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Dynamic Effects of Word of Mouth in Multiple Online Communication Channels

구전의 온라인 커뮤니케이션 채널별 동적 효과에 관한 연구

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이 논문을 경영학 석사 학위논문으로 제출함
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As literature on Word of Mouth (WOM) emphasizes the needs for analyzing dynamic effects of WOM and for examining effects of WOM in online communication channel level, I perform Dynamic Linear Model (DLM) in order to analyze the dynamic effects of WOM in multiple types of online communication channels. To explain such effects, I consider two important attributes of WOM: Volume and Valence, copy wear-out effects: important factor for implementing the dynamic system, and finally interaction effects among WOM in multiple types of the channels inside this Bayesian dynamic model.

The model is applied to the time-series data on the Hyundai automobile company, and the estimation is done through Forward Filtering and Backward Sampling algorithm, derived for application of Gibbs Sampling to normal Gaussian state space models. The estimation result indicates that the effects of copy wear-out and those of volume are differential across channel types. In addition, the interaction effects of blog and community site types are negative and significant, where as those of twitter is turned out to be nonsignificant. Lastly, the effects of valence in each of three different channel types are positive and significant.

This paper provides the following contributions to the literature. For the academical implication, I extend earlier research on WOM by introducing a generalized model for estimating the dynamic effects of WOM in multiple types of online communication channels and the interaction effects among the WOM inside each types of channels. This methodology would help researchers to examine both dynamic and interaction effects simultaneously and achieve more explanatorily powerful results, bridging the gap between two different research streams. For the practical implication, this paper would help practitioners in durable good markets to derive optimal strategies by discovering channel mix that would maximize the dynamic effects of WOM.

Keywords : online Word of Mouth, Bayesian Dynamic Linear Models, Gibbs Sampling, Online Communication Channels, Copy Wear-out effects, Forgetting effects, Durable goods

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1. Introduction

Online Word of mouth (WOM) is defined as communication, without any restriction, between potentially infinite numbers of online users (Stauss 1997), and numerous researches and papers on online WOM are published so far. This research stream indicates that there are two important attributes of online WOM: volume, total amounts of WOM interactions, and valence, degree of positivity determined by analyzing emotions behind words within messages and posts (Liu 2006). In addition, the literature concludes that both volume and valence generally affects purchasing intention and sales positively (Dewan and Ramprasad 2009; Doh and Hwang 2009; Lin, Wu, and Chen 2013).

However, because online WOM is such a broad and compounded phenomenon, there are always several limitations at each papers. Among these limitations, what catch my interest are two different research streams inside literature on WOM: analyses on the dynamic effects of WOM and on the effects of WOM in multiple types of online communication channels. The first stream is about analyzing the dynamic effects of WOM. In advertising literature, it has been argued that just as the effects of advertising accumulates over time, those of WOM must also be examined dynamically (Bruce, Foutz, and Kolsarici 2012). In addition, I find that WOM dynamically influences demand or customer acquisition (Liu 2006; Moe and Trusov 2011). The second stream tries to examine the effects of WOM in each communication channels. Most of the previous research considers a single online communication channel as subject of the analyses, and only small part of research considers several channels, such as Jeon et al. 2019 and Seok, Lee, and Kim 2018. According to

Rosario et al. 2016, analyses with a single channel would not provide sufficient grounds for explaining the effect of WOM. In addition, Williams and Buttle 2011 remarks that since each channels have their own unique characteristics, they would have different degree of the effects. Therefore, because it is important to employ a dynamic system in studying the effect of WOM in the digital environment (Duan, Gu, and Whinston 2008) and to examine the effects of WOM in several types of communication channels, I find the need for bridging the gap between these two streams.

To bridge the gap by integrating some key factors at each streams into a single model, I have raised several research questions: How different are the dynamic effects of WOM in several types of online communication channels? What factors cause such dynamic effects? How different are the effects of these factors? How strong are the interaction effects when several different types of channels are introduced? How can one accurately assess these overall effects in a single model?

To respond these questions, I choose to use Bayesian Dynamic Linear Model (DLM), which allow researchers to sketch dynamic path of parameters in interest and which presents a better method for handling nonstationarity (Bass et al. 2007). To implement the dynamic system, I consider copy wear-out effects, which have been pointed out as one of possible sources of WOM dynamics (Bruce, Foutz, and Kolsarici 2012), to explain the dynamic effects. The specified DLM framework is in the form of the state space model of West and Harrison 1997, and the parameters are estimated by employing Gibbs sampling.

Data I construct for this paper is from multi-sources. I have chosen the Hyundai automobile company as the sample because I can build reliable time-series data and because there are rare amounts of research on relationship between WOM and durable good (Chung and Kim 2011; Jeon et al. 2019). This data has 74 time periods starting from January, 2014 and has monthly sales, representative product attributes information, and finally volume and valence in twitter, blog, and community website. the details will be explained in §4.

This paper makes both academical and practical contributions. For the academical implication, I extend earlier research on WOM by introducing a generalized model for estimating the dynamic effects of WOM in multiple types of online communication channels and the interaction effects among the WOM in multiple types of channels. This methodology would help researchers to examine both dynamic and interaction effects simultaneously and achieve more explanatorily powerful results, unifying the two different research streams into a single stream. For the practical implication, it would help practitioners in durable good markets to find an optimal channel mix under limited resources. According to Chung and Kim 2011 that measures the effects of online WOM on the cell phone industry, it was shown that online WOM positively affects the sales of durable goods. Based on this result, firms selling durable goods should also make an attempt to increase their sales through online WOM, and this paper would help them to derive optimal strategies by discovering a channel mix that would mostly increase the dynamic effects of WOM.

The remainder of the paper is organized as follows. In §2, I provide a brief review of the relevant literature on WOM with particular emphasis on dynamic effects and interaction effects. In §3, I present the details of the model I specified in DLM framework. In §4, I discuss about the data collected. In §5, I explain more about the estimation strategy. In §6 and §7, I analyze the estimation result and finally conclude this paper with an overview of findings, implications, and limitations of the study.

2. Literature Review

In this chapter, I review the literature on Word of Mouth (WOM) in greater details. I also present some arguments that it is necessary to capture the dynamic effects of WOM, and introduce copy wear-out effects that should be considered for implementing the dynamic system. Furthermore, I introduce some previous literature that emphasizes need for taking into account the effects of WOM in multiple types of online communication channels, and explain why the interaction effect should also be considered together.

2-1. Word of Mouth

Word of Mouth (WOM) is defined as an oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial regarding a brand, product or service (Arndt 1967). WOM has long been a interest of numerous researchers, and considerable amount of literature on the power of WOM exist (Katz and Lazarsfeld 1955). For example, WOM has been widely seen to be much more influential than information provided from newspapers and magazines, personal seller, and radio advertising (Herr, Kardes, and Kim 1991; Lam and Mizerski 2005). Yet, this research stream confronts rise of the Information Technology and therefore naturally shifts its interest to online Word of Mouth.

Stauss 1997 defines online WOM to be communication, without any restriction, between potentially infinite numbers of online users.

Online WOM allows consumers to not only directly gather information about certain products and services but also read opinions of consumers from all over the world (Lee et al. 2006; Ratchford, Talukdar, and Lee 2001). Indeed, WOM becomes more and more noticed as a useful tool and beneficial phenomenon, so most consumers start to seek for information from more than one source before making purchasing decision (Blackwell, Miniard, and Engel 2006; Cheung and Lee 2012; Frambach, Roest, and Krishnan. 2007). Therefore, ever since this shift, numerous researches and papers on online WOM are introduced, and importance of online WOM has been continuously emphasized. Noticeably, the literature generally agrees that there are two important attributes of online WOM: volume and valence. Volume is known as total amounts of WOM interactions, and valence as degree of positivity, determined by analyzing emotions behind words within messages and posts (Liu 2006).

The researches on the effects of volume are as follows. Liu 2006 has examined the relationship between the movie industry and online WOM and concluded that the volume of online WOM significantly affects the sales of movies. The research explains that volume of online WOM produced at online websites increases movie awareness among consumers, and, in turn, such awareness increases the sales of movies. Also, Dewan and Ramprasad 2009 has found that the volume of online WOM positively affects the sales of recorded music, and it suggests that the volume increases the awareness of albums so increases the demand in turn. In addition, Rosario et al. 2016 proposes that the volume causes an increase in product awareness and a decrease in uncertainty because the volume of online WOM reflects the number of consumers who purchase and use products.

The researches on the valence of online WOM are as follows: First, Liu 2006 has indicated that the valence of online WOM in the movie industry does not significantly affect movie sales because large difference in consumers' movie preferences may cause consumers not to rely too much on the online WOM. Yet, there are still some part of literature concluding that as positivity of online WOM increases, attitudes and purchasing intentions toward movies and the credibility of the online WOM are positively influenced (Doh and Hwang 2009). Although the effects of valence in the movie industry are still on debate, those in other industries are mostly concluded as providing positive effects on sales and purchasing intention. The degree of positivity or negativity behind online WOM significantly influences intention of delivery, which is defined as degree of consumer's intention to deliver opinions on certain product to the others, and the influence is greater when valence of WOM is more negative (Baker, Donthu, and Kumar 2016). According to Luo 2009, which examined the effect of online WOM on stock price, when the degree of negativity in online WOM increases, its short-term and long-term influences on stock price become more negative.

Last but not least, there are some other researches that extends the boundary of knowledge on WOM. It has been found that groups of people exposed to positive product reviews have greater purchasing intentions than those who are exposed to the negative reviews (Yoo, Ahn, and Park 2011). Also, study on influence of online customer reviews on sales in hotel industry concludes that 1 percent increase in customer ratings would yield about 2.6 percent increase in sales per room (Ogut and Tas 2012). Furthermore, it has been researched that when contents of online WOM are more positive, the sales of smart phones increase, and the sales are negatively affected when the online WOM of competing companies' products becomes more positive (Gopinath, Thomas, and Krishnamurthi 2014).

Additionally, according to Chevalier and Mayzlin 2006, which analyzes the relationship between online WOM and book sales, degree of the effects of negative evaluations on book are greater than those of positive evaluations, and negative reviews negatively affect the sales. Lin, Wu, and Chen 2013 have examined the effects of both volume and valence of online WOM on purchasing decisions and concluded that the volume of online WOM positively affects purchasing intention. In addition, Cui, Lui, and Guo 2012 examined the relationship between online reviews and sales of video games and concluded that both volume and valence of reviews have positive effects on the sales. Lastly, Seok, Lee, and Kim 2018 has examined the mediation effect of volume of online WOM between corporate social responsibility news reports and firm value and found out that increase in corporate social responsibility news reports boosts the volume of online WOM and thereby affects firm value.

Regarding these preceding studies, it is generally concluded that as online WOM becomes positive and as its volume increases, the online WOM tends to positively affect the brand's sales, and that degree of the effects is different from that of negative online WOM. However, online WOM is such a broad and compounded phenomenon, so it is necessary to extend the literature further as WOM dynamically affects demand or customer acquisition (Liu 2006; Moe and Trusov 2011) and as there are only a few researches considering several channels: Jeon et al. 2019 and Seok, Lee, and Kim 2018.

2-2. Need for Dynamic Effects

In advertising literature, the effects of WOM is also examined because WOM has been known as a great influencer to consumers' purchasing decisions and for having interaction effects with advertising (Gopinath, Thomas, and Krishnamurthi 2014). The difference lies in that the literature emphasizes the time-varying nature. The literature argues that just as the effects of advertising accumulate over time, WOM's effects should also be examined dynamically (Bruce, Foutz, and Kolsarici 2012). Through additional investigation on this issue, I could find that WOM dynamically influences demand or customer acquisition (Liu 2006; Moe and Trusov 2011). Especially, Duan, Gu, and Whinston 2008 argues that it is important to employ a dynamic system in studying the effect of WOM in the digital environment. Therefore, in line with one of the limitations that numerous authors have mentioned in literature on the effects of WOM, examination of the dynamic effects needs to be performed.

To implement the dynamic system, I consider copy wear-out effects that are treated as an important factor for explaining dynamic effects in advertising literature. Yet, before proceeding to introduce the copy wear-out effects, it is important to mention about several underlying factors influencing the dynamic effects and about the distinction among those factors. First, it is important to recognize the distinction between the effects of wear-out and those due to forgetting. In advertising literature, the term wear-out refers to a decline in the quality or effectiveness of an advertisement (Calder and Sternthal 1980; Grass and Wallace 1969; Greenberg and Suttoni 1973; Pechmann and Stewart 1990), where as the forgetting leads to a decrease in aggregate brand awareness as time goes (Mahajan, Muller, and Sharma 1984). In other words, the forgetting refers to the degree of decline in the memory of advertising or WOM. In this paper, I do not directly relate the forgetting to the dynamic effects of WOM, but instead I apply this effect to a term goodwill, which summarizes the effects of current and all past WOM on demand (Nerlove and Arrow 1962). More details will be discussed in §3

Broadly speaking, there are two sources of wear-out in advertising literature: repetition wear-out and copy wear-out (Naik, Mantrala, and Sawyer 1998). Repetition wear-out occurs when a customer is exposed to ads repeatedly: one can be bored and irritated, or simply lose interest as the benefits of processing the advertising become more and more worthless (Berlyne 1970; Greyser 1973; Weilbacher 1970), so it depends on the amount of advertising. In this paper, which concentrates on WOM, I do not consider this effect because of two reasons. First, WOM is a phenomenon consisting of astronomical amounts of informative posts from multiple channels, so it would be unlikely that people watch certain specific post several times unwillingly. Second, as WOM includes numerous posts, it is hard to check the number of repetition for every single post shown to online users.

Bruce, Foutz, and Kolsarici 2012 points out that copy wear-out effects is one of possible sources of the dynamics. This effect is defined as decline in advertising or WOM effects due to the passage of time, which is independent of repetitiveness or the level of frequency. Many researchers have sought for reasons why this wear-out occurs, and several sources have been identified so far. First, such a decay may be the result of a change in consumers' conditions such as increased knowledge about product attributes over time (Calantone and Sawyer 1978). For example, Assmus, Farley, and Lehmann 1984 argues that the impact of advertising copy dilutes when consumers start to acquire experience with the brand. Second reason is the imitation of an ad strategy by competing firms or by firms in other product categories (Axelrod 1980). In other words, advertising style gets copycatted by other firms, thereby lowering the noticeablility from other styles (Groenhaug, Kvitastein, and Gronmo 1991). Though these reasons are investigated in advertising literature, they are still applicable in WOM literature, especially the first reason, and thereby numerous studies have introduced copy wear-out effects in implementing the dynamic system for investigating WOM (Bruce, Foutz, and Kolsarici 2012; Gopinath, Thomas, and Krishnamurthi 2014). Following such application, this paper also take the copy wear-out effects into account to explain the dynamic effects of WOM

2-3. Need for Multiple Channels

Numerous researches on the effects of WOM call for examining the effects of WOM in several different types of communication channels. Jeon et al. 2019, Seok, Lee, and Kim 2018, and Williams and Buttle 2011 has remarked that most of the previous research choose only one online communication channel or aggregated numbers of WOM in several different channels for the subject of their analyses, and argued that because channels have their own unique characteristics, they would have different degree of the effects. For example, Jeon et al. 2019 has considered WOM in two different types of channels, twitter and blog, inside a single model, and found that unlike the effects of twitter's volume that significantly affects sales, those of blog's volume are not turned out to be significant.

Furthermore, Gopinath, Thomas, and Krishnamurthi 2014 supports the argument as it presents one of possible reasons that the effects could be differentiated. In this research, the authors classify WOM into three categories: recommendation, attribution, and emotion, examine their dynamic effects, and conclude that valence of online WOM consisting of recommending characteristics significantly affects cellular phone sales. Through these findings, the effects of WOM could be divided into channel levels as WOM can be classified into several different groups, and therefore it is necessary to examine the effects of WOM in multiple types of online communication channels in order to help generalizing the effects of WOM.

In dividing online communication channels, I search through literature on WOM to understand what roles do each channels have, and choose three channels that have distinct roles: twitter, blog, and community website. Community site differs from the other types as it provides a place for its members and visitors to come together, ask or answer questions, and get peer-to-peer support. Therefore, unlike visitors of blog and twitter, who usually are not so familiar with a certain product and hence seek for information, participants of community site tend to be aware of certain product before entrance (Wu and Zheng 2012). Instead, both blog and twitter can reach to numerous people who have interest but might not be so familiar with certain product or who does not have interest yet. However, according to Kozinets et al. 2010, unlike blog that can provide long information in a detailed way with pictures, charts, and even video clips, twitter is mostly used for providing brief information or promoting other sites where one can find further information. In other words, twitter can be considered as an entrance to information on the product, which provides brief informative introduction to the product, raises consumers' interest, and leads the consumers to further details that might exist in blogs, community sites, and other channels. Such definement is also used at Stevens 2013, which hypothesizes and concludes that twitter users act as gatekeepers of WOM for their networks.

While going through the literature, I decide to introduce and examine interaction effects among WOM in multiple channel types because one of the strength for introducing such terms is to provide additional information on analyzing and hopefully generalizing the effects of WOM. In addition, this system would reflect the real world more clearly as most consumers seek for information from more than one source before making purchase decisions (Cheung and Lee 2012; Blackwell, Miniard, and Engel 2006). In other words, modern consumers search for information on certain product from multiple sources, and such behavior causes interactions between what consumers learn and feel in each sources. Furthermore, presence of interaction effects is quite common when studying for the effects of certain variable, especially when the number of interest is more than one or when subjects of interest occurs in multiple groups simultaneously. For example, in WOM literature, numerous studies have introduced interaction effects between volume and other variables (Chong et al. 2017; Khare, Labrecque, and Asare 2011; You, Vadakkepatt, and Joshi 2015). In advertising literature, interaction effects between advertising and other marketing mix variables or other promotions have been well-documented (Krishnamurthi and Raj 1985; Naik, Raman, and Winer 2005; Winer and Moore 1989). Therefore, just as Rosario et al. 2016 remarks that analyses with a single channel do not provide sufficient grounds for explaining the effect of WOM, introducing the multiple channel types and the interaction effects would provide additional information on analyzing and hopefully generalizing the effects of WOM. Furthermore, just as Allsop, Bassett, and Hopkins 2007 argues that it is necessary to find out what communication channel mix will give the biggest boost to the effects of WOM, such introduction would also help practitioners to find out an optimal channel mix.

In sum, this paper aims to extend the literature on WOM by examining the dynamic effects of Word of Mouth in multiple types of online communication channels.

3. Model Development

In this chapter, I introduce the Dynamic Linear Model (DLM), and change some specification so that the model properly reflects characteristics of WOM. According to Bass et al. 2007, there are two advantages of applying a DLM model. First, it is possible to better understand how parameters in interest change over time. In observing the differences in WOM effectiveness of several different channel types, evaluating differences in mean parameter values does not provide sufficient ground for the evaluation because even if the average effect of the parameters may be the same across three channels, their parameter paths may be substantially different over time. Some researchers so far have employed a random coefficients specification to model time-varying parameters (Jedidi, Mela, and Gupta 1999). Such models are known to be able to control for the time-varying nature of parameters, but they do not provide estimates of the parameter at certain point in time. Second, it is possible to handle non-stationary nature of parameters in interest. In time-series analysis, it has been known that researchers often filter the data by taking first- or higher-order differences in order to make the series stationary. West and Harrison (1997) points out that these filtering methods affect the interpretation of the model by confounding different model components. Furthermore, sources of the non-stationarity deviated by the implication of the filter are not captured. The authors therefore suggest the use of DLM presenting a better method for handling the non-stationarity. Becuase of these advantages, many researchers use DLM systems to address important marketing topics from dynamic market structure (Van Heerde, Mela, and Manchanda 2004) to paid search advertising (Rutz and Bucklin 2011).

In this paper, the DLM links WOM in three different channel types to automobile sales through an aggregate sales response function, while allowing their effects to vary over time. First, I look up a model proposed in Nerlove and Arrow 1962 (hereinafter, the N.A. model). In this paper, to capture dynamic effects, the authors suggest the use of goodwill stock, which essentially summarizes current and all past effects on demand. This system can be demonstrated as follows: WOM on the Hyundai and its products, one of the best selling models of the Hyundai automobile company, in certain time period builds the goodwill stock toward Grandeur, and in turn, this goodwill drives the demand for the product. Second, Naik, Mantrala, and Sawyer 1998 extends the above N.A. model by making effectiveness parameters to be time dependent: let the parameters to be a function of times and advertising expenditure. The rationale for such approach is that their model allows to capture different types of wear-out effects: repetition and copy wear-out (details in Literature Review). Lastly, Bass et al. 2007 generalizes the above models to accommodate multiple advertising themes, and the authors capture dynamic effects of each themes and even interaction effects among these themes. Based on this series of development, the process of model specification for this paper is as follows.

According to original N.A. model, the rate of change in goodwill G(t) is a function of valence per month VAL(t). Specifically,

$$\frac{dG(t)}{dt} = qVAL(t) - \delta G(t)$$

Equation (1)

where

q = effectiveness of valence (assumed constant in N.A. model).

δ = rate of decay of goodwill due to forgetting.

$VAL(t)$ = valence in each time period t.

$G(t)$ = goodwill in each time period t.

More generally, one can use a function of valence f(VAL(t)), which allows the model not to be linear as in original N.A. model. Note that the N.A. model include valence term, instead of advertising expenditure variable, at Right Hand Side (RHS) of Equation (1). Since this paper's interest is in the effects of WOM, I change the advertising expenditure variable to valence variable. In addition, for helping readers to understand the model more easily, I do not divide valence into several different channel types and therefore do not include the interaction effects in this model

From differential equation specified in Naik, Mantrala, and Sawyer 1998, I define the evolution of effectiveness parameter q over time as follows.

$$\frac{dq}{dt} = (1 + copy) \times q(t-1) + c \times \ln VOL(t)$$

Equation (2)

where

$copy$ = fixed rate of copy wear-out effects.

c = effectiveness of volume.

$\ln VOL(t)$ = natural log of volume in each time period t.

In the above equation, there are two types of effects. The effects of valence is captured by copy wear-out parameter $copy$. Note that copy wear-out does not depend on the amount of posts. Original model in Naik, Mantrala, and Sawyer 1998 does not consider the effect of volume on the valence effectiveness on goodwill. However, since my interest is in the effects of WOM, I add volume variable at RHS of Equation (2), and such setting is not so rare. The movie literature shows that WOM affects demand for films, but it is quite complicated to tell whether volume or valence works as a better predictor (Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007; Duan, Gu, Whinston 2008; Liu 2006). Therefore, I take both into account by linking the goodwill to valence in Equation (1) and the valence effectiveness to volume in Equation (2). According to Bass et al. 2007, this formulation can be interpreted as follows: volume of WOM influences valence effectiveness, and favorable WOM with positive valence boosts goodwill and purchase. The research performs subsequent tests of alternative formulations for WOM valence, volume, or both in these equations, and the results support this specification.

Based on the generalized model specified in Bass et al. 2007 that accommodates several themes of advertising, I define the model that allows to examine the dynamic effects of WOM in multiple types of online communication channels. Like the model used in Bass et al. 2007, the below modified model is also an additive function of WOM in several channel types with the interaction effects, and it is based on generalization of N.A. and Naik, Mantrala, and Sawyer model.

Specifically,

$$\frac{dG}{dt} = \sum_{i=1}^{m} q_i(g(VAL_i) + \lambda_i \sum_{\substack{j=1 \\ i \neq j}}^{m} h(VAL_i, VAL_j)) - \delta G$$

Equation (3)

where

m = the number of channel types

q_i = effectiveness of WOM in channel type i.

$g(VAL_i)$ = a function of the valence in channel type i.

G = goodwill

Note that both goodwill and valence vary over time and that inclusion of interaction effects among valence in each channels would help understanding the aggregate effects of WOM more deeply. The term below

$$\lambda_i \sum_{\substack{j=1 \\ i \neq j}}^{m} h(VAL_i, VAL_j)$$

is an interaction effects for the ith channel type. I estimate separate interaction effects parameter λ_i for each channel type, and this specification allows for possible asymmetric effects. Notice that this specification is an overall measure of how the ith channel type interacts with all other channels. It is possible to estimate interaction effects for all pairwise combinations of channel types. However, I estimate only one coefficient for each type for the sake of parsimony, and it is quite complicated to explain the nature of pairwise interactions, which might depend on the nature of each channels, their unique systems, or characteristics of users.

In the estimation, I use following semi-log specification.

$$g(VAL_i) = \ln(1 + VAL_i)$$
$$h(VAL_i, VAL_j) = \ln(1 + VAL_i) \times \ln(1 + VAL_j)$$

Justification for use of the semi-log specification and of the interaction term as the product of two natural log terms can be found in numerous researches (Bass et al. 2007; Bruce, Foutz, and Kolsarici 2012; Doyle and Saunders 1990).

The change in WOM effectiveness q_i is given by the following modified equation:

$$\frac{dq_i}{dt} = (1 + copy_i) \times q_i(t-1) + c_i \ln VOL_i(t), \qquad i = 1, 2, \ldots, m$$

Equation (4)

where

$copy_i$ = fixed copy wear-out parameter for channel type i.

c_i = effectiveness of volume in channel type i.

$\ln VOL_i$ = natural log of volume in channel type i.

Note that there are three different equations for Equation (4), one for each channel types: twitter, blog, and community site, and that q_i and $\ln VOL_i$ terms vary over time. In addition, for tractability, I assume that the rate of change defined in Equation (4) for each channel types are independent of each other. There is some support for the assumption of independence in the study performed by Blair and Rabuck 1998, which concludes that an analysis of over 500 case studies indicates that commercials within a campaign wear out independently. In addition, Bass et al. 2007 emphasizes that even though there may be some similarities, such a dependency would complicate the estimation of the dynamic parameters, and it also emphasizes that cross-sectional heterogeneity between the channel types is controlled by estimating separate dynamic parameters for each types. Therefore, this model allows for the estimation of dynamic effects of WOM in multiple types of online communication channels in the presence of wear-out effects. For estimation of parameters, I apply the Gibbs sampling as explained in West and Harrison (1997). The estimation strategy is discussed more deeply in §5

4. Sample and Measurement

To check the dynamic effects of Word of Mouth (WOM) in multiple types of online communication channels, I choose the Hyundai automobile company in the Korean automobile industry. There are three underlying reasons for such a selection. First, the Korean automobile industry is going through severe internal competition (Seok, Lee, and Kim 2018). According to Jeon et al. 2019, online WOM is considered to be an important method for achieving competitive advantage, and such competitive environment of the market can help revealing the effects of WOM. Second, the Korea Automobile Manufacturers Associations (KAMA) and Korea Automobile Importers and Distributors Association (KAIDA) publicize the monthly sales of each automobile models of the Hyundai automobile company, so I can collect reliable sales data. Third, research on the relationship between online WOM and durable goods is quite rare. Most of the previous research on online WOM used data on temporary experience goods, such as books and movies (Chevalier and Mayzlin 2006; Liu 2006; Qin 2011). However, in research that measures the effect of online WOM on the cell phone industry (Chung and Kim 2011), it was shown that online WOM affects the sales of durable goods positively. Therefore, more research is required to check the effects of WOM on durable goods sales.

Data is collected from three different sources. The first is a website called Danawa (auto.danawa.com). It collects data from KAMA and KAIDA and summarizes each models' sales information, so I can gather and use monthly sales data as our dependent variable. The second source is Socialmetrics, a big data solution platform managed by Daumsoft. When a certain keyword is entered in a Socialmetrics, it returns monthly volume in such channels as twitter, blog, and community website and the number of positive, negative, or neutral words. The valence variable in this paper is defined as the ratio of positive words to total words. The third source is the Naver (auto.naver.com), the biggest search engine in Korea. It offers detailed information on 115 automobile brands, including such information as price, fuel efficiency (FUEL), displacement (CC), automobile size (e.g. compact, mid-size, full-size, etc), and so on. Through this source, I could collect the characteristics of certain model from the Hyundai.

It is quite natural to select twitter and blog for subjects of online communication channels because research on WOM considers these types to be important channels and tends to focus on volume and valence created in these channel types. Adeyinka 2014 remarks that the main characteristic of twitter is the feature of transmitting short messages up to 140 characters, and twitter is usually used for publishing short news or promoting other sites. In blog, content is considered to be the most important element (Kargar et al. 2008). I also choose community website as the other subject of this paper. Since there is an increasing interest placed on the role of consumer networks, groups, and communities, ongoing topics are the roles of WOM in community website where numerous users actively participate (Cova and Cova 2002; Hoffman and Novak 1996; Vargo and Lusch 2004). In such literature, consumers are regarded as active co-producers of value and meaning, whose usage of WOM can be idiosyncratic, creative, and even resistant (Brown, Kozinets, and Sherry 2003; Kozinets 2001; Thompson and Sinha 2008), and this type of channel has its own unique characteristics (Karger et al. 2008). The authors argue that marketers use new tactics and metrics to deliberately and directly target and influence the consumer or opinion leader, and that market messages and meanings are actively exchanged among members of the consumer network. Furthermore, participants transform commercial promotion and characteristics of certain products to communally valuable information. In other words, message and meanings of the WOM communication are affected by the promotional characteristics of the WOM campaign and related aspects, such as the type of product or service and the product's brand equity. Based on these perspectives, I choose twitter, blog, and community website as representative communication channel types.

Since the goal of this paper is to clarify the dynamic effects of online WOM on the Hyundai in three different types of online communication channels, twitter, blog, and community website, I need to generate representative value of price, fuel efficiency, displacement, and automobile size because the Hyundai sells several different models, such as Sonata, Grandeur, Santa Fe, etc. To do so, I first collected data on the product characteristics for the top 3 monthly best-selling models (Peng et al. 2014). I have confirmed that sales of the top three best-selling models of the Hyundai account for 80 percent of total sales, so if the representative values are calculated from characteristics of the top three models, most of the brand-wise characteristics can be satisfactorily controlled (Seok, Lee, and Kim 2018). Therefore, such monthly weighted averages for each of these control variables are assumed to be the representative values.

For example, the representative price of the Hyundai in January, 2014 is calculated as follows: The top three best-selling models for the month were the Porter2, Santa Fe, and Grandeur. The sales amounts were 7541, 7160, and 6798 respectively, and the prices at maximum trim were KRW 1,877, KRW 3,678, and KRW 3,603 ten thousand respectively. Calculating the value using Equation (5), I defined the representative price of the Hyundai to be KRW 3022.57 ten thousand.

$$(1877 \times \frac{7541}{7541+7160+6798}) + (3678 \times \frac{7160}{7541+7160+6798}) + (3603 \times \frac{6798}{7541+7160+6798}) = 3022.57$$

Equation (5)

In sum, I collected time-series data on the Hyundai for 74 months time periods, which starts from January, 2014. Summary on each variables is in Table 1, and descriptive statistics is in Table 2. Table 3 indicates correlations between valence in each types. Lastly, Figure 1 presents plots of the valence in each types over time.

<Table 1> measurement and source of each variables

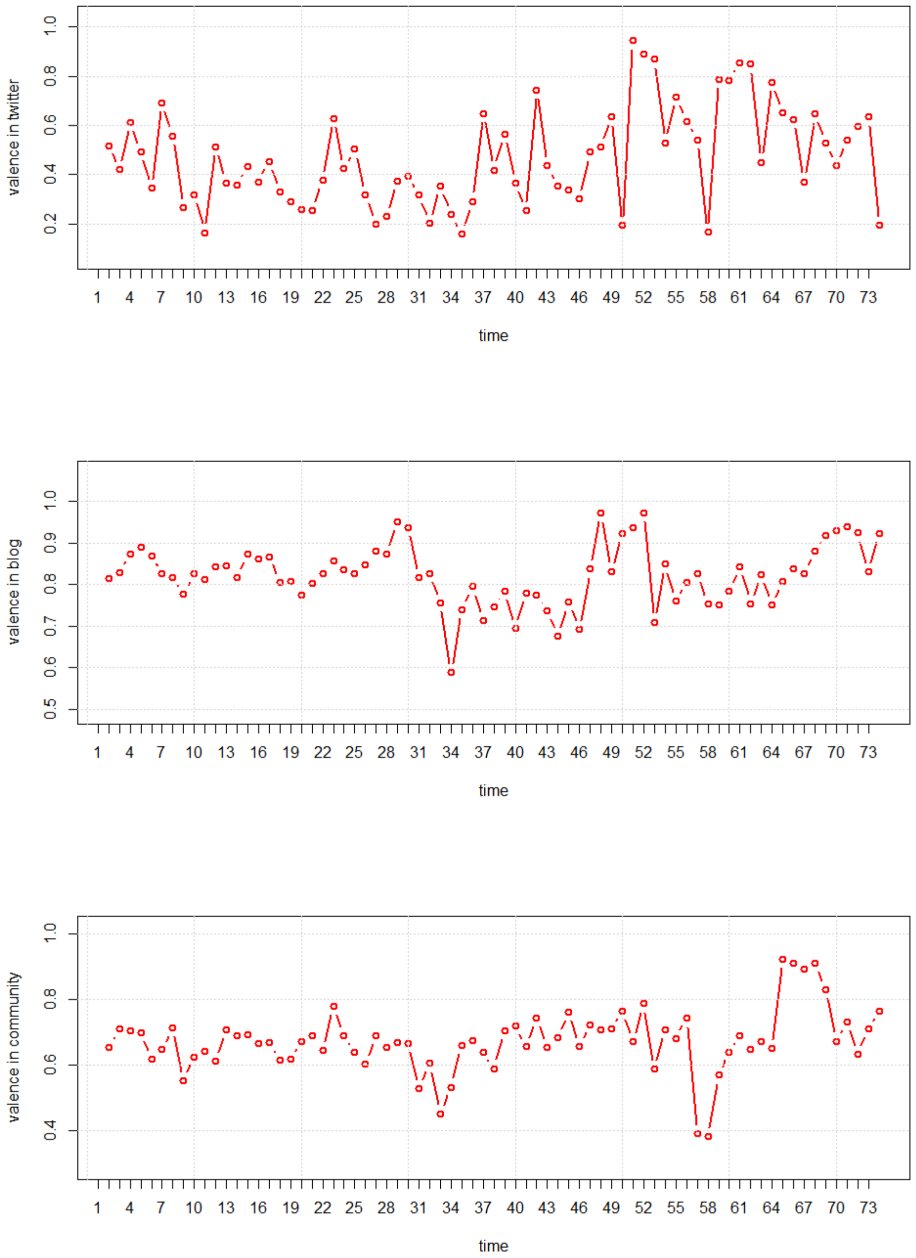
Natural Log of Sales [ln$SALES_t$]
Natural log of sales at time t source: auto.danawa.com
Natural Log of Price [ln$PRICE_t$]
Weighted average of price at time t (unit: KRW thousand) source: auto.naver.com
Fuel Efficiency [$FUEL_t$]
Weighted average of fuel efficiency at time t (unit: km/l) source: auto.naver.com
Natural Log of Displacement [lnCC_t]
Natural log of weighted average of displacement at time t (unit: 1cc) source: auto.naver.com
Size of Automobile [$SIZE_t$]
Weighted average of size of automobile at time t (1: light, 2: subcompact, 3: compact, 4: mid-size, 5:full-size) source: auto.naver.com
Natural Log of Volume [lnVOL_{it}]
Natural log of volume in channel i at time t source: the socialmetrics
Valence [VAL_{it}]
Valence of posts in channel i at time t source: the socialmetrics

<Table 2> Descriptive Statistics of Main Variables

	Mean	Std.Dev
Natural Log of Sales [$lnSALES_t$]	10.897	0.154
Natural Log of Price [$lnPRICE_t$]	7.925	0.089
Fuel Efficiency [$FUEL_t$]	12.724	1.833
Natural Log of Displacement [$lnCC_t$]	7.760	0.094
Size of Automobile [$SIZE_t$]	3.506	0.427
Natural log of Volume in twitter [$lnVOL_1$]	9.443	0.712
Natural log of Volume in blog [$lnVOL_2$]	8.922	0.352
Natural log of Volume in community [$lnVOL_3$]	8.265	0.279
Valence in twitter [VAL_1]	0.467	0.199
Valence in blog [VAL_2]	0.822	0.073
Valence in community site [VAL_3]	0.673	0.095

<Figure 1>

plot of Valence in each channel types over time



5. Estimation Strategy

I model the demand for the Hyundai's automobile sales at time t as a function of goodwill G_t, and vector X_t with the representative variables: price, fuel efficiency, displacement, and automobile size, and mean-zero normally distributed error at time t :

$$\ln(sales_t) = G_t + \beta X_t + \varepsilon_t \quad \text{where } \varepsilon_t \sim N(0, \sigma_\varepsilon^2).$$

Equation (6)

To estimate the parameters, I rewrite the generalized model in more formal state space notation:

$$\ln SALES_t = [1\ 0\ 0\ 0] \begin{bmatrix} G_t \\ q_{1t} \\ q_{2t} \\ q_{3t} \end{bmatrix} + \beta' X_t + \varepsilon_t$$

Equation (7)

$$\begin{bmatrix} G_t \\ q_{1t} \\ q_{2t} \\ q_{3t} \end{bmatrix} = \begin{bmatrix} (1-\delta) & \bar{g}(VAL_{1t}) & \bar{g}(VAL_{2t}) & \bar{g}(VAL_{3t}) \\ 0 & (1+copy_1) & 0 & 0 \\ 0 & 0 & (1+copy_2) & 0 \\ 0 & 0 & 0 & (1+copy_3) \end{bmatrix} \begin{bmatrix} G_{t-1} \\ q_{1t-1} \\ q_{2t-1} \\ q_{3t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ c_1 \ln VOL_{1t} \\ c_2 \ln VOL_{2t} \\ c_3 \ln VOL_{3t} \end{bmatrix} + \begin{bmatrix} \omega_{0t} \\ \omega_{1t} \\ \omega_{2t} \\ \omega_{3t} \end{bmatrix}$$

Equation (8)

Where

$$\text{for } i=1,\ \bar{g}(VAL_{1t}) = g(VAL_{1t}) + \lambda_1 \sum_{\substack{j=i \\ i \neq j}}^{m} h(VAL_{1t}, VAL_{jt})$$

$$g(VAL_{1t}) = \ln(1+VAL_{1t})$$
$$h(VAL_{1t}, VAL_{jt}) = \ln(1+VAL_{1t}) \times \ln(1+VAL_{jt})$$

The Equations (7) and (8) can be rewritten in a more compact notation to obtain the standard Bayesian dynamic linear model (DLM) of West and Harrison (1997):

$$y_t = F_t \Phi_t + \beta X_t + \varepsilon_t$$
$$\Phi_t = H_t \Phi_{t-1} + u_t + \omega_t$$

Equation (9)

where

$$\varepsilon_t \sim N[0, \sigma_\varepsilon^2], \text{ and } \omega_t \sim N[0, W]$$

Equation (10)

As shown above, $\boldsymbol{\Phi_t}$ is the state vector whose first element is goodwill and remaining elements are the effects of valence in each channel types during time t. The 4 by 4 transition matrix $\boldsymbol{H_t}$ captures the time-varying effects of copy wear-out and forgetting effects on WOM and goodwill across time. The constant vector $\boldsymbol{F_t}$ presents the impact of goodwill on the automobile sales. Error terms ε_t and ω_t are assumed to be mean-zero independent normals.

State space methods tend to rely on maximum likelihood estimation (MLE) for estimation (Harvey, Ruiz, and Shephard 1994). However, the DLM is based on Bayesian estimation, and West and Harrison 1997 indeed suggests the use of traditional Monte Carlo Markov chain (MCMC) techniques, such as Gibbs sampling. There are several reasons that the DLM is particularly appropriate for studying time-varying effects. Compared to the static Bayesian models seen in the marketing literature (Allenby and Rossi 2003), the DLM offers relatively improved estimation through adaptation and Bayesian learning. Moreover, with suitable informative priors, relatively accurate forecasts can be produced from series that are too short for purely data driven (frequentist) analyses (Bass et al. 2007). Indeed, there are several recent papers employing Gibbs sampling in DLM framework (Bass et al. 2007; Bruce, Foutz, and Kolsarici 2012; Neelamegham and Chintagunta 2004; Van Heerde, Mela, and Manchanda 2004). In addition, Leichty 2005 also employs Gibbs sampling to study the dynamic development of consumer preferences in a conjoint application. Therefore, I estimate the above system of discrete Equations (9) and (10) by specifying priors for the model parameters and using MCMC simulation of the full posterior based on the entire data series.

According to Petris, Petrone, and Campagnoli 2009, Gibbs sampling approach require researchers to simulate from full conditional densities of state parameters Φ_t and non-state parameters. While the second density is problem specific, the authors point out that general expression of the first density and efficient algorithms for sampling are available. This method is based on Carter and Kohn 1994, Früwirth-Schnatter 1994, and Shephard 1994, and is now widely known as Forward Filtering Backward Sampling (FFBS) algorithm. The FFBS algorithm can be described as follows:

1. Run Kalman Filter for time t=1,2,...,T ;
2. Draw state parameter$_T$ from normal distribution with filtered mean and variance at time T ;
3. For t = T-1,...,0, draw the parameter$_t$ from normal distribution with the mean and variance at time t, derived from smoothing process.

The Kalman Filter mentioned in the first step is the recursive algorithm for sequentially computing the filtering densities in DLM, which is state space model assuming Gaussian distribution for any t. It has been widely known that one of advantages of state space models is that, due to the Markovian structure of the state dynamics and the assumptions on conditional independence for the observables, the filtered and predictive densities can be computed by a recursive steps. The Kalman Filter algorithm works as iterate following steps for each time period:

1) compute the one-step-ahead predictive density for the states from the filtered density ;
2) compute the one-step-ahead predictive density for the observations from the predictive density for the states ;
3) compute the filtering density from the above densities ;

More details on the characteristics of state space model and the computational description for the Kalman Filter can be found at Petris, Petrone, and Campagnoli 2009.

Since full conditional density of non-state parameters is problem specific in Gibbs sampling approach, I assume that the prior on variance of error terms ε_t and ω_t is inverse gamma and prior on other non-state parameters is normal, and assume conjugacy for all priors in the analysis.

Finally, the estimation strategy summarizing above process is as follows:

a) Set initial values for Non-State Parameters.
b) FFBS
    1] sample State Parameters given Non-State Parameters and data
        1-1) Run Kalman Filtering
        1-2) Draw sample for State Parameters at t=T
        1-3) Draw sample for State Parameters at t=T-1,……,0.
    2] sample Non-State Parameters given State Parameters and data
c) Iterate

6. Result

I report results of the estimation in Tables 3 to 6. For cross validation, I compare the predictive performance of model with several specifications and compute the mean absolute deviation (MAD) and the mean square error (MSE), natural process when one has only one time-series (Davydenk and Fildes 2016; Hyndman 2006). To compute these values, I collect data on the Kia automobile company, another representative firm in the Korean automobile industry, and create another sample that has similar data structure with the Hyundai sample. The results are on Table 3, and the MAD and MSE values in both sections are the lowest for the model 5, which has price, fuel efficiency, and displacement variables. In addition, I provide the mean absolute percentage error (MAPE) in Table 4, known as a standard fit statistic for model comparisons (Bass et al. 2007; Gopinath, Thomas, and Krishnamurthi 2014; Neelamegham and Chintagunta 2004), and it also remarks that the model 5 has the lowest value. Based on these criteria, I choose model 5 for the analyses.

<Table 3> Comparison of Several Specifications

Predictive Performance

Specification	Description	MAD	MSE
Model 1	All variables included	0.371	0.267
Model 2	with lnPRICE and SIZE interaction	0.868	1.196
Model 3	with lnPRICE and lnCC interaction	1.435	3.250
Model 4	with SIZE and lnCC interaction	0.394	0.239
Model 5	***No SIZE variable***	***0.280***	***0.127***
Model 6	with lnPRICE and lnCC interaction	1.310	2.908
Model 7	No SIZE and lnCC variable	1.325	4.376

<Table 4> Comparison of Several Specifications

Model Forecast Performance

Specification	Description	MAPE
Model 1	All variables included	3.411
Model 2	with lnPRICE and SIZE interaction	7.964
Model 3	with lnPRICE and lnCC interaction	13.173
Model 4	with SIZE and lnCC interaction	3.617
Model 5	***No SIZE variable***	***2.566***
Model 6	with lnPRICE and lnCC interaction	12.024
Model 7	No SIZE and lnCC variable	12.146

In Table 5, I present the estimates of the model 5 and report the 95% highest probability density interval (HPDI). I note that fuel efficiency and displacement have significant effects on demand at 95% confidence level as the HPDI does not include zero. On the other hand, HPDI on price variable does include zero, so the effects of price is turned out to be nonsignificant at 95% level. Such result might be from the notorious endogeneity and multicollinearity problems. Bass et al. 2007, which also uses DLM for its analyses, remarks that some omitted factors can influence price, suggesting the endogeneity problem (Villas-Boas and Winer 1999). In addition, using price variable directly in the model might cause potential multicollinearity problem. For example, one can easily expect that as size of car, displacement, fuel efficiency, or other unknown factors changes, price would naturally change. Indeed, I find that there is a significant correlation between displacement and price at 5% confidence level, but no correlation between fuel efficiency and price. However, I proceed to analyze the other estimators as the price effect is not this paper's main interest.

<Table 5> Estimates by channel type

Parameters	Estimates	Std.Dev	95% HPDI	
Price β_1	-1.967	1.797	-5.470	1.594
Fuel Efficiency β_2	0.991	0.087	0.821	1.160
Displacement β_3	3.728	1.813	0.112	7.232
Forgetting δ	0.161	0.060	0.045	0.278
Initial Goodwill G_0	-17.360	0.911	-19.130	-15.578
Observation Variance σ_ε^2	0.210	0.040	0.137	0.292
System Variance on Goodwill σ_{ω_0}	0.00517	0.00095	0.00348	0.00684
Twitter				
Copy wear-out a_1	-0.781	0.095	-0.968	-0.596
Volume c_1	0.851	0.104	0.647	1.051
Initial effect q_{10}	8.633	1.000	6.649	10.553
System Variance σ_{ω_1}	0.00547	.00127	0.00321	0.00784
Blog				
Copy wear-out a_2	-0.935	0.116	-1.162	-0.711
Volume c_2	1.013	0.125	0.768	1.256
Initial effect q_{20}	8.549	1.366	5.788	11.141
System Variance σ_{ω_2}	0.00351	0.00078	0.00217	0.00502
Community site				
Copy wear-out a_3	-0.931	0.118	-1.161	-0.700
Volume c_3	1.009	0.128	0.761	1.259
Initial effect q_{30}	8.052	1.143	5.755	10.262
System Variance σ_{ω_3}	0.00435	0.00100	0.00257	0.00623

The forgetting rate is 0.161, significant and consistent with values obtained in earlier studies in several fields of literature (Bass et al. 2007; Naik, Mantrala, and Sawyer 1998). This result represents that consumers' goodwill, which summarizes the effects of current and all past WOM on demand, tends to decrease at 16.1% rate in each time period, aligning with an expectation that people tend to forget some parts of information exposed to them.

The copy wear-out effects are all negative and significant, -0.781, -0.935, and -0.931 in twitter, blog, and community website respectively. The wear-out effects are generally large, and the effects in blog and community are about 15% higher in absolute value. One of possible reasons for such difference is that each channel types have their own unique characteristics. In advertising literature where researchers have cooperated to figure out how characteristics of advertising cause change in advertising effects, Pechmann and Stewart (1990) has presented that rational advertising tends to have high degree of copy wear-out parameters. In other words, general nuance of posts in each channels matter. Furthermore, unlike twitter, which can only deliver relatively short information, blog and community can express detailed personal experience and information with pictures, video clips, and so on (Jeon et al. 2019). Therefore, such difference can be partially derived from the nuance and the amount of detailed information exposed to consumers.

The effects of volume on state parameters of valence in each channel types are all positive and significant. Because both volume and valence are considered two important predictor in WOM literature (Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007; Duan, Gu, and Whinston 2008), I link the goodwill to valence and valence effect to volume, the formulation tested with other alternatives and supported in Bruce, Foutz, and Kolsarici 2012. In this setting, the results indicate that as volume of WOM increase, the effects of valence on goodwill and sales would increase positively. Interesting point of this result is that the effects of volume in twitter are smaller than those in the other types. Just as other social networking service (SNS), twitter updates list of posts quickly, so even if the number of posts increase, the marginal increase in chance of exposure would be low. In addition, since the number of characteristics in each twitter posts is limited to 140 characters (Adeyinka 2014), the information it provides would be limited and overlapped with other posts. Therefore, even if the volume increase, it might be less effective in increasing valence effectiveness than volume in other channels.

In Table 6, I present interaction effects of the three channels and report the 95% HPDI.

<Table 6> Channel Valence Interactions

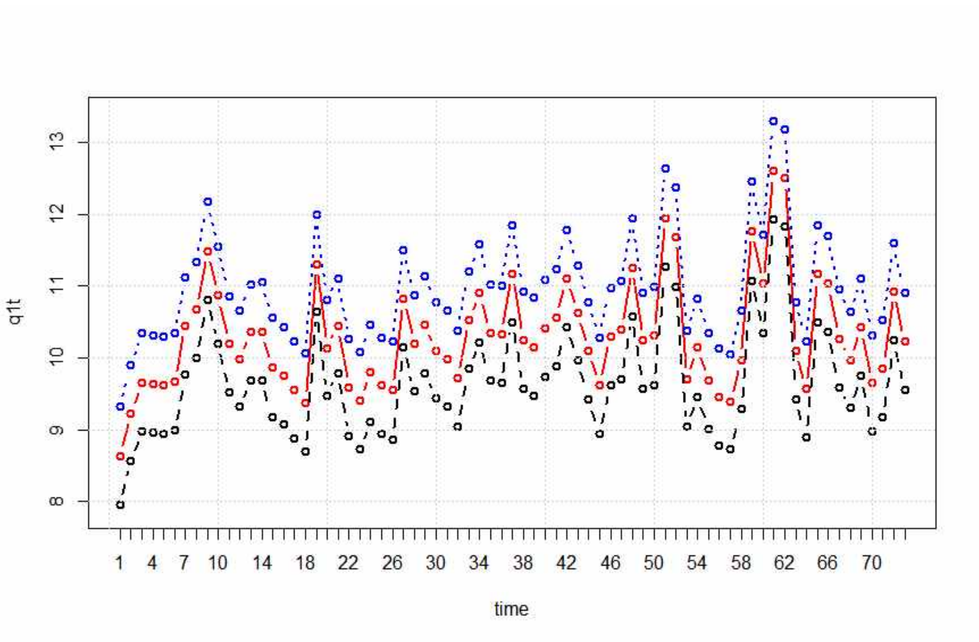
	Estimates	Std.Dev	95% HPDI	
Twitter	−0.134	0.227	−0.579	0.310
Blog	−1.157	0.299	−1.730	−0.565
Community site	−1.127	0.344	−1.809	−0.456

Based on estimation, interaction effects of blog and community site are negative and significant. The negative parameters suggest that the interaction effects between the different channel types mitigate the goodwill generated by the WOM. There is considerable evidence for negative interaction between messages or posts in different channels. For example, Calder and Sternthal 1980 show that when consumers get used to content of messages over a period of time, they have negative evaluations of the message and the associated product, indicating diminishing attention to other messages. As Karger et al. 2008 remarks that content is considered to be the most important element of the blog and community, overlapping of contents might cause negative impacts on each other. Descriptive statistics indicate that the mean values of valence in blog and community site are 82.2% and 67.3% respectively. Since these types have similar informative characteristics, increase in valence in other channel might cause diminishing willingness to seek for other messages. In addition, Reimer and Benkenstein 2016 indicates that too good WOM can hurt sales, finding that consumers become skeptical about products with too much positivity. Consumers may assume that too good reviews were possibly generated by representatives from the company or their public relations agency. Furthermore, Doh and Hwang 2009 suggest that a few negative messages can increase attitudes and perceived credibility, indicating importance of possessing some fraction of non-perfect reviews. In other words, if positivity is so great that consumers perceive that negativity is censored, then it would lose credibility, lowering its effects on sales. Therefore, the negative interaction effects agree with findings of Zhang, Craciun, and Shin 2010 that too positive valence of WOM may hurt product sales. Unlike the interaction effects of blog and community, those of twitter turn out to be nonsignificant. As mentioned in Literature Review, twitter works as the entrance to further information on certain product by offering a brief informative introduction to the product, raising consumers' interest, and leading consumers to further details. In other words, valence of other channels might not significantly interact with that of twitter because twitter tends to be seen at the early stage of searching process for product information. Therefore, the estimation result that interaction effects of twitter is not significant occurs from such characteristics.

Lastly, Figure 2 shows the evolution of the effects of valence in each of three different channel types q_{it} with their 95% HPDI, in order of twitter, blog, and community website. All three effects show sharp increase in the early stage, and then they start to fluctuate. There are wide fluctuations after the 46^{th} time period, and this result might be caused by the wide fluctuations in valence data during the same time period (details in Figure 1). This result therefore supports the need for examining dynamic effects of WOM in multiple types of online communication channels.

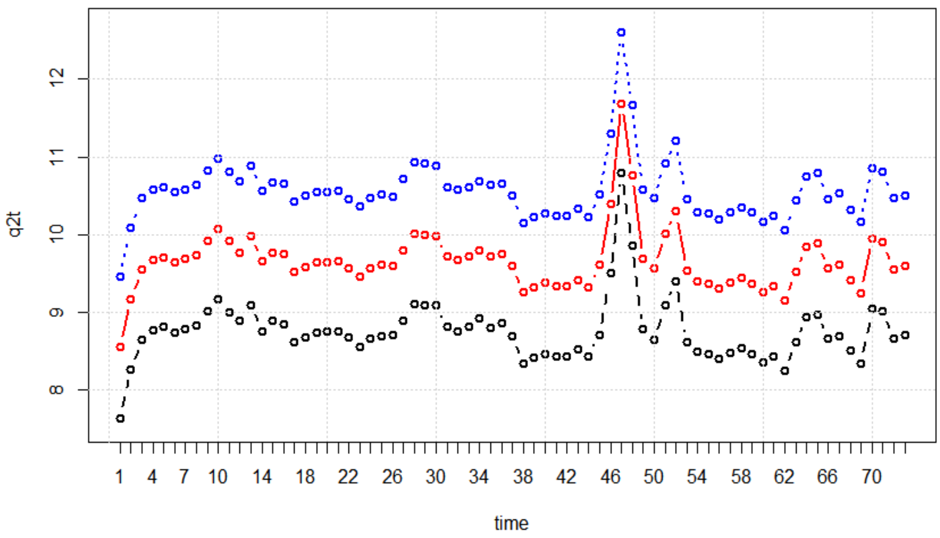
<Figure 2>

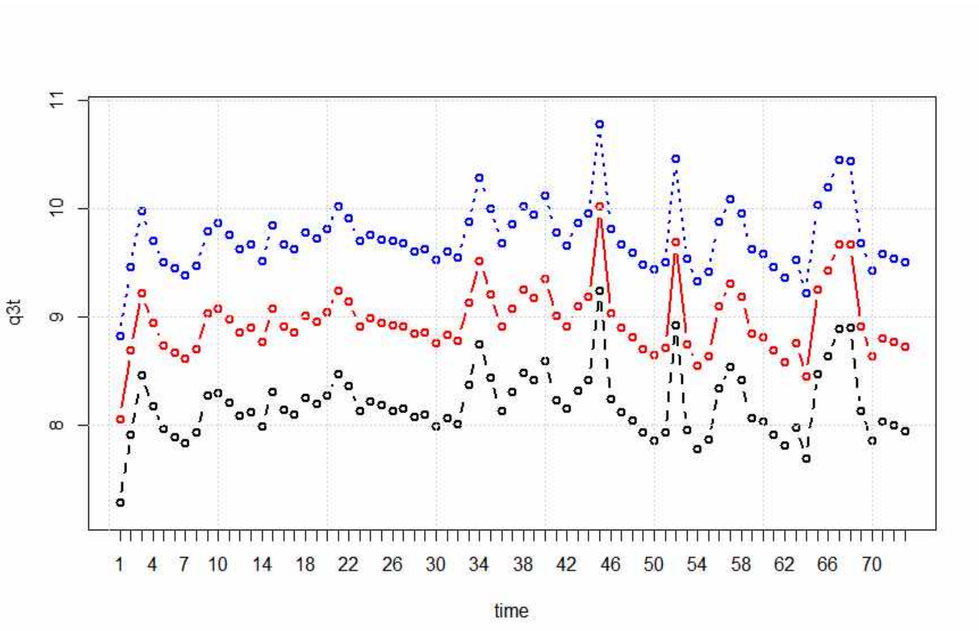
Dynamic effects of valence in each channel types



<Figure 2>

Dynamic effects of valence in each channel types





6. Conclusion

I have introduced a model of demand that considers the dynamic effects of Word of Mouth in three types of online communication channels. To the extent of my knowledge, this is a first attempt to help managers allocate their limited resources across different online communication channels. I modify and change specification in the model introduced at Bass et al. 2007 which is modified from the Nerlove-Arrow specification, which has been shown to perform the best (Naik, Mantrala, and Sawyer 1998). The model used in this paper considers copy wear-out and forgetting effects, and WOM is assumed to affect goodwill which in turn affects demand for a product. In addition, the model is developed for considering the evolution of goodwill and WOM effectiveness over time across three types of online communication channels : twitter, blog, community site, and it also helps to study the interaction effects among WOM in these channel types. I employ dynamic linear Bayesian estimation techniques (West and Harrison 1997) to estimate the model parameters.

The forgetting effects indicate that the goodwill decrease at 16.1 percent over time. Copy wear-out effects in each channel types are all negative and significant. The effects of blog and community site are higher, and such difference can be partially derived from the nuance and the amount of detailed information exposed to consumers. The effects of volume on valence effectiveness are all positive and significant. The effects of volume in twitter are smaller than those in the other types, and this might be cause by limited information delivery and quick post updating system. The interaction effects of blog and community site types are negative and significant, and the reason is that as valence increase, people start losing their willingness to seek for another posts and that people become skeptical when they perceive valence to be too high. Interestingly, the interaction effects of twitter is turned out to be nonsignificant, and such result is due to twitter's unique characteristics that it works as the entrance to further information on certain product by offering a brief informative introduction to the product, raising consumers' interest, and leading consumers to further details. Lastly, the effects of valence in each of three different channel types are positive and significant. Their evolutions support the need for examining dynamic effects, and the difference in degree of the effects in each channels supports the need for testing the effects of WOM in multiple channels.

This paper makes both academical and practical contributions. For the academical implication, I extend earlier research on WOM by introducing a generalized model for estimating the dynamic effects of WOM in multiple types of online communication channels and the interaction effects among the WOM inside each types of channels. This methodology would help researchers to examine both dynamic and interaction effects simultaneously and achieve more explanatorily powerful results, unifying the two different research streams into a single stream. For the practical implication, this paper helps practitioners in durable good markets to find optimal channel mix under limited resources. According to Chung and Kim 2011 that measures the effect of online WOM on the cell phone industry, it was shown that online WOM positively affects the sales of durable goods. Therefore, firms selling durable goods should make an attempt to increase their sales through online WOM, and this paper would help them to derive optimal strategies by discovering a channel mix that would mostly boost the dynamic effects of WOM.

Despite making various contributions, this paper also has several limitations. First, this research only focuses on automobile industry in Korean market. Because most research studying online WOM has gathered data on temporary experience goods, such as books and movies, I choose to focus on durable good to overcome such limitations. However, this research by itself does not ensure a generalization of the paper's conclusion, and I cannot fully exclude the possibility that the conclusion is partially derived from characteristics of Korean consumers. Therefore, future research shall includes some other types of durable goods and gathers data from various countries to overcome this limitation and provide new insight. Second, I could not consider each channels' characteristics with more details. Because each channels have their own unique characteristics, more details, such as general nuance, degree of reputation, and the numbers of significant influencers, need to be controlled in each channel types. However, techniques for gathering such information is too complicated, and defining criteria for making such decision is even harder. Yet, if such problems can be solved and integrated into my model, I believe it will return more fruitful implications. Lastly, I assume exogeneity of price variable and independence between valence effectiveness when modifying the model. Although the effects of price are not this paper's main interest, it would be much better if I could handle this issue by introducing some instrument variables as the effects are turned out to be nonsignificant. In addition, the result would be more fruitful and reliable if I could allow dependence structure of valence effectiveness. Therefore, future research shall overcomes these limitations to provide better implications.

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구전의 온라인 커뮤니케이션 채널별 동적 효과에 관한 연구

구전 (Word of Mouth)관련 문헌에 의하면, 구전의 효과를 분석하는데 있어 이들의 동적 효과를 고려해야 하며, 각 online communicatio channels에서 이들을 검토해야 할 필요성을 강조하고 있다. 따라서 본 논문은 동적 선형 모델 (Dynamic Linear Model)을 활용하여 구전의 온라인 커뮤니케이션 채널별 동적 효과를 분석하고자 한다. 이러한 Bayesian 모형 안에서 구전의 효과를 설명하기 위하여, 본 논문은 구전의 의 두 가지 중요한 속성인 Volume and Valence (Liu 2006), 동적 시스템에서 중요하게 다루는 copy wear-out 효과, 그리고 마지막으로 각 유형의 온라인 채널에 속하는 Valence들 간의 상호작용 효과를 고려하고자 한다.

이 모델은 현대 자동차 회사의 월별 판매 및 제품 속성, 가계 대출 금리, 그리고 3 가지 유형의 온라인 커뮤니케이션 채널 (Twitter, 블로그 및 커뮤니티 웹 사이트)에서의 volume과 valence에 대한 시계열 데이터에 적용되었다. 이에 따른 추정방법은 normal Gaussian state space model에 Gibbs 샘플링을 적용하기 위해 도출된 Forward Filtering and Backward Sampling 알고리즘을 통해 진행되었다 (Fruhwirth-Schnatter 2006).

추정에 따른 결과에 의하면, copy wear-out효과와 volume의 영향이 채널 유형에 따라 다르다는 것을 나타내고 있었고. 트위터와는 다르게 블로그 및 커뮤니티 사이트의 상호 작용 효과는 부정적이며 significant하게 나오는 것을 확인하였다. 마지막으로, 세 개의 서로 다른 타입의 채널에서의 valence의 영향은 모두 긍정적이고 significant하다는 것을 확인하였다. 이러한 효과들이 시점에 따라 변화하는 과정을 통해서 구전의 효과는 동적이라는 점을 시사하고 있으며, 채널 간 효과들의

차이를 통해서 구전의 효과를 분석할 때에는 구전을 다양한 채널로 나누어 분석해야 한다는 점을 시사하고 있다.

본 논문은 다음과 같은 의의를 가진다. 학문적 의의로써 각각의 온라인 통신 채널에서 구전의 동적 효과 및 각 채널의 구전 간의 상호작용 효과를 동시에 추정할 수 있는 일반화된 모델을 도입함으로써 구전에 관한 연구에 기여한다. 또한, 이러한 방법을 통해서 각기 다른 방향으로 진행되던 동적효과에 대한 연구와 구전을 채널별로 분석하는 연구를 연결시켜주는 역할을 할 수 있을 것이다. 실질적인 의의로써 본 논문은 내구재 시장의 실무자가 한정된 자원에서 구전의 역동적 효과를 극대화할 수 있는 채널 믹스를 발견함으로써 최적의 전략을 도출하는 데 도움이 될 것이다.

주요어 : 온라인 구전, Bayesian Dynamic Linear Models, 깁스 샘플링, Online Communication Channels, Copy Wear-out effects, Forgetting effects, 내구재

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