ABSTRACT
A faster growing Social Media based Brand Community (SMBC) is expected to be conducive to better organizational outcomes. However, there is limited understanding of the dynamic relationships between users’ participation measured by their comments, shares, and likes and the growth rate of SMBCs. In this study, we examine these relationships. Our initial analysis suggests interesting relationships and dynamics between the metrics of measuring user participation and the growth rate of SMBCs.

KEYWORDS: Social media, brand communities, consumers, comments, shares, likes

INTRODUCTION
As a non-hierarchical and open platform, social media enables the real-time interactions among people in which they create, share, or exchange information and ideas. It is shifting the paradigm of information flow and consumer interactions (Kaplan and Haenlein 2010). Some well-known social media platforms include Facebook, Twitter, and YouTube. All these social media platforms have rapidly grown in size and importance in recent years. For example, as of September 2013, the online social networking site Facebook has over 1.19 billion monthly active users and the number is still fast growing (Facebook 2013). Individuals and businesses can create a Facebook page without a fee. In particular, it allows firms to create two-way communications and connect with their customers, market their products and services, and build their online brand community (e.g., Aral, Dellarocas, and Godes 2013; Goh, Heng, and Lin 2013).

Brand community has been widely recognized of its significant role in achieving organizational benefits (e.g., McAlochler, Schouten, and Koenig 2002; Muniz and O’Guinn 2001; Schau, Munitz, and Arnould 2009). These include learning customer perceptions of product offerings, influencing community members’ evaluations and actions, gaining and enhancing customer loyalty, increasing market efficiency, etc. To take advantage of the capabilities of both social
media and brand community, organizations have started using social networking sites to support the creation and development of Social Media based Brand Communities (SMBCs) (Fournier and Lee 2009; Goh et al. 2013; Kaplan and Haenlein 2010; Park and Kim 2014). Recent studies suggest that consumers are becoming pivotal in engaging in the conversations between firms and consumers and among consumers themselves in the SMBCs (Gensler et al. 2013; Habibi, Laroche, and Richard 2014; Hollebeek, Glynn, and Brodie 2014). Such conversations enable consumers to integrate their own brand-related experiences and thoughts into the process of brand community building. Traditionally, firms have most control on their marketing messages and brand management. However, in the current digital era, consumers are now more empowered than ever before to create and share their own brand stories through posting, commenting, and sharing activities on the social media (Fournier and Lee 2009; Hoffman and Fodor 2010). These consumer-generated contents can be instantly passed onto thousands of other online users through consumers’ social networks. As Scott Cook, the co-founder of Intuit, emphasizes: “A brand is no longer what we tell the consumer it is – it is what consumers tell each other it is.”

Despite the recognition of the significant role that consumers may play in building SMBCs, it is yet to understand the dynamic effects of consumers’ actual participating activities on the building of brand community. Indeed, while the number of organizations jumping on the “social media bandwagon” is continuously growing, the measurement of various social media effects is an increasing concern for various organizations (Hoffman and Fodor 2010; Larson and Watson 2011). Intuitively, the more fans join and participate in an organization’s social media brand community, the better organizational outcome it is expected to be conducive to (Goh et al. 2013). Especially, with the Word-of-Mouth effect in the context of social media, a faster growth of online brand community in terms of fan base may signal and eventually drive a future growth in firm’s sales revenue (Chevalier & Mayzlin 2006; Liu 2006; Stephen & Galak 2012). Anecdotal evidence has been reported regarding the significant role that consumer fans may play in building and growing social media brand community (Fournier and Lee 2009; Hoffman & Fodor 2010). Yet, it remains systematically unclear about how consumer engagement reflected in their actual participating activities may speed up or slow down the building of a social media brand community over time.

Therefore, in this study, we aim to shed light on the dynamic effects of the user participation measured by commenting, sharing, liking activities among consumers. In particular, this study seeks to address the following questions: Is there a significant relationship between users’ participating activities and the growth rate of SMBCs in terms of size? If so, what are the dynamics of the relationship between them?

THEORETICAL BACKGROUND

Traditional view on the roles and relationships of the firm and the customer considers the customer as exogenous to the firm and as passive recipient of the firm’s active value creation efforts (Deshpande 1983). However, recent years have seen the emergence of a different perspective - Customers can co-create value and even become endogenous to the firm (Schau et al. 2009). In this new shift, brand communities have been considered as taking the role of a catalyst for co-creation. They allow sharing of essential resources such as information and experiences; strengthening the cultural norms and values of the brand (Muniz and O’Guinn 2001), and shaping the dynamic relationships of consumer-consumer and of consumer-brand (McAlexander et al. 2002). The potential benefits of having a strong online brand community...
have been widely recognized (e.g., Fournier and Lee 2009; Laroche et al. 2012). For example, it builds customer loyalty, lowers marketing costs, enhances brand images, and attracts new customers to grow the business (Gensler et al. 2013; Schau et al. 2009).

As creation and sharing of contents being a hallmark of social media platform, social media has enabled and facilitated the realizations of the most important aspect of brand community – creation and sharing of meanings. Thus, the intersection of the two – social media based brand community (SMBC) - would be an ideal environment for creating and sharing of contents, meaning, and values (Habibi et al. 2014). In this context, consumers are empowered to create and share their own brand stories through posting, commenting, and sharing activities. When these consumer-generated contents are shared and passed on through consumers’ online social networks, it becomes a form of Electronic Word-of-Mouth (E-WOM) (Godes and Mayzlin 2004).

It has been argued that social media and subsequently social media based brand community may be an effective vehicle for credible WOM (Chevalier and Mayzlin 2006; Fournier and Lee 2009; Liu 2006). Once consumers are aware and engaged, they are in a good position to communicate their opinions to others. Satisfied and loyal customers communicate their positive attitudes toward the brand itself and its products to prospective customers both online and offline (Anderson 1998; Hoffman and Fodor 2010). It appears that the positive impacts can be associated with the effects of E-WoM that online brand community generates. Recent research has shown such positive effects of E-WoM as shaping consumers’ brand perceptions, acquiring new clients, and boosting sales (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Kazienko et al. 2013; Liu 2006; Sonnier et al. 2011; Stephen and Galak 2012). The E-WoM derived from consumers’ commenting, sharing, and liking activities in a firm’s SMBC would expand the reach to new prospects that may then join the firm’s brand community.

One of the motivations for consumers to join online brand communities on social media is to support their favourite brand (Habibi et al. 2014; Park and Kim 2014). According to Fournier and Lee (2009), people are more interested in social links that come from brand affiliations than in the brands themselves. By posting comments as well as sharing and liking the posts in social media based brand communities, the participants are essentially enhance and expand their social connections. It has been recognized that social interactions should be categorized by the associated level of engagement, for example, a ‘comment’ or a ‘share’ has more value than a ‘like’. Such “engagement” levels share certain similarity to what marketing research predicts for theoretically derived involvement aspects that drive consumer actions (Peters et al. 2013; Arora 1982). Along these lines, we posit the following: Users’ participating activities measured by comments, shares, and likes have a predictive relationship with the growth rate of SMBCs in terms of size; among these metrics, there is predictive effect differential.

Further, prior literature has demonstrated the dynamics of responses to online user-generated contents in such contexts as firm sales and stock prices (e.g., Sonnier et al. 2011; Tirunillai and Tellis 2012). In particular, Tirunillai and Tellis (2012) show that user reviews are related to stock returns with wear-in effect, which is defined as how much time it takes before the stock market response to user reviews reaches the peak. A shorter wear-in effect means a faster predictive value, which indicates the urgency of the predictive relationships. In the case of brand communities, when a user makes a comment or likes a post, it might take days or weeks to see their impacts on attracting new prospects. It might also take various time periods for new prospects to act on the information received, for instance, by joining a brand community. In others words, it is expected that there is a dynamics in user participation and its effects. In our
case, we expect that there is dynamics in the predictive relationships between different metrics measuring user participation and the continuous growth rate of SMBCs.

RESEARCH CONTEXT AND METHODOLOGY

Research Context

As mentioned earlier, we collected the data from Facebook-based brand communities for this study. We selected firms, products, and markets on several criteria to ensure the feasibility, validity, and reliability of the study. First, the sampled markets should represent a cross section of markets. Our sampling frame consists of an array of eight brand communities across diverse sections of product categories and markets: Automobile (Jeep, Mini Cooper), Computers and Electronics (Oracle, Sony), Footwear and Apparel (Nike, New Balance), and Toys and Games (Mattel, LeapFrog). Second, the product categories must have rich data in terms of users’ comments, shares, and likes over the time period of investigation. Following the definitions in prior literature (Goh et al. 2013), posts are initial postings from the firms (or marketers) whereas comments are follow-ups to posts. For each post, we focus on the number of comments as well as shares and likes generated from individual consumers or users, not marketers. Our data sample period spans from July 3, 2012 to December 15, 2013 for the analysis. Third, prior research suggests that the higher levels of aggregation of temporal data (e.g., monthly or quarterly) may lead to biased estimate (Tellis and Franses 2006), whereas lower levels of aggregation (hourly or daily) may result in sparse data (Tirunillai and Tellis 2012). In addition, taking into consideration that it may take a few days for a user to respond to the shared comments in an online community, we chose the weekly level of analysis.

User generated comments on social media can be characterized by several metrics. In particular, the number of comments, the number of shares, and the number of likes have been considered as the most relevant metrics for measuring the effectiveness of social media efforts (e.g., Hoffman and Fodor 2010; Liu 2006). Because the user generated contents such as comments, shares, and likes on the social media platforms are not efficient to collect or process manually, we resort to automated techniques for data collection and analysis. We employed a custom software agent using API to collect the number of comments, shares, and likes from their Facebook-based brand community pages of the sample firms. The technique of crawling webpages with an automated software agent from public websites has been used in the prior literature (e.g., Luo et al. 2013; Sonnier, McAlister, and Rutz 2011).

For each firm, the above data collecting process yielded the following data on a weekly basis: the number of comments, the number of shares, and the number of likes. In addition, the number of page likes is also counted, which is used as a proxy to calculate the weekly growth rate of the community size. Following the literature on measuring the effects of user generated contents (Sonnier, McAlister, and Rutz 2011; Tirunillai and Tellis 2012), we control for exogenous variables: advertising, new product announcements, and media citations.

Empirical Model

In order to examine the dynamic effects of users’ commenting and sharing activities on the growth rate of SMBCs over time, we turn to a time series technique called vector-autoregressive model with exogenous covariates (VARX) (Dekimpe and Hanssens 1999; Lütkepohl and Krätzig 2004; Adomavicius, Bockstedt, and Gupta 2012). VARX has several advantages over other time
series models. VARX is suitable for our study for several reasons. First, it allows us to examine the immediate, short-term as well as the long-term, cumulative effects of commenting activities on building an engaging community. Second, it accounts for biases such as endogeneity, serial correlation, and reverse causality. The endogenous treatment in VARX model implies that it captures both carry-over effects (explained by the past of a variable itself) and cross effects (explained by the past of each other). Third, it allows us to account for direct and indirect feedback effects, i.e., it can model complex chained effect in a complete cycle - feedback loop. The general reduced-form VARX model with lag order \( k \) is:

\[
Y_t = \alpha + \delta_t + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_k Y_{t-k} + \epsilon_t,
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where \( Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})' \) denotes an \((n \times 1)\) vector of time series variables, \( \alpha \) is an \((n \times 1)\) vector of constant terms, \( \delta_t \) is \((n \times 1)\) vector of coefficients, \( A_k \) is an \((n \times n)\) coefficient matrices, and \( \epsilon_t \) is an \((n \times 1)\) vector of disturbances that have zero mean and are serially uncorrelated.

We are specifically interested in the predictive relationships between the number of comments by the individual users (short as Comts), the number of shares (Shares), the number of likes (Likes), the combined number of comments and shares (ComtsShares), the combined number of comments and likes (ComtsLikes), the combined number of shares and likes (SharesLikes), the combined total number of all three metrics (UserTotal), and the growth rate in terms of community size (CommRate). Therefore, it is natural for us to choose these five variables (i.e. the corresponding time series) to make up the VARX system.

The underlying rationale for determining the appropriate lag order \( k \) of a VARX model is to choose the lag length so that it maximizes the fit between the observed time series and the estimated predicted process (Lütkepohl and Krätzig 2004). Two commonly used measures for selecting lag order are Bayesian Information Criterion (SIC) and Final Prediction Error (FPE). In the specification of our VARX model with the four time series in our data set, the SIC and FPE agreed that the optimal lag length was four.

The estimates of VARX regression coefficients typically are not as informative as analyzing relationships among variables because of complicated dynamics inherent in VARX model (Dekimpe and Hanssens 1999; Lütkepohl and Krätzig 2004). Instead, Granger-causality tests, impulse response functions, and generalized forecast error variance decompositions are used in the analysis (Adomavicius et al. 2012). In particular, we conduct the Granger-causality tests to test for the presence and direction of a causal relationship between each metric of commenting and sharing activities and the growth rate of brand community. Then, in order to model the dynamics (i.e., the short-term and long-term or accumulated relationships) in the VARX system, we resort to the impulse response function. This is because it is not sensitive to the causal ordering of the variable entering the system. Further, the relative impact of the metrics of user commenting and sharing on the growth rate of community is assessed by using generalized forecast error variance decompositions. We provide the preliminary results of the analysis and discussion in the next section.

**PRELIMINARY RESULTS AND DISCUSSION**

We conducted the initial tests for Granger causality, the impulse response functions, and generalized forecast error variance decompositions respectively. Overall, the preliminary results suggest that, while sharing or commenting alone is not a significant indicator of the growth rate of brand communities, the combined sharing and commenting activities by consumers have significant predictive relationship with the growth rate of brand communities. In addition, sharing
is found to have relatively stronger and faster predictive relationship with the growth rate of brand community, followed by commenting and liking.

This study informs managers in several aspects. First, social media brand community provides a public platform for firms to enable their customers engage in various activities. Through various engaging activities such as making comments, sharing posts, liking a page, etc., customers often send out powerful messages and feedback about their experiences and opinions to firms as well as to other consumers. Our findings on the predictive relationships between some of consumer engaging activities and the growth rate of their fan base in brand community provide supporting evidence that, in order to further grow their fan base at a fast pace, managers should leverage their social media brand community to foster customers participation and positive interactions (Verhoef et al. 2010). This will eventually lead to the new way of nurturing and sustaining their customer base (Gruca and Rego 2005), which, in turn, is related to looking beyond the traditional approach in measuring and managing customer value in today’s social media age.

The measurement and management of customer value has traditionally focused on purchase behavior, i.e., increasing customers’ spending with a company over time (e.g., Kumar 2007; Reinartz et al. 2004). Nevertheless, it has come to realization that long-term and sustainable competitive advantage is tightly associated with a firm’s ability to attract, retain, and nurture its customer base (Gruca and Rego 2005). In today’s digital era, nurturing and sustaining customer base demands firms to look beyond transactional purchase behavior alone. In this regard, social media based brand community offers a great tool and new opportunities for firms to do so.

Second, our study reveals the differential effects of different types of consumer feedback. Through monitoring consumer feedback occurring in firms’ social media brand community, managers can take proactive actions to respond to consumer requests and address their concerns. This will increase customer satisfaction and reduce customer churn. Prior studies indicate that a minor increase in customer satisfaction can lead to a major increase in a firm’s overall value (Anderson et al. 2004). Also, it has been suggested that consumers who actively participate and engage in the brand community are willing to pay higher prices for the brand (Laroche et al. 2012; Park and Kim 2014). Thus, timely and appropriate actions from managers may potentially impact firms’ financial performance in the long run. Further, while firms are building their social media based brand communities, firms should act as observers as well as moderators (Godes et al. 2005). Specifically, firms may want to go a step further by actively stimulating and promoting positive consumer-generated brand-related contents.

Third, firms should be aware of the important dynamics that affect the opinions that customers post about products. The decision to express an opinion may be influenced by other posters and the sentiment of their previously posted views. However, negative feedback does not necessarily mean that a firm’s brand or product is uniformly disliked despite some adverse effects in the short term. A careful analysis of the dynamics can help identify when a firm should take actions to address an issue raised by a negative feedback (Moe, Schweidel, and Trusov 2011). In this study, we have looked into dynamic relationships by examining wear-in effects. In particular, a shorter wear-in effect means a faster predictive value, which indicates the urgency of the predictive relationships. Therefore, the wear-in time period is useful for managers to adjust their social media strategies in a timely manner.
The findings, however, should be interpreted within limitations of the empirical data analysis. With respect to external validity and generalizability, it should be noted that the adoption of social media based brand community was still in its evolving stage during the examination window (2012-2013). Whether its effects found in this study extend beyond this period is a question that future research may explore. Also, the sample represent U.S.-based firms, thus it would be interesting to test the impacts of social media in other types of organizations and in other regions/countries.

In this study, we have only considered the volume of consumer sharing and commenting. It would also be interesting to take into account the valence of comments such as whether the overall comment is positive or negative. While most research on consumers-generated contents in social media have primarily focused on the valence of positive and negative, Sonnier et al. (2011) recently suggest that, in addition to positive and negative online communications, neutral ones also have significant effect on firms’ daily sales performance. Hence, further research on clarifying the role of the valence of comments is needed.

REFERENCES
References available upon request.