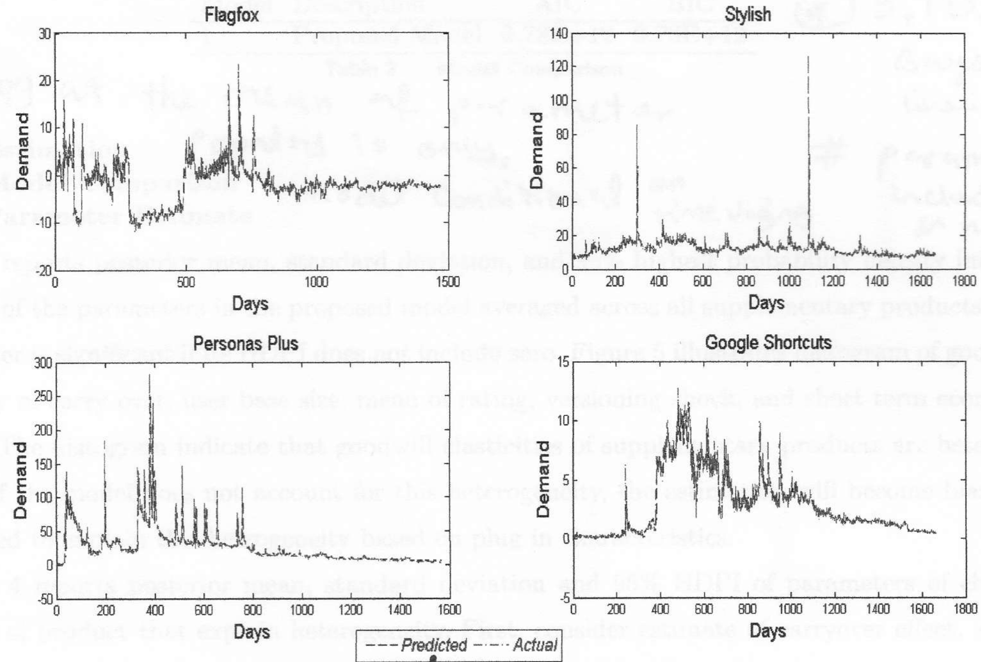
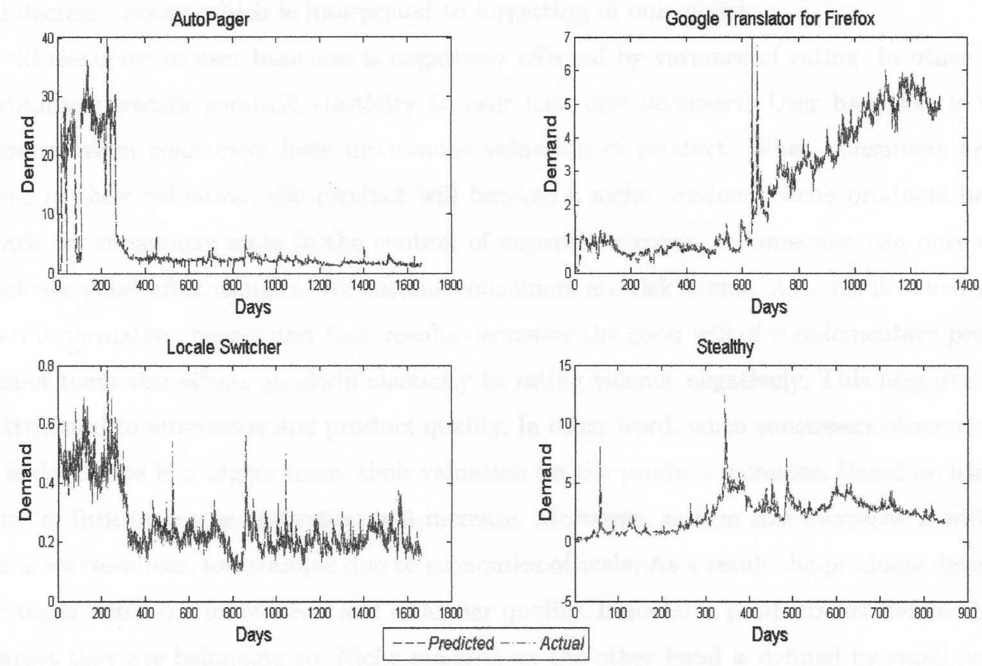


Figure 3 **Examples of Predicted Versus Actual Demand**

Report in set of MAD & MSE

one step a head



make clear it is in sample

Solid line ↓ actual

Figure 4 **Examples of Predicted Versus Actual Demand Cont.**

table 5 & figure 4 go together

in R it is reported

Report DIC → Hierarchical

mean of log likelihood one step ahead & sum every cycle → mean ①

Model	Description	AIC	BIC
1	Proposed Model	9.78E+12	9.78E+12

Table 2 Model Comparison

(*) $y_t \mid D_{t-1}$ marginal Bays factor likelihood

Ⓝ then log at the mean of parameter penalty is only.

parameter → is fixed including variance & not Dynamic

model conditional on time varying

4.2. Estimation

4.3. Model Comparison

4.4. Parameter Estimate

Table 3 reports posterior mean, standard deviation, and 95% highest probability density interval (HDPI) of the parameters in the proposed model averaged across all supplementary products. The parameter is significant if its HDPI does not include zero. Figure 5 illustrates histogram of goodwill elasticity of carry over, user base size, mean of rating, versioning shock, and short term economic shocks. The histogram indicate that goodwill elasticities of supplementary products are heterogeneous. If the model does not account for this heterogeneity, the estimation will become bias. We then tried to explain this hetrogeneity based on plug in characteristics.

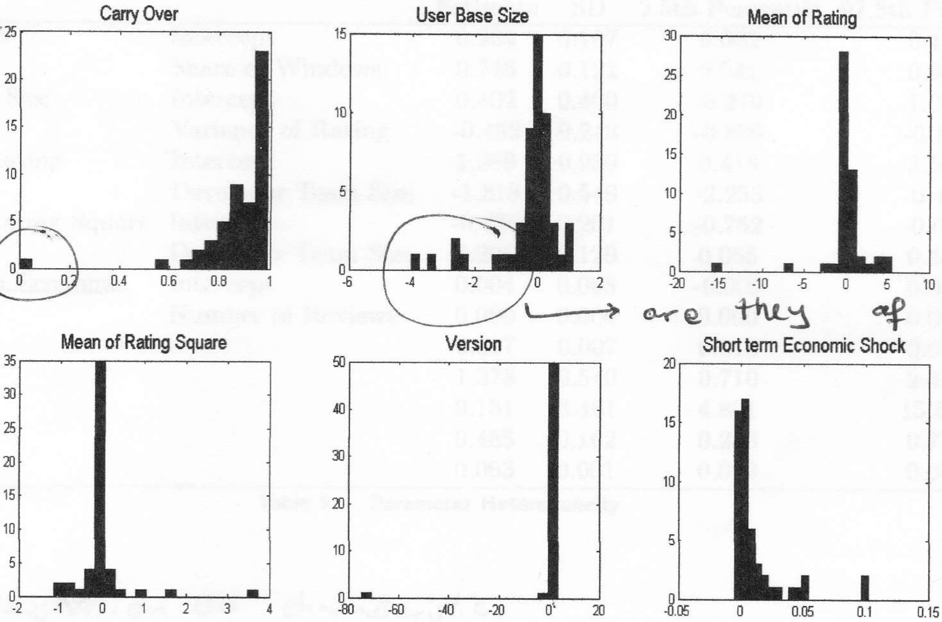
Table 4 reports posterior mean, standard deviation and 95% HDPI of parameters of characteristics of product that explain heterogeneity. First, consider estimate of carryover effect. As we expected when the share of a dominant platform, Windows, increases forgetting rate would be lower. This finding can be attributed to the diffusion process. As size of the population increases the probability of exposure to consumers of the same type increases. This higher exposure during time will decrease decay, which is interpreted to forgetting in our model.

Goodwill elasticity to user base size is negatively affected by variance of rating. In other word, as uncertainty increases goodwill elasticity to user base size decreases. User base size is useful to consumers when consumers have unanimous valuation of product. When consumers are not unanimous in their valuation, the product will become a niche product. Niche products become problematic for consumers more in the context of experience goods, as consumer can only evaluate experience good after using it. We assume consumers are risk averse. As a result when rating becomes uninformative, bigger user base results decreases the good will of supplementary product.

Developer team size affects goodwill elasticity to rating valence negatively. This negative effect can be attributed to innovation and product quality. In other word, when consumers observe that a product is developed in a bigger team, their valuation for the product increases. Based on litrature as the size of firm increases innovation will increase. Moreover, as firm size increases it will have access to more resources, for example due to economics of scale. As a result the products developed in larger teams are more innovative, and of higher quality. Innovative products are defined by the niche market they are belonging to. Niche markets on the other hand is defined by small number of product substitutes. When consumers face a product that have less substitute they are prone to discount the rating, due to not having any other choice. Therefore, developer team size negatively explain why positive & negative

are they significant

Litrature
① Zhu, Zhang & ref
② Trusov & ref
③ Norris & ref
④ list of litr



explain why

Can you tell story

You have to explain all table

are they of high user base or not

individual level analys
what drives negativity
anything else

Figure 5 **Histogram of Goodwill Elasticity across Supplementary Products**

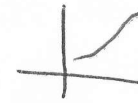
Could be deminishing return story as user base to certain point download deminish

title at top

	~~Estimate~~ mean	SD	2.5th Percentile	97.5th Percentile
Carry Over (δ_i)	0.878	0.158	0.835	0.921
User Base Size (γ_{i1})	-0.307	1.064	-0.596	-0.018
Mean of Rating (γ_{i2})	0.047	2.866	-0.732	0.826
Mean of Rating Square (γ_{i3})	0.009	0.651	-0.168	0.186
Version (γ_{i4})	0.629	2.986	-0.183	1.440
Short term Economic Shock	0.012	0.023	0.006	0.018
~~Variance~~	0.109	0.267	0.036	0.181
Weekend Dummy (β_i)	-39.799	0.000	-39.799	-39.798
W	4.168	16.664	-0.361	8.697

→Put in basic Stat for mean v_i

Table 3 **Mean Elasticity Parameter Estimate Across Supplementary Products**



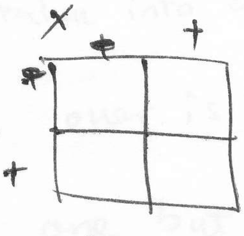
look at downlad curve

affects goodwill elasticity to rating. Number of product reviews positively affects goodwill elasticity to short term economic shocks. This shocks either could be supply or demand shocks. Based on Litrature consumers self select themselves to review products that are important for them. Consequently, as products become important through short term economic shocks, consumers will review the product more, and this importance will affect goodwill elasticity to short term economic shocks positively.

5. MANAGERIAL IMPLICATION

6. CONCLUSION

References



wear in & wear out

(*) always declining initially
explain why it is

explain in each what means

(*) help initially then less useful

(*) immediate down deminish at increasing rate

search
replace

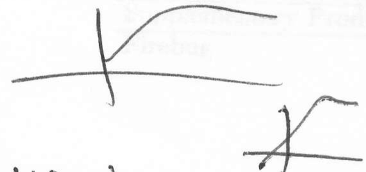
		Estimate	SD	2.5th Percentile	97.5th Percentile
Carry Over	Intercept	0.239	0.107	0.062	0.412
	Share of Windows	0.746	0.122	0.541	0.948
User Base Size	Intercept	0.402	0.400	-0.270	1.047
	Variance of Rating	-0.482	0.248	-0.889	-0.109
Mean of Rating	Intercept	1.989	0.939	0.416	3.506
	Developer Team Size	-1.318	0.549	-2.253	-0.441
Mean of Rating Square	Intercept	-0.426	0.201	-0.752	-0.076
	Developer Team Size	0.291	0.120	0.085	0.486
Short term Economic ~~Shock~~	Intercept	0.004	0.008	-0.009	0.018
	Number of Reviews	0.000	0.000	0.000	0.000
M1		0.017	0.007	0.010	0.030
M2		1.378	0.540	0.710	2.410
M3		9.151	3.461	4.801	15.525
M4		0.465	0.162	0.253	0.775
M5		0.003	0.001	0.002	0.004

Table 4 **Parameter Heterogeneity**

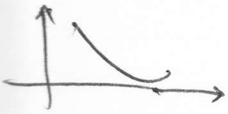
* offline Regression on characteristic
which download this chract

* suggest
it suggest
if too Commited there would be problem
expres in this
could be with humiliation
not totally Commited

Carryover:
* The number in the past affect in future
nature of product internet product ⟹ WOM & Communicate
Recommending product
intertemporal Correlation
we confirm that there is dynamic in this process
& not taken into accout it will become bias
we found Carry over is important, so dynamic is important
not only for one but all, so dynamic is important



wear in or
wear out or
wear out right away



why rating wear out so quickly?

rating does not give information so what is important why rating negative

→ Explore deeply individual & Then heterogeneity

→ what people have done about rating

what is contribution

→ if versioning significant why, what does positive versioning

Supplementary Product	MAD	MSE
Firebug	2.168	9.257
Flagfox	0.729	2.097
Web developer	0.260	0.246
IE Tab	0.730	1.472
Test Pilot	0.072	0.044
User Agent Switcher	0.344	0.507
Stylish	1.099	12.367
Text Link	0.099	0.056
DownThemAll	0.999	3.196
FireFTP	0.599	0.863
AllYouTubeDownload	0.025	0.007
Personas Plus	3.329	104.469
MinimizeToTray revived	0.108	0.051
Status-4-Evar	0.069	0.078
Classic Compact Options	0.019	0.001
Scriptish	0.084	0.117
Google Shortcuts	0.320	0.335
Super Start	0.075	0.038
Print pages to Pdf	0.035	0.010
SkipScreen	0.313	0.990
ReminderFox	0.311	0.522
AutoPager	0.515	2.380
Iplex to ALLPlayer	0.027	0.006
Tilt 3D	0.038	0.029
Cheevos for Firefox	0.017	0.003
ImTranslator	1.171	5.030
Google Translator for Firefox	0.098	0.054
Quick Locale Switcher	0.070	0.012
gTranslate	0.120	0.054
New Tong Wen Tang	0.040	0.004
Romanian Language Pack	0.023	0.001
Locale Switcher	0.026	0.001
Adblock Plus	4.165	41.455
Adblock Edge	0.063	0.199
Password Exporter	0.075	0.012
Stealthy	0.133	0.129
FEBE	0.184	0.215
The Camelizer	0.022	0.005
ChatZilla	0.089	0.054
Thumbnail Zoom Plus	0.035	0.013
ProCon Latte Content Filter	0.049	0.005
New Tab Homepage	0.062	0.009
Screengrab	0.027	0.005
Greasemonkey	1.600	26.361
Flashblock	0.277	0.220
Session Manager	0.091	0.021
PDF Viewer	0.056	0.021
Add-on Compatibility Reporter	0.198	0.323
Secure Login	0.051	0.008
Nightly Tester Tools	0.128	0.106
Translate This!	0.024	0.005
Quick Maps	0.050	0.036

Table 5 **Mean Absolute Deviation and Mean Square Error**

Discuss Report only the best ones

based on 1-step ahead plot

Five or 6 best ones

Big one are bad series & should not be

fit statistic

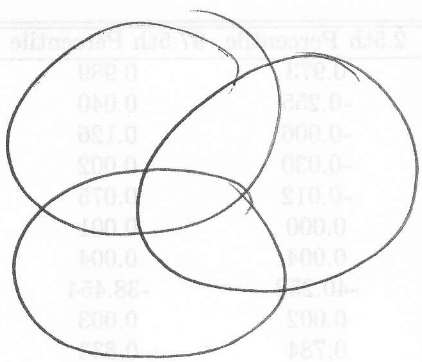
Could be → important about how express it
understand limitation

potentially since it is not experiment

① what was done

1st task Clean up table

Summerize



① Dynamic Download => by Carryover

none

- Stack up

② hetrogenty

2nd task Abstract layout & Introduction Say what is it about

what you do

and Paragraph listing Contributes

before end of Intro

Why this paper has done

then here is my Contribution

① Why dynamics important => bias parameter

② Why rating

Read what they have discovered

& what you have discovered

③ Begin Intro with say what we know

. . . . yet . . . these are substantive

questions These paper makes these Conditions

$\Phi_t | y_{t-1}, D_t \sim N(m_t, C_t)$

$\Phi_t | D_{t-1} \sim N(a_t, R_t)$

$u_T = \beta_i X_{it}$

$y_t = G_t + V_t \quad V_t \sim N(0, V)$

$G_t = \delta G_{t-1} + a_T + \omega_t$

$\omega_t \sim N(0, W)$

(*) one solution ⇒ use hyper parameters to get the density.

$f(y, \theta, \varphi) = f(y|\theta) f(\theta|\varphi) f(\varphi)$

$y_i | \theta_i$

$\theta_i | \varphi$

$\varphi | \psi$

data $y_i \sim N(\theta_i, \sigma^2)$

$\theta_i \sim N(\varphi, \omega)$

200 6:43

600

mean & variane from equation 3

---

① likelihood

mean (likelihood)

$r = g C_t \cdot g' + w$

$q = F' \cdot r \cdot F + v$

likelihood of mean

$a = g m_t + UT(:, t)$

forecast $= F' \cdot a$

$sv = sv + 0.5(e' q^{-1} e + \log(\det q))$

---

(1), (2) ⇒ estimate G_it (obs & state eq.)

(2), (3) ⇒ estimate d_i (eq 2 - likelihood, eq 3 - prior)

(3) ⇒ estimate φ ⇒ with vage prior

in other word likelihood is getting updated Only for those that I explain

⚠ Both week end and other cross sections

S0Inv, b0 → need to be updated

$[i]$ k=6

$k\begin{bmatrix} \cdot & & \\ & \cdot & \\ & & \cdot \end{bmatrix}$

$b_i = 4 u_i$ ⟷

$S0Inv = \begin{bmatrix} 0 & & 0 \\ & \cdot & \end{bmatrix}$

$[\ ]$ alpha $\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$ ⇒ Prior for each add on is different

S0Inv

B0

Yb0

YS0Inv

$j\{[\vdots]()$

⇒

Tasks

① update DIC & likelihood

② update significance tables

③ update parameter heterogenity table

Solve problems first then go forward

next things to do: (1) save current values & run likelihood for it

(2) update the kalffbs Int to calculate likelihood ⇒ put in different array for diff iteration

x no need

(1) updat other models to calculate likelihood for mean of all param

✓ (3) for all remaining models als include C_t & m_t to be saved

---

- one step likelihood at the means of its hyper parameters
- 1-step forecast in filtering, start values m_0, C_0

⇒ rerun only Kalman filter step to form likelihood of $y_t | D_{t-1}$

- update code for getting across all add-ons
- mean of LL and LL at the mean
- (DIC, -2xLL, PD)

① run the code & calculate LL at every iteration at end of run take mean of saved LL's (mean (LL))

② take mean of start values (only need m_0 and C_0) & hyper param for each add-on. Re-run filter to get LL (means)

means g & F

across 1000 iterations

since the rest is automatically calculated by code

only for 1000 iterations that keep

after variances estimated & m_0 and C_0 become available

⇒ Don't forget y_t values to be updated for ffbs_likelihood

$\sum_{i=1}^{M} y_{it} | D_{it-1}$

✓ first → Collect sg add-on mean

Second ⇒ Coll followe

⑥

---

morning ① save result of execution for each separately

② run the remaining part of likelihood

⑦

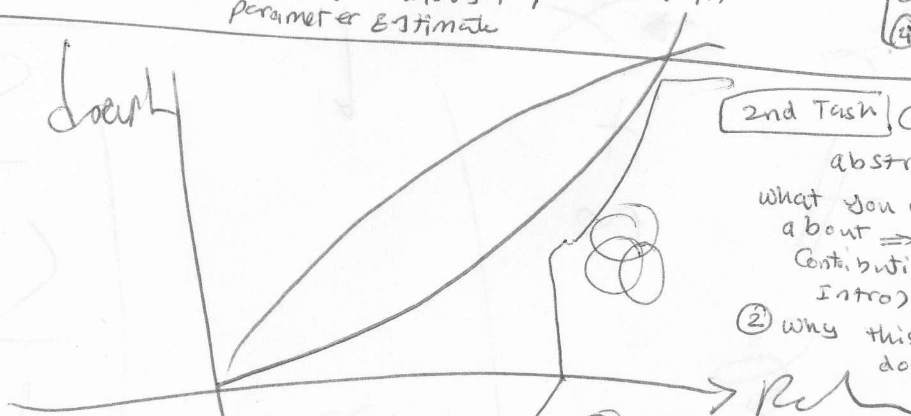
③ Check significance of explanatory (d_)

Compare DIC's

Night:
① Print Confirmation letter
② Correct ~~Alex's~~ Hw's

findings
① dynamic effect of product rating on demand
② heterogenity of product rating ⇒ & explanation
③ user base size ⇒ lower uncertainty positive effect
④ Product rating significant explains demand only when substitute product exists

use powerpoint
① positioning & results (findings)
② Research question
③ abstract overview
④ describe data, institutional & pag
  ① usage visible
  ② Average rating
  ③ distribution of rating visible
  ④ Versioning
⑤ use previous paper draft in parameter estimate



2nd Task
① layout abstract & intro
what you do, & what it is about ⇒ paragraph listing Contribution (Befor end of Intro)
② why this paper has been done? here is Contrib
③ why dynamic importnt? Bias Pram
④ why rating
⑤ Begin intro with what we know..., yet

these are substantive question & contrib

Norris's remaining Commnts
① suggest why hetrogenity, Could be ⇒ understand limitation of study
② Explain ~~the~~ histogram, why it is so ⇒ individual discussion
③ institution:
Carryover is significant ⇓ dynamic is important (all & not one) ⇐ nature of product experience good, internet product, wom & Communicate - the # past affect future - Recommend intertemporal Correlation
we Confirm that there is dynamic in the proes that if not taken into account ⇒ bias estimate

$$
\begin{array}{c|ccccc}
 & \text{Share of windows} & \text{Ver rating} & \text{Developer} & \text{Number of Rev} \\
\hline
\text{Product 1} \Rightarrow & & & & \\
 & a_{11} & 0 & 0 & 0 \\
 & 0 & a_{12} & 0 & 0 \\
 & 0 & 0 & a_{23} & 0 \\
 & 0 & 0 & a_{13} & 0 \\
 & 0 & 0 & 0 & 1
\end{array}
$$

main loop 1000 iter

$y_{it} = F\theta_{it} + \varepsilon_{it}$ ~ simple reg V

$\theta_{it} = G\theta_{it-1} + w_{it}$ → W

FFBS (1000)

W

G, W

- perhapse because
- such decay occurs when cons becom ① more know about prod ② less interested in product ③ use other alt ...

$+\beta X$ - ... is negative (-...) implying that ...

ffbs

- This may ori

① ~~check the result of dynamic~~ ② ~~write the model section~~ or 4.5 observational learning litrature

③ motivating question ④ complete estimation, managerial implication

⑤ write ~~conclusion~~ & ~~abstract~~ ⑥ go back & solve problems of

waris ⑦ read one paper of American science then modify your pa

⑧ read Joseph williams & compare side by side

⑨ match with American science

Regret

① send email Gronlea & Ozalp

② run simple model

- perhapse because...
- capture non-lenearity
- explain everything & reasons for hetrogenity
- use excel sheet

Fig 6: histogram
tab 8: mean elast
tab 9: signif effect
Fig 7: effect rating valence (type 1)
Fig 8: eff " (type 2)
Fig 9: negative rating
~~Fig 10: Neg effect~~ user base
Tab 10: hetrogenity parameter

x_i

x

Stack all together

④ significant standard deviation

Heterogenity

$\beta_i = \beta$
$\delta_i = \delta$
$\gamma_i = \gamma$

Next
① how non-hetrogeneous model
② how optimization & simulation

Counterfactual

fake reviews

④ recovery of uT & y

One for to incinde uT

unstack

ffbs

row

k

n Columns

n Column

Q

Dynamic effect of product rating? 3

is there hetrogeneity in these effects

Why supplementary product differed → role of platform owner 4

1

observational learning ⇐ whether signals such as user base size affects demand? → why important

2

Role of uncertainty 5

6 whether developer team size explains hetrogeneity

how rating affects demand ⇒ ~~prospect~~ increasing return

2

Rephrase questions

7 – what explains sensitivity of product category search ⇒ Number of product reviews

What explains hetrogeneity of effect of user base size signal ⇒ variance of rating (uncertainty)

6 – what affects heterogeneity in carry over ⇒ share of windows

innovation

+

–

Type 1

I Explain Context

Tell before

1 ✓
2 2 ✓
3 ✓
4 ✓
5 ✓
6 6 ✓
7

critical writing

institutional

Why these? Important

Open in technology is Jargon

Granting access

Explain more

Planely in English

evidence of Litrature for importance

Litrature of observation learning

Joseph williams side by side comparison

II Why Gap important & shld be filled

Perhapse

Correct yet there is a gap & then explain why it is important

doesnt fit

less certain voice

sensitive

Team size

+

–

not sensitive

simplicity

Common thought & Coherent

X repitition Big words bad

~~subject~~ + action

Common thought of paragraph

Causal writing

crispy

First sentence, complexity about what paragraph about

Transition

Last sentence

3 uncertainty

Explain for non Experts

endogeneity is question of future study

For add-on another section

Write & Come back

① Hetrog
② Dyn
③ increasing return
④ ~~observ~~

① observation lrn
② rating