

**Consumers' Social Learning on Videogame Consoles  
through Multiple Website Browsing**

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## **Abstract**

This study investigates the micro-level correlation between traditional marketing actions (TV ads and public relations (PR)) and consumers' social learning about newly launched videogame consoles (Wii and PS3 in 2006) via browsing on product community websites. We postulate that consumers learn about these products in two ways - from other consumers ("social" learning) and from product review websites ("reason-based" learning). We assume that pageviews of community websites indicate the level of consumer's engagement via social learning. We also assume that the social learning is correlated with regular reason-based learning which is measured by other pageviews of videogame related websites. We expect that inferences from the two learning processes affect consumer's purchase decisions differentially. In summary, our working research questions are (a) do traditional ads and PR campaigns enhance consumer learning and, (b) what is the relative importance of the two types of learning on consumer purchase choice.

We use pageview data from multiple websites using a clickstream panel to calibrate the consumer learning process via online communities. We propose a bivariate Bayesian learning model combined with complementary purchase choices. From preliminary results we find that companies' traditional marketing actions (TV ads and PR) have positive impact on social learning at the pre-launch period. This suggests that firms can manage to enhance consumers' learning and promote higher engagement with the product, potentially resulting in product purchase.

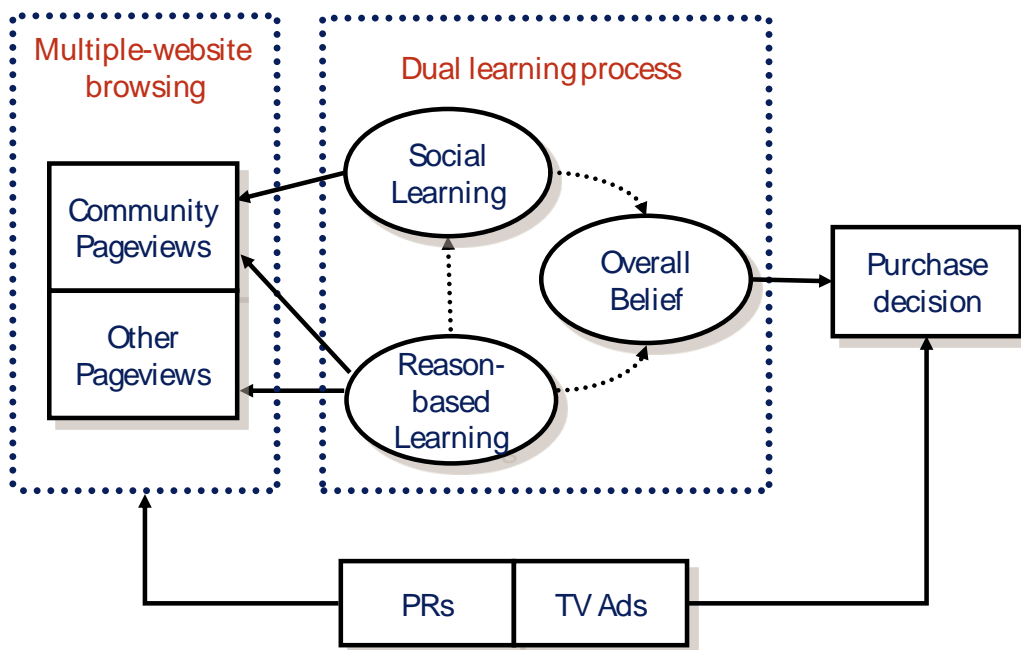
## 1. Introduction

Recent development of internet communication tools and online social networks enables consumers to conduct “social learning” about products easier. Social learning is the learning process that is promoted by exchanging information among diverse consumers in (online) communities (Jayanti and Singh 2010; Calder, Malthouse and Schaedel 2009). On the other hand, as a similar concept, “consumers’ engagement” is a new keyword among advertising circles. Since 2006, the Association of National Advertisers (ANA), American Association of Advertising Agencies (AAAA) and the Advertising Research Foundation (ARF), have worked together to develop the definition and metric of consumers’ engagement (ARF Defining Engagement Initiative). There is no established definition yet, but the consumers’ engagement is defined as consumer’s prospect of a brand idea which is enhanced and stimulated by online interaction with other consumers not only by the offline one-way marketing communications. In practice, consumer’s engagement is measured as, for example, duration, frequency and/or recency of visiting, viewing high-value or medium-value content, providing personal information, and posting customer reviews and comments in online communities. Firms conduct engagement marketing to enhance social learning which leads to construct a long-term customer loyalty and maximize purchase conversions.

This study explores individual level correlation between traditional marketing activity (TV ads and public relations (PR)) and online communication (consumer’s social learning) about newly launched videogame consoles (Wii and PS3 in 2006) via browsing on product community websites. For example, an anecdotal story about an advertising campaign of introducing Wii videogame

console in Japanese market tells that Nintendo intentionally hid full information of Wii at the beginning of the campaign. First, the company showed only the silhouette of the console, and then gradually provided a little part of the information time by time until its release in December 2006. By being given only limited information at the beginning, consumers were driven to search information and discussing their expectations of the console in online communities. Throughout the learning, consumers were expected to be highly engaged, then this may potentially result in buying the product.

Figure 1: Outline of research



As outlined in Figure 1, we postulate that consumers learn about these products in two ways - from other consumers (“social” learning) and from product review websites (“reason-based” learning). We assume that pageviews of community websites indicate the level of consumer’s engagement via social learning. We also assume that, at the same time, consumers conduct

another mode of learning process, the regular reason-based learning by other pageviews of videogame related websites, and the two processes are correlated with each other. Each learning process is expected to prompt a different type of consumer's information searching behavior – community pageviews and the other pageviews. We also anticipate that inferences from the two learning processes affect consumer's purchase decisions differentially. In summary, our working research questions are (a) do traditional ads and PR campaigns enhance consumer learning and, (b) what is the relative importance of the two types of learning on consumer purchase choice. By quantifying the impact of traditional marketing media, firms can manage to enhance consumers' learning and promote higher engagement with the product, potentially resulting in product purchase.

The rest of the paper is organized as follows. Section 2 reviews the literature and discusses our hypotheses. In section 3, we describe the data. Then we discuss the model next in Section 4. Section 5 contains the preliminary results and we conclude in Section 6.

## 2. Literature review

In the marketing literature, many studies explored how consumers learn about quality of products from the information in the market and suggested that the consumer's learning is occurred through dual or multiple processes. Petty and Cacciopo (1986) conceptualized the dual learning processes of systematic and heuristic routs. Other papers introduced emotional or experiential response in addition to cognitive processing (*e.g.*, Meyers-Levy and Malaviya 1999; Forgas 1995; MacInnis and Jaworski 1989; Edell and Burke 1987; Batra and Ray 1986). On top of

these existing well-known learning processes, social learning may also play an important role for consumer's purchase decision. Social learning is the learning process that is promoted by exchanging information among diverse consumers in problem-solving communities. For instance, Jayanti and Singh (2010) examined the social learning process about health care in online BBSs (Bulletin Board Systems).

Calder, Malthouse and Schaedel (2009) discussed effectiveness of advertising on consumer engagement by experiments using eight different online experiences on websites. They examined two types of engagements with online media - Personal and Social-Interactive Engagement. They found that both types were positively associated with advertising effectiveness. Moreover, Social-Interactive Engagement was strongly correlated with advertising after controlling for Personal Engagement.

Luan and Neslin (2010) and Erdem et al. (2005) investigated product learning processes through word-of-mouth communication, but they did not differentiate social learning from personal learning. They also used only aggregate product-level datasets and assumed a structure to estimate individual learning process based on their naïve assumptions.

Bucklin (2008) reviews past studies using clickstream data in details. In his article, the literature were categorized into three types of insights: (1) attracting visitors to the site, (2) understanding site usage behavior, predicting purchase, and managing the site, and (3) assessing activity across multiple sites and multiple channels. Our research intends to explore the issues in categories (1) and (2). As in the category (1), Ilfeld and Winer (2002) examined the impact on website visits from online and offline advertising expenditures using aggregated data. They found

that website visits were positively correlated with online ad spending but negatively correlated with offline ad spending. They also found that website visits as independent variable were positively correlated with awareness and brand equity measure in return. In contrast to their study, we examine dynamic aspect of individual's learning process using individual panel of clickstream data. The other studies considered the impact only from online marketing activities, banner ads (Chatterjee, Hoffman and Novak 2003; Manchanda, Dube, Yong Goh and Chintagunta 2006) and email ads (Ansari and Mela 2003). As in the category (2), many studies explore the predicting power of the website browsing behavior. Moe and Fader (2004) found that past visit behavior at the Amazon website increased the future probability of purchase conversion. Sismeiro and Bucklin (2004) and Montgomery, Li, Srinivasan and Liechty (2004) explored the predictive power of consumer's browsing path or completion of successive tasks to purchase. Those all studies limited to examine only consumer's browsing behavior within the single e-commerce website. Our research is interested in browsing behavior in broader websites, since consumers try to learn about product information from many websites and compare the information.

## 2. Data

We use user-centric internet clickstream data collected by Video Research Interactive, Inc., which maintained a panel of approximately 12,000 Japanese panel members whose websites browsing behavior was recorded over time by a firm's proprietary software installed on their computers at home. The collected data contain information regarding sites' URLs which

individuals visit and when they visit. The company has also conducted annual written surveys to a randomly selected part of its existing panelists. There were 7,053 subjects who responded to the annual survey in November 2007 (around one year past after releasing Wii and PS3 in December 2006). As shown in Table 1, 24 percent of the subjects owned one of available videogame consoles at the date of the survey conducted. Wii gained 25.5% share among all the videogame users. In contrast, the share of PS3 was 4.5% and 1.6% of the videogame users owned both consoles.

Table 1: Data description: Videogame console possessions

	# Users	Percentage	Share
Wii users	434	6.2%	25.5%
PS3 users	77	1.1%	4.5%
Both (Wii & PS3) users	28	0.4%	1.6%
Other console users	1,160	16.4%	68.3%
All videogame users	1,699	24.1%	100.0%

We are interested in pre-purchase website browsing behavior of the subjects who bought the newly released game consoles, Wii or PS3 and both. For this purpose, we translated their website browsing records into the daily number of pageviews of videogame related websites. We selected major 49 videogame related Japanese websites as listed. In addition, we classified the part of these videogame related websites as community-based, when the website had community features such as BBS (Bulletin Board System) or users' review posting systems. Then, we also counted pageviews of the community-based websites and use them as the indicator of the social learning process. For the empirical analysis, we only use observations from the panelists who owned any of the available videogame consoles and visited the videogame-related websites more than two pageviews during the analysis period from April to December 2006. This condition resulted in 1,078 panelists remained for the analysis. The daily average numbers of pageviews of the subjects are reported in Table 2.



Table 2: Mean pageviews of videogame-related websites

	All videogame sites		Community-based sites	
	Mean	s.d.	Mean	s.d.
Wii users	1.14	4.02	0.32	1.72
PS3 users	1.47	4.02	0.34	1.29
Both (Wii & PS3) users	1.36	1.54	0.16	0.33
Other console users	0.70	2.21	0.11	0.45

Video Research Interactive, Inc. has also reported TV GRPs of all commercials which were aired in major Japanese markets. We used the aggregated TV GRPs of videogame ads which were segmented in male/female and teen/20's/30's/40's/50's/60's, and matched the segmented GRPs with the pageview data of the subjects who were in the same demographic segment. In addition, we classified the types of the videogame TV ads into console ads and software ads by Nintendo, Inc. and SCE (Sony Computer Entertainment, Inc.). Table 3 shows the daily mean of the videogame TV ads by each type.

Table 3: Mean GRPs of videogame ads and PRs

	Wii (Nintendo)		PS3 (SCE)	
	Mean	s.d.	Mean	s.d.
Console TV ads				
Wii users	10.80	27.07	2.85	15.70
PS3 users	10.71	26.66	2.83	15.55
Both (Wii & PS3) users	9.41	23.22	2.53	13.40
Other console users	10.97	27.51	2.88	15.85
Software TV ads				
Wii users	10.90	40.59	6.67	21.97
PS3 users	10.92	40.26	6.77	22.26
Both (Wii & PS3) users	9.95	36.30	6.70	21.45
Other console users	11.09	41.46	6.77	22.22
Other consoles & software TV ads				
Wii users	103.25	56.44	99.69	57.32
PS3 users	104.97	55.86	101.19	57.38
Both (Wii & PS3) users	90.39	46.74	96.46	52.48
Other console users	103.78	56.31	99.96	57.83
PRs	0.07	0.25	0.08	0.28

It should be noted that, due to the limitation of the data set, we only observe which video game consoles the panel of consumers has at the date of responding the annual survey. As we described above, the survey was conducted around one year after the new products have launched in the Japanese market. We cannot figure out when the panel subjects bought a new videogame console. This leads to the problem that we cannot directly match the consumers' beliefs about product quality with their purchase decision on their buying date. In the next section, we will discuss this data limitation again and show a way to deal with this issue in this study.

### 3. Model

The full model consists of two parts, a model of learning about product quality over time and a model of purchase choice.

#### 3.1 A learning model of product quality

As discussed above, we assume that the consumers conduct two different modes of learning processes. In the first case below, we describe a simpler single process model which only considers the reason-based learning process. Our unique formulation of the signal information enables the estimation procedure to become simpler. Then, in the second dual learning processes case, we proposed the model which is extended from bivariate Bayesian learning model by Ackenberg (2003). Our proposed model considers the possible correlation between two learning processes at the entire updating processes.

#### **Basic case: a single learning process**

The reason-based learning is expected to capture cognitive aspects of the products and construct cognitive belief about the quality of products over the time. Thus,  $\tilde{C}_{ij}$  denotes consumer  $i$ 's cognitive belief about the product  $j$  at date  $t$ .  $C_{ij}$  denotes the true quality of the product  $j$  for the consumer  $i$ . Following the standard context of the Bayesian learning process (e.g. Erdem and Keane 1996), the consumers have uncertainty about the true quality of the product but have some beliefs about its value.

At the date of  $t=0$ , the consumer  $i$ 's initial prior belief about the quality of the product  $j$  is assumed to be normally distributed. We also assume that the mean of the initial belief  $c_j^0$  is also normally distributed among the consumers.

$$(1) \quad \tilde{C}_{ij0} \sim N(c_j^0, \sigma_{c0}^2), \quad c_j^0 \sim N(0, \sigma_{c0}^2).$$

As assumed above, we expected that the videogame related website browsing behaviors of consumers can indicate their level of engagement or strength of their interest in products which are driven by the beliefs about the product quality. Therefore, we consider the number of pageviews indicating a signal of the consumers' cognitive belief. The signal,  $S_{ijt}^C$ , is assumed to follow normal distribution.

$$(2) \quad S_{ijt}^C \sim N(C_{ij}, \sigma_{\tilde{C}}^2).$$

However, the pageviews are biased indicators of the signal of the product quality, because other factors may also lead the website browsing, for example, seasonal factors such as the weekends and the holidays. In addition, we are interested in the impact of firms' marketing actions such as TV ads and PRs. Thus, we formulate the log number of pageviews as the additive

combination of the signal of the product belief, seasonal factors and the company's marketing actions as Equation (3.3).

$$(3) \quad \ln(n_{it}) = S_{ijt}^C + \beta_0 \text{Seasonal}_t + \beta_1 \text{AD}_{jt} + \beta_2 \text{PR}_{jt} + \eta_{ijt}.$$

This equation is can be rewritten as below by substituting Equation (3.2).

$$(4) \quad \ln(n_{it}) = C_{ij} + \beta_0 \text{Seasonal}_t + \beta_1 \text{AD}_{jt} + \beta_2 \text{PR}_{jt} + v_{ijt}, \quad v_{ijt} \sim N(0, \sigma_C^2).$$

It leads that the consistent estimate of the consumer's product belief can be expressed as Equation (3.5) on condition of available information by the date  $t$ .  $\hat{\beta}_0$ ,  $\hat{\beta}_1$  and  $\hat{\beta}_2$  denote consistent estimates of the covariates via linear regression and  $\overline{\ln(n_{i(t)})}$ ,  $\overline{\text{Seasonal}_{(t)}}$ ,  $\overline{\text{AD}_{j(t)}}$  and  $\overline{\text{PR}_{j(t)}}$  are means of log number of pageviews, seasonal factors, TV ads and PRs up to the date  $t$ .

$$(5) \quad \hat{C}_{ij(t)} = \overline{\ln(n_{i(t)})} - \left( \hat{\beta}_0 \overline{\text{Seasonal}_{(t)}} + \hat{\beta}_1 \overline{\text{AD}_{j(t)}} + \hat{\beta}_2 \overline{\text{PR}_{j(t)}} \right) \sim N(C_{ij}, \frac{\sigma_C^2}{t}).$$

Finally, by combining the prior belief and the information from the signals, the posterior belief about the product quality results in being normally distributed and an updating formulation on the date  $t=1, \dots, T$ .

$$(6) \quad \tilde{C}_{ijt} \sim N(\bar{C}_{ijt}, \Sigma_{Cijt}),$$

$$\text{where } \bar{C}_{ijt} = \Sigma_{Cijt} \left( \Sigma_{Cij(t-1)}^{-1} \tilde{C}_{ij(t-1)} + \frac{t}{\sigma_C^2} \hat{C}_{ij(t)} \right) \text{ and } \Sigma_{Cijt} = \left[ \Sigma_{Cij(t-1)}^{-1} + \frac{t}{\sigma_C^2} \right]^{-1}.$$

The advantage of this formulation is that it does not require simulations in its estimation procedure. The standard methods of the learning model need to infer the mean value of the signal information by simulating to recover its distribution. In our model, the consistent estimates of the signals are simply provided from the linear regression of the pageview as in Equation (3.5).

### Extended case: bivariate learning processes model

As we discussed, we assume that there is another mode of learning in addition to the reason-based learning. The social learning is conducted through interactions with other consumers in community websites and leads to construct social belief about the product quality. The social belief is assumed to be correlated with the individual's cognitive belief. Akerberg (2003) proposed bivariate learning processes. However, the correlation of the two beliefs was considered only at the initial belief in his model. In contrast, our model takes the correlation into account both at the initial belief and at the entire updating processes as below.

$$(7) \quad D_{ij} = \gamma C_{ij} + d_j$$

Now we rewrite Equation (3.1), the consumer  $i$ 's initial cognitive and social beliefs about the quality of product  $j$  on the date of  $t=0$  and the distribution of different signals.

$$(8) \quad \begin{cases} \tilde{C}_{ij0} \sim N(c_j^0, \sigma_{c0}^2), & c_j^0 \sim N(0, \sigma_{c0}^2), \\ \tilde{D}_{ij0} = \gamma c_j^0 + d_j^0, & d_j^0 \sim N(0, \gamma^2 \sigma_{c0}^2) \end{cases}$$

$$(9) \quad \begin{cases} S_{ijt}^C \sim N(C_{ij}, \sigma_C^2), \\ S_{ijt}^D \sim N(D_{ij}, \sigma_D^2) \end{cases}$$

As explained in the data section, we also counted the pageviews of the community-based websites among the videogame related community websites. We assume that the pageviews of the community-based websites are led by the signal from the social belief and the other confounding factors as the similar discussion in the single learning process case. Then, we can show the consistent estimate of the cognitive and the social beliefs as follows.

$$(10) \quad \begin{cases} \ln(n_{it}) = C_{ij} + \beta_0 \text{Seasonal}_t + \beta_1 AD_{jt} + \beta_2 PR_{jt} + v_{ijt}, & v_{ijt} \sim N(0, \sigma_C^2) \\ \ln(n_{it}^{COM}) = D_{ij} + \beta_0^{COM} \text{Seasonal}_t + \beta_1^{COM} AD_{jt} + \beta_2^{COM} PR_{jt} + v_{ijt}^{COM}, & v_{ijt}^{COM} \sim N(0, \sigma_D^2) \end{cases}$$

$$(11) \quad \begin{cases} \hat{C}_{ij(t)} = \overline{\ln(n_{i(t)})} - \left( \hat{\beta}_0 \overline{\text{Seasonal}_{(t)}} + \hat{\beta}_1 \overline{AD_{j(t)}} + \hat{\beta}_2 \overline{PR_{j(t)}} \right), \\ \hat{D}_{ij(t)} = \overline{\ln(n_{i(t)}^{COM})} - \left( \hat{\beta}_0^{COM} \overline{\text{Seasonal}_{(t)}} + \hat{\beta}_1^{COM} \overline{AD_{j(t)}} + \hat{\beta}_2^{COM} \overline{PR_{j(t)}} \right) \end{cases}$$

$$\begin{bmatrix} \hat{C}_{ijt} \\ \hat{D}_{ijt} \end{bmatrix} \sim NVN \left( \begin{bmatrix} C_{ij} \\ P_{ij} \end{bmatrix}, \begin{bmatrix} \frac{\sigma_C^2}{t} & \frac{\gamma\sigma_C^2}{t} \\ \frac{\gamma\sigma_C^2}{t} & \frac{\sigma_D^2}{t} \end{bmatrix} \right)$$

Finally, as similar in Equation (3.6) of the single learning case, based on the initial beliefs and the signal information updates, the posterior beliefs of the product quality follow bivariate Bayesian learning process on  $t=1, \dots, T$ .

$$(12) \quad \begin{bmatrix} \tilde{C}_{ijt} \\ \tilde{D}_{ijt} \end{bmatrix} \sim NVN(m_{ijt}, \Sigma_{ijt}),$$

$$\begin{aligned} m_{ijt} &= \begin{bmatrix} \bar{C}_{ijt} \\ \bar{D}_{ijt} \end{bmatrix} = \Sigma_{ijt} \left( \Sigma_0^{-1} m_0 + t\Phi^{-1} \hat{Z}_{ijt} \right), & m_0 &= \begin{bmatrix} 0 \\ d_j^0 \end{bmatrix}, & \Sigma_0 &= \begin{bmatrix} \sigma_{c_0}^2 + \sigma_{c_0}^2 & \gamma\sigma_{c_0}^2 \\ \gamma\sigma_{c_0}^2 & \gamma^2\sigma_{c_0}^2 \end{bmatrix}, \\ \Sigma_{ijt} &= \left( \Sigma_{Cij(t-1)}^{-1} + t\Phi^{-1} \right)^{-1} & \hat{Z}_{ijt} &= \begin{bmatrix} \hat{C}_{ij(t)} \\ \hat{D}_{ij(t)} \end{bmatrix}, & \Phi &= \begin{bmatrix} \sigma_C^2 & \gamma\sigma_C^2 \\ \gamma\sigma_C^2 & \sigma_P^2 \end{bmatrix} \end{aligned}$$

### 3.2 Purchase choice based on the cumulative product beliefs

We assume that the consumers rely on their belief about product quality when they decide to buy a new product. However, due to the limitation of the data, we only observed which video game consoles the panel of consumers had on the date of responding the annual survey which was around one year after the new products launched in the Japanese market. This results in that we cannot match the consumers' purchase decision with their product beliefs on their purchase date. To deal with this problem, we only try to examine the correlation between product choices and the cumulative beliefs about the product quality on the date of the product release. In other words, we assume that consumers' beliefs may not largely change after the product released until the date of their purchase. Obviously, after the products are available, consumers' quality beliefs

should be updated by, for instance, product experiences that consumers actually play the videogames somewhere, or by reputation and word-of-mouth from other consumers who already own and play games. However, from CESA report in Japan one third of unit sales of Wii was achieved by the first four months in the fiscal year of 2007 (<http://report.cesa.or.jp>). Thus, we can expect that many subjects in the panel bought the products in the early stage and those confounding factors may not have much impact on our analysis.

When there are two products available in the market, at their purchase decision consumers choose one of the following options {0, 1, 2, 1&2}, where 0 denotes buying neither product and 1&2 means buying both products. By using complementary bundle choice model of Gentzkov (2007), the expected mean utility functions are assumed as follows.

$$(13) \quad \begin{cases} E\bar{u}_i(0) = 0, \\ E\bar{u}_i(j) = \theta_1 \bar{Q}_{ijT} + \theta_2 (\bar{Q}_{ijT})^2 + \alpha_1 Price_j + \alpha_2 CumAd_{jT} + \alpha_3 CumPR_{jT} + \xi_{ji} & j = 1, 2, \\ E\bar{u}_i(1 \& 2) = u_i(1) + u_i(2) + \Gamma. \end{cases}$$

where the mean of overall quality beliefs,  $\bar{Q}_{ijT}$ , are assumed to be a convex combination of the mean of the cognitive beliefs and the mean of the social beliefs on the date of the products launched,  $T$ , as  $\bar{Q}_{ijT} = \lambda \bar{C}_{ijT} + (1 - \lambda) \bar{D}_{ijT}$ ,  $0 < \lambda < 1$ .  $CumAd_{jT}$  and  $CumPR_{jT}$  denote summations of the all TV ads and the all PRs from the dates  $t=0$  to  $T$ . The parameter  $\Gamma$  indicates the complementarity (if it is positive) between two products. The error terms (or consumers' persistent taste),  $\xi_{ji}$ , indicate the consumers' persistent taste about the products and they are distributed as bivariate normal.

$$(14) \quad \begin{bmatrix} \xi_{1i} \\ \xi_{2i} \end{bmatrix} \sim MVN \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \right).$$

More specifically, denoting  $k=0,1,2,3$  to indicate the element of the choice options {0, 1, 2, 1&2}, the indirect expected utility can be defined over the choice options as follows.

$$(15) \quad EU_{ik} = E\bar{u}_i(k) + \varepsilon_{ik}.$$

We assume that the error term,  $\varepsilon_{ik}$ , follows the type-I extreme distribution. Then the probability that the consumers choose to purchase the products given the consumers' persistent taste vector  $\xi_i$  can be written as the multinomial logit formulation.

$$(16) \quad \Pr_i[y_i = k, Data_{iT}, \xi_i, \Omega | \Theta] = \frac{\exp[EU_{ik}]}{\sum_{k'=1}^3 \exp[EU_{ik'}]}$$

where  $\Theta$  is the set of parameters includes  $\{\lambda, \theta_1, \theta_2, \alpha_1, \alpha_2, \alpha_3, \Gamma\}$  and  $\Omega$  is the set of parameters which are determined through the dual learning processes denotes  $\{d_j^0, \gamma, \sigma_{c0}, \sigma_{c0}, \sigma_c, \sigma_D, \vec{\beta}\}$ .

### 3.3 Identification and estimation

In the estimation, we need to normalize the first element of the variance of the initial beliefs as  $\sigma_{c0}^2 + \sigma_{c0}^2$  to 1 for identification purpose in Equation (3.12). Finally, we can integrate out error terms,  $\xi_i$ , from Equation (3.16) and form the conditional likelihood function as in Equation (3.17). To replicate the error distribution, we apply simulated maximum likelihood method in our empirical parameter estimation.

$$(17) \quad L = \prod_{i=1}^N \int \Pr_i[y_i = k, Data_{iT}, \xi_i | \Theta] dF(\xi_i | \sigma_{12}, \sigma_2).$$

## 4. Preliminary results

Before estimating the full model, we first estimated simpler models as a preliminary analysis. Instead of the proposed learning model, we estimated two pageviews – community-based and the others - regressions of Equation (10) by hierarchical Bayse regression estimation with



heterogeneous coefficients over individuals. Then, the heterogeneous constant estimates were used as the consumer's cognitive and social beliefs about the videogame consoles quality in a purchase choice model. To analyze the purchase decisions, we employed a simpler hierarchical Bayes multivariate probit model of four choices (i.e., none, Wii, PS3 and both) rather than the proposed multinomial logit model with the complementary effect.

The preliminary results from the pageview equations in Tables 4 and 5 suggest that many of advertisings and public relations have positive and significant correlation with community-based pageviews, but only GRPs of PS3 software ads are significantly related with the other pageviews. Moreover, the Wii public relations have the largest magnitude of impact on community-based pageviews. These results suggest that traditional marketing activity may have stronger impact on consumers' social learning from browsing community-based websites than reason-based learning.

From the purchase choice estimation results in Table 6, we find that positive relationship of consumers' social belief with consumers' choice utility. On the other hand, cognitive belief correlates with individual purchase decisions in risk-taking formula. This means that consumers are likely to buy videogame consoles in case that consumers' social belief is large and/or in either cases that perceived cognitive product quality is at high or low levels not mediocre level. In addition, cumulative values of companies' public relations and cumulative GRPs of software advertisings are positively and significantly correlated with purchase decisions.

Table 4: Estimates of community-based pageviews equation

	Mean	s.d.	5%	50%	95%	HPDI
Constant	-11.4486	0.0381	-11.4928	-11.4487	-11.4059	**
Trend	0.0001	0.0002	-0.0001	0.0001	0.0004	
Tuesday	0.0017	0.0207	-0.0306	0.0013	0.0358	
Wednesday	-0.0068	0.0210	-0.0412	-0.0067	0.0275	
Thursday	0.0134	0.0210	-0.0194	0.0134	0.0466	
Friday	0.0174	0.0208	-0.0161	0.0176	0.0505	
Saturday	0.0583	0.0210	0.0241	0.0586	0.0925	**
Sunday	0.0346	0.0213	-0.0003	0.0348	0.0686	
Holiday	0.0115	0.0293	-0.0372	0.0120	0.0599	
ALL pageviews	0.0028	0.0001	0.0026	0.0028	0.0029	*
PR (Wii)	0.0482	0.0232	0.0107	0.0479	0.0870	**
GRP (Wii)	-0.0004	0.0004	-0.0010	-0.0004	0.0003	
GRP Software (Wii)	0.0007	0.0003	0.0002	0.0007	0.0011	*
PR (PS3)	0.0054	0.0214	-0.0297	0.0059	0.0401	
GRP (PS3)	0.0010	0.0006	0.0000	0.0010	0.0019	*
GRP Software (PS3)	0.0005	0.0004	-0.0003	0.0004	0.0011	

\* The table presents the estimates for the population means and standard deviations of the parameters after 50,000 runs and 25,000 burn-ins.

\* Significant code by HPDI (Highest posterior density interval): 0.01 ‘\*\*\*’, 0.05 ‘\*’, 0.1 ‘.’

Table 5: Estimates of reason-based pageviews equation

	Mean	s.d.	5%	50%	95%	HPDI
Constant	-11.2257	0.0753	-11.3048	-11.2267	-11.1465	**
Trend	0.0013	0.0003	0.0008	0.0013	0.0018	**
Tuesday	-0.0852	0.0410	-0.1505	-0.0860	-0.0184	**
Wednesday	-0.0029	0.0418	-0.0697	-0.0028	0.0672	
Thursday	0.0557	0.0415	-0.0111	0.0555	0.1217	
Friday	0.0300	0.0417	-0.0370	0.0309	0.0962	
Saturday	0.0508	0.0422	-0.0182	0.0518	0.1182	
Sunday	-0.0070	0.0419	-0.0759	-0.0067	0.0627	
Holiday	-0.0071	0.0584	-0.1047	-0.0061	0.0870	
ALL pageviews	0.0084	0.0002	0.0082	0.0085	0.0087	**
PR (Wii)	0.0707	0.0451	-0.0026	0.0712	0.1444	
GRP (Wii)	-0.0005	0.0007	-0.0016	-0.0005	0.0006	
GRP Software (Wii)	0.0000	0.0005	-0.0007	0.0000	0.0008	
PR (PS3)	-0.0200	0.0399	-0.0855	-0.0199	0.0455	
GRP (PS3)	0.0004	0.0010	-0.0013	0.0004	0.0021	
GRP Software (PS3)	0.0016	0.0008	0.0003	0.0016	0.0029	*

\* The table presents the estimates for the population means and standard deviations of the parameters after 50,000 runs and 25,000 burn-ins.

\* Significant code by HPDI (Highest posterior density interval): 0.01 ‘\*\*\*’, 0.05 ‘\*’, 0.1 ‘.’

Table 6: Estimates of purchase choice - MVP

	Mean	s.d.	5%	50%	95%	HPDI
Cognitive Belief	-0.000336	0.000441	-0.001405	-0.000104	-0.000025	**
Cognitive Belief^2	0.000024	0.000037	0.000002	0.000007	0.000107	*
Social Belief	0.000070	0.000074	0.000012	0.000055	0.000170	*
Social Belief^2	0.000000	0.000000	0.000000	0.000000	0.000001	.
Cog x Soc Belief	-0.000001	0.000002	-0.000006	0.000000	0.000000	*
Price	-0.001751	0.002499	-0.006871	-0.000477	-0.000093	**
Cum PR	0.003479	0.005095	0.000048	0.000663	0.014493	*
Cum GRP Console	0.000003	0.000006	-0.000001	0.000000	0.000017	
Cum GRP Software	0.000004	0.000006	0.000000	0.000002	0.000017	*

\* The table presents the estimates for the population means and standard deviations of the parameters after 50,000 runs and 25,000 burn-ins.

\* Significant code by HPDI (Highest posterior density interval): 0.01 ‘\*\*\*’, 0.05 ‘\*’, 0.1 ‘.’

## 5. Discussion and Conclusion

In this research, we used disaggregate data on individual multiple-website browsing behavior in order to link consumers’ social learning about newly launched videogame consoles with their purchase decisions. From the preliminary analyses of three data sources – traditional marketing activity (TV advertising and PRs), online communication (Web page views) and market outcomes of two videogame consoles among Japanese panel subjects, we found that companies’ traditional marketing actions have positive impact on social learning at the pre-launch period. This suggests that firms can manage to enhance consumers’ learning and induce higher engagement about the product, which resulting in purchasing the product. Results from the proposed full model have not been obtained yet. We also need to assess the full results in further research.

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