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CONSUMERS' ENDORSEMENT EFFECTS ON MARKETER AND USER-GENERATED CONTENT IN A SOCIAL MEDIA BRAND COMMUNITY

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Abstract

The effects of marketer-generated content (MGC) and user-generated content (UGC) on inducing consumers' responses have been widely studied as stand-alone main effects. Extending these research, this paper studies the interaction effects of consumers' endorsements on MGC and UGC posts in a social media brand community (SMBC) of a popular Asian fashion retailer. We examined if passive and active consumers' endorsements have enhancement effects on MGC/UGC and if they are also effective in inducing consumers' expenditure by themselves. Passive endorsement refers to "likes" on social network sites (SNS), while active endorsement refers to the more involved act of "commenting" on a post. We found evidence that active endorsements positively moderate the effects of MGC in inducing consumers' expenditure. However, passive endorsements negatively moderated MGC, making it less effective in inducing expenditure. Interestingly, the results were reversed for UGC whereby passive endorsements positively moderated UGC, while active endorsements negatively moderated UGC in inducing expenditure. Meanwhile, active endorsements through social-tagging on brand fans were found to be very effective, with recipients of social-tags spending $6 more than non-recipients in a particular week. Additional robustness checks on selection bias were conducted, and results remain qualitatively similar.

Keywords: Social media brand community, MGC and UGC, Digital advertising, E-business

1 INTRODUCTION

Social media have become too big to ignore for digital marketers. Nearly 1.01 billion people log on to Facebook on a daily basis and almost 50% of 18-24-year-olds check Facebook when they wake up (Facebook 2015). Capitalizing on these new opportunities, marketers created social media brand communities (SMBC) to engage their consumers on social media. Through the creation of SMBC, marketing communication has transformed from being a passive monologue to rich conversations with consumers (Rowley 2004; Deighton and Kornfeld 2009). However, this phenomenon has also introduced a trade-off: marketers are unable to precisely control their message diffusion (Berthon et al. 2008; Malthouse et al. 2013). They are bombarded with a constant stream of content from users. Questions arise on whether such user content adds value to businesses.

Fortunately, prior research provides evidence that marketer-generated content (MGC) and user-generated content (UGC) content on social network sites (SNS) benefited businesses by inducing higher expenditure and store visits in customers (e.g., Chevalier and Mayzlin 2006; Dhar and Chang 2009; Goh et al. 2013; Rishika et al. 2013). However, this field of research typically simplified SNS dialogues into simple total posts count (volume) and simple average sentiment score without capturing the full richness of two-way dialogues in SMBC. For instance, how would conversations between consumers and marketers (C2M), and between consumers and consumers (C2C) through comments, change the effectiveness of the original post? Research have shown that consumers do not completely trust the information in MGC due to information asymmetry and the suspicion of hidden motive in marketers (Escalas 2007; Goh et al. 2013). In contrast, consumers seem more trusting of UGC since word-of-mouth (WOM) recommendations originate from users with whom they believe to share similar tastes and preferences (Trusove et al. 2009; Bakshy 2012; Goh et al. 2013).

Despite the various research that has been carried out on MGC and UGC effects, we find a lack of literature that empirically investigates consumers' endorsements in a SMBC. This paper aims to research on whether consumers' endorsements affect the strength of the MGC/UGC in inducing expenditure. We examined endorsements on two levels: (1) Passive endorsements through "likes", and (2) Active endorsements through commenting or the act of social-tagging someone in a post. Backed by this research objective, our research question is as such: How are consumers' purchase behaviour influenced by MGC and UGC under the influence of customers' endorsements and whether and how the strength of endorsements differ for MGC and UGC.

To answer our research question, we collected UGC, MGC and customers' endorsements data from a fashion retailer's brand community on a popular social media site. We then matched community members' purchase from the retailer's customer reward program database. Our econometric specification models consumers' weekly expenditure per transaction as a function of UGC, MGC and consumers endorsements as well as consumer's endorsements as moderator variables for UGC and MGC controlling for other factors.

Our findings show that passive endorsements on MGC and active endorsements on UGC increase consumers' expenditure like a WOM, Interestingly, active MGC endorsements through social-tagging caused the recipient of the tags to increase their purchase by $6 in a single week

Active endorsements also make MGC more persuasive in inducing expenditure, while passive endorsements cause MGC to be less effective. In comparison, passive endorsements increased the persuasiveness of UGC content, while active endorsements decreased the persuasiveness of the UGC in inducing expenditure.

With our findings, marketers now have evidence that engaging brand fans by soliciting responses from them proves beneficial to their marketing communication strategies. In fact, they can leverage on these synergistic effects to co-create an effective communication strategy.

This paper makes a few key contributions. First, our study empirically showcased the positive business value of garnering SMBC members' responses in the form of endorsements. Such effects can be capitalized on to create a more persuasive marketing communication strategy since endorsements make UGC/MGC more effective. Second, our findings demonstrate the differential impact of endorsements on different forms of content, by contrasting the impact of active and passive endorsements on MGC and UGC. This shows that garnering endorsements should not be a one-size-fits-all approach. Finally, to the best of our knowledge, our research is one of the first that quantifies the direct business value of customers receiving a social tag from their peers. This was found to be the most powerful form of active endorsement.

2 LITERATURE REVIEW

2.1 Brand Community

A brand community is defined as "a fabric of relationships in which the customer is situated" (McAlexander et al. 2002). Customers identify themselves with a brand community due to their positive relationship with the brand (Algesheimer et al. 2005). According to McAlexander (2002), these customers also tend to volunteer as "missionaries" carrying WOM around, and thus are more forgiving than others regarding product failures or lapses in service quality. Through this common brand identification, customers are motivated to form relationships with one another and they volunteer in a few roles such as mentor, learner, and guide, to keep the community running (Fournier and Lee 2009). In terms of business value, a SMBC's strength can affect a brand's profitability. Brodie et al. (2013) showed that engaged consumers in a brand community exhibit "greater consumer loyalty, satisfaction, connection, emotional bonding, trust, and commitment". Therefore, customers have the influential capability to work with marketers and co-create the whole brand experience.

From this brand community phenomenon, we can see that customers have an urge to interact with firms and "co-create" to extract greater value and satisfaction from the transaction (Prahalad and Ramaswamy 2004; Lusch and Vargo 2006). Customers are known to actively co-create brand identities with marketers and shape brand meanings, thus boosting the overall brand relevance and value (Bendapudi and Leone 2003; Payne et al. 2009). We believe these co-creation effects occur too in the SMBC scene. We expect customers to have an intention to interact and endorse MGC/UGC due to their desire to become "missionaries" for their favourite brands (McAlexander et al. 2002). They want to contribute useful comments or show approval through "liking" the post, or even actively endorsing and recommending brands to their friends through "social-tagging".

2.2 Communications

SNS essentially represent communication platforms between customers and marketers. In communication theory, the major components of communication are (1) The Source (2) The Message (3) The Audience (4) The Channel and (5) The Intended Effects (Berger 2014). Many studies have been done on (1), where numerous researchers compared the relative effects of MGC and UGC on inducing expenditure (Goh et al. 2013; Scholz et al. 2013). These papers added MGC and UGC dimensions to volume (total count) and valence measures of SNS and found that consumers generally perceive UGC to be more credible sources than MGC, and thus UGC tends to be more effective. There has also been much research done on (2), with some applying NLP techniques and others performing a content analysis (Goh et al. 2013; Lee et al. 2014; Gopinath et al. 2014). In Gopinath et al.'s paper, content was dissected into attribute-focused messages and emotion-focused messages while in Lee et al.'s paper, content was grouped into informative vs persuasive dimensions. In Goh et al.'s paper, a manual process was used to measure the information richness in the messages. There is also literature covering (3), where communications were split according to directed or undirected communication (Goh et al. 2013). Similarly, there have been much studies done on (5), where WOM effects were studied for stock price performance, number of store visits, and multi-stages consumers' decision model (Luo 2009; Rishika et al. 2013; Scholz et al. 2013). Few research papers have examined the effects of group conversations on SNS, where marketers or users start topics, and users can support by endorsing the message through “liking” or commenting in response to it. This paper tries to do so by focusing on (1), where we examine mixed-sources content due to the effects of endorsements on the original MGC/UGC, (2) the effects of endorsements’ content on the original message, and (3) by examining the effects of social-tags as a form of active endorsements.

2.3 Customers’ endorsements

One key feature that SNS has is endorsements (i.e., “likes” and comments), which are publicly visible to other brand fans. Prior research has grouped endorsers into a few categories. They include celebrities, spokespersons, experts and consumers (Fireworker and Friedman 1977). Prior works on endorsements have mostly been done on celebrity endorsements. The meaning transfer model proposes that meaning and attributes passed from celebrity to the product and from the product to the celebrity (McCracken 1989). However, not much work has been done on investigating the mechanism of customers’ endorsements despite them becoming increasingly prevalent in recent years due to the emergence of SNS and online consumer reviews (OCR). Fireworker and Friedman (1977) proposed that customers’ endorsements significantly improve the overall attitude of other customers towards the product, thereby increasing the expected retail price. There has been some research on the motive of contributing an online endorsement. In Lee et al.’s (2016) paper, it was found through an experimental design that most users participate in virtual endorsements because they enjoyed the content, and want to maintain interpersonal relationships with other brand fans in SNS. Virtual endorsements also serve as a form of expressing public support. Attachment to a brand has also been suggested as a reason for consumers to advocate for other users and support MGC messages in a social networking scene (VanMeter et al. 2015). Consumers are also more willing to engage in brand communities in the form of ”likes”, “shares” and comments when they feel a personal connection to the brand (Chen et al. 2015). We find a lack of literature on the empirical impacts of online customers’ endorsements in a SNS site and this paper serves to fill the gap.

3 RESEARCH MODEL AND HYPOTHESES

We first examine the effects of passive endorsements on MGC in inducing expenditure. Passive endorsements can be viewed as a form of WOM albeit the lack of content (Stacey et al. 2013). It signals support for the MGC from the brand fan. Thus, we speculate that a greater extent of passive endorsements can directly influence expenditure of customers.

Besides direct effects, we also propose positive moderating effect of passive endorsements on MGC. Research have proposed that trust in communication is related to the perceived trustworthiness and expertise of the source (Hovland and Weiss 1951). In this case, the marketers are the source who have great knowledge of the products they produce/own. Despite this expertise, users do not trust MGC as much as UGC as they feel that marketers can manipulate their product knowledge by employing trickeries and exaggeration, to persuade customers to make a purchase in the pursuit of higher profits (Mishra et al. 1998; Escalas 2007; Goh et al. 2013). Meanwhile, consumers generally perceive passive endorsement as a less biased source as other users typically do not have no hidden agenda. They see passive endorsement as a form of verification and approval of the MGC content. Their trust on other customers’ endorsements may transfer positively on the original MGC, thus inducing customers to be more accepting of the original marketing message and result in purchases (Uzzi 1996; Stewart 2003). Thus, we postulate that a greater extent of passive endorsements on the original MGC post will reduce the amount of scepticism, hence increasing customers’ trust in MGC and as a result increase their expenditure. In addition, by giving passive endorsements to the post, a brand fan is also sending out signals to his/her friends, who may also be members of the same fan page. This will cause their friends to be more receptive to the MGC message due to a strong-tie effect (Ryu and Feick 2007). Hence, we propose:

Hypothesis 1A (Main Effect): A higher extent of passive endorsements on MGC posts is positively related to a higher level of consumer expenditure.

Hypothesis 1B (Moderating Effect): There is an interaction effect between the extent of passive endorsements on MGC and the volume of MGC posts, such that as the extent of passive endorsements increases, the positive relationship between the volume of MGC posts and consumer expenditure is strengthened.

Next, we move on to active endorsements. Similar to passive endorsements, active endorsements may serve as valuable WOM and persuade consumers to increase their expenditure. Moreover, active endorsements also contain more useful information as compared to passive endorsements. Consumers may be more trusting of this additional information and thus use them to make a more informed decision.

In addition, an active endorsement may sometimes be directed to another customer and thus has a social-tagging feature. We postulate this as a stronger form of WOM. Research has shown that social tags help organize content and deliver the most relevant content to the right person (Nam & Kannan, 2014). Social tagging can also be seen as a form of narrowcasting and helps deliver useful and relevant information to targeted recipients. According to Barasch and Berger (2014) the benefits of narrowcasting, a form of one-to-one communication, comes in the heightening of attention on the recipient's end. Similarly, Goh et al.'s (2013) paper has provided empirical evidence that directed content is effective in inducing expenditure. We also theorize that consumers have an urge to reciprocate to tags as a result of peer pressure (Mittone and Ploner 2010). Thus, we propose that consumers may increase their expenditure from direct exposure to active endorsements.

In addition, these active endorsements also portray a good level of social affinity and interaction among brand community members and marketers, and consumers who are exposed to these endorsements may reciprocate by paying more attention to the original post (Cheng et al. 2011; Lewis 2015). Furthermore, past research has supported and showed that consumers' endorsements are effective. Consumers' endorsements can be as effective as celebrities and experts endorsements, having the power to change the taste and intent-to-purchase of other customers (Friedman et al. 1976). Similarly, according to Strub and Priest (1976), buyers tend to trust a seller more if they receive endorsements from other consumers vouching for the brand, and this applies regardless whether the potential buyers have dealt with the seller. Thus, a higher extent of active MGC endorsements may lead to consumers becoming more receptive of the original MGC message leading to an eventual increase in expenditure. Thus, the corresponding hypotheses are:

Hypothesis 2A – (Main Effect): A higher extent of active endorsements on MGC posts is related to a higher level of consumer expenditure.

Hypothesis 2B – (Moderating Effect): There is an interaction effect between the extent of active endorsements on MGC and volume of MGC posts, such that as the extent of active endorsements increases, the positive relationship between the volume of MGC posts and consumer expenditure is strengthened.

We move on to passive endorsements on UGC. First, passive endorsements on UGC signifies supports from brand fans and hence popularity of a brand. Consumers may take this popularity as a form of observational learning on the brand and decide to consume more of the brand (Cai, Chen and Fang 2009). Thus, having a higher extent of passive endorsements may lead to consumers spending more.

According to Goh et al. (2013), UGC in a brand community has been empirically shown to influence purchase expenditure through both informative and persuasive communications. Passive endorsements can also increase the persuasive communication component of UGC as it can portray the amount of group agreements and support for UGC content. These passive endorsements may be utilized by other consumers as a form of consensus heuristic, thus pushing them more towards a purchase decision (Purnawirawan et al. 2014). Thus, a consumer will be more convinced by UGC posts with more passive endorsements as they use these signals as extra evidence for the credibility and usefulness of the original post, and may then be more receptive to making a purchase.

Hypothesis 3A – (Main Effect): A higher extent of passive endorsements on UGC posts is related to a higher level of consumer expenditure.
Hypothesis 3B – (Moderating Effect): There is an interaction effect between the extent of passive endorsements on UGC and volume of UGC posts, such that as the extent of passive endorsements increases, the positive relationship between the volume of UGC posts and consumer expenditure is strengthened.
Similar to the prior argument, active endorsements on UGC is postulated to serve as WOM as they contain textual information about the brand and its' products. Thus, we believe greater extent of active endorsements on UGC will lead to increased expenditure.

Next, prior arguments for the previous hypothesis have argued that communication trust is based on trustworthiness and expertise of the author (Hovland and Weiss 1951). Despite an absence of hidden agenda in brand fans, the trustworthiness of UGC may still be an issue as most users may not be familiar with the consumer who is posting the WOM. They may wonder if the UGC originator has the same taste and preference as the average person in the community. Having extra information through active endorsements on UGC can allow consumers to conduct cross references and further validate the truth of the original UGC. In addition, active endorsements are usually fewer in quantity compared to passive endorsements since it takes minimal effort for people to endorse a post passively. Thus, there will be more focus on the originator of these endorsements, and consumers may pay attention to the identity and even photo of the endorsers when looking at UGC. Visual and textual information have been shown to be used by online users to form trustworthiness of another party (Toma 2010). With such trust, consumers may have a greater propensity to change their attitude towards the brand. Empirically, research has supported that consumers' endorsements on social media can shape and influence audience's attitudes (Freberg et al. 2011). Thus, we propose the following, which are similar to active endorsements on MGC:
Hypothesis 4A – (Main Effect): A higher extent of active endorsements on UGC posts is related to a higher level of consumer expenditure.
Hypothesis 4B – (Moderating Effect): There is an interaction effect between the extent of active endorsements on UGC and volume of UGC posts such that as the extent of active endorsements increase the positive relationship between the volume of UGC posts and consumer expenditure is strengthened.

4 RESEARCH METHODOLOGY

4.1 Research Context

Our research context is an international apparel's SMBC [1]set up in July 2009 in Asia. The retailer has provided us with customer information from their customer loyalty program.

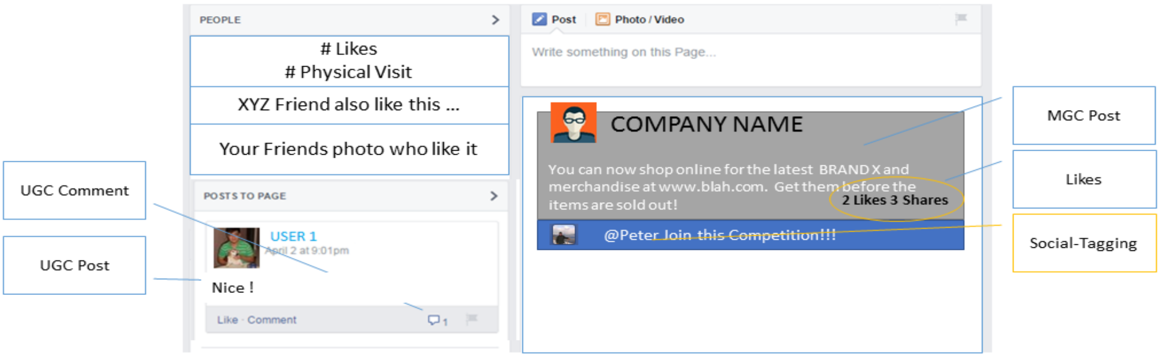

Figure 1. Illustration of layout of the SNS site

[1] Unfortunately, due to non-disclosure agreements, we are not allowed to disclose the identity of the retailer as well as the SNS platform.

Consumers can "like" the page which allows them to subscribe to content and posts from the retailer on their personalized feeds. They can also share interesting posts on the page and tag their friends on posts, which will then prompt a private notification. Whatever posts they have started on the fan page will also appear in their friends' newsfeed. Consumers can also respond to posts by commenting on them, which also triggers a notification on their friends' newsfeed. The first page of the SMBC website contains marketer's posts that fill up the major proportion of the screen while consumers' UGC appear in a corner of the screen.

4.2 Data Description

Our dataset combines four sources: (1) a longitudinal dataset on SNS posts content, (2) SNS panel dataset that gives SNS account details such as the number of friends, (3) panel level transaction data from the retailer and (4) customer loyalty program data containing demographic data of customers. We adopted a weekly convention for our measures. In total there are 117 weeks that correspond with the period from 15-09-2009 to 13-12-2011. In total, we have 1,247 users who are both loyalty program customers and also SMBC fan members.

In our research, we measured purchase behaviour by quantifying the mean expenditure of each customer. This is computed by taking the sum of all revenue in each week divided by the number of transactions that happened in the week. As for MGC and UGC, we only considered posts that are topics on the brand community fan page. Meanwhile, we operationalize passive endorsements as "likes" on SMBC and active endorsements as comments and social-tags on the SMBC. The table below give a summary of the key variables:

Categories	Variable	Mean and Range	DESCRIPTION
Dependent Variable	Expend	3.24 [0-501]	Average expenditure per shop trip in a week for the focal customer
MGC	Mgctopics	2.48 [0 - 10]	Volume of posts started by the marketer in a week
	Mgctopics.Likes	31.5 [0 - 445]	Volume of fans' "likes" on the posts started by the marketer in the week
	Mgctopics.Comments	5.74 [0 - 79]	Volume of fans' comments as reply on posts started by the marketer in the week
	Mgctopics.Comments. Valence	0.12 [0 - 1]	Average sentiment score of all text content of fans' comments on MGC posts in the week
	Mgctopics.Valence	0.21 [0 - 1.28]	Average sentiment score of the text content of all posts started by the marketers in the week
	Mgc.Received.Tags	0.00014 [0 - 9]	Volume of social tags received by the focal customer on MGC posts in the week excluding tags originating from marketers[2]
UGC	Ugctopics	1.39 [0 - 10]	Volume of posts started by brand fans in the week
	Ugctopics.Likes	1.53 [0 - 85]	Volume of fans' "likes" on UGC posts started in the week
	Ugctopics.Comments	0.82 [0 - 12]	Volume of fans' comments on posts excluding the author's own comment
	Ugctopics.Comments. Valence	0.052 [-0.08 - 0.71]	Average sentiment score of all text content of comments on UGC in the week
	Ugctopics.Valence	0.089 [-0.21 - 1.54]	Average sentiment score of the text content of all posts started by the fans in the week
Demographics Data			

[2] Only a small number of customer receive tags on MGC posts. There are no tags on UGC posts comments other than marketers' replies to UGC.

Probit Variables / PSM	Phonedis	0.46 [0-1]	Dummy indicating whether customer is opened to receiving phone calls for promotional deals
	Maildis	0.09 [0-1]	Dummy indicating if a customer is opened to receive email promotional content
	Age	32.22 [7.89-42.80]	Age of focal customer
	Loyalty.Mem.Age	3.28 [0 – 2.42]	Years of focal customers being part of the brand customer loyalty program
	Average.Exp	3.22 [0-34.59]	Average expenditure of customer per week
	Transaction.Per.Week	0.08 [0 – 0.50]	Average number of transaction per week for customer
	Monthly.Income	2893 [0-7501]	Monthly income of customers in their local currency
	Gender.Male	0.107 [0-1]	Dummy variable to indicate if customer is a male

Table 1. Selected explanations of various independent variables

In order to check and control for potential self-selection (into the SMBC) effect, we first performed propensity score matching (PSM) on our 1,247 customers to identify a separate set of 1,247 users who are loyalty program members but did not join the SMBC. They have similar selected attributes (e.g., willingness to be phoned, mailed, and years in the loyalty program) with the 1,247 fan members, and this total of 2,494 customers' data is used in our Heckman selection model for robustness checks.

Variables	**Before PSM Mean Value**		**After PSM Mean Value**		**T-statistics of diff**		**T-test p-value**	
	Control	*Treated*	*Control*	*Treated*	*Before*	*After*	*Before*	*After*
Phone.Dis	0.43	0.46	0.43	0.43	1.74	-0.32	0.08*	0.75
Mail.Dis	0.08	0.09	0.08	0.09	1.13	0.98	0.26	0.33
Age	31.47	32.22	31.47	31.27	3.55	-0.63	0.00***	0.53
Loyalty.Memb.Age	3.39	3.28	3.39	3.39	-9.89	0.25	0.00***	0.80
Average.Exp	3.03	3.22	3.03	3.09	1.45	0.32	0.15	0.75
Transaction.Per.Week	0.07	0.08	0.07	0.07	0.88	0.17	0.38	0.86
Monthly.Income	2239.09	2893.77	2239.09	2235.08	10.94	-0.04	0	0.96
Gender.Male	0.10	0.107	0.109	0.09	-0.25	-1.05	0.80	0.29

Table 2. T-test of various attributes between non-SNS fan control group and treatment group

4.3 Empirical Model

We classified our SNS exposures into 2 x 3 dimensions according to exposure types (MGC, UGC) and post type (topics, "likes" and comments). We lagged SMBC exposures variables and ran a panel regression with consumers' expenditure as the response variable. We included interaction effects for "likes" and comments on MGC/UGC topics.

$$Expend_{c,t} = \beta_1 Mgctopics_{t-1} + \beta_2 Mgctopics.Likes_{t-1} + \beta_3 Mgctopics.Comments_{t-1} +$$
$$\beta_4 Mgctopics.Comments.Valence_{t-1} + \beta_5 Mgctopics.Valence_{t-1} +$$

$$\beta_6 Mgctopics.Received.Tags_{c,t-1} + \beta_7 Ugctopics_{t-1} + \beta_8 Ugctopics.Likes_{t-1} + \beta_9 Ugctopics.Comments_{t-1} + \beta_{10} Ugctopics.Comments.Valence_{t-1} + \beta_{11} UGCTopics.Valence_{t-1} + \beta_{12} Mgctopics_{t-1}\ x\ Mgctopics.Likes_{t-1} + \beta_{13} Mgctopics_{t-1}\ x\ Mgctopics.Comments_{t-1} + \beta_{14} Ugctopics_{t-1}\ x\ Ugctopics.Likes_{t-1} + \beta_{15} UGCTopics_{t-1}\ x\ Ugctopics.Comments_{t-1} + \sum_k \beta_k\, Smbc_{CONTROLS_{c,(t-1)}} + \sum_j \beta_j\, Controls_{c,t} + \phi_t + \alpha_c + \varepsilon_{i,t}$$

Where *c* denotes the individual, *t* denotes the week number, ϕ_t denotes month and year dummy variables to control for seasonality, α_c represents individual specific effect and $\varepsilon_{i,t}$ represents the residual term of the regression. k represents the number of SMBC controls and j represents the number of demographic and purchase related controls. For the sentiment score, we used a bag of words approach to compute the average sentiment of the posts for the week in an open source R package titled QDAP. SMBC control variables include the years of individual *c* on the SNS platform, the number of SNS friends the individual has, the number of SNS friends who are part of the fan page, the volume of photo posts, the volume of photo comments, volume of photo likes, as well as interaction of volume of photo posts with photo likes and photo comments. For the other controls, they include demographic variables such as the age of the individual, a dummy variable to control for loyalty program birthday month promotion, whether any loyalty program benefits are being used in the week, the average discount in the week versus prices last month, gender, and the average price of products in that week .

In our Heckman selection procedure, we first introduced a probit selection equation and then combined it with the main model. The probit equation predicts the probability of an individual joining the SNS fan page. Given variables Z which are time-invariant and their coefficients γ:

$$BRAND_{COMMUNITY_c^*} = \gamma Z = \gamma_1 Age + \gamma_2 Income + \gamma_3 Loyalty.Memb.Age + \gamma_4 Phone.Dis + \gamma_5 Mail.Dis + \gamma_6 Gender.Male$$

$$\Pr(BRAND\_COMMUNITY_c = 1|Z_c) = \Phi(Z_c\gamma)$$

$$\Pr(BRAND\_COMMUNITY_c = 0|Z_c) = 1 - \Phi(Z_c\gamma)$$

$$EXPEND_{c,t}\ Observed\ if\ BRAND\_COMMUNITY_c = 1$$

In specifying the models, we made a few assumptions to simplify matters. Our first assumption is that we are expecting consumers to read all new posts in the same week when the posts are created. We believe this is reasonable as 48% of them log in to the platform every day (Statisticbrain.com, 2015). Second, we assume that all fan responses (e.g., "likes", comments and tags) occur within the same week as the creation of the original post.

5 RESULTS AND DISCUSSION

5.1 Preliminary Analysis And Results

We first carried out data checks such as correlation analysis and variance inflation factor (VIF) analysis. There were a few pairs of variables with correlation greater than 0.7. Nevertheless, these variables were still found significant in our models and were not causing collinearity problems according to our VIF analysis, thus we kept them in our model. Next, we started off modelling with a pooled-OLS, followed by a Random Effect (RE) model and then finally Fixed Effect (FE) model using a within-estimator. A Hausman test was conducted and we found that the RE model was inconsistent (χ2 =1293.66, df=99, p-value < -2.2 x 10-16). Thus, we rejected the RE model. Furthermore, we ran a fixed-effect Heckman selection model as described above. However, the inverse mills ratio (-0.75, SE: 2.16) was not found to be significant, indicating the absence of strong selection effects. Rho was at -0.057, indicating a non-significant selection effect. We thus take the FE model as our final model.

Furthermore, we ran an Arellano standard error procedure on our FE model to correct for the potential bias due to cross-sectional dependence. Most coefficients still retained their significance except a single control variable which measures the amount of focal customer's own post in the week. Thus, our final model is the FE model with an adjusted r-square of 15.1% and F-stats value of 412.104.

	Dependent variable: Mean revenue per transaction/ weekly			
	1: Pooled OLS	**2: Random Effects**	**3: Fixed Effects**	**4: Heckman Fixed Effects**
Mgctopics	0.143***	0.142***	0.139***	0.143***
Mgctopics.Likes	0.010**	0.010**	0.011**	0.01**
Mgctopics.Comments	-0.129***	-0.129***	-0.137***	-0.129***
Mgctopics X Mgctopics.Likes	-0.004***	-0.004***	-0.005***	-0.005***
Mgctopics X Mgctopics.Comments	0.024***	0.024***	0.024***	0.024***
Mgc.Received.Tags	6.188***	6.191***	6.277***	6.189***
Ugctopics	-0.166***	-0.165***	-0.197***	-0.166***
Ugctopics.Likes	-0.030	-0.028	-0.037	-0.03
Ugctopics.Comments	0.349***	0.345***	0.364***	0.349***
Ugctopics X Ugctopics.Likes	0.038***	0.038***	0.042***	0.038***
Ugctopics X Ugctopics.Comments	-0.058***	-0.057***	-0.056***	-0.058***
Other control variables included. Demographics controls included only for RE and pooled OLS.				
Constant	3.640***	3.635***	-	4.253**
Observations	112,911	112,911	112,911	244,013
R2	0.166	0.172	0.153	0.166
Adjusted R2	0.166	0.171	0.151	0.165
F Statistic	448.474*** (df = 50; 112860)	467.391*** (df = 50; 112860)	412.104*** (df = 49; 111615)	

Table 3. Results for the various form of regression. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5.2 Main Results

We first present a few charts to aid understanding of moderating effects.

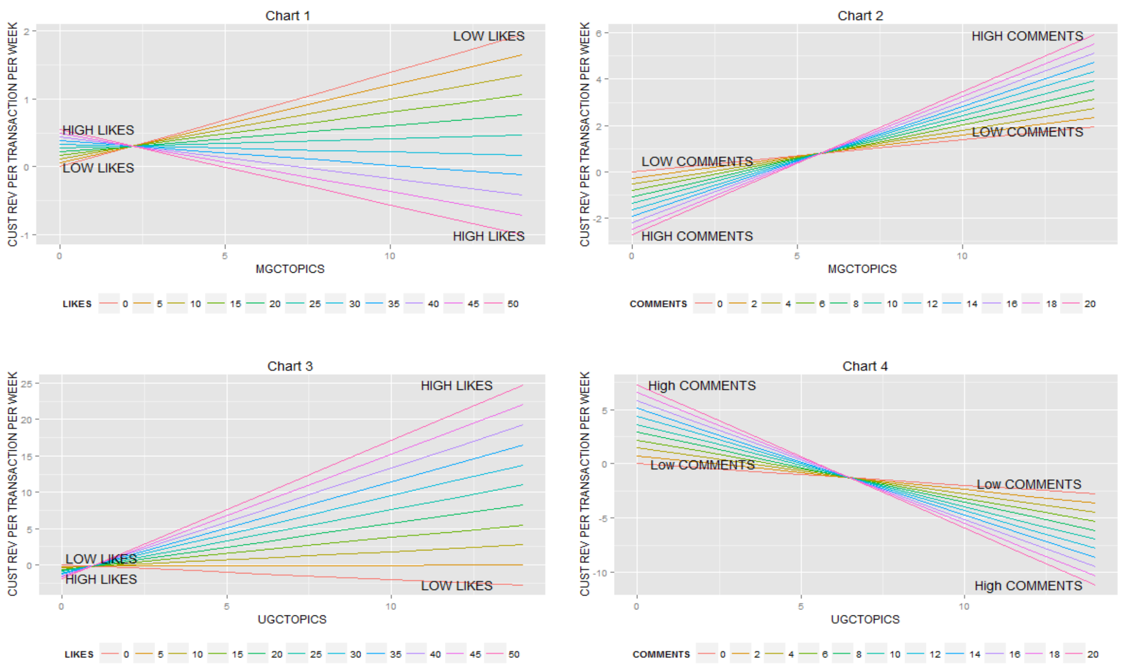

Figure 2. Charts illustrating moderating effects given other variables=0 (Top: MGC, Bot: UGC)

For the first hypothesis (H1A), "likes" on MGC (Mgctopics.Likes) was found to be the significant main effect for consumers' expenditure (β=0.011; p-value<0.05). This validated H1A and suggests that passive endorsement functions like a kind of WOM signal. Generally, consumers are cognizant of the number of likes around MGC posts in a week and react to passive endorsements like WOM, despite the lack of content. For H1B, the hypothesis is rejected as the beta coefficient of the interaction effect Mgctopics.Likes x Mgctopics was found to be in the opposite direction (β=-0.005; p-value<0.01; Chart 1). Thus, passive endorsements do not positively moderate MGC. Conversely, more "likes" actually decreased the effectiveness of MGC in promoting expenditure.

For H2A, active endorsements through comments on MGC (Mgctopics.Comments) were found not supportive of the hypothesis (β=-0.137; p-value<0.01). The negative coefficient seems to hint that comments on MGC served as negative WOM instead. Contrastingly, active endorsements through our alternative operationalization which is social tags on MGC (Mgc.Received.Tags) supported the hypothesis. In fact, it was proven to be very effective, with each social tag causing the consumer to spend $6.00 more in future purchases (β=6.277; p-value<0.01). Therefore, we found mixed evidence for H2A.

For H2B, comments on MGC (Mgctopics.Comments) was found to moderate MGC positively via the variable Mgctopics.Comments X Mgctopics (β=0.024; p-value<0.024; Chart 2) and is thus supported. Therefore, a greater extent of active endorsements through comments on MGC boost the original MGC content in persuading consumers to increase their expenditure.

For H3A, "likes" on UGC (Ugctopics.Likes) was not found to have any effect on consumers' expenditure (β=-0.037; p-value>0.1). For H3B, "likes" on UGC was found to make UGC posts more effective based on the coefficients of the variable Ugctopics.Likes X Ugctopics (β=0.042; p-value<0.01; Chart 3). In fact, it is the strongest among all moderator effects being tested. This means that more passive endorsements through "likes" actually make the original UGC message more effective in persuading consumers to increase their expenditure.

For H4A, comments on UGC (Ugctopics.Comments) was found to directly influence future expenditure (β=0.364; p-value<0.01). Thus it seems that consumers do use additional information from active endorsements on UGC to decide on consuming the brand and product. For H4B, comments on UGC does not make UGC more influential. This is deduced from the coefficient of the variable Ugctopics.Comments X Ugctopics (β=-0.056; p-value<0.01; Chart 4). Our results show that more active endorsements on UGC have no effects on accentuating the UGC's impact on inducing consumers' expenditure. The table below summarizes the results of our hypotheses tests.

Main Effects

	Passive Endorsements	**Active Endorsements**
MGC	H1A supported	Mixed. "Comments" do not support H2A and has a negative coefficient. Social-tags do support H2A
UGC	No. H3A not supported. Not significant.	H4A supported

Moderating Effects

	Passive Endorsements	**Active Endorsements**
MGC	No. H1B not supported. Opposite result found.	H2B Supported.
UGC	H3B supported	No. H4B not supported. Opposite result found

Table 4. Summary of results

5.3 Discussions

In this section, we start off we discussing all our negative findings for the main effects first then the moderating effects. For H2A, at first glance, one might wonder why active endorsements on MGC (via comments on MGC) have a direct negative relationship with consumers' expenditure as a main effect. This seems counter-intuitive. While this may warrant further investigation, we want to caution against interpreting the coefficient of main effect variables directly with the presence of interaction effects. Even though the beta coefficient for active endorsement is negative for MGC main effect variable, it does not mean that more comments on MGC lead to lower future revenue. The coefficient indicates the hypothetical increase in future average week expenditure given that other moderating variables are zero-valued. The real per-unit increase of comments on MGC depends on the number of MGC. In fact, given a high number of MGC, comments on MGC leads to increased expenditure per customer.

We note here that there are four sets of cross-over interaction effects here. On low volume of MGC, passive endorsements do complement and positively boost the effectiveness of MGC (fig 2, chart 1). However, on a high volume of MGC, active endorsements start taking over and positively moderate MGC (fig 2, chart 2).

Contrastingly, on low volume of UGC, active endorsements boost the effectiveness of UGC (fig 2, chart 4). At a higher volume of UGC, passive endorsements start to dominate (fig 2, chart 3), possibly due to consumers looking out for popularity cues as a form of consensus heuristic for expenditure decision.

Moderating Effects

	MGC	**UGC**
Low Volume	Passive endorsements better	Active endorsements better
High Volume	Active endorsements better	Passive endorsements better

Table 5. Table to illustrate cross-over effects

For MGC, a unit increase in passive endorsements leads to an increase in consumers' expenditure only in weeks with a low volume of MGC. With a high volume of MGC, active endorsements are better. Perhaps, consumers require more lengthy information through active endorsements in the event of more information uncertainty from the increase in MGC content (Lauraeus-Niinivaara et al. 2007). Consumers may be using these active endorsements to support their decision in face of a high volume of MGC.

For UGC, a unit increase in active endorsements on UGC increases expenditure but only in weeks of low volume for UGC. With a low volume of UGC, since there is a lack of information supplied through UGC, active endorsements on these UGC may serve to carry more new information and support consumers in their information search pre-sales decision(Urbany et al. 1989). With a high volume of UGC, since there is enough informational value in UGC, passive endorsements (expressed through "likes" become more important as they convey popularity (de Vries et al. 2012). These postulations require further validation in experimental settings.

5.4 Limitations and Future Research

We observed various limitations while conducting our research. First, our research is based on observational data and was not generated from randomized trials or field experimentations. This prevents us from conclusively declaring a causal link between the focal variables. Furthermore, usage and analysis of secondary or observational data do not provide insights into the underlying psychological mechanisms of consumers.

Although we performed a robustness check against Heckman's selection model, our Heckman selection did not include correction for heteroskedasticity and panel data structure

In addition, we adopted a simplified research design and did not differentiate MGC/UGC according to their type of messages. For instance, we did not differentiate endorsement effects between informative content and persuasive content as described in Dokyun et al.’s (2014) paper. Furthermore, the data was obtained from a single Asian fashion retailer, and thus may not be sufficient to represent the complexities of brand communities as a whole.

Potential extension of our research could include investigating consumers’ purchase decision based on a multi-stage decision model. Secondly, future research can investigate if consumers’ endorsements have differing impacts on different types of contents (e.g., promotion-orientated versus light-hearted content).

6 CONCLUSION

This paper brings about the following contributions. First, we empirically examined the effects of passive endorsements in the form of “likes” and active endorsements in the form of comments and social-tags in a SMBC. We found that passive endorsements on MGC, active endorsements (through social-tags) on MGC, and active endorsements on UGC all work to influence a customer's expenditure positively the following week. In other words, this means that more ”likes” and social-tags on MGC posts, and more comments on UGC posts positively led to increased customer spending in subsequent weeks. Interestingly, this paper finds strong evidence of active endorsements through social-tags on MGC being very effective. We found that recipients of social tags increased their subsequent week’s expenditure with the brands by about $6.00. We thus present new set of evidence that SMBC members’ endorsements can bring about positive business values to any company.

Second, we are one of the pioneer efforts to examine moderating effects of these endorsements. We found that active endorsements boosted the effectiveness of MGC in increasing subsequent months’ purchase while passive endorsements weakened the effects of MGC. This means that more comments on MGC actually leads to the original MGC content being more effective while more ”likes” on MGC actually weakens the persuasiveness of MGC in inducing expenditure. As for UGC, we discovered a different finding for the moderating effects. Passive endorsements were found to be positive moderators for UGC content while active endorsements were found to be negative moderators. Our findings catalogue the differential impact of endorsements on different forms of content, by contrasting the impact of active and passive endorsements on MGC and UGC.

Our results bring about practical implications. Marketers must understand that marketing on a SMBC is not a mere one-way communication, and the “amount of airtime” for marketers must be evenly matched with consumers’ responses to produce synergy. Marketers should deploy strategies to engage and encourage brand fans to participate more on their SNS. In doing so, customers’ endorsements such as “likes”, comments and social-tags would help boost the overall effectiveness of the marketer’s goal to increase consumers’ expenditure. For instance, marketers can try to start an online contest and encourage users to post photos of them with their products. This can create buzz and conversations on the social network platform and have beneficial effects to the brand ultimately.

Our study highlights the importance of earning endorsements from rallying SMBC brand fans and that these responses complement other content on the SMBC. This allows social media marketers to build impactful and cost-effective communication strategies in contrast to traditional advertising strategies that require significant investment into traditional advertising. They can tap into their customers to further amplify their online SMBC advertising strategies.

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